An Economic Framework for Modeling Mail Processing Costs

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By

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I. Introduction

This paper provides an empirical framework for estimating the marginal cost of processing letters and flats in USPS Processing and Distribution Centers using the data on workhours and mail volumes collected by the USPS as part of the Management Operating Data System (MODS). It extends the model developed in an earlier paper "An Empirical Model of Labor Demand for Mail Sorting Operations" that I prepared for the Office of the Consumer Advocate of the Postal Rate Commission in May 2002 (hereafter, Roberts (2002)). That paper shows how to estimate the relationship between the number of labor hours used in letter and flat sorting operations and the volume of letters and flats sorted. Estimates of the volume variability of labor use have been an important component of the USPS methodology for attributing mail processing costs in all recent rate cases and Roberts (2002) provides an alternative way to use the MODS data to estimate this relationship.

This paper generalizes the earlier framework to recognize that not all pieces of mail receive the same degree of sorting within the plant so that labor use will depend on the levels of preparation by mailers and the final depth of sorting at which the mail is dispatched from the plant. This paper shows how to incorporate different categories of mail, which are defined based on the amount of processing they require, into the model of labor demand. The marginal cost of processing an additional piece of mail may now differ across these categories. To examine the feasibility of this approach, the MODS data is used to separately measure the mail flow that is sorted in the outgoing operations versus the incoming operations in each plant. This is one important dimension in which the degree of sorting differs. The empirical model is estimated distinguishing these two categories of output and the implications for labor use of an increase in each output is measured. Overall, the estimated model parameters indicate that a one percent expansion of the volume of letters in both the incoming and outgoing categories, which represents a one percent increase in the plant's total output of sorted letters, results in a one percent increase in total labor usage in letter-sorting operations. For flats, a one percent increase in the volume of flats in both categories results in a 0.7 percent increase in total labor usage in flat sorting operations.

The framework applied in this paper and in Roberts (2002) differs in some important ways from the methodology that the USPS has used, most recently in Docket No. R2005-1, USPS-T-12, to estimate labor demand equations. A second goal of this paper is to put the economic models underlying each methodology on a common footing so that the reasons for the differences can be understood and the models can be compared. This comparison reveals that the two frameworks differ in the way that input substitution, specifically substitution between different sorting operations, is treated. The USPS framework is built on a production model that is restrictive and cannot accurately capture the effect of substitution of automated equipment for manual processing, which is the major change in mail processing technology over time. I also show that the USPS estimates of the volume variability, the elasticity of labor demand with respect to total pieces fed, in each sorting operation can be interpreted as the correlation between the capital and labor input used in the sorting operation and not, as desired, the correlation between mail volume and labor input.

The final section of this paper suggests a number of ways in which data construction, and the theoretical and empirical models can be improved in order to estimate labor demand equations and, ultimately, the marginal cost of processing different shapes and categories of mail.

II. A General Model of Production and Input Demand in Mail Sorting Operations

The model developed in the remainder of this paper is inherently a simplification of the production process in P & DC facilities, but it is designed to capture the important elements of the mail sorting technology. It recognizes the use of a mix of manual and automated operations which are sometimes substitutes for one another and other times complements. It provides a clear definition of the output of the processing plant, which can be measured and compared across plants and is not dependent on the type of automated processing equipment or the intensity with which it is used in the plant. It recognizes the importance of mail shape in the cost of processing and can provides estimates of the marginal processing cost for each shape of mail. Finally, it also provides a basis for measuring both the change in labor and capital usage resulting from a change in mail volume in the plant.

Each mail processing plant is treated as receiving unsorted or partially sorted letters, flats, and parcels and then using various types of labor inputs, measured as hours in different sorting activities, and capital services, measured as the number of hours that different types of sorting machinery are operated, to produce an output of letter, flats, and parcels that are more finely sorted than when they arrived .

II.A Separability by Shape of Mail

The nature of the production process allows us to impose some structure on the model of production. Plants sort the three shapes of mail in entirely different ways using different machinery and in different locations in the plant. This implies that a useful and accurate simplification is to view the plant as a combination of three production processes, one for each shape of mail. This assumption, known as a separability assumption, implies that changes in the technology of sorting one shape of mail have no implications for the input use of the other shapes. For example, the introduction of the AFSM technology into a plant will not affect the sorting of letters. To simplify the discussion in the remainder of this section I will develop the economic model for letter sorting only but the framework can be applied directly to flat or parcel sorting.[1]

II.B Heterogeneity in Arriving and Destinating Mail

In Roberts (2002) the output of the letter-sorting operation is the *number of sorted letters* produced in the plant. The goal of the plant is to convert L unsorted letters into L sorted letters and thus L is the measure of output produced in the plant. This corresponds to the volume of letters received for processing in the plant. This definition of output can be further refined by recognizing that not all letters receive the same amount of sorting in the plant. The arriving mail stream in a plant is a heterogenous mix of unsorted and presorted mail and the destinating mail stream is a heterogeneous mix of mail sorted to different final levels. To simplify this heterogeneity in developing the general model, I will treat the plant as producing two different outputs. The first output will be the *number of letters* receiving an "initial" sort and be denoted L_I. The second output will be the *number of letters* receiving a "final" sort and be denoted L_F. In

[1] Not all processing steps in a plant are separable by shape. The operations dealing with the movement of mail into or out of the plant (platform, dispatch, opening, pouching) or cancellation will handle more than one shape. The labor input in these operations should be modeled as a function of the volume of all shapes of mail. In a comprehensive model of the processing plant these operations should be included as additional processing steps along with the separable letter, flat, and parcel operations and their costs should contribute to the marginal cost of each shape of mail.

the initial sort, the plant receives unsorted mail from the public and processes it partially, for example, to the 3-digit zip code level. Thus the first output L_I is the number of pieces receiving this level of processing. In the final sort, the plant takes partially-sorted letters and processes them to a finer zip code level and then dispatches them to local post offices. The second output L_F is the number of pieces receiving this type of processing. The plant produces the bundle of outputs (L_I, L_F) and the total number of letters handled in the plant is $L_I + L_F$.[2]

The difference between the initial and final sorting operation is the depth of sorting performed in each step. In the initial operation, the number of sorted destinations could be relatively small and be able to be accomplished in one pass on automated bar-code sorting equipment. The initial operation will also be the stage where a bar code is attached to any mail that does not have one. In the final-sorting operation all arriving mail will already be bar-coded so that step in the processing flow is avoided. The level of sorting conducted at this stage could also be more extensive, requiring multiple passes on automated sorting equipment to reach the final level at which it is dispatched. The important distinction is that the two types of arriving mail will go through different processing steps and require different quantities of inputs to reach the level at which they are dispatched. Rather than treating every letter as receiving an identical amount of

[2] It is simple to generalize this to more than two categories of output, but all of the important conceptual issues can be illustrated with two categories. One way to think of the two different outputs is that they correspond to the number of letters receiving an outgoing sortation in the plant and the number of letters receiving an incoming sortation. These can be further subdivided into more categories with different levels of preparation (i.e. presorting and barcoding) in the initial sort and dispatched at different levels (i.e. carrier route or DPS level) after the final sort. The output of the plant will now consist of more processing categories, but in each category the output will be the number of letters receiving that category of processing. The total number of letters processed in the plant, $L_I + L_F$, will always stay the same but just be distributed across a larger number of output categories.

processing, I will distinguish categories of letters that require different amounts of processing in the plant.

Assuming that mail processing technology is separable by shape and that the heterogeneity in arriving and destinating mail sortation can be represented by two categories, is obviously a simplification of the characteristics of the mail stream handled by a plant, but captures the important distinctions that are necessary for production modeling.

II.C The Production Model for Letter Sorting

Focusing on the process for sorting letters, we can view the plant as consisting of a stock of specialized capital equipment used to sort letters (i.e. bar code sorting machines and optical character readers). This capital stock is denoted as K_L. The plant receives the flows of letters L_I and L_F from outside the plant. The sorting of L_I and L_F is done using three inputs: manhours running the automated/mechanized machinery, denoted A_L , manhours in manual operations, denoted $M_{L,}$ and capital equipment, K_L.[3] The L subscript denotes that these inputs are all devoted to the sorting of letters. Notice that A and M both represent manhours of labor, but in different letter-sorting activities.

Given this description of the production process for letter sorting, the transformation

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[3] At this point we are aggregating all machinery used to sort letters into a single capital input. This is just to simplify the theoretical model. K_L can be viewed as a vector of different types of capital equipment. In the empirical model used by Roberts (2002) letter-sorting capital was disaggregated into five distinct types. Similarly, there can be multiple types of automated labor or manual labor. All the important distinctions for the empirical model can be made with this simplified framework that recognizes one type of capital, labor in automated/mechanized operations, and labor in manual operations. Again, for simplicity, we will refer to all sorting operations other than manual as automated operations.

function for sorted letters can be written implicitly as: $L(A_L, M_L, K_L, L_I, L_F) = 0$. The constraints on the manager's input choices are the output levels L_I and L_F and the capital stock K_L.[4] The plant manager chooses the staffing pattern and utilization of the equipment to minimize the plant's expenditure on labor. That is, the manager chooses the number of manhours A_L and M_L to minimize the plant's total expenditure on labor. When the manager chooses these labor inputs he or she is implicitly deciding how to allocate the sorting of each shape of mail between manual and automated operations.

This description of the plant's technology and choice problem results in a cost function for letter sorting that takes the form: $C_L(K_L, L_I, L_F, WA_L/WM_L)$. C_L is the total expenditure on all labor in all letter sorting operations, manual and automated. This cost function depends on the capital input used in that shape, the total amount of sorted output in both the outgoing and incoming operations, and the relative price of labor in automated and manual (*WA/WM*) operations. The model implies two labor demand functions for letter sorting: manhours in manual operations, manhours in automated operations. Specifically, the two input demand functions for letter sorting are:

	manhours in automated/mechanized operations	$A_L(WA_L/WM_L, K_L, L_I, L_F)$
(1)	manhours in manual operations	$M_L(WA_L/WM_L, K_L, L_I, L_F)$

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[4] Given that the capital stocks are in place in the plant, we treat the cost of a machine hour as zero. A more general approach would recognize that use of the capital stock might lead to both physical depreciation and a need for maintenance and repair expenses to keep it running efficiently. These would represent costs of a machine hour that should be taken into account when minimizing the total expenditure on inputs. However, we will not be able to measure these costs in the data and, since expenditure on these items is likely to be small relative to the expenditure on labor hours, we will treat the plant as minimizing the total expenditure on labor.

The same arguments can be used to derive labor demand equations for inputs used in flat and parcel sorting.[5] These labor demand equations embody one minor extension of the framework in Roberts (2002). They recognize that the plant produces multiple outputs, represented as a number of letters in the inital and final operations, and that the level and mix of the outputs will affect input use. A plant with a higher proportion of its mail stream in the initial operation will tend to use a different mix of labor and capital inputs than a plant with a high proportion of its mail stream in the final operation, because there are differences in the steps used and in the depth of the final sorting. In Roberts (2002), the initial and final sort processes are treated as identical so that only the total number of letters $L = L_I + L_F$ entered the labor demand equations. This has now been extended so that the number of letters in the initial and final processes can each have a different effect on input use.

II.D The Marginal Cost of a Letter

The ultimate goal of the model of production is to estimate the marginal cost of an additional piece of mail. In this section I describe how the labor demand equations in (1) can be used to estimate the marginal cost of a letter-shaped piece of mail. To simplify the derivation, view the plant as having a single output type so that the output of the plant is the number of sorted letters L.[6] The cost of processing the letter-shaped mail C^L is the sum of the expenditure on manual and automated labor:

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[5] Since the production function is separable by shape of mail, only the capital, outputs, and wages relevant to the shape of mail will enter the input demand functions for that shape.

[6] When there are multiple outputs the same steps can be used to derive the marginal cost of each output L_I and L_F.

(2)

$$C^L(WM_L / WA_L, K_L, L) = WM_L * M_L(WM_L / WA_L, K_L, L) + WA_L * A_L(WM_L / WA_L, K_L, L)$$

It is a function of the same arguments as the labor demand functions A_L and M_L, the relative price of the two types of labor, the capital stock in letter sorting, and the output of sorted letters.

The marginal cost of an additional letter is defined as the derivative of C^L with respect to output L:

(3) $$\frac{\partial C^L}{\partial L} = WM_L\left(\frac{\partial M_L}{\partial L}\right) + WA_L\left(\frac{\partial A_L}{\partial L}\right)$$

It is a weighted sum of the derivatives of the labor demand equations with respect to output. The weights are the wage rates of each type of labor. This can be rewritten in elasticity form. Define the elasticities of manual and automated labor demand with respect to output as:

$$\eta_M = \left(\frac{\partial \ln M_L}{\partial \ln L}\right) \text{ and } \eta_A = \left(\frac{\partial \ln A_L}{\partial \ln L}\right).$$

Marginal cost can then be rewritten as a weighted sum of the two output elasticities:

(4) $$\frac{\partial C^L}{\partial L} = \left(\frac{WM_L * M_L}{L}\right)\eta_M + \left(\frac{WA_L * A_L}{L}\right)\eta_A$$

Defining $\theta_M = (WM_L*M)/C^L$, the share of expenditure on manual labor in total letter processing costs, and $\theta_A = (WA_L*A)/C^L$, the cost share for automated labor, and multiplying the right-hand side of equation (4) by C^L / C^L gives the final equation for marginal cost:

(5) $$\frac{\partial C^L}{\partial L} = (\frac{C^L}{L})(\theta_M \eta_M + \theta_A \eta_A) .$$

This equation says that the marginal cost of a letter-shaped piece of mail is the average cost multiplied by the cost-share weighted sum of the output elasticities for the two types of labor input. The cost shares θ_M and θ_A sum to one. If the two output elasticities are each one, implying a proportional increase in output leads to an equal proportional increase in both labor inputs, then the marginal cost of a letter is equal to the average cost of a letter. If the output elasticities are less than one, then there are scale economies in letter processing and the marginal cost of a letter will be less than the average cost.[7]

Formula (5) can be used to measure the marginal cost of a letter. The average cost *(C^L/L)* can be measured by dividing the sum of the expenditure on labor in manual and automated sorting by the volume of letters. The cost shares θ_M and θ_A can be measured using the expenditures on each of the two categories of labor. All of these variables could be measured at the plant level using the MODS data or could be constructed at the aggregate cost pool level using data summed

[7] This equation can be compared to the method used by the USPS to measure unit volume variable cost in sorting operation *j.* (R2005-1, USPS-T-12, p.18-22). The average cost *(C^L/L)* multiplied by θ_M is the expenditure in a cost pool (i.e. manual labor) divided by letter volume. It is multiplied by the variability of labor demand in the cost pool with respect to output. This is what the USPS methodology refers to as unit-volume variable cost for this manual cost pool. Marginal cost is the sum of the unit-volume variable costs over the two input cost pools. This formula does not make any attempt to distribute the marginal cost across classes of mail as the formulas in USPS-T-12 do. In this paper the issues arising from defining marginal cost will be kept separate from the issues related to distributing the costs across mail classes. In fact we will develop the formulas as if there was only a single rate class of mail and this will isolate the assumptions being made about the production technology. It is also important to note that the output elasticities in equation 4 are defined with respect to the volume of letters in the plant *(L)* and not with respect to a separate "cost driver" in each operation. This difference is discussed in section III below.

over all processing plants. The output elasticities η_M and η_A can be constructed from econometric estimation of the labor demand equations for A_L and M_L and that is the focus of the empirical modeling in Roberts (2002).

This formula for marginal cost can also be extended to the case where the plant produces the two outputs, L_I and L_F. In this case the marginal cost of L_I can be defined using equation (5) by replacing L with L_I and defining the labor demand elasticities with respect to a change in L_I. Similarly for L_F. Each of these would measure the change in mail processing cost resulting from a change in the amount of one output, holding the other output fixed. The cost effect of an expansion of both outputs would be measured by summing the marginal cost of L_I and the marginal cost of L_F.

II.E Extending the Framework to Multiple Technologies and Additional Outputs.

The labor demand equations in (1) are stylized, allowing only one kind of automated input and two categories of output. It is simple to extend the framework further to include more than one automated operation. There will now be a separate labor demand function for manhours in each automated operation (OCR, MPBCS, and DBCS in the case of letter sorting). Most importantly, *the capital stock for every automated operation will enter every input demand function*. This allows, for example, an increase in DBCS capital stock in the plant to increase the demand for labor hours in the DBCS operation, since they are complementary inputs, but decrease the manhours in MPBCS, since that is a substitute input. This type of input substitution, where automated operations replace manual and are then replaced by newer generations of automation, is an important feature of mail processing over the last decade. It is important that a model of production in mail processing plants be able to capture this substitution and the model outlined in section II.C does this.

The extension to more than two outputs is also simple. The categories over which output is defined can be expanded to recognize that there are different levels of mailer preparation and different depths of sort for the dispatched mail. An output "type" or category would be defined as a combination of a level of preparation and a level of dispatch. For example, the letters processed in the outgoing mail operation could be divided into two categories based on their characteristics when they arrive at the plant: unsorted and presorted. Letters processed in the incoming mail operation could be divided into two output categories based on the depth of final sorting: DPS level and non-DPS level (5 digit zip code level). This would give a total of four output categories in the plant. In each case, *the level of output of one type would be the number of pieces of mail of that type*. The sum of the outputs across the four types would always equal the total pieces of mail processed in the plant. By defining the output types more narrowly, the researcher is more finely controlling for the heterogeneity of the mail stream, but the total number of pieces of mail processed does not change as the level of aggregation changes. In practice, defining the output types will require, as all production modeling does, a tradeoff between the realism and accuracy of simplifying assumptions and the variables that can be measured and number of parameters estimated with a given data set.

III. A Comparison With the USPS Methodology

The model of production presented by the USPS in R2005-1, USPS-T-12 is a refinement of a basic model of labor demand that has been presented in rate cases since 1997. The current version adopts several aspects of the model in Roberts (2002) but does not incorporate all aspects of that framework. The current testimony differs from R2001-1, USPS-T-12 in several ways. The labor demand equations include the relative wage rate of labor in automated versus manual operations, they drop the “manual ratio” variable (the fraction of piece handlings of a given shape that are done in the manual cost pool) which was present in many earlier versions of this model, and they include a more disaggregated set of capital variables (although the disaggregation is still insufficient). The current testimony also adopts the instrumental variables estimator utilized by Roberts (2002) to handle problems of simultaneity and measurement error, although it only uses the IV methods in the manual, but not automated, operations. Despite these improvements, several specification problems remain. In this section I will first provide an overview of the USPS approach and then discuss the differences and implications.

One difficulty in comparing the methodology utilized in the USPS testimony with the framework developed in section II of this paper is that, while discussed in general terms as a separable production process, the model of plant production that gives rise to the specific labor demand equations estimated in USPS-T-12 is never explicitly developed. It is also complicated by the fact that the methodology used is both measuring marginal cost (implicitly) and allocating it across rate classes of mail at the same time, so that the assumptions made about the technology (cost drivers) and the assumptions made to allocate costs across rate classes (the distribution key) are intertwined (USPS-T-12, section II.A.5). In this section I will focus on the assumptions underlying the form of the labor demand equations independently of the issue of how to allocate costs across rate classes. The formulas will be the relevant ones if there was just a single rate class for letter-shaped mail. This is a useful way to simplify the model since it allows us to highlight the assumptions about the technology and their implications. What follows is my attempt to formalize the model that underlies the USPS testimony in terms of the stylized model of production in section II.C. By doing this the reasons that the models differ can be identified. While I believe this formulation is consistent with their framework, it is based on my interpretation of the verbal descriptions offered in the USPS testimony. If it is not accurate, it would be very helpful if the USPS could provide a representation of their model which is consistent with the general framework developed in section II.C.

The basic idea underlying the USPS framework is that mail processing consists of a number of distinct, independent steps that can be modeled and examined in isolation from the other processing steps in the plant (R2005-1, OCA/USPS-T12-4-5). In addition, each processing step has a "cost driver" that is *unique to that operation*. It's possible to make some progress in relating this production framework to the model developed in section II. As in section II, begin by assuming that the production process for letter sorting depends on one manual labor input (M_L) and one automated operation, that itself depends on two inputs: labor (A_L) and capital (K_L). The USPS framework now assumes that each sorting operation can be viewed as a stand-alone production process. In terms of our stylized model this implies that capital and labor in automation can be aggregated into a distinct automation production step. Under this assumption, the production function for letter sorting can then be written as:

(6) Assumption 1 (Separability): $L = L(\, M(M_L),\, A(A_L\,,\, K_L)).$

This implies that the production function is separable into two aggregate inputs, a manual input (M) and an automation input (A). Each of these aggregates is produced by combining a more disaggregated group of inputs that are specific to each operation. For example, the manhours and capital stock in the automated operation A_L, and K_L, are combined into the aggregate automation input *A*. This form restricts the substitution patterns among the inputs, specifically, it implies that the marginal rate of substitution between labor and capital in automation is not affected by the amount of manual labor used. The model implies that there are two layers of input substitution possible for the plant. In producing total output *L*, the plant can substitute between *M* and *A*, varying the mix of these aggregated manual and automated inputs. The plant can then substitute between the disaggregated inputs within each aggregate (for example, A_L and K_L) to produce the desired level of the aggregate *(A).* The cost function associated with this production function has the form:

$$C = (C^M (WM_L , L), C^A (WA_L , K_L , L)). \tag{7}$$

The cost function can be divided into separate components, one for costs in the manual labor pool and one for costs in the automated labor pool. The manual labor cost pool will depend only on the level of output and the price of manual labor. The automated labor cost pool will depend on the level of output, price of automated labor, and the capital stock in the automated operation. Finally, the labor demand equations for the two types of labor have the form:

(8) manhours in automated operations $A_L (WA_L, K_L , L)$

manhours in manual operations $M_L (WM_L, L)$

Notice that the labor demand equation for manual hours does not depend on the level of capital in automation. If the production function is separable into distinct manual and automated steps, as assumed in (6), then the level of the capital stock determines the level of the labor in the automated operation, but not the level of manual labor.[8] In general, if the production function is separable into multiple stages (i.e. OCR, MPBCS, DBCS, and manual) then the labor demand in each stage is determined only by the level of plant output L and the capital stock *in the same stage*. For example, the capital stock in DBCS will determine the labor demand in the DBCS operation but not in any other operation. The labor demand equations under the separability assumption (8) are different than the labor demand equations derived in the more general model in section II.C, equation (1). They are also more restrictive. In the model from section II.C, the capital stock in every sorting operation will enter as an argument in every labor demand equation and that reflects the more general pattern of input substitution allowed in that model.[9] In Roberts (2002), the capital stocks in one sorting operation were often significant determinants of labor use in other operations.

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[8] There is also just a single factor price in each labor demand equation. This follows from the fact that there is only a single variable input (labor) in each of the separable production stages, manual and automated. With only a single variable input, there is no role for the factor price to explain variation in input use and the factor prices could be dropped from these equations (input demands are homogeneous of degree zero in factor prices). Labor use in manual operations will be determined only by the level of output, and labor use in automated operations will be determined only by output and the capital stock. If there were two or more variable inputs in a production stage, then the relative prices of the inputs would determine labor demand reflecting substitution between the variable inputs. In the model in section II.C, both automated and manual labor are variable and so the relative price of the two types of labor (WA_L/WM_L) enters into both labor demand functions, equation (1).

[9] An analogy that can help illustrate the implication of separability assumptions is drawn from the production of a car. Suppose a car is composed of one engine, one body, and four tires. The production processes for engines, bodies, and tires are separable. That means, for example, that any change in factor prices, capital stocks, or technology for producing engines has no effect on the inputs used to make bodies or tires. In addition, the demand for labor in engine production depends only on the factor prices of the other variable inputs in engines, the capital stock in engines, and the number of cars. The labor demand equations for each of the three stages can be modeled independently of any inputs used in the other stages.

The USPS framework makes an additional set of assumptions. In each processing stage, there is a unique “cost driver” that is related to the volume of mail but that is not the volume of mail. Rather, changes in the volume of mail lead to changes in the level of the driver and this determines the labor use in each sorting operation. It is variously described as “an intermediate output”(USPS-T-12, p. 19) or “value added” for the sorting operation (OCA/USPS-T-12-4). While the USPS testimony never relates the cost driver to the form of the underlying production function, it appears that the cost drivers for the manual and automated operations are simply the aggregate inputs M and A which are defined as part of the separability assumption on the production function (6). Notice that to reformulate the production model in terms of a set of cost drivers requires that the production process be separable into stages that will correspond to the drivers.

To introduce this into the model derived above, define the cost driver for the manual operation as $D^M(L)$ and for the automated operation as $D^A(L)$. Both are written as functions of L to denote that they will change with the volume of letters to be sorted. Substituting these into the labor demand equations in (8) gives labor demands defined in terms of the cost drivers:

(9)	manhours in automated operations	$A_L\,(\,WA_L, K_L\,, D^A(L))$
	manhours in manual operations	$M_L\,(\,WM_L, D^M(\,L))$

We can now use this model to define the marginal cost of L analogously to the steps used in equations (2)-(5) in section II.D.[10] The total cost function for letter-shaped mail is:

(10) $C^L(WM_L, WA_L, K_L, L) = WM_L * M_L(WM_L, L) + WA_L * A_L(WA_L, K_L, L)$

The marginal cost of an additional letter is the derivative of (10) with respect to *L*:

$$(11) \qquad \frac{\partial C^L}{\partial L} = WM_L\left(\frac{\partial M_L}{\partial D^M}\right)\left(\frac{\partial D^M}{\partial L}\right) + WA_L\left(\frac{\partial A_L}{\partial D^A}\right)\left(\frac{\partial D^A}{\partial L}\right)$$

This differs from equation (3) because it now depends on how *L* affects the drivers and how the drivers affect labor use. Define the elasticities of manual and automated labor demand with respect to the *driver in the operation* as:

$$(12) \qquad \varepsilon_M = \left(\frac{\partial \ln M_L}{\partial \ln D^M}\right) \quad \text{and} \quad \varepsilon_A = \left(\frac{\partial \ln A_L}{\partial \ln D^A}\right).$$

Define the elasticities of the drivers with respect to *L* as:

$$13) \qquad \delta_M = \left(\frac{\partial \ln D^M}{\partial \ln L}\right) \quad \text{and} \quad \delta_A = \left(\frac{\partial \ln D^A}{\partial \ln L}\right).$$

Marginal cost in (11) can now be rewritten in terms of these four elasticities:

$$(14) \qquad \frac{\partial C^L}{\partial L} = \left(\frac{WM_L * M_L}{L}\right)\varepsilon_M \delta_M + \left(\frac{WA_L * A_L}{L}\right)\varepsilon_A \delta_A$$

[10] This derivation is the same as that used in the USPS framework to derive volume variable cost for a sorting operation. The difference is that the focus here is on an equation for the marginal cost of a letter, not marginal cost in each sorting operation.

Next, rewrite this using the cost shares $\theta_M = (WM_L{*}M_L)/C^L$ and $\theta_A = (WA_L{*}A_L)/C^L$, which gives:

$$(15) \qquad \frac{\partial C^L}{\partial L} = \left(\frac{C^L}{L}\right)(\theta_M \varepsilon_M \delta_M + \theta_A \varepsilon_A \delta_A) \, .$$

When this equation is compared with equation (5), the only difference is that the labor elasticities with respect to volume η_j in (5) have been replaced with the product of two elasticities ε_j δ_j, the labor elasticity with respect to the driver and the elasticity of the driver with respect to volume.

The elasticities ε_M and ε_A are not observable and the USPS framework develops an econometric model to estimate them based on the labor demand equations in equation (9).[11] These are the estimates provided in USPS-T-12. The elasticities δ_M and δ_A are also not observable and the USPS framework makes one additional assumption in order to proceed. They assume that the driver in each sorting operation is proportional to *L:*

(16) Assumption 2 (Proportionality): $D^M(L) = \alpha^M L$ and $D^A(L) = \alpha^A L.$

[11] The labor demand equations that are actually estimated in USPS-T-12 are slightly different than equations (9). First, the relative wage of manual to automated labor is included as an explanatory variable but, as explained in footnote 7, this is not consistent with the assumption that the processing stages are separable with one labor input in each stage. Second, the total capital stock over all automated operations is included as an explanatory variable in all the labor demand equations. This is also not consistent with the assumption that the production stages are separable. Only the capital stock in the same sorting operation should enter the labor demand equation. While it is clear that some type of separability assumption underlies the empirical model, it is not clear what assumptions are being made about the technology to generate the form of the labor demand equations that are actually estimated.

where α^M and α^A are constants.[12] It implies that the production of each unit of *L* requires α^M units of the cost driver or "output" of the manual stage and α^A units of the cost driver or "output" of the automation stage. This is not an innocuous assumption. In terms of the production function (6), it is an assumption about how the production of *L* combines the aggregate inputs *M* and *A*. In this case the production function (6) for sorted letters has the form:

(17) $$L = \min\, [\, (1/\alpha^M)\, M\, ,\, (1/\alpha^A)\, A\,]$$

This is a fixed-proportions production function. In order to produce *L* sorted letters the plant needs $(1/\alpha^M)\, M$ units of the manual sorting input and $(1/\alpha^A)\, A$ units of the automated sorting input. This production function implies that there is no substitution between the aggregate inputs *M* and *A,* they are always used in fixed proportions.[13] This is not a realistic assumption to make

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[12] This assumption is justified as either an approximation to a more general relationship between the driver and volume (USPS-T-12, p. 20) or as measuring the effect of small, local changes in volume on the driver (USPS-RT-3, p. 11). In either case, it should be justified with empirical evidence that the measured driver and volumes are proportional. In the derivation of marginal cost that follows it is necessary that the proportionality assumption hold at all levels of *L*.

[13] A case where this assumption would be appropriate is in the car example in footnote 7. Every car requires 1 engine, 1 body, and 4 tires. The cost drivers in the engine, body, and tire segments are, respectively, the number of engines (E), bodies (B), and tires (T) and the factors of proportionality are $\alpha^E = 1$, $\alpha^B = 1$, and $\alpha^T = 4$. Notice, the cost drivers are the physical outputs from each of the separate initial production stages. The production function for the number of cars *(C)* has the form $C = \min\, [\, (1/\alpha^E)\, E\, ,\, (1/\alpha^B)\, B,\ (1/\alpha^T)\, T\,] = \min\, [E, B, (1/4)\, T]$. Every combination of E=1, B=1 and T=4 produces one car. An extra tire T=5, does not increase the number of cars produced. There is no way to substitute among the aggregate inputs of 1 engine, 1 body, and four tires, to produce a car, even though it may be possible to substitute among the mix of disaggregated inputs used to produce each of these aggregates..

with respect to mail processing. The trend over the last decade has been the substitution of automated operations for manual. Also the substitution of later generation automation (AFSM or DBCS) for earlier generations (FSM881 and FSM1000 or LSM and MPBCS). At the very minimum this requires that the factors of proportionality vary over time and across plants with differences in the technologies in place, but even this is a very restrictive assumption about how input substitution should be included in the production model. Finally, it is important to note that the factors of proportionality in assumption (2), α^M and α^A, are *parameters of the production model*, they are not variables that change in response to the economic environment. Ideally, they should be estimated along with the parameters of the factor demand equations in order to provide a complete characterization of the technology of mail sorting.

The proportionality assumption (16) places strong restrictions on the form of the production function for letter sorting, much stronger than the separability assumption (6) by itself. It does, however, greatly simplify the construction of marginal cost using equation (15). It implies that the derivative of the driver with respect to L is the factor of proportionality

$\left(\frac{\partial D^j}{\partial L}\right) = \alpha^j = \frac{D^j}{L}$, $j = M, A$. This is equivalent to assuming that the elasticities $\delta_M = \delta_A = 1$.

Substituting this assumption into equation (15) gives the final expression for marginal cost of a letter.

(18) $$\frac{\partial C^L}{\partial L} = \left(\frac{C^L}{L}\right)(\theta_M \varepsilon_M + \theta_A \varepsilon_A)$$

Equation (18) shows that the marginal cost of a letter is the sum of the “unit volume variable cost” of the manual $(C^L/L)\,\theta_M\,\varepsilon_M$ and automated $(C^L/L)\,\theta_A\varepsilon_A$ operations. This is equivalent to the expression for marginal cost in USPS-T-12, p19, eq. 5 and in USPS-RT-3, p.12 if there is a single class of mail and the summation is taken over the cost pools.[14]

Comparing equations (5) and (18) illuminates a difference between the production model developed in section II.C and the one used in USPS-T-12 as a basis for estimating marginal cost. The general model in equation (5) uses the labor demand elasticities with respect to total volume of letters L, η_M and η_A. The output of the plant is the number of sorted letters (or, in the more general case, the multiple outputs L_I and L_F) and this is the output to use in measuring the labor demand elasticities. It does not rely on either the separability or proportionality assumption. This is the basis for the empirical model in Roberts (2002) and estimates of the η parameters from that paper could be used to estimate marginal cost using equation (5).

The USPS model uses the elasticities with respect to the cost drivers in each operation ε_M and ε_A. The goal of the empirical model in USPS-T-12 is to estimate these elasticities. The only reason that these elasticities can be used to measure the marginal cost of a letter is because of the

[14] There is no distribution key component in this equation because there is only a single class of mail. The distribution key is used in the USPS framework to allocate a cost pool across rate classes of mail and its implementation is based on approximating the elasticities relating the volume and cost drivers, δ_M and δ_A , with shares of each rate class in total volume when there is more than one rate class. With multiple rate classes it still relies on an assumption similar to the proportionality assumption in equation (16) (specifically, that the driver is a linear homogenous function of the volume of mail across all rate classes processed in the operation) and does not generalize the implicit assumption that the overall production function has the fixed-proportions form (17). The assumption of a single rate class of mail in deriving the equation for marginal cost (18) is helpful in isolating the implications of the assumptions about the technology from the assumptions used to distribute cost to the rate classes.

proportionality assumption, equation (16). If the cost driver is proportional to the number of letters then, and only then, does the labor elasticity with respect to the cost driver equal the elasticity with respect to mail volume. Essentially, the proportionality assumption makes it possible to ignore the relationship between the volume of mail *L* and the aggregate inputs *M* and *A* when calculating marginal costs. The cost of that assumption is an unrealistic restriction on the substitution among sorting stages in the plant. The empirical model in USPS-T-12 does not attempt to estimate the production parameters α^M and α^A that underlie the proportionality assumption. Since the goal of the model is to measure volume variable costs by operation using the pieces in equation (18) it is not necessary to have estimates of α^M and α^A as long as the proportionality assumption is imposed. This will limit the usefulness of the empirical results in USPS-T-12 as an overall description of mail processing technology. It will not be possible to use the parameter estimates to learn about substitution between manual and automated inputs or between different generations of automated inputs. It will also not be possible to learn about the relationship between the volume of mail in the plant and the levels of the aggregate inputs. Measurement of those effects requires knowledge of α^M and α^A.

To see the implications of this model for input substitution, think of the simple case where the plant introduces additional AFSM equipment and substitutes away from hours in both manual and FSM881 operations and toward hours in AFSM operations. The total number of flats to be processed remains unchanged. The USPS model would describe the effect of this substitution in two ways. First, the capital stock in automated flat processing (QIMHE) may or may not change. The integration of AFSM equipment will raise the capital index and the retirement of FSM881 equipment will lower it so the net effect is ambiguous, or at the least, the actual increase in capital is attenuated. The aggregation of both types of capital into a single index will not correctly isolate the substitution effect in the empirical results and this is probably the reason that the coefficient on the capital stock variable is usually close to zero and rarely statistically significant in the USPS results. Second, the substitution will show up as a reallocation of the cost drivers across the three sorting operations in the plant. There will be a reduction in TPF in manual and FSM881 categories and an increase in TPF in AFSM and the model would measure the effect of these "output changes" on labor hours in each operation separately. But the reduction in TPF in manual and FSM881 will not be identical to the increase in TPF in the AFSM operation. In the USPS testimony there is no way of knowing how the three operations are substituting for each other because there is no way to map the changes in TPF in the three operations. This would require knowing how the different sorting operations are combined in producing mail volume, the α parameters in equation (16). It is also the case that total plant "output" as they define it (the sum of TPF over all operations) is constantly changing as a result of substitution among different processing operations. The exact same problem arises in letter processing due to the substitution of DBCS for the older MPBCS equipment and manual sorting. The use of a single capital variable (QIAHE) in all letter-sorting operations is inappropriate for controlling for the effect of the replacement of the MPBCS with the DBCS equipment.[15] Overall, the treatment of

[15] The replacement of MPBCS with DBCS equipment may also be accompanied by an increase in the depth of the final sort of the incoming mail. This substitution in the capital equipment will result in more of the mail leaving the plant sorted to the DPS level and less to the carrier route level. The way this should be handled is by dividing the letters into two output categories distinguished by the level of final sortation. Rather than plant outputs being L_I and $L_{F,}$ the latter would be further divided into two categories: mail that is sorted to the 9-digit level L_{F9}

substitution among the processing steps, which follows from the separability and proportionality assumptions, is a major weakness of the USPS framework.[16]

Equation (15) provides the formula for marginal cost assuming separability and the existence of a cost driver for each stage, but not making the proportionality assumption. The proportionality assumption implies $\delta_M = \delta_A = 1$ and leads to the use of equation (18) in the USPS analysis. Comparing these two equations it can be seen that mismeasurement of δ_M and δ_A is just as serious as mismeasurement of ε_M and ε_A in terms of the error it will impart to estimates of marginal cost. While an enormous effort has been devoted to estimating ε_M and ε_A and estimating them using flexible functional forms that place fewer restrictions on the technology, there is virtually no discussion in the past testimony justifying the assumption that $\delta_M = \delta_A = 1$. Estimation of marginal costs or volume variable costs requires equal care in the measurement of the δ elasticities and the ε elasticities.

On theoretical grounds the production model used by the USPS makes two assumptions

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and incoming mail that is sorted to the DPS level L_{FD}. Each of these outputs would still only count each letter one time and it would still be the case that the sum $L_I + L_{F9} + L_{FD}$ would be the total number of letters sorted in the plant. What we will measure is, not an increase in total number of letters sorted in the plant, but rather an increase in the number of letters in the L_{FD} category and a decrease in the number of letters in the L_{F9} category.

[16] Contrast this with how the model developed above or in Roberts (2002) would identify the substitution patterns among operations. First, the capital variable would be disaggregated into MPBCS capital and DBCS capital. Both capital variables would enter into all three labor demand equations. The increase in DBCS capital should increase the demand for DBCS labor and lower the demand for MPBCS and manual, since they are substitute operations. There would also be no change in plant output, because there is no change in the FHP count in the plant. The substitution of one operation for another is correctly identified as resulting from changes in the two capital variables and not the result of an unmeasured reallocation of “output” among operations.

that are restrictive. The disaggregation of letter processing into separable stages and the use of separate cost drivers for each stage can provide some simplification in the specification of the empirical labor demand equations, particularly when there are many inputs, but at the cost of mispecifying the relationship between cost and mail volume. However, the number of inputs in mail sorting operations is fairly small. In letter sorting there are OCR, MPBCS, DBCS, and manual operations, while in flat sorting there are FSM881, FSM1000, AFSM, and manual. When the number of inputs is this small there is relatively little simplification provided by the separability assumption. The big advantage of the USPS framework is that the proportionality assumption makes it unnecessary to measure mail volume in the plant. It allows measurement of the relationship between cost and mail volume by only measuring the relationship between cost and the cost drivers in the different stages. This is an advantage if volume data is not available but an alternative that is preferable is to develop measures of mail volume in the plant. If mail volume can be constructed then separability and proportionality assumptions are not needed and marginal cost can be estimated directly from equation (5). This is the approach taken in Roberts (2002). Given the importance of quantifying the relationship between cost and mail volume as part of the postal rate setting process, it is important to avoid unnecessary restrictions and to justify the ones that must be made. The next section discusses more practical questions dealing with the measurement of key variables using the MODS data with particular focus on the measurement of output and the cost drivers and interpretation of the estimated production parameters.

IV. The Measurement of Sorting Output

One of the key differences between the model proposed in section II.C and the one used in USPS-T-12 is the treatment of output. The last section focuses on the differences in the production models and the definitions of output, the number of sorted letters or the cost driver in a sorting operation. This section focuses on measurement. Given the definition used in each of the theoretical models, how well is it measured using MODS data?

IV. A FHP as a Measure of Plant Output

The model developed in Roberts (2002, p.8-11) and expanded in section II focuses directly on the number of sorted letters L (or, in the more general case, the disaggregated bundle L_I and L_F) as the measure of output. In an empirical application using the MODS data, every variable in the labor demand equations (1) needs to be measured as closely as possible. Roberts (2002) uses the FHP count of letters in a plant as the measure of output L. There are two main reasons why this is appropriate. First, and most importantly, the FHP count corresponds more closely than any other variable in the data set to the definition of the output level L in the theoretical model. The FHP variable attempts to count each letter processed in the plant one time, just as L does. Second, FHP is exogenous to the plant. It depends on the activities of mailers, just as L does, not the decisions of the plant managers regarding how the mail is to be sorted. This corresponds closely to the idea that the output level in the plant is an exogenous constraint that determines the choice of sorting inputs in the plant.

Despite these strengths, the FHP count is not a perfect measure of L. It is subject to measurement error because, rather than being a count of the number of pieces of mail, it is derived from the weight of the mail and a conversion factor (pieces/pound). Roberts (2002) shows that the problems caused by this type of measurement error can be addressed with the use of instrumental variables estimators. A second criticism of the FHP count, which is made by Dr. Bozzo in USPS-T-12, is that it is an incomplete measure of output because it does not recognize differences in the depth of sort. The use of plant FHP as the measure of *L* implicitly assumes that all letters arriving in the plant are equivalent in terms of the amount of processing they require. This was a simplification made in Roberts (2002) because of the data available at the time (FHP by processing operation) and the fact that it was a reasonable simplification given the number of other issues, particularly econometric ones, that were being addressed in that paper. As shown in section II.C above, it is straightforward to allow for heterogeneity in the amount of processing that is required by defining multiple categories for arriving and destinating mail. The categories should be defined based on the amount of presorting and automation processing the letters have received before being accepted at the plant, and the final level of sorting at which they will be dispatched from the plant. For simplicity, the model in section II distinguishes two categories, initial and final, where the number of letters in each category are denoted L_I and L_F.

Defining the output of the plant in this way allows for the fact that an additional piece of mail in the initial sortation step may lead to different input use than an additional piece of mail in the final sortation step. Notice, that including just the sum $L_I + L_F$ as a single output in the labor demand equations will account for much of the variation in input use across plants and over time. The extension to two outputs is controlling for a more subtle effect, the fact that two plants with the identical level of total output $L_I + L_{F,}$ might use different amounts of labor inputs because they have a different *mix* of L_I and L_F. This extension is only likely to have a measurable effect on input use, and thus output elasticities, if the differences in the sorting methods used in the initial and final sorting steps are sufficiently large.

The empirical issue raised when trying to implement this extension is how to best measure L_I and L_F using the MODS data. Ideally, we would like to have FHP counts for categories of mail that distinguish the amount of preparation that the mailers have undertaken. For example, having separate FHP counts for letters that are, or are not, barcoded would be useful because mail that is already barcoded can skip initial processing stages and be entered directly at the BCS stage. It would also be desirable to have the FHP count of the mail that will be finalized to a 3-digit, or 5-digit, or DPS level. The MODS data does not report FHP counts in these categories, but some progress can be made by using the MODS data disaggregated by 3-digit operation. At this level, the data distinguish FHP counts by processing stage and by whether the mail was handled in the incoming or outgoing operations in the plant. As discussed in section V.A below, these 3-digit operations data will be used to construct two output variables that proxy L_I and L_F and that are included in the labor demand equations estimated in section V.

Overall, the solution to the criticism that *total plant* FHP does not account for differences in the depth of sort is to disaggregate the total into the FHP counts in multiple categories where the categories reflect differences in the amount of prepartion of the arriving mail and the level of final sorting of the destinating mail. The total plant FHP will continue to be the sum of the FHP across all the categories, just as $L = L_I + L_F$ in the theoretical model. All the variables will continue to be exogenous to the plant, depending on the activities of mailers and requirements on the depth of the final sortation, and not on the decisions made on how to allocate sorting inputs within the plant.

Rather than relying on FHP to measure plant output, the USPS framework applied in the rate cases back to 1997 has relied on the count of total pieces fed (TPF) in a sorting operation j as a measure of the cost driver in operation j, $D^j(L)$. It is useful to ask if the TPF counts in the different sorting operations would be appropriate measures of output in the labor demand equations developed in section II of this paper, equations (1). The answer is no. The labor demand equations (1) do not use the assumptions that are needed to specify the model in terms of separable processing steps and cost drivers. They are also developed using very specific definitions of plant output, L or (L_I, L_F) which are the appropriate output measures to use in the empirical labor demand equations. Regardless of what TPF counts in each sorting operation do measure, it is clear that, individually or collectively, they do not measure L or (L_I, L_F).[17] Each piece of mail L will be counted multiple times in a plant. It will be counted at least once in each

[17] Another way of saying this is that TPF variables in equation (1) would be subject to measurement error because they do not accurately measure L_I and L_F (or their sum). Even if TPF variables are *perfect measures* of the number of pieces of mail fed through the sorting machinery, they are not perfect measures of the output variables L_I and L_F and thus subject to measurement error if used as regressors in equation (1). They are also likely to be much less accurate as measures of L_I and L_F than FHP counts and thus measurement error biases are likely to be worse if TPF variables are used to estimate (1). This illustrates the broader point that measurement error in a regressor does not disappear because the regressor is a perfect measure of *something*, it only disappears if the regressor is a perfect measure of the conceptually correct variable that should be in the regression. The theoretical framework in section II.C is helpful for the empirical model because it identifies what output concept is most appropriate as a regressor in the labor demand model and thus can guide the measurement of the output variable to help reduce measurement errors.

sorting operation it passes through and multiple times in an automated sorting operation if it requires multiple passes through the machinery. There is not a fixed relationship between L and TPF counts in a sorting operation or TPF summed over all sorting operations. Rather the relationship will depend on the entire configuration of processing operations in the plant. The labor demand equations (1) should not be estimated using TPF counts in any form as the measure of output.

IV.B TPF in a Sorting Operation as a Cost Driver

The separable model of production used in the USPS analysis relies on the specification of a cost driver in each sorting operation. From the discussion in section III, the cost driver should be proportional to the volume of letters in the plant, not be a measure of the inputs of labor or capital in the sorting operation (i.e. A_L and K_L) but rather a measure of the "output" of the sorting operation (the aggregate inputs M and A), and be measurable independently of the inputs used in the sorting operation.[18] In the USPS framework, the count of total pieces fed (TPF) in the sorting operation (TPH in manual operations) is used as the cost driver. TPF is viewed as a "measure of the amount of sorting work performed" (USPS-T-12, p.12) in the operation and therefore should be closely related to labor use. The main motivation for the use of TPF is that it is closely tied to the labor hours required to run the automated equipment and "there is little in the way of causal

[18] In the automobile analogy used above, the number of engines, number of car bodies, and number of tires would satisfy these criteria to be the unique cost drivers for the three production stages. In particular, note that to estimate the labor demand equations for the three disaggregated stages it is necessary to be able to measure the number of engines, car bodies, and tires produced as well as the capital and labor inputs used in each stage.

avenues for workload measures other than TPF to enter the relationship between hours and mail processing ‘outputs’” (USPS-T-12, p.14).

Even in the context of the separable model of production, the use of TPF in operation *j* as a measure of the cost driver in operation *j* is problematic. It does not meet the criteria outlined in the last paragraph. First, it is not a constant proportion of a plant’s volume of mail as required by the proportionality assumption, equation (16). The level of TPF in sorting operation *j* , for example, manual letters, depends on the whole configuration of processing stages and inputs used to sort letters, OCR, BCS, and DBCS, and will vary across plants and time periods with differences in the use of other inputs and processing steps, even if the volume of mail is the same across plants and time. As a result, the ratio of TPF in a sorting operation to the plant’s mail volume depends on the whole set of inputs used in the plant and is not a constant that will be fixed across plants.

It is possible to use the MODS data to develop some evidence on whether or not the proportionality assumption holds in the data. If it is correct, then the ratio of TPF in flat-sorting operation *j* (i.e. manual) to the volume of flats in the plant should be the same for all time periods and all plants. Table 1 presents summary measures of the ratio of TPF in each of the four flat-sorting processes to the total of FHP in flat sorting(FHP_{flats}). The top half of Table 1 reports the median value of the ratio of TPF_j / FHP_{flats} across all plants that use the operation in the first quarter of each of the six years 1999-2004 under study. If the proportionality assumption is correct, the numbers in each column should be constant. Even allowing for some randomness due to measurement errors, it is clear that the ratios are not constant but vary systematically as they move down the column. The pattern reflects the substitution among processing operations. The ratio for manual operations drops from .237 to .105 and the ratio for FSM881 drops from .702 to .210 over time as the use of these two operations are reduced. The ratio for the FSM1000 operation initially rises as it is phased in during the early part of the time period and then falls as it is replaced by the AFSM. The ratio for the AFSM ratio rises over time as it is phased in during 2001 and 2002. For the median plant, the ratio of TPF_j to FHP is not constant, but varies with the whole configuration of sorting operations that are present.[19]

The lower half of Table 1 presents evidence that the ratio is also not constant across plants at a point in time. If the proportionality assumption is correct the ratio should be the same for all plants, and thus the inter-quartile range, the difference in the ratio between the plant at the 75th percentile and the 25th percentile of the plant distribution, should be zero. The lower half of the table reports the inter-quartile range and the values, even recognizing that the result will not hold exactly, are not zero. The plants do not use the same proportion of TPF_j to FHP_{flats} for any operation or at any point in time.

Table 2 presents similar ratios of TPF in the four letter sorting operations to total FHP in letters (FHP_{Letter}). A similar pattern of time-series variation appears for the letter-sorting operations in the top half of the table. The pattern reflects the substitution of the DBCS operation for the other three over time. These patterns of time-series and cross-sectional variation in the ratio of the cost driver to mail volume are inconsistent with the proportionality assumption that is implicit in the USPS production model.

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[19] The same pattern is present for the mean value of each ratio over time.

An alternative way of making this same point is to recognize that the ratio of TPF to the volume of letters is not a parameter of the production model, like α^M and α^A in (16), but rather an endogenous economic variable that reflects the whole mix of technologies used and operating decisions made in the plant. Roberts (2002) characterized TPF as an endogenous variable in this way and argued it was inappropriate to use as a cost driver in a sorting operation. In USPS-T-12 Dr. Bozzo disagrees with this characterization of TPF as endogenous and believes that the arguments made in Roberts (2002) are inconsistent with the organization of sorting operations and "greatly overstates the role of management discretion in directing mailflows among the operations" (USPS-T12, p 15). Rather operation plans are pre-determined and the mail is distributed to operations based on its characteristics (shape, amount of pre-sorting, and barcoding) and thus TPF is not a variable that is affected by management decisions or control. This is, of course, true on a day-by-day basis. However, this criticism misses the fact that the data frequency in this analysis is quarterly and it is necessary to think about adjustments made over this time period. Any adjustment of the plant's operation plans over the course of the quarter, such as to accommodate new capital equipment, turnover in the workforce, changes in the downstream destinations, equipment breakdowns, or to shift sorting schemes across different vintages of sorting equipment, would all lead to changes in the way that mail volume is translated into TPF by operation. They will lead to changes in the ratio of TPF to mail volume which is what leads to the endogeneity concern.

During a visit to the Harrisburg P&DC in May 2002, the operations staff spent a significant amount of time explaining how their sorting routines were set up. They had substantial flexibility in configuring the sorting routines on automated equipment and could vary them over time to, for example, pull out specific high-volume destinations earlier in the processing stream at different times of the year or to respond to requests from the downstream P&DC's or AO's for different sorting depths. They also explained how they had developed secondary sort plans that were used on some of their older BCS equipment to process letters that were rejected by the DBCS in order to "give it one last chance" to be sorted on automated equipment before being sent to the manual operation. These secondary plans were specifically developed to take advantage of underutilzed capital equipment in the plant. TPF counts will depend directly on the sorting routines used on automated equipment and those are under the control of the plant managers. As a result of the management's decisions, the TPF counts by operation are likely to vary over postal quarters and across plants, even if the number of letters being handled is the same. TPF does not satisfy the requirements of a cost driver in the separable model of production and should not be used as the basis for measuring labor variabilities and marginal cost, even if the model assuming separability is adopted.

IV. C Including TPF in a Model of Production

Even though TPF does not satisfy the requirements of a cost driver, a useful question to examine is: What information does TPF provide about the sorting technology? Or, how can information on TPF in each sorting operation be integrated into a coherent model of mail sorting? In his testimony, Dr. Bozzo (USPS T-12, p.14) shows the relationship between TPF and the number of machine hours on the sorting equipment:

$$\text{Runtime} = \text{TPF} / \text{Throughput rate.}$$

The throughput rate is a measure of the operating speed of a machine. Runtime is a measure of the number of machine hours required to process a given level of TPF on a piece of equipment. This measure of machine hours used in the processing operation is exactly analogous to the number of manhours used in the operation. Each is a measure of the flow of services, in one case from the capital stock and in the other case from the employees, that are used in the operation. Both are measures of inputs used in the operation. If the throughput rate is constant for a given type of technology used in a sorting operation, then the equation above shows that TPF in a sorting operation is proportional to the machine hours in the sorting operation. In other words, *TPF in a sorting operation is a measure of the capital input used in that operation.*

With this interpretation, we can see a second reason why TPF is not an acceptable measure of the cost driver in a sorting operation. It is not an independent measure of output of the sorting stage, but rather a measure of one of the inputs used to produce sorted letters in that operating stage. This provides a different interpretation of the output variabilities estimated the USPS-T-12. They are partial correlations (holding capital stocks and relative wages fixed) between the two *inputs*, labor hours and machine hours, in each sorting operation. These are, of course, related. A plant with more hours of use of its capital equipment will also have more hours of labor use . They are not, however, correlations between labor hours in the sorting operation and a measure of output in the sorting operation. The preferred estimate of the elasticity for the BCS/DBCS operation (USPS-T-12, Table 5), is .85. This says that an increase in the number of machine hours by 1% is associated with a .85% increase in the number of manhours. This implies something about the comovement of the capital and labor services in the BCS operation but it does not provide any information on the change in sorting output that would correspond to this input change. It is not a measure of one of the ε elasticities in equation (15).

While TPF is not a satisfactory cost driver, it is a potentially useful variable and it is worth considering how it might be integrated into the general model of production in section II.C. To do this it is first necessary to be more specific about what is meant by the capital input in the production function. In the model above, the capital stock of automated equipment is K_L and this is included as the capital input in the production function. This is a simplification. Ideally, the measure of capital to use in the letter-sorting production function is the flow of capital services that is derived from the capital stock, call it S_L. This would, ideally, be a measure of the number of hours that each type of capital equipment is in operation. It is analogous to the number of labor hours worked. In most empirical applications of production it is impossible to measure S_L and instead researchers assume that the flow of capital services is proportional to the capital stock. A doubling of the capital stock results in a doubling of the flow of capital services. Under this assumption the capital stock K_L can be used in the production function as the measure of the capital input S_L.

Given the fixed capital stock K_L and output levels L_I, L_F, it is possible to generalize the model of section II.C to allow the plant to choose the level of capital input S_L along with the two labor inputs M_L and A_L. Given that the capital stock is in place, the cost of an hour of machine time is assumed to be zero and the plant continues to minimize the total expenditure on labor. This will result in three factor demand equations, one for each type of labor and one for capital services:

	manhours in automated/mechanized operations	$A_L\ (WA_L/WM_L, K_L\ , L_I, L_F)$
(19)	manhours in manual operations	$M_L\ (WA_L/WM_L, K_L\ , L_I, L_F)$
	machine hours	$S_L\ (WA_L/WM_L, K_L\ , L_I, L_F)$

It is now possible to estimate an input demand equation for capital services using TPF in the automated operation as the measure of S_L. In this equation, the coefficients on the output variables would measure how changes in the number of letters affect the number of machine hours used. This information could possibly be incorporated into a more complete accounting of the marginal cost of an additional piece of mail, an accounting that recognized that fluctuations in mail volume lead, not just to changes in labor costs, but also in capital costs. For example, the estimates would show that a 1% increase in mail volume creates an X% increase in machine hours and this could be combined with information on the cost of the capital equipment to estimate the cost of providing the additional X% increase in machine hours needed. The details of how to do this remain to be thought through but the basic information on machine use and mail volume would seem to allow some progress on this question.

V. Estimation of the Model of Labor Demand Developed in Section II.C

V.A Variables Included in the Demand Equations.

In this section I report estimates of the labor demand equations for letter and flat sorting operations. In the case of letter sorting there are four operations: manual, and three mechanized/automated operations, OCR, MPBCS, and DBCS. There are also four operations for flat sorting: manual, FSM881, FSM1000, and AFSM. The empirical specification closely follows the one used in Roberts (2002, section III) where a more thorough justification of each variable is provided. Each demand equation expresses the logarithm of the total manhours in the operation as a function of the following variables:[20]

- the logarithm of the FHP count of letters in all incoming sort operations (FHP_{IN}).

- the logarithm of the FHP count of letters in all outgoing sort operations (FHP_{OUT}). The measurement of these variables is discussed below.

- the quantity indexes for capital equipment in the operations. These are the variables QIOCR, QIMPBCS, and QIBCS for the letter sorting operations and QIFSM881, QIFSM1000, and QIAFSM100 for flat sorting. These variables are provided in LR-K-56.

- Two technology dummy variables indicating whether the MPBCS or DBCS operation is used in the plant in time period *t* if it is a letter-sorting operation and three technology dummies to distinguish the use of the FSM881, FSM1000, and AFSM technologies if it is a flat-sorting operation. The variables equal one if there was positive TPF for the operation in the time period.

- The relative wage for manhours in automated versus manual operations. An increase in the wage represents an increase (decrease) in the relative wage for automated (manual)

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[20] A number of variables that are incorporated in the USPS model reported in USPS-T-12 are not included in this model. Variables that measure characteristics of the service area and lagged values of the output variables are not included because there is no clear theoretical reason why they should be included and because Roberts (2002, section VII.B and VII.C) examined their impact in this model and found they were either unimportant, or in the case of lagged output variables, also reduced the precision of the estimated output elasticity.

operations.

- A set of five year dummy variables representing each year from 2000-2004. The omitted or base group is 1999.

As in Roberts (2002), we continue to use simple log-linear regression equations, rather than quadratic or trans-log models with interaction terms among the regressors. We do this for two reasons. First, one of the benefits of quadratic models in this application is that the output elasticities will now vary across plants with changes in the capital stocks, output level, and other variables, but this benefit is not utilized in any of the subsequent analysis. The focus of the analysis in USPS-T-12 is to produce a single point estimate for each sorting operation. This can be done more simply and directly with a linear model which provides exactly that. Second, when estimating quadratic models, the coefficients on interaction terms will generally be less precisely estimated than the coefficients on the first-order terms. They will often be insignificant, the "wrong sign", or both. By then using combinations of these higher-order coefficients to produce estimates of the output elasticities, we can observe output elasticities that vary widely across observations but that are hard to understand or accept as reasonable. Given these limitations, we prefer to analyze the data with relatively simple models, control for the major econometric problems that are present, and then, after uncovering inconsistencies or difficulties in interpretation, work to expand the model or check for sensitivity to the functional form.

The new variables utilized in this paper, which have not been used in either Roberts (2002) or USPS-T-12 , are the FHP counts for incoming and outgoing flats and letters. The total FHP count for each plant and time period for each of the flat and letter processing operations was provided by the USPS as part of the MODS data sets for the R2005-1 rate case in USPS-LR-56.

This can be aggregated over sorting operations to provide the total FHP in letters and flats for each plant and time period. This was the method used by Roberts (2002) to construct the output variables used in his study. The FHP in each operation represents an aggregate over mail in many categories, including whether the mail is part of the incoming or outgoing mail processing streams and the data available in LR-K-56 cannot be disaggregated into finer categories that could help distinguish mail flows based on the extent of presorting or depth of final sort. In order to disaggregate the FHP into finer categories, the USPS provided us with the FHP data for each 3 digit MODS category. There are 185 three-digit categories in 1999 and this number rises over time to 259 categories in 2004. After eliminating categories which never had FHP in them, we were left with 212 three-digit categories that contained FHP data in one or more years. The three-digit categories are differentiated by, among other things, sorting operation, whether it is incoming or outgoing, and whether it is primary or secondary sorting. We chose to aggregate the categories by shape (which is what is required by the production model in section II) and by whether it was an incoming or outgoing process. The choice to distinguish incoming and outgoing processing was that the amount and nature of processing in each group is different and it is relatively straightforward to identify which of the three-digit MODS categories fall into each group. If a plant has a relatively large fraction of its FHP in the outgoing sorting stages we would expect it to have a different level and mix of labor hours across sorting operations than if it had a large fraction of its FHP in the incoming sorting stages. Disaggregating plant FHP into these two categories should be sufficient to demonstrate if the measurement of multiple outputs is feasible with the MODS data and if it makes a difference in the estimation of the labor demand elasticities.[21]

To assist with the aggregation of the MODS categories the USPS also provided us with a spreadsheet that contained the name of each three-digit MODS category and a mapping of each to the 52 operations groups used as part of their productivity studies. The 52 groups are listed in LR-K-56.doc on page 32. The 52 operations groups are distinguished by whether they are an incoming or outgoing operation. Each of the 52 operations groups, and all of the three-digit MODS categories within them, were assigned to the incoming and outgoing categories based on their title. However, the operations groups do not provide exhaustive coverage of all 211 MODS categories which have FHP data. Each of the remaining MODS categories was assigned to the incoming or outgoing group based on the title.[22]

Because these variables have not been introduced in the discussion of mail processing costs to date, we provide a summary of the aggregate patterns in these variables in Table 3. The first two columns report the aggregate FHP counts for the incoming and outgoing operations, respectively, and the third column reports the incoming count as a share of the total. The figures are reported for the first quarter of each sample year. Two patterns are obvious. First, the FHP

[21] It may be possible to aggregate the 212 categories in other ways to capture finer categories that differ in the amount of preprocessing or depth of sort. This will require going through each category and understanding the characteristics of the mail in that category. This obviously requires assistance from USPS staff who have much greater expertise in the processing stages and MODS coding than I have been able to apply to this question. At this point I cannot tell how feasible it will be to extend this methodology farther using the disaggregated MODS data.

[22] A spreadsheet mapsfinal.xls that accompanies this report contains the name of each three-digit MODS category, its assignment to the sorting operations in LR-K-56, its assignment to the operations groups in LR-K-137, and a discrete variable,OUTGOING, that is equal to 1 if the category was assigned to the outgoing group and 0 if it was assigned to the incoming group.

letter count in incoming operations is approximately two thirds of the total. Second, the FHP in the incoming operation has risen over time while the FHP level in the outgoing operations has fallen. The same two patterns are present in the aggregate counts of FHP flats, except that the incoming operations are an even more substantial share of the total. They account for more than 80 percent of the total in each time period. This differential is consistent with the presence of presorted mail that bypasses the outgoing sorting steps but is processed in the incoming operations. One implication of the difference in magnitude between FHP_{IN} and FHP_{OUT} is that a one percent increase in each variable does not represent an equal increase in the number of pieces of mail of each type.

V.B Estimation Methods and Sample Selection

Roberts (2002) discusses the econometric issues involved in estimating the labor demand equations using plant-level panel data collected in MODS. All of the discussion in section V of that paper remains relevant here and will not be repeated. Two important issues are the inclusion of plant-specific fixed effects in the demand equations and the use of instrumental variables estimators to control for the simultaneity of the FHP variables. In this paper we utilize the fixed-effects instrumental variables (FE/IV) estimator to address both of these issues. There are two endogenous variables, FHP_{IN} and FHP_{OUT}, for letters in the regression equations for letter-sorting operations. Building on the insights in Roberts (2002), we use FHP_{IN} and FHP_{OUT} for flats as the instrumental variables. These two variables are strongly correlated with the two FHP variables for letters, but are unlikely to be correlated with the measurement error in the FHP variables for letters, which is the likely source of the endogeneity in the regression.

The sample of plants that are used in estimation are a subset of the 351 plants included in the MODS data supplied in LR-K-56. The approach we have taken to editing the data involves deleting groups of plants that do not report the key variables, hours and FHP, or that differ in some clear way from the typical plant in their mix of operations. Specifically, the following observations have been deleted from the analysis:

- 47 plants that do not report FHP in most years are deleted.

- when estimating labor demand for flat- sorting operations, 15 plants that only use manual operations are deleted. These plants are included for the letter-sorting operations.

- in each automated/mechanized operation that is phased in or out during the sample period, the first 4 or last 4 quarters of use are deleted. These often had small or erratic data on hours as the operation was phased in or out of production.

. - some observations are deleted for automated operations that report positive hours or tpf but report zero capital input for the operation. The inconsistency between the MODS based hours/tpf/fhp data and the capital data are a cause for concern in this project but we have not been able to do much to check or better understand the capital data.

- a small number of plants are deleted if they would have fewer than 3 observations in the regression.

Overall, sorting operations that are present in every year, manual, OCR, MPBCS, and DBCS, have between 270 and 293 plants included in the estimation. The AFSM analysis generally uses the data for 214 plants from 2002-2004 and the FSM881 analysis relies on up to 243 plants, although the number declines over time. Also the data in 2004 is not used for this operation because many of the plants were likely to retire the equipment after the sample period ended.

V.C Labor Demand Estimates

Table 4 provides the coefficient estimates for the four letter-sorting operations. Each column is derived from estimation of a separate labor demand equation. The first two rows report the elasticities for the two outputs, FHP_{IN} and FHP_{OUT}. A one percent increase in the FHP count in the incoming sorting routines raises the *total* manhours in manual sorting by .869 percent and a one percent increase in FHP in the outgoing sorting operations raises *total* manual hours by .045 percent. Together a one-percent increase in the total FHP count in the plant (FHP_{IN} + FHP_{OUT}) raises total hours in manual operations by .914 (= .869 + .045) percent. Notice that you must sum the elasticities over the output categories to measure the effect of an increase in total mail volume on total hours in the operation, which is comparable to the elasticities being measured in Roberts (2002).

What accounts for the difference in magnitude between the elasticities for the two outputs? FHP in the incoming operation accounts for between 63 and 71 percent of total FHP, so a one percent increase in FHP_{IN} represents an increase in the number of letters that is two to almost three times larger than a one percent increase in FHP_{OUT}. In addition, the incoming sorting routines rely more heavily on manual sorting than the sorting of the outgoing mail which has a heavy concentration of presorted mail and fewer destinations.

The output coefficients for the three capital-based operations are reported in the remainder of the first two rows. For OCR, the two coefficients are .703 and .207, with the one for FHP_{IN} being larger. Overall labor usage in the operation rises .91 percent for each one percent increase in total FHP. The DBCS operation has output elasticities of 1.100 and .111 for the two outputs, giving a total labor demand elasticity of 1.211.   Interestingly, the magnitude of the coefficient for the incoming FHP is ten times larger than for the outgoing. This is consistent with the fact that the incoming letters will pass through multiple sorts on the equipment to get them to the final level at which they are dispatched. This requires more labor, and more machine usage, than an equivalent number of outgoing letters. Finally, the most anomalous results are for the MPBCS operation. Here there is no statistically significant labor response to the incoming FHP and a small effect from an increase in the outgoing FHP. This operation is being gradually phased out during the time period of study and it is possible that the operation is used in different ways across plants and that the other controls in the model, particularly the technology and time dummies, do not adequately capture these differences.

The remaining coefficients in the labor demand equation summarize a very reasonable set of labor demand shifters. In the manual equation, the two technology variables, one for the presence of the MPBCS operation and one for DBCS, are negative indicating that the presence of these technologies in the plant lowers manhours in manual sorting. The negative effect is much larger when DBCS sorting equipment is present. The three capital variables indicate that plants with more OCR and DBCS capital use fewer manual hours, but MPBCS capital is positively correlated with manual hours. The latter may be reflecting a time effect as the capital stock and hours both fall over time as the DBCS operation increases in use. The relative wage is positive, as expected, indicating that as the wage in automated operations rises relative to the wage manual sorting there is increased use of manual hours. Finally, the year dummies pick up the clear pattern of substitution out of manual sorting into the other operations. The demand for manual hours shifts inward each year.

Focusing on the other coefficients for the three capital-intensive operations, OCR, MPBCS, and DBCS, a very reasonable pattern of substitution and time effects is seen. The capital coefficients are positive in the own operation and negative in the other two, indicating that more labor hours are used in the operation if the plant has more capital of that type, but the increases in capital in another operation leads to substitution out of the others. This is exactly the pattern that is expected if the operations are partially substitutes for each other. The relative wage is always negative indicating the substitution out of these automated operations as the wage rises. Finally, the time dummies indicate systematic decreases in the demand for OCR and MPBCS labor and a systematic increase in the use of DBCS labor, exactly reflecting the substitution effects present from the introduction and increased use of the DBCS technology.

Table 5 reflects the full set of coefficient estimates for the four major flat sorting operations. The coefficients for the manual operations are reported in the first column. The coefficient on incoming FHP is .526 and the coefficient on outgoing FHP is .078 and is not statistically significant. The substantially larger coefficient for FHP_{IN} reflects both the much larger share of FHP flats in the incoming operation (tabel 3, column 6) and the finer depth of sorting performed in the incoming operations. The elasticity of manual hours with respect to an increase in both FHP variables is .604, implying a one percent increase in the total number of flats handled will increase manual labor hours by .604. This is a fairly small response of manual hours to an increase in the number of flats processed and this estimate is substantially smaller than the estimate of .884 for manual flat sorting reported in Roberts (2002, table 4) while the standard error is larger. The major change in flat sorting operations between this time and the one analyzed in my earlier paper is the introduction and rapid diffusion of the AFSM technology. The prior estimates predated the use of this technology and it is possible that its introduction has altered the previous empirical relationship between output and manual hours. In particular, it seems to have reduced the fluctuations in manual hours from quarter to quarter and, instead, the quarterly fluctuations are now taken up by fluctuations in the hours in the AFSM operation.   In effect, the quarterly variation in output is largely accounted for by variation in the use of the AFSM operation so that the amount of manual flat sorting done in the plant has fallen in both the level and sensitivity to quarterly fluctuations in output. This could account for both the smaller coefficient and the larger standard error found in this study relative to the earlier one.

The remaining coefficients in the manual labor demand equation are all the expected sign and generally statistically significant. The use of any of the automated operations reduces the labor demand in manual sorting, with the FSM1000 and AFSM technologies having much larger effects than FSM881. Increases in the capital stock of each of the three also reduce the use of manual labor. Overall, the effects of the FSM881 technology in the plant, both in terms of its discrete effect and its effect through the capital stock, are not statistically significant while the other two technologies are. The relative wage is positive as expected, an increase in the relative wage reflects that manual sorting labor has become relatively less expensive, but not statistically significant. Finally, the year dummies reflect the steady decline in the demand for manual labor as the mechanize operations have taken over.

Labor demand elasticities for the three mechanized operations are reported in the last three columns of the table. The FSM881 and FFM1000 operations have output elasticities of labor demand equal to .723 and .651 for the incoming operation. In both cases the elasticity with respect to FHP in the outgoing operation is negative but not statistically significant. Overall, we find no response to fluctuations in the volume of outgoing FHP. This can reflect the fact that volume of outgoing flats is small relative to the volume of incoming flats and that it is basically hard to detect any systematic relationship between this category of FHP and manhours using data at the quarterly level. The remaining coefficients for these two operations are as expected. The presence of other mechanized operations in the plant lowers the labor demand for each of these, with the big effect coming from the introduction of the AFSM technology. An increase in the amount of capital in one of the operations will raise the demand for labor in that operation but lower it in the other, further reflecting substitution among the technologies. The relative wage is negative as expected, although not statistically significant, and the time dummies reflect the pattern of adoption and abandonment of the technology over time. Note that the time dummies for the FSM1000 operation increase in magnitude from 2000 until 2002 as the technology is adopted and then decline in 2003 and 2004 as it is replaced by the AFSM operation. This is a nice example of the value of the separate year dummies because a time trend could not fit this pattern.

The final sorting operation examined is AFSM, which was not present in the earlier study I conducted. The output elasticity of labor demand in this operation is .791 with respect to an increase in FHP_{IN} and .218 with respect to FHP_{OUT}. Adding the coefficients indicates that a one percent increase in the FHP total in the plant will increase labor use in this operation by 1.009 percent. The presence of the other two mechanized operations in the plant, or an increase in the capital in either of those other operations, reduces the demand for labor hours in AFSM but the effects are generally not significant. The one unexpected coefficient is that the capital input in the AFSM operation has a negative and significant effect on labor use in the operation, implying that capital and labor in the operation are substitutes, not complements as we observe for all the other mechanized or automated operations in letters and flats.[23]

One strong pattern that appears in the estimates in Tables 4 and 5 which is new to this analysis is the difference in the labor demand elasticities between mail volume in the incoming and outgoing sorting stages. The labor demand elasticities are larger for the mail volume in the incoming operations as compared with the outgoing operations. This reflects the fact that the volume of incoming mail is larger than the volume of outgoing, but also that the incoming mail is sorted to a greater depth than the outgoing. Separating the FHP count into these two components allows estimation of the separate elasticities for each category of output, thus capturing differences in labor use for different categories of mail. This is one way of addressing the fact that a simple count of FHP does not account for differences in the depth of sort in the plant. It may be possible to disaggregate the FHP measure into finer categories to capture more subtle differences in the amount of processing which different categories of mail undergo, but this will require deeper knowledge of the MODS data collection process than I currently have.

One final issue to examine is how the output elasticity estimates in the model using two output variables differ from the estimates if only a single output was included. I reestimate the labor demand equations using the log(FHP_{IN} + FHP_{OUT})as the output measure and the elasticities

[23] An explanation of this coefficient is going to require more detailed study of how the capital input measure (QIAFSM100) is constructed in the LR-K-56 data sets.

for each operation are reported in Table 6. For the letter sorting operations, the four output elasticities range from .969 for manual to 1.421 for DBCS. For each of the operations, the single output model gives a larger total output elasticity than the two output model. For example, in the manual operation we estimate that a one percent increase in total output will raise labor use by .969 percent in the model with a single output and by .914 percent (= .869 + .045) in the two output model. While this difference is very small, the three automated technologies show a larger increase in the elasticity when the single output model is used. In the case of flat sorting, the single output coefficient reported in Table 6 is generally close to the sum of the two output coefficients in Table 4. The disaggregation of flats into two outputs that receive different levels of processing does not have much impact on conclusions about the effect of an increase in total plant FHP.

V.D Output Elasticities for Aggregate Letters and Flats

Roberts (2002, Section II.D) shows that the output elasticities for the individual sorting operations for a shape of mail can be aggregated to produce an estimate of the proportional change in total labor hours for that shape with respect to a proportional change in FHP_{IN} or FHP_{OUT} of that shape: an elasticity of labor demand for each output by shape. In the case of letters, the overall elasticity is the share-weighted sum of the elasticities of the four sorting operations (manual, OCR, MPBCS, and DBCS). The share weights are the hours in each operation as a share of total hours in letter sorting. Similarly, the overall elasticity for flats is the hours-share weighted sum of the elasticities in manual, FSM881, FSM1000, and AFSM.

Table 7 reports these elasticities, and standard errors, for each output for each shape. The first line of the table, reports that a one-percent increase in FHP of letters in the incoming sorting operations leads to a .890 (s.e. = .079) percent increase in total hours in letter sorting. This number is a weighted average over the four operation-level coefficients in the first row of Table 4.[24] The effect of a one-percent increase in FHP_{OUT} on total labor use in letter sorting is .100 (s.e.=.016). This nine-to-one difference in the two elasticities reflects both the larger amount of FHP in the incoming operations and the fact that it will be sorted to a deeper level, both of which imply more labor usage. These two elasticities can be summed to measure the effect of a one-percent increase in total plant FHP. This elasticity is .990 (s.e.=.081). This can be compared with the estimates reported in Roberts (2002, Table 7, column 2). The comparable elasticity reported in that paper varies from .951 (s.e.= .023) to 1.025 (s.e.= .050) depending on the IV estimator used and the level of disaggregation for the BCS operation. The current estimate, which is based on 1999-2004 data, is unchanged from these earlier estimates that were based on data from 1994-2000.

Comparable estimates for flats are reported in the second row of Table 7. The total labor elasticity for flats in the incoming operation is .655 (s.e. = .070) and for flats in the outgoing operations is .049 (s.e. = .035). The latter estimate is not statistically different than zero, which in turn results from the large standard errors for the individual manual, FSM881, and FSM1000 operations reported in Table 5. Aggregating the two together implies that a one-percent increase

[24] The weights are the hours shares in each letter-sorting operation. On average over all observations, these are: .431 for manual, .079 for OCR, .077 for MPBCS, and .412 for DBCS. For flats the average hours shares are: .339 for manual, .234 for FSM881, .217 for FSM1000, and .209 for AFSM.

in the total FHP of flats results in a .704 (s.e.= .079) percent increase in total labor in flat sorting. When compared with the corresponding estimates from a single output model reported in Roberts (2002, Table 7, column 1), it is seen that this elasticity is smaller. The ones reported in the earlier paper vary from .838 (s.e. = .046) to .956 (s.e. = .029) depending on IV estimator used and the level of disaggregation of the FSM operation. Tracing the difference back to the underlying coefficients for the operations, one source of the decline is a drop in the output elasticity for manual flats. In Table 5 we report a total elasticity for manual hours in flats of .604 (= .526 + .078), while in the earlier project we estimated an elasticity of .884 to .961 depending on IV estimator.[25] A clear drop in the sensitivity of manual labor hours to FHP over the current period, 1999-2004, compared with the earlier 1994-2000 period is responsible for much of the decline in the total elasticity for flats. It's likely this has something to do with the introduction of the AFSM technology but the exact link is not clear.

V.E The Role of Yearly and Quarterly Variation in Hours and FHP

A substantial amount of effort has been devoted in past rate cases to assessing the role of cross-plant size variation on the estimates. The entire discussion of whether or not plant fixed effects are necessary in the regressions is really about what role is to be given to the "between plant" data variation in estimating the relationship between hours in each sorting operation and output. Including plant fixed effects, which both the USPS and I have done in our empirical

[25] There is also a decline in the estimated elasticity for FSM881 from .80 or .948 in the earlier paper to .706 here but the decline for manual is more substantial and the manual elasticity gets a larger weight in calculating the aggregate elasticity for flats.

work, removes much of the between plant variation in the data and leaves the coefficients to be estimated from time series movements in hours and output for individual plants.

The time series movements in these variables comes from at least four sources: (1) technical change which results in the gradual replacement of one technology (FSM881) by another (AFSM), (2) short-term fluctuations as new equipment is integrated into the production stream, (3) systematic quarterly variation in mail volume due to the actions of mailers, (4) high-frequency variation arising from day-to-day fluctuation in mail volume, equipment breakdowns and repairs, staffing changes, or many other sources of disturbance. Each of these sources of data variation is either exploited or controlled for in estimating the output elasticities in section IV. Source (4) is minimized, although not removed entirely, by summing the data to the quarterly level. Source (2) is controlled for by eliminating the first year of observations when a new technology is introduced. Source (1) is controlled for by including measures of the other technologies used in the plant, the amount of capital of each type, and dummy variables for the year. Source (3) is used explicitly to estimate the output elasticities.

An important issue in estimating a model like the one in section IV is which of these sources of data variation are useful to use in estimating the output elasticities and which are a nuisance that need to be removed in order to get consistent estimates of the elasticities. We can demonstrate the importance of the long term and cyclical variation in the data by examining the aggregate hours and FHP levels for flats. The top panel in Figure 1 plots the total FHP for the incoming and outgoing flat-sorting operations over time. The bottom panel plots the total hours for the four flat-sorting operations.[26] In the plot of FHP, the incoming FHP has a pronounced quarterly cycle, with the fourth quarter always having the smallest FHP followed by the second, third, and first, respectively. The incoming FHP also has a steady upward trend over time. The outgoing FHP, while much lower in level, has different cyclical and trend patterns. The third quarter is always the peak and there is a steady downward trend over the six year time span. The hours data in the bottom panel show how the use of the four main sorting operations vary from quarter to quarter. These will be affected by the demand patterns present in the FHP variables. The quarterly variation is clearly reflected in hours of FSM881 and manual over the first two years of the period, and in the AFSM hours over the last three years. The hours data are also affected by the shifting in technologies from manual, and the earlier FSM machines, to the AFSM. Overall, cyclical demand variation, long-term trends in demand, and technological replacement are all affecting the level of hours observed in each sorting operation. The goal of the empirical model is to attribute the movement in hours to the movement in mail volume.[27]

This attribution will be affected by how the quarterly fluctuations and yearly trends are treated in the regression model. To demonstrate this, figure 2 shows the patterns of total FHP

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[26] Because these pictures are based on total FHP and hours over plants they will not provide any insights into the amount of time series variation that occurs at the plant level, but they are useful in illustrating the importance of the secular and quarterly trends that are present in the data.

[27] The value of the plant-level data is doing this attribution is substantial, even when relying only on the time-series patterns for the plant. Different plants will have different adoption points for the new technologies (or may not adopt at all) and different magnitudes of quarterly and long-term FHP movements reflecting differences in demand for mail services in their area. It's the fact that not all of the plants are on the same schedule that makes the micro data much more valuable than the aggregate time-series data for estimating these relationships.

(FHP_{IN} + FHP_{OUT}) and total hours over all flat sorting operations, with different combinations of yearly and quarterly variation removed. The top panel plots total hours and total FHP, with each expressed as deviations from their overall mean. The pattern reflects all of the forces, long term demand increase/decreases, quarterly variation, and the substitution of the AFSM operation for the other technologies that were more hour intensive. The substitution effect dominates and accounts for the decline in hours. The simple correlation between these two variables is -.131 but is not statistically significant (p-value=.543). This negative correlation clearly does not reflect the type of movement in hours and FHP that would be generated by plants adjusting their hours in response to different mail volumes that arrive in the plant. It is not the type of data variation that would be appropriate for estimating output elasticities of labor demand.

One simple way to begin to control for the differences in technology over time is to remove year effects from each variable. In this case removing the year effects will also remove the trend in FHP resulting from the upward trend in FHP_{IN} and the downward trend in FHP_{OUT}, that is, it removes both effects of technology shifts and long term shifts in demand. The middle panel of Figure 2 shows the time-series patterns for the two variables after the yearly means have been subtracted from each observation. The quarterly variation clearly dominates each series and the correlation between the two variables is now .727 and statistically different than zero (p-value==.000). The relationship between FHP and labor now reflects the quarter-to-quarter variation in the variables. This relationship could be spurious, resulting from some other variable that moves both hours and FHP, but that is unlikely. The FHP variable has a systematic cyclical movement resulting from the seasonal cycle in mailing catalogs and the plants respond to these movements in mail volumes by expanding and contracting hours. The quarterly movement is the kind of variation that we want to use in estimating output elasticities.

Finally, we can remove both the yearly and quarterly effects from the variables and the bottom panel of Figure 2 expresses the two variables as deviations from the year and quarter mean. By removing the yearly and quarterly means, much of the systematic variation in hours and FHP has been removed from the aggregate series and what remains are the cumulative contribution of all factors that vary at higher frequencies. In the aggregate data, this correlation is again negative (-.114) but not statistically significant (p-value = .596). At the micro level, this type of idiosyncratic variation can be useful in estimating the output elasticities if it comes from fluctuations in FHP that we can measure and that the plant responds to. It can also reflect noise in the hours or output data and the econometric model must separate these different contributing sources.

What figure 2 demonstrates is that the relationship between FHP and hours will depend on the way that year and quarterly effects are treated in the model. The importance of long-term trends in the FHP variables, the shift in technologies which introduce trends in the hours data, and the seasonal mailing patterns of the public induce movements in FHP and hours that may be useful or harmful to the estimation of output elasticities. It does not show that one type of correction is “right” and another “wrong”, only that it will matter.

This basic point will carry over to the estimation on the micro data. The necessary question to ask is: which source of data variation reflects the type of response we are interested in measuring in an output elasticity? What we are trying to estimate with the output elasticity is how the plant responds, in terms of labor hours, to the fact of different volumes of mail arrive at the plant to be sorted. Hours movements that are a response to high versus low levels of mail arriving to be sorted are the right source of data variation to use. Hours movements that arise from long-term shifts in technologies or from cyclical movements in the mix of full-time and part-time workers are not.

Using year dummies, or a time trend, in the regression is one way (along with technology variables and capital measures) to correct for the shifts in technology over time and thus remove the hours variation that is not appropriate to use in estimating the output elasticity. This is what a comparison of the top and middle of Figure 2 shows at the aggregate level. Unfortunately, this will also remove much of the trend in mail volume over time, which Figure 1 demonstrated was upward from incoming flats and downward for outgoing. The latter would be legitimate output/hours variation to use in estimating the elasticity, but it will be eliminated by the year dummy variables.[28] Given the importance of the technology shifts in altering observed hours, it is important to correct for them as completely as possible, even at the expense of eliminating some useful information on the longer term trends in FHP.

Looking at the quarter-to-quarter variation in the data, the technology shifts are not important, but rather the seasonal fluctuations in the activities of the mailers, which generates the fluctuations in FHP, are what dominate the data. This is a useful source of data variation to exploit when estimating the output elasticities but including quarterly dummy variables in the

[28] In the micro data, the variation that will remain after including year dummies are deviations of each plant's hours and FHP data from the average yearly effect. This is a legitimate source of data variation to use in estimating the output elasticities.

regression will remove much of this. This is what a comparison of the middle and lower panels in figure 2 shows.[29] Including quarterly dummies will also remove any common seasonal effect in hours arising for other reasons. One possibility is a changing mix of part-time and full-time workers which affects the quality of the plant's workforce systematically in different quarters of the year. If the variation in FHP is the dominant source of quarterly fluctuation in hours then including quarterly dummy variables in the regression equations is removing information that is appropriate to use in estimating the output elasticities.

Whether quarterly dummy variables are included in the labor demand models does matter but this issue has not been discussed in the prior testimony in this area. The models estimated in section V.C and results reported in Tables 4 and 5 do not include quarterly dummy variables. Table 8 reports the output elasticities from the same models that include quarterly dummy variables. Comparing the first two rows of Table 8 with the first two rows of Table 4, two changes can be seen. Every coefficient in Table 8 is less than its counterpart in Table 4, except for DBCS, and virtually every standard error is much larger. Removing the common quarterly fluctuations in FHP and hours results in a smaller estimated response of hours to changes in FHP and it is less precisely estimated. Comparing the coefficients for flats in Table 8 with the first two rows of Table 5, the same changes are observed. The coefficients are smaller, except for the coefficient in AFSM with respect to incoming FHP, and the standard errors are larger, at least for

[29] In the micro data, the variation that will remain after including quarterly dummies are deviations of each plant's hours and FHP data from the average effect in each quarter. This is a legitimate source of data variation to use in estimating the output elasticities but it will be much smaller than if the common component of the quarterly variation was used. This will result in less precise parameter estimates in models where quarterly dummies are included.

FHP_{IN}.

The implication of this discussion is that the treatment of quarterly and year effects in the model is important and its implications need to be systematically examined and the sources of quarterly variation in hours need to be better understood. This parallels the discussion of plant effects in the recent rate cases but it has not received the same degree of attention. It appears to warrant further study and discussion. It also suggests the need to think about examination of the data at something finer than quarterly frequencies.

VI. Directions for Future Work

The USPS testimony on mail processing has relied on micro data on inputs and output collected on a consistent basis for a large number of processing plants over a long period of time. While not perfect, the MODS data and related information on capital stocks contain the type of information needed to estimate models of production and quantify the marginal cost of processing. However, I think it still remains an open issue whether this data can provide robust, believable estimates of the relationship between mail volume and labor use that are of sufficient quality that they can be relied upon in the rate setting process.

There are several changes in the USPS framework that would help improve the quality and usefulness of the empirical estimates.

1. The Theoretical Model

The theoretical model relies on the assumptions that processing steps are separable and that mail volume in the plant and the output of each processing step are proportional to each other and the proportion is fixed over time and across plants. If true, these assumptions are useful because they allow measurement of the effect of a change in volume on labor use, without having data on mail volume. If false, the model places restrictive conditions on the patterns of substitution among processing stages that will not be consistent with the patterns observed in the data. At a minimum, the theoretical model needs to be developed in more detail, with a specific focus on the combination of manual and automated operations used in these plants, the assumptions that are made need to be fully discussed in terms of their implications for the production parameters, and empirical support for them needs to be presented. The empirical evidence provided in Tables 1 and 2 indicate that the proportionality assumption is not reasonable. The theoretical framework developed in section II does not rely on these assumptions about the technology and is a more general alternative.

2. Data on Mail Volume

Data on mail volume needs to be incorporated into the empirical analysis. Ultimately, the goal is to estimate how processing costs change in response to changes in mail volume and any attempt to do this without measuring mail volumes is going to have limitations. FHP is collected in the MODS system and appears to be the best measure available of mail volume in the plant. If other measures are not available, then further efforts should be made to improve the FHP data for use in the empirical model. Ideally, FHP counts would be disaggregated into categories that correspond to the amount of mailer preparation (presorting and barcoding) on the arrival side and the depth of final sorting (5 digit, carrier route, or DPS) on the destination side. This will allow measurement of marginal cost for a piece of mail, letter, or flat, that goes through different levels of processing in the plant. The measurement of FHP for parcels and priority mail needs to be better developed so that the production model can be used to estimate marginal cost for those shapes.

3. Endogeneity of FHP

The endogeneity of FHP is an important econometric issue that must be addressed in estimation. The use of IV estimators will generally result in less precise estimates than non IV estimators but the latter are not an appropriate basis for inference. Interpretation of the results and the use of the coefficient estimates in rate setting must recognize the degree of imprecision in the estimates.

4. Assessing the Results of the Complete Model

In presenting results of the model, much more information is needed to provide a convincing case that the estimates accord with what is known about mail processing. Output elasticity estimates and standard errors alone are insufficient for judging the ability of the model to estimate the technology accurately. For example, patterns of substitution among operations over time and the impact of introducing new, or retiring old, technologies on labor use should be summarized as one way of assessing the reasonableness of the estimated model.

5. Capital Data

The capital data needs to be improved and integrated with the MODS data in a more timely way. When a new technology is introduced into a plant it is frequently the case that the MODS data will show TPF, FHP, and/or labor hours in the new technology category many quarters before the capital data indicates any capital stock in that category. This was particularly evident in the AFSM processing operation in the current case. Across the four quarters of 2001, the number of plants reporting positive values for hours and TPF in the AFSM operation is 98, 115, 129, and 148. However, only three plants in each quarter report positive amounts of capital input (QIAFSM100). In 2002 the number of plants reporting positive TPF and hours rises to 216, but in each quarter 116 plants report no capital input. It appears that the capital data, which is not collected as part of the MODS system, is either collected with a lag or was improperly merged with the MODS data for hours and output.[30]

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[30] These observations with positive hours and zero capital input were not used in the estimation reported in section V, but it raises concerns that the capital input in later years is not

6. Standardizing the Set of Plants

The set of plants to be used in this analysis needs to be standardized based on a comparison of the kind of processing they perform. The MODS data set used in the current case contains 351 plants that vary greatly in size and the mix of sorting operations that they utilize. For example, following its introduction in 2000, the AFSM equipment was adopted by 226 plants by the third quarter of 2002 and this number remained constant through the end of 2004. At the same time there are 61 plants that had no mechanized or automated flat sorting operations in 2004. It does not appear that the assumption of an identical technology can be applied to these two groups and including them all in a regression to estimate the demand for labor in manual flat sorting would not be appropriate without effort to recognize and control for these differences. A second example is seen with the use of the DBCS technology. By the beginning of 1999, the technology had been widely diffused and 201 of the 351 plants were using the DBCS operation. The number of users increased over the sample period, but in any quarter there were at least 115 plants that did not use the technology. Are these 115 plants fundamentally different than the remaining 236, so that assumptions about the use of common technology should be questioned? Computer selection rules that include or delete plant observations based on whether or not a small set of variables is available runs the risk of pooling together very heterogeneous plants. It can also lead to coefficient estimates that are sensitive to the inclusion or deletion of a small numbers of observations. To reduce the impact of this kind of heterogeneity it would be desirable to identify the core group of P&DC facilities that can be viewed as representative or typical. The selection

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correct.

criteria could include, for example, whether the plant performs all the major sorting operations, receives new technology in a timely way, and is not excessively specialized. Once this group is identified they could become the group that is analyzed in the empirical models. This kind of selection cannot be done based solely on looking at the historical MODS data, but must involve knowledge of the processing plant and can only be undertaken with input from USPS staff. By focusing on a consistent, representative, core group of plants, it should be possible to reduce some of the sensitivity in the estimates that results from adding or deleting plants that may not be comparable with the other others in the data set.

7. The Source of Data Variation

The finding that the output elasticities of labor demand are sensitive to the way that year and quarterly time effects are incorporated in the regressions is not surprising. There are large cyclical effects in mail volume as well as longer term trends and how that information in the data is utilized matters. A systematic look at the sensitivity of results and the reasons for the cyclical variation in hours would be helpful in deciding how to model these time effects. Finally, some analysis on higher frequency data, such as monthly level, might be helpful in isolating the kind of volume fluctuations that are most useful for estimating the output elasticity of labor demand.

VII. Conclusion

This report has two main goals. First, is to understand and narrow the differences in the modeling approaches to mail processing labor demand that have been developed by Roberts (2002) and the USPS, most recently in USPS-T-12. Second, is to develop and estimate an extension of the Roberts (2002) model that recognizes that different types of mail receive different degrees of processing within a plant. With respect to the first point, Sections II and III link the models in a common framework and identify the implications of the separability and proportionality assumptions used the USPS framework. Section IV provides a critique of the use of TPF as a cost driver in the in the USPS model. With respect to the second point, section V estimates a labor demand model which disaggregates the measure of plant mail volume, FHP, into two outputs: FHP that is processed in outgoing mail operations and FHP that is processed in the incoming operations. We find that changes in each have different implications for the respond of labor hours by sorting operation.

Conceptually, the model can be extended to allow for more categories of mail, where each category is distinguished by the amount of preparation the mail receives prior to arriving at the plant and the depth of sorting at which it leaves the plant. It is unclear whether the MODS data will be detailed enough to allow further disaggregation in this dimension. If it does, then output elasticity estimates for each category of mail could be used as a basis for measuring differences in marginal cost across the categories of mail. Finally, what remains is to integrate these estimates with the larger issue of cost allocation across rate classes of mail.

Table 1

Ratio of TPF $_j$ / FHP$_{flats}$

(for all plants using sorting operation *j* during the time period)

Year: quarter	Manual	FSM881	FSM1000	AFSM
Median Across Plants				
1999:1	.237	.702	.293	
2000:1	.228	.706	.328	
2001:1	.222	.561	.309	.408
2002:1	.163	.326	.189	1.004
2003:1	.113	.386	.137	1.094
2004:1	.105	.210	.143	1.091
Inter-Quartile Range Across Plants				
1999:1	.329	.226	.201	
2000:1	.348	.268	.183	
2001:1	.381	.309	.211	.369
2002:1	.270	.544	.200	.337
2003:1	.165	.633*	.106	.217
2004:1	.157	.325*	.171	.205

* less than 50 plants use the FSM881 operation in these time periods.

Table 2

Ratio of TPF $_{j}$ / FHP$_{letters}$

(for all plants using sorting operation *j* during the time period)

Year: quarter	Manual	MPBCS	DBCS	OCR
Median Across Plants				
1999:1	.147	.389	1.245	.254
2000:1	.134	.326	1.309	.242
2001:1	.126	.246	1.434	.233
2002:1	.107	.226	1.492	.220
2003:1	.095	.221	1.556	.220
2004:1	.080	.190	1.599	.194
Inter-Quartile Range Across Plants				
1999:1	.069	.246	.378	.078
2000:1	.065	.267	.393	.083
2001:1	.052	.255	.405	.087
2002:1	.052	.260	.368	.089
2003:1	.051	.273	.362	.092
2004:1	.046	.265	.333	.098

Table 3

FHP Counts for Incoming and Outgoing Sorting Operations

(Totals over 294 plants with full reporting, millions of pieces)

Year: quarter	Letters			Flats		
	FHP_{IN}	FHP_{OUT}	Share of FHP_{IN}	FHP_{IN}	FHP_{OUT}	Share of FHP_{IN}
1999:1	25,715	13,508	.656	4,731	1,143	.805
2000:1	27,147	13,433	.669	4,870	1,151	.809
2001:1	28,222	13,154	.682	5,064	1,127	.818
2002:1	27,588	12,501	.688	5,124	1,038	.832
2003:1	27,945	12,082	.698	5,463	1,005	.845
2004:1	28,116	11,600	.708	5,494	936	.854

Table 4

Labor Demand Coefficients: Letter Sorting Operations

FE/IV estimator
(standard errors in parentheses)

	Manual	OCR	MPBCS	DBCS
log (FHP_{IN})	.869 (.091)*	.703 (.225) *	.076 (.514)	1.100 (.130)*
log (FHP_{OUT})	.045 (.020)*	.207 (.046) *	.243 (.082) *	.111 (.028)*
Capital MPBCS	1.811 (.366)*	-.550 (.802)	49.83 (1.679)*	-.614 (.523)
Capital DBCS	- .312 (.102)*	-.842 (.222) *	-4.655 (.460) *	.910 (.145) *
Capital OCR	-1.162 (.248)*	2.045 (.550) *	-4.999 (1.127) *	-1.019 (.354)*
TECH MPBCS	-.018 (.012)	-.018 (.029)	n.a.	-.055 (.017) *
TECH DBCS	-.309 (.082)*	-.526 (.376)	n.a.	n.a.
Relative Wage	.647 (.029)*	-.228 (.065) *	-.389 (.145) *	-.289 (.041)*
Dummy 2000	-.168 (.009) *	-.018 (.022)	-.229 (.049)*	.090 (.014) *
Dummy 2001	-.357 (.012) *	-.082 (.028) *	-.271 (.062)*	.121 (.017) *
Dummy 2002	-.494 (.011) *	-.108 (.027)*	-.310 (.059) *	.155 (.016)*
Dummy 2003	-.668 (.012) *	-.155 (.028) *	-.354 (.060) *	.177 (.017)*
Dummy 2004	-.800 (.014) *	-.289 (.035)*	-.509 (.074) *	.154 (.020)*
Intercept	-.132 (.344)	-1.785 (1.011)	-.042 (2.100)	-2.327 (.508)*
$\hat{\sigma}$	.170	.367	.725	.242
R^2	.845	.764	.389	.885
Sample size	6812	6257	5690	6812
Hausman Test Statistic (p-value)	5.98 (.003)	4.48 (.011)	5.07 (.006)	39.77 (.000)

* Reject that the coefficient is equal to zero at the .01 significance level with a two-tailed test.

Instrumental variables used are log(FHP_{IN}) for flats and log(FHP_{OUT}) for flats

Table 5

Labor Demand Coefficients: Flat Sorting Operations

FE/IV estimator
(standard errors in parentheses)

	Manual	FSM881	FSM1000	AFSM
log (FHP_{IN})	.526 (.140)*	.723 (.081)*	.651 (.206)*	.791 (.085) *
log (FHP_{OUT})	.078 (.073)	-.017 (.070)	-.088 (.085)	.218 (.027) *
Capital FSM881	-.756 (1.412)	11.909 (1.995)*	-6.644 (1.711) *	-.016 (.628)
Capital FSM1000	-5.579 (1.303)*	-.970(1.386)	17.155 (1.727)*	-.788 (.568)
Capital AFSM	-.833 (.308)*	-16.329(3.352) *	-.731 (.390) *	-.562 (.138)*
TECH FSM881	-.012 (.039)	n.a.	-.134 (.053)	-.093 (.016)*
TECH FSM1000	-.758 (.038)*	-.158 (.041)*	n.a.	-.035 (.022)
TECH AFSM	-.594 (.062) *	-.761 (.070)*	-.889 (.085)*	n.a.
Relative Wage	.072 (.077)	-.110 (.069)	-.019 (.149)	-.112 (.072)
Dummy 2000	-.060 (.027)*	-.053 (.012)*	.084 (.036)*	n.a.
Dummy 2001	-.124 (.034)*	-.081 (.018)*	.259 (.049) *	n.a.
Dummy 2002	-.225 (.045)*	-.191 (.032)*	.468 (.070)*	n.a.
Dummy 2003	-.218 (.051) *	-.526 (.046)*	.191 (.079)*	.044 (.019) *
Dummy 2004	-.247 (.053)*	n.a.	-.183 (.081)*	-.057 (.019)*
Intercept	1.156 (.342)*	.901 (.210)*	.333 (.557)	.100 (.259)
$\hat{\sigma}$	.555	.198	.652	.140
R^2	.223	.801	.392	.884
Sample size	5064	2085	3980	2055
Hausman Test Statistic (p-value)	5.00 (.007)	0.97 (.381)	2.48 (.084)	38.27 (.000)

* Reject that the coefficient is equal to zero at the .01 significance level with a two-tailed test.

Instrumental variables used are log(FHP_{IN}) for letters and log(FHP_{OUT}) for letters

Table 6

Output Elasticity Estimates From a Single Output Model

FE/IV estimator

(standard errors in parentheses)

Letters	Manual	OCR	MPBCS	DBCS
log ($FHP_{Letters}$)	.969 (.091)*	1.374 (.222)*	1.148 (.467)*	1.421 (.130)*
Flats	Manual	FSM881	FSM1000	AFSM
log (FHP_{Flats})	.610 (.143)*	.769 (.086)*	.674 (.222)*	.928 (.083)*

* Reject that the coefficient is equal to zero at the .01 significance level with a two-tailed test.

Instrumental Variables are log(FHP_{IN}) and log(FHP_{OUT}) for the other shape.

Table 7

Output Elasticities of Labor Demand by Shape of Mail

(Standard Errors in Parentheses)

	FHP_{IN}	FHP_{OUT}	Total FHP
Letters	.890 (.079)	.100 (.016)	.990 (.081)
Flats	.655 (.070)	.049 (.035)	.704 (.079)

Table 8

Output Elasticity Estimates Using Quarterly Dummies

FE/IV estimator
(standard errors in parentheses)

Letter Sorting

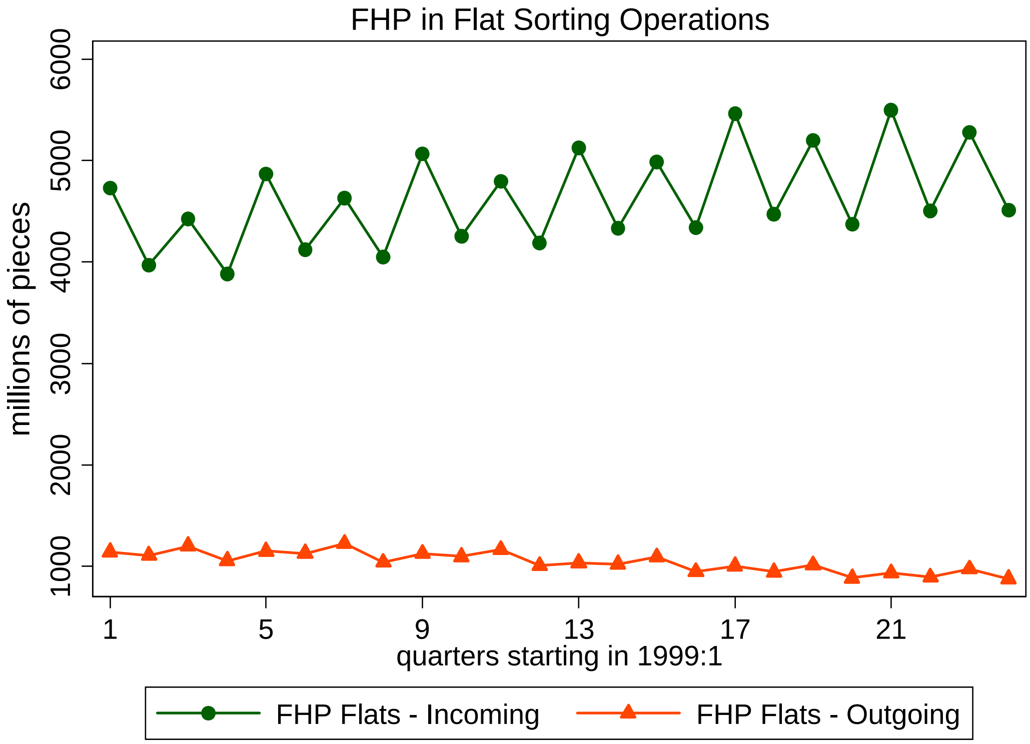
	Manual	OCR	MPBCS	DBCS
log (FHP_{IN})	.668 (.134) *	.385 (.371) *	-1.586 (.978)	1.909 (.218) *
log (FHP_{OUT})	.025 (.019)	.195 (.047) *	.211 (.084) *	.100 (.082) *

Flat Sorting

	Manual	FSM881	FSM1000	AFSM
log (FHP_{IN})	.220 (.230)	.702 (.150)	.533 (.393)	1.01 (.498)
log (FHP_{OUT})	.017 (.075)	-.153 (.077)	-.157 (.088)	.135 (.025) *

* Reject that the coefficient is equal to zero at the .01 significance level with a two-tailed test.

Figure 1


FHP in Flat Sorting Operations
millions of pieces
1000
2000
3000
4000
5000
6000
1
5
9
13
17
21
quarters starting in 1999:1
FHP Flats - Incoming
FHP Flats - Outgoing

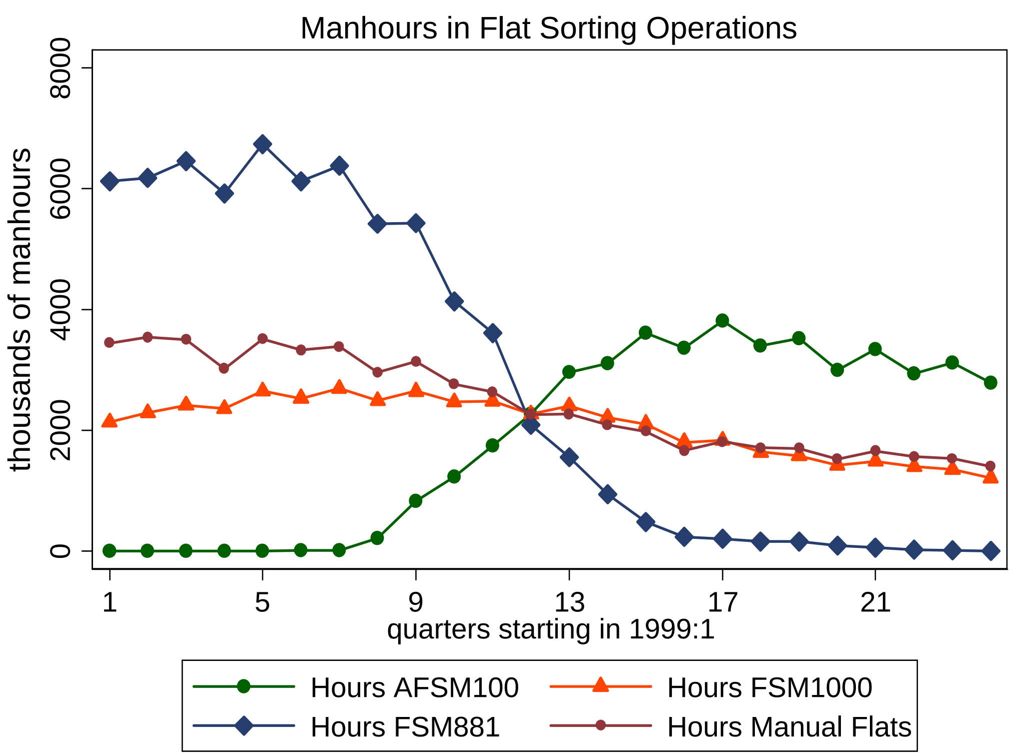
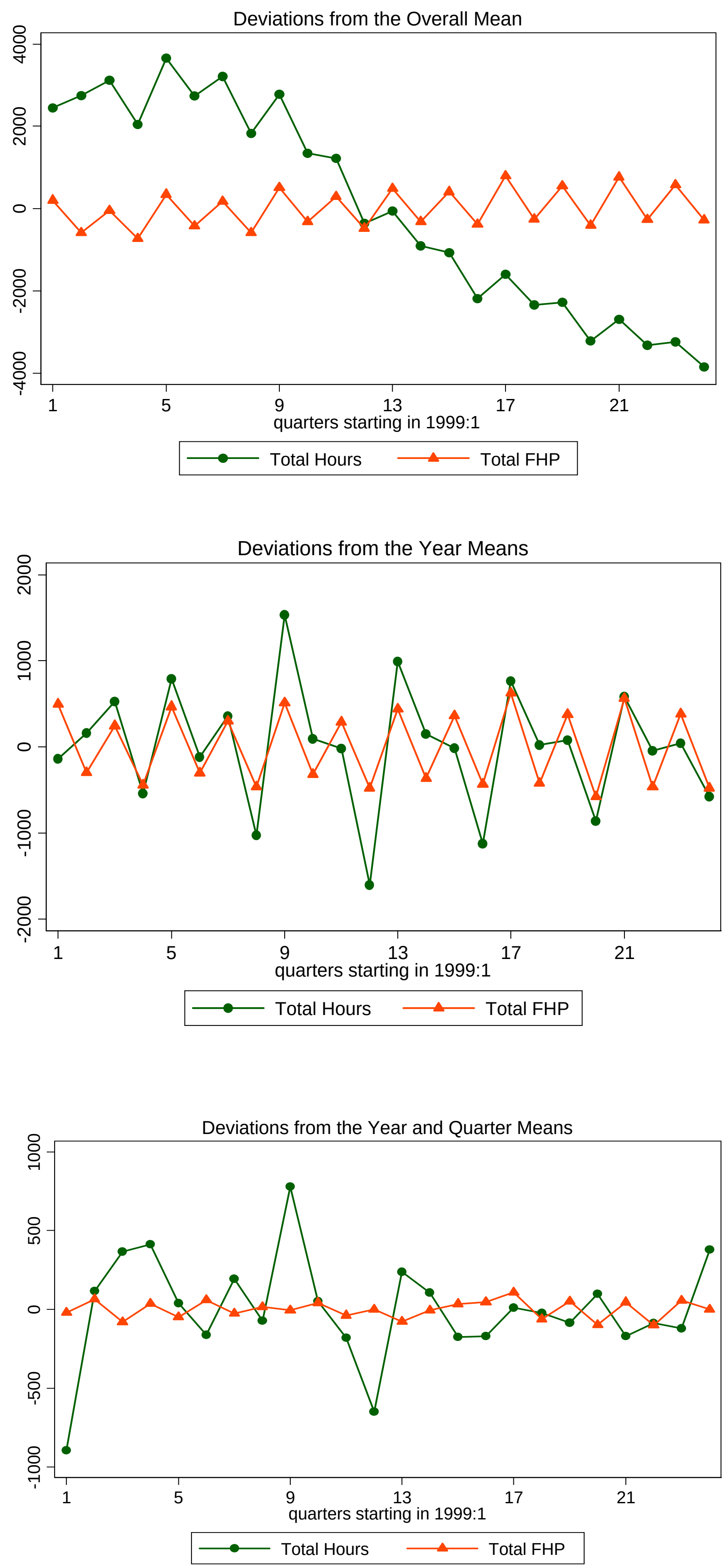

Manhours in Flat Sorting Operations
thousands of manhours
0
2000
4000
6000
8000
1
5
9
13
17
21
quarters starting in 1999:1
Hours AFSM100
Hours FSM1000
Hours FSM881
Hours Manual Flats

Figure 2


Deviations from the Overall Mean
-4000
-2000
0
2000
4000
1
5
9
13
17
21
quarters starting in 1999:1
Total Hours
Total FHP
Deviations from the Year Means
-2000
-1000
0
1000
2000
1
5
9
13
17
21
quarters starting in 1999:1
Total Hours
Total FHP
Deviations from the Year and Quarter Means
-1000
-500
0
500
1000
1
5
9
13
17
21
quarters starting in 1999:1
Total Hours
Total FHP