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POSTAL RATE AND FEE CHANGES, 2006 Docket No. R2006-1

DIRECT TESTIMONY OF
MARK J. ROBERTS
ON BEHALF OF
THE OFFICE OF THE CONSUMER ADVOCATE
THE POSTAL RATE COMMISSION

October 26, 2006

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**Library Reference to be Sponsored with OCA-T-1**

OCA-LR-L-2 Programs and Data for Econometric Estimation of Labor Demand Models in Mail Processing (Roberts)

**Autobiographical Sketch**

My name is Mark J. Roberts. I am Professor of Economics at The Pennsylvania State University and a Research Associate in the Productivity program at the National Bureau of Economic Research (NBER). I received my Ph.D. in Economics from the University of Wisconsin in 1980 and have been employed since then as an Assistant Professor (1980-1985), Associate Professor (1985-1989), and Full Professor (1989-date) at The Pennsylvania State University. I have been affiliated with the NBER since 1996.

My research area is applied microeconomics with emphasis in applications of the theory of the firm in industrial organization, productivity analysis, and production modeling. My research has been published in *The American Economic Review, The Quarterly Journal of Economics, The Rand Journal of Economics, The Journal of International Economics, The Journal of Development Economics, The International Journal of Industrial Organization, The Journal of Political Economy, The Economic Journal,* and *The Review of Economics and Statistics* among others. My undergraduate teaching has been in the areas of economic statistics, econometrics, industrial organization, micro theory, and environmental economics. My graduate teaching is in industrial organization.

Outside of my research and teaching, my professional activities focus on issues related to the measurement of economic activity, particularly at the micro level. I have been serving as a member of the American Economic Association's Advisory Committee to the U.S. Census Bureau since 2001 and chaired the committee for two years. I am currently a member of a panel for the National Research Council of the

National Academy of Sciences that is reviewing the U.S. government's system of business data collection. Since 2001 I have been a member of the Executive Committee of the Conference on Research in Income and Wealth, a seventy-year old professional organization of academic, government, and business economists devoted to issues of economic statistics and measurement. I have received research grants from the National Science Foundation and have served on several review panels for the NSF.

I have completed two previous studies for the Office of the Consumer Advocate dealing with labor demand modeling in mail processing plants. In May 2002, I completed a paper, *An Empirical Model of Labor Demand in Mail Sorting Operations*. In March 2006, I completed a second paper, *An Economic Framework for Modeling Mail Processing Costs.* At the time they were completed, both papers were presented in seminars at The Postal Rate Commission.

## Purpose and Scope of Testimony

The purpose of this testimony is to provide econometric estimates of the variability of labor hours with respect to changes in the volume of mail in mail processing plants. The estimates are provided for three letter-sorting operations, manual, OCR, and BCS, three flat-sorting operations, manual FSM1000, and AFSM, two Priority Mail sorting operations, manual and SPBS, and the aggregate cancellation operation. The estimates are intended to be alternatives to those provided by the Postal Service in R2006-1, USPS-T12.

Supporting documentation for this testimony is provided in Library Reference OCA-LR-L-2. It contains the data sets and programs used to prepare the data and estimate the econometric models. It also contains the output files for all results presented in this testimony.

# I. Introduction and Summary of Findings

The goal of this testimony is to estimate the variation in labor use, and thus labor cost, with respect to changes in the volume of mail in mail processing plants. Estimates of this relationship have been used by the Postal Service to measure volume variable costs for use in all rate cases since 1997. The econometric model used by the Postal Service measures the relationship between labor hours and total pieces fed (TPF) in individual mail sorting operations for letters, flats, parcels, Priority Mail, and cancellation. Under some fairly stringent conditions on the sorting technology, this relationship can provide information that is needed to measure the variation in cost with respect to changes in mail volume. The most stringent condition is that a proportional expansion of mail volume in the plant must lead to an equal proportional expansion in TPF in all sorting operations. This assumption allows the Postal Service to estimate the impact of changes in mail volume on cost without using data on mail volume.

In this testimony I utilize an empirical model that differs from the one used by the Postal Service in some important ways. It does not make the same stringent assumptions on the sorting technology. In particular, it does not assume any specific relationship between mail volume and TPF in any sorting operation. A one-percent expansion in mail volume may lead to a greater than or less than one-percent expansion in each sorting operation. The model is estimated using data on the volume of mail processed in the plant. This is measured using the count of first handled pieces (FHP) in the plant. In contrast to the Postal Service model, the relationship between labor hours and mail volume is estimated using data on these variables.

In an earlier paper, summarized in the next section, I provided a theoretical comparison of the model used in this paper and the Postal Service model. In this testimony I show that the estimates from the two models can be reconciled empirically if additional information on the relationship between TPF and mail volume is utilized. Specifically, the assumption, which underlies the Postal Service model, that a proportional expansion of mail volume in the plant leads to an equal proportional expansion in TPF is violated in the data. Once this relationship is measured empirically it provides an additional piece of information that is helpful in reconciling the estimates of the Postal Service and the ones provided in this testimony. By themselves, the Postal Service estimates of the relationship between labor hours and TPF do not provide all the information needed to estimate the cost impact of a change in mail volume.

Econometric estimates of the elasticity of labor hours with respect to the volume of mail for a number of sorting operations are reported in Section VIII. At the risk of greatly oversimplifying the findings, the estimates of the elasticities for letter sorting operations are: 1.946 for manual labor, 1.093 for OCR, and 1.046 for BCS which gives an aggregate elasticity for letter sorting of 1.361. The estimates for flat sorting operations are: .590 for manual labor, 1.681 for FSM1000, and .844 for AFSM which gives an aggregate elasticity for flat sorting operations of .954. For Priority Mail the aggregate elasticity is 1.184 if plants use only manual sorting and 1.033 if they use a combination of manual and SPBS. For cancellations operations the elasticity is .918. While the estimates for letter sorting, Priority Mail and cancellation are reasonably precisely estimated, the elasticities for flat sorting operations are not estimated with enough precision that I can recommend their use in the rate setting process.

## II. Review of Prior Studies

In *An Empirical Model of Labor Demand in Mail Sorting Operations*, hereafter Roberts (2002), I build an internally consistent model that relates labor use by sorting operation to the total volume of mail processed in the plant for a given shape.[1] The MODS data for 1994-1999 is used to estimate labor demand elasticities for manual, BCS, DBCS, and OCR operations with respect to the volume of letter-shaped mail, for manual, FSM881, and FSM1000 operations for flat-shaped mail, and for manual and SPBS operations for priority mail. The First Handled Pieces (FHP) count of letter and flat-shaped mail is used to measure the volume of mail processed in the plant. The paper discusses in detail a number of econometric issues that arise in estimating labor demand models with plant-level panel data, including corrections for plant-level fixed effects and measurement error in the key output variables. In particular, the use of instrumental variables estimators is developed to deal with the endogeneity of the FHP variable in the demand equations. Estimates of the elasticity of total labor use in letter-sorting with respect to an increase in the volume of letters vary between .951 and 1.026 depending on the level of aggregation of the sorting operations and the econometric methods employed. The elasticity of total labor use in flats varies between .838 and .917 depending on the level of aggregation and econometric details.

In a second paper, *An Economic Framework for Modeling Mail Processing Costs*, hereafter Roberts (2006), I extend this model to account for variation in the amount of

[1] Both of my papers are available on the website of the OCA at: http://www.prc.gov/main.asp?Left=OCA.asp&Right=../OCA/OCAIndex.htm
The web site also contains the data and programs used in the analysis and a transcript of the seminars.

sorting that is done to different categories of mail. I now view the plant as sorting multiple categories of letters and flats, where each category can represent a different combination of processing prior to arrival at the plant and depth of sorting conducted in the plant. The outputs of the plant are now the volume of mail processed in each category and the labor demand elasticities are estimated with respect to mail volume in each category. In the empirical application, the mail stream for each shape is divided into the volume of mail, measured as FHP, in the outgoing mail stream and the incoming mail stream. This division of output into two categories recognizes that mail processed in the outgoing sorting stage is handled differently than mail in the incoming stage and so may have different impacts on labor use and cost. The MODS data for 1999-2004 is used to construct the FHP count for incoming and outgoing letters and flats and labor demand equations are estimated for each of the sorting operations. The average elasticity of total labor use in letter-sorting is estimated to be .990, a one-percent increase in both incoming and outgoing FHP results in a .99 percent increase in total labor use. The increase in incoming mail accounts for a .89 percent increase in labor and the increase in the outgoing mail accounts for the remaining .10 percent. For flats, the overall elasticity is estimated to be lower, .704. A one-percent increase in incoming flats raises labor use by .655 percent and a one percent increase in outgoing flats raises it by .049 percent. The reduction in the elasticity, relative to the 1994-1999 period, for flats results from a decrease in the elasticity in manual flat sorting, which appears to be related to the introduction of the AFSM machinery.

Roberts (2006) also presents a comparison of this plant-based modeling framework with the sorting operation model that has been used as the basis for the

USPS estimates. In particular I develop the implications of the “separability” and “proportionality” assumptions that underlie the USPS framework and show how they simplify the empirical modeling but at the cost of imposing a strong assumption on the relationship between the volume of mail received by the plant and the amount of processing done in each sorting operation.

## III. Overview of the current study

This testimony will continue to extend and apply the modeling framework developed in Roberts (2002, 2006). Some of the new aspects of the analytical framework and results include:

1. I further develop the comparison of the modeling framework I have adopted, which links data on labor use with the total volume of mail in the plant, with the one used by the USPS, which links data on labor use and total pieces fed (TPF) in sorting operations. The USPS framework begins with the assumption that the sorting process is separable into stages. This allows the Postal Service to decompose the elasticity of labor hours used in a sorting operation with respect to mail volume into the product of two components: the elasticity of labor hours with respect to pieces fed in the operation and the elasticity of piece feedings with respect to mail volume. An additional assumption (proportionality) is made that says that piece feedings in each operation are proportional to mail volume in the plant, which implies that the elasticity of piece feedings with respect to mail volume is equal to one. This allows the response of labor hours to changes in mail volume to be estimated without using any information on the total volume of

mail in the plant. In Section IV, I empirically estimate the elasticities of TPF in each sorting operation with respect to the plant's mail volume and show they are not equal to one. The proportionality assumption which underlies the USPS model is violated in the MODS data. I also show that estimates of this elasticity provide a missing link which reconciles my estimates of labor elasticities with respect to mail volume, which are generally greater than or equal to one, with the USPS estimates of labor elasticities with respect to TPF, which are always less than or equal to one. This provides both a theoretical and empirical reconciliation of the two frameworks. It also shows that the USPS estimates are only providing part of the information that is necessary to estimate marginal cost by shape or allocate costs across rate classes.

2. I estimate the labor demand models for letter, flats, and priority mail, and cancellation operations using MODS data for 2002-2005 and provide estimates of the elasticities of labor hours with respect to mail volume. The analysis uses these four years rather than the longer period 1999-2005 used in the USPS analysis in order to minimize the changes in technology that occurred during the sample. During this period the AFSM and DBCS technologies were the major automated technologies for flat and letter sorting and were widely deployed across the plants. We find that there are important changes in the labor demand elasticities for flat sorting operations that result from the impact of the AFSM technology on labor use and the time period analyzed affects the results.

3. I extend the disaggregation of plant outputs to account for differences in the amount of pre-processing of the letter-shaped mail. I use the disaggregated,

three-digit MODS data to divide the volume of mail handled in the outgoing sorting stage into the quantity which is bar-coded and the quantity that is not. I also disaggregate the incoming mail stream into the component that is first processed in a BCS operation, indicating it has a barcode, from the component that is first processed in an OCR/ISS operation. While it appears feasible to measure this difference in the plant-level data, the resulting elasticity estimates are not precise enough to be of use in the rate setting process. I think the analysis identifies the limits of the MODS data for estimation of plant-level labor demand models.

4. I introduce an alternative method for utilizing the substantial quarterly variation in plant FHP to estimate the labor response to volume changes. In Roberts (2006) I showed that the quarterly variation in FHP was a major source of exogenous data variation available to estimate the labor demand elasticities and that the results are sensitive to how it is treated in estimating the model. In this paper I develop another way to exploit the quarter-to-quarter variation in mail volumes to estimate the key output parameters. This involves using quarterly dummy variables as additional instrumental variables when controlling for the endogeneity of output.

5. The estimates of the overall labor demand elasticities with respect to changes in letter volume, measured as FHP, vary from 1.26 to 1.36 depending on the sample used, the set of instrumental variables, and the level at which the sorting operations are aggregated. A one-percent increase in FHP in the incoming sorting stage accounts for three-quarters of the total labor response, while a one-

percent increase in the FHP in the outgoing sorting stage accounts for the remaining one-quarter.

6. The estimate of the overall labor demand elasticity for flat sorting varies from .717 to 1.098 depending on the sample of plants, the econometric method employed, and the level of aggregation. The introduction of the AFSM technology had a major impact on the use of labor in the other sorting operations, particularly manual, and the estimated elasticities reflect this. The parameters, particularly for operations other than AFSM are not precisely estimated and it is not possible to draw precise conclusions about the magnitude of the flat-sorting elasticities.

7. The overall labor elasticity for priority mail varies between .883 and 1.184 depending on model specification, including whether the SPBS operation was used or whether it was only sorted with manual operations.

8. The overall labor elasticity for cancellation operations varies from .918 to .944 depending on the time period studied. A one-percent increase in FHP for letters accounts for between 75 and 85 percent of the total increase in labor use, while a one-percent increase in the volume of flats accounts for the remainder.

## IV. Reconciling Alternative Models and Estimates of Labor Demand

In the current rate case the USPS continues to refine and apply a model of labor demand that was first introduced in 1997. The goal of the empirical model is to quantify the relationship between labor hours and the “output” of each sorting operation, where the latter is measured as total pieces fed (TPF) in the operation. Estimates of this relationship are key components of the volume variable cost, a measure of the marginal cost due to a change in mail volume, for a rate class, which is the ultimate item of interest. In Roberts (2002 Section II and 2006 sections II.C-II.E) I develop an alternative model of a processing plant that quantifies the relationship between the total volume of mail of a given shape and the labor hours in each sorting operation.

Roberts (2006, section III) provides a "side-by-side" comparison of these two models. The goal of that comparison is to put the two models in the same setting and show how they differ in underlying assumptions and implications. I show that the USPS framework relies on two assumptions. The separability assumption says that the production of sorted mail is composed of distinct operations, where the substitution between labor and capital in each operation is unaffected by the inputs used in any other operation. It also implies that there is an aggregate "output" for each operation which is then measured empirically as TPF. The second assumption is that the aggregate output in each operation, TPF, is used in a fixed proportion to the volume of mail in the plant. If the volume of mail in the plant doubled, TPF in each operation would also double. Fluctuations in mail volume lead to a scaling up or down of all the operations in the plant by the same proportion and there is no adjustment in the mix of operations. This is an important assumption because it allows the labor response to a change in volume to be estimated without using any data on the total volume of mail in the plant, rather only the TPF in each operation needs to be constructed. Together, the separability and proportionality assumptions are restrictive, locking the use of the sorting operations into a fixed relationship, which assumes away any ability to substitute among operations in response to changes in mail volume.[2]

In the rest of this section, I provide empirical evidence from the MODS data that shows that the sorting operations are not used in a fixed relationship as volume changes. The proportionality assumption is not an accurate description of the way that sorting plants respond to changes in mail volume. At the same time I will show that estimates of the relationship between mail volume and TPF are needed to estimate marginal cost and, that when they are constructed, they go a long way toward reconciling differences in the hours elasticities presented in R2006-USPS-T-12 and in this testimony.

In Roberts (2006, equation 5, p.10), I showed that the marginal cost of an additional letter could be written as a weighted sum of the elasticities of labor use in each operation *j* with respect to the volume of letters. These elasticities are denoted

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[2] In USPS-T-12 Dr. Bozzo argues that the model in Roberts (2006) effectively makes a similar assumption and so the models differ only in the details of how the relationship between mail volume and handlings in each operation are treated (USPS-T-12, p. 40). More precisely, they differ only in how they specify the matrix A in equation 5 (p.39). This is not correct and misses an important distinction. When estimating the labor demand models, the proportionality assumption implies that the matrix A is a constant that is identical for every observation, plant and time period. A scaling up of the mail volume V results in a scaling up of all the piece handlings H. Even if one uses the separable model of production, the matrix A should not be treated as a constant, but rather allowed to vary by plant and time period as the mix of technologies and capital stocks vary across observations. How an increase in letter volume gets translated into changes in handlings in OCR, MPBCS, DBCS, and manual sorting operations depends on the quantity and type of capital equipment in the plant and the matrix A is something that needs to estimated as part of the production model, just like the elasticities between piece handlings and labor are estimated. The model used in my work avoids the whole issue of how volume and piece handlings are related and instead estimates the relationship between labor hours and mail volume directly using data on these variables.

$\eta_j$.[3] I also showed in equation 15 (p.19) that, in the USPS model with separability imposed, $\eta_j$ can be rewritten as the product of two terms, the elasticity of labor with respect to the output of operation *j*, denoted $\varepsilon_j$ , and the elasticity of output in operation *j* with respect to letter volume, denoted $\delta_j$. When separability is true, then $\eta_j = \varepsilon_j \delta_j$ and you can measure marginal cost be either measuring $\eta_j$ or both $\varepsilon_j$ and $\delta_j$ for each sorting operation.

The model I have implemented in my earlier papers, and that I continue to use in this testimony, estimates $\eta_j$ directly from plant data on labor use in each letter sorting operation and the volume of letter-shaped mail in the plant, where the latter is measured with the plant's FHP. I do not use the information on TPF in each sorting operation. In contrast, the USPS model estimates $\varepsilon_j$ from data on TPF and labor use in operation *j*. They do not use the data on the plant's FHP and thus do not use any direct measure of the volume of mail in the plant. They also do not estimate the $\delta_j$ terms but instead assume that they all equal one, which is the proportionality assumption, and thus construct marginal cost estimates using only estimates of the $\varepsilon_j$.[4]

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[3] In that equation there are two operations, one manual (M) and one automated (A). The formula can be extended to any number of letter sorting operations.

[4] The use of a distribution key to allocate a pool of volume variable costs across rate classes does not relax the proportionality assumption. The volume variable cost of an output is the marginal cost of the output multiplied by the level of output, so it is simple to move between the two definitions. In the simplest case here, there is a single output which is the number of letter-shaped pieces of mail. The formulas I derive are for the marginal cost of a letter-shaped piece of mail and they require information on either $\eta_j$ or both $\varepsilon_j$ and $\delta_j$ for letter-shaped mail. The marginal cost is the same for all letter-shaped pieces of mail, regardless of what rate class they fall into. The pool of volume-variable cost then covers all letter-shaped pieces of mail. It can be divided up into fractions attributable to each rate class by multiplying it by the share of letter-shaped mail in each rate class (a distribution key). This allocation across rate classes is different than measuring the volume variable cost pool. Using a more general method for allocating volume variable cost across rate classes (i.e. allowing the distribution key

It is possible to use the same data used in both studies to estimate the $\delta_j$ terms and to test if they are equal to one. This can also provide a way of resolving the choice between estimates of the $\eta_j$ reported later in this paper, which are often greater than one, with the estimates of the $\varepsilon_j$, which are generally less than one, reported in the USPS analysis.

I use the model developed in Roberts (2006, Section V), and further outlined in Section VI in this paper, to estimate the $\eta_j$ parameters. Essentially, I regress the log of labor hours in each letter (flat) sorting operation on the log of FHP for letters (flats), using an instrumental variables estimator. To make the comparison as simple and direct as possible I just estimate the volume elasticities using total plant FHP as a single output, rather than $FHP_{IN}$ and $FHP_{OUT}$, as separate outputs.[5] The estimates are reported in the first column of Table 1. The top part of the table reports estimates for letter operations and the bottom part for flats operations. The flats estimates are reported separately for plants using the AFSM and plants that do not use AFSM because, as will be seen in more detail in section VIII.D below, the flat sorting technology is sensitive to this distinction. The estimates for letters are always greater

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to change over time) does not generalize restrictions, such as the proportionality assumption $\delta_j$ =1, that were used in constructing marginal cost or the volume variable cost pool in the first place. The use of the proportionality assumption and the application of the distribution key are always mingled together in the discussion of this point in the USPS testimony (See USPS-T-12, Appendix A). In my discussions I have isolated the role of the proportionality assumption to show the important role that it plays in underlying the USPS estimates of volume elasticities. These points can all be extended to the case with multiple outputs, such as incoming and outgoing letter mail, or any number of rate classes within the output group, without altering the fundamental role of the proportionality assumption.

[5]A more complete set of estimates and sensitivity analysis is provided in Section VIII.A-C and Tables 3-7 below.

Table 1

**Reconciling Estimates with the USPS Model**

| Sorting Operation | Roberts' Model | USPS Model | | |
|---|---|---|---|---|
| | Estimated η | Estimated ε | Estimated δ | Implied η |
| **Letters** | | | | |
| Manual | 1.837 (.057) | .993 (.035) | 1.726 (.069) | 1.714 |
| MPBCS | 1.621 (.257) | .723 (.080) | 2.210 (.207) | 1.598 |
| DBCS | .905 (.043) | 1.009 (.053) | .866 (.034) | .874 |
| Agg BCS | .986 (.037) | .982 (.045) | .951 (.033) | .934 |
| OCR | 1.058 (.108) | .622 (.051) | 1.675 (.064) | 1.042 |
| **Flats - plants with AFSM** | | | | |
| Manual | .396 (.124) | .374 (.107) | .716 (.132) | .268 |
| FSM1000 | 1.270 (.214) | .879 (.050) | 1.044 (.117) | .918 |
| AFSM | .654 (.027) | .837 (.028) | .792 (.017) | .663 |
| **Flats - plants without AFSM** | | | | |
| Manual | .867 (.095) | .834 (.058) | 1.057 (.106) | .882 |
| FSM881 | 1.202 (.153) | .877 (.050) | 1.237 (.098) | 1.085 |
| FSM1000 | .391 (.102) | .115 (.081) | .372 (.069) | .043 |

than .9 and for three operations, particularly manual, are greater than one. The elasticities for flats in plants with AFSM are low for both of the key operations, manual and AFSM. For plants without AFSM the manual elasticity is larger, but still less than one.

To estimate the $\varepsilon_j$, I reestimate the same equations but replace log FHP with the log $TPF_j$ in the operation. The sample of plants and all other aspects of the model are kept the same, the only difference is the change in the one right-hand side variable. The estimates of the $\varepsilon_j$ are reported in the second column of Table 1.[6] The interesting pattern is that they are always one or less, as are the estimates reported in the USPS-T-12, Table 1.

The final piece is to estimate the relationship between plant FHP and TPF in each sorting operation. To estimate the $\delta_j$ I begin with the same equations as the labor demand equations used in this paper, and replace the log hours variable on the left-hand side with the log TPF in the operation. This gives an empirical model explaining log $TPF_j$ as a function of the log of plant FHP which I estimate with the instrumental variables estimator. All other control variables and the sample of observations are kept the same, so that the only difference is that this equation measures the elasticity between $TPF_j$ and FHP rather than the elasticity between labor hours and FHP. The estimates of the $\delta_j$ are reported in the third column of Table 1.

[6] These estimates are not the same as the USPS estimates in T-12, although the model, a regression of labor hours on TPF, is the same. There are numerous differences in sample, other control variables, and econometric technique that will cause the estimates to differ. The estimates here are designed to replicate the USPS model while holding other elements of the comparison fixed and the estimates do replicate the general pattern of $\varepsilon_j$ that are less than or equal to one.

There are several points to notice. First, the estimates of the $\delta_j$ often deviate from one. Of the 5 letter operations in Table 1, the hypothesis that the parameter equals one is rejected in four of the cases. Of the 6 flat operations, we reject that $\delta_j$ =1 for four of the operations. The implication is that TPF in most sorting operations is not in a fixed proportion to letter volume measured as FHP and that expansions or contractions of mail volume result in a changing mix of sorting operations. The second point to notice is that the $\delta$ parameters are often greater than one. A one percent increase in plant FHP is associated with a greater than one percent increase in piece feedings in some operations (manual letters, MPBCS, OCR) and a less than one percent increase in others (DBCS and aggregate BCS). This is inconsistent with the proportionality assumption in the USPS analysis and reemphasizes the point that estimation of marginal cost requires information on the relationship between hours and plant mail volume and not just the relationship between hours and piece feedings in the operation.

Finally, given the separability assumption, the estimated $\varepsilon_j$ and $\delta_j$ can be multiplied together to give an implied estimate of $\eta_j$. These are reported in the last column of Table 1. For the letter-sorting operations the implied volume elasticities are very close to the direct estimates reported in the first column. In particular, the high estimate for the volume elasticity of manual labor (1.837) is consistent with the combination of an elasticity between labor hours and piece feedings within the operation of .993 but an elasticity between piece feedings in manual operations and plant mail volume of 1.726. In other words, an expansion of mail volumes (FHP) results in more than a proportional increase in the use of the manual operation (TPF in manual), but an increase in manual labor hours that is proportional to the increase in TPF. Overall, the elasticity of labor hours with respect to mail volume is greater than one. In each letter operation, the estimate of $\delta_j$ provides a key piece of information that is necessary to construct marginal cost in the separable model and helps reconcile the differing estimates of labor response with respect to piece feedings or total mail volume.

For the flat sorting operations the division into two components is consistent with the estimated volume elasticity for two important operations, the AFSM operation ($\eta$ = .654), and the manual operation in plants without AFSM ($\eta$ = .867). It does not provide much additional insight in the FSM1000 operations. This can reflect the fact that the separability assumption might be particularly inappropriate for this case or that there are changes in the technology which are making it difficult to estimate a stable relationship between volume, hours, and TPF.[7]

Overall, this exercise illustrates clearly the need to incorporate data on plant mail volume into the estimation of labor demand elasticities and marginal cost. The MODS data is not consistent with the proportionality assumption which allows marginal cost to be estimated using only data on hours and piece feedings in an operation. What the results indicate is that the USPS model does not provide an appropriate framework for measuring the relationship between the volume of mail and the marginal cost of processing it.[8] In the remainder of this paper I will further develop the model to

[7] This issue will be explored in more detail when the full set of estimates for flat sorting are presented in Section VIII.D.

[8] The fact that column 4 and column 1 estimates in Table 1 are close for letter-sorting operations should not be used as evidence that the separable model using TPF as the output variable is an appropriate model. The estimating models are simplified to a single output and may not hold up when output is disaggregated. When using the full sample of data for 1999-2005, one implication of separability, that capital stocks in other

estimate the $\eta_j$ using the relationship between FHP and labor hours.

## V. Data Issues and Sample Selection

### V.A Selection of Plants and Time Period

The data that is used in this paper is for the years 2002-2005. This time period, rather than the longer time period 1999-2005, is used because the introduction of the AFSM technology for sorting flats has completely changed the relationship between volume and labor hours, particularly in manual sorting. Since the empirical model requires each operation to be analyzed while controlling for the overall mix of technologies used in the plant, standardizing the set of plants based on the technologies used is important, and limiting the time period of analysis to the years in which the AFSM equipment was operating helps this. It is also important when constructing estimates that will be used to allocate costs for future years, that the estimates reflect the mix of technologies that are currently and likely to be in place in the immediate future. Limiting the time period of analysis to 2002-2005 also helps to standardize the set of operations used in letter sorting. The DBCS technology had been in use for several years by this time and was generally a much larger share of total BCS hours than MPBCS. The MPBCS technology was still being phased out in some plants and that will be the main source of technology differences across plants that must be controlled for. I do report a set of estimates using the longer time period 1999-2005 and find that it makes little difference for the letter sorting operations.

To choose the sample of plants to analyze I begin with the set of 368 plants

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operations should not have any effect on labor demand, is clearly rejected.

provided in USPS-LR-L56. I immediately eliminate 64 plants because they do not report FHP or capital stocks consistently over time. The remaining 304 plants are subjected to additional data cleaning. As a result of this, I eliminate all or part of the data for 17 additional plants because of obvious errors in FHP or total labor hours or the division of labor hours across sorting categories. A small number of additional observations are lost because the instrumental variables, particularly the outgoing FHP for flats and the destinating letters, flats, and parcels, were zero or not reported. This leaves a sample of 4445 observations for 287 plants which is the largest sample used in any of the regressions. If a sorting operation is not used in a plant, then the labor demand for that operation is estimated using only the observations with positive hours. Finally, because of the change in flat sorting technology following the introduction of the AFSM operation, I analyze two smaller, more homogeneous samples for flat sorting. One sample consists only of the plant/time observations where the AFSM had been phased in and the second is the set of observations without any AFSM equipment or hours reported. Finally, to test the sensitivity of results I restrict the sample further from the original group of 304 to a group of 247 plants that were always classified as P&D facilities by the USPS before applying the other selection criteria. This eliminates a group of plants that were classified as customer service facilities, priority mail facilities, delivery distribution centers, international service centers, or as MODS2 facilities. The latter group are generally smaller plants that used a different data collection system for part of the time period.

**V.B Capital Data.**

The empirical model requires a measure of capital stocks in each sorting operation as controls. I adopt a different methodology for constructing these variables than is used in the USPS study, although the underlying data on investment expenditures on each type of equipment in each plant is the starting point for both sets of measures. I aggregate the expenditure data into 5 categories - FSM, DBCS, MPBCS, SPBS, and all other. I deflate the expenditure in each category in each year by the USPS price index for new capital equipment and then add across all the years to construct a constant dollar capital stock for each category in each year. These are the variables I use as capital stocks in the labor demand equations. This differs from the method used by the USPS. They use these expenditure data to construct plant-level shares over all plants and then allocate an aggregate measure of capital services across plants using the plant shares. They claim this constructs a measure of capital services for each capital type in each plant. In practice, while the level of the variables will be different for my series and the USPS series, the cross-plant and over time variation is driven by differences in the underlying expenditure data so the correlation between the variables is fairly high and it will probably not be an important source of difference in results.

The method I use only gives a total capital stock for the FSM category in the plants and it is desirable to disaggregate this into separate stocks of FSM881, FSM1000, and AFSM equipment. The USPS used more detailed data on individual contracts for each type of equipment to construct capital measures for the three types of FSM equipment. To disaggregate my measure of the FSM capital stock across the three categories I multiply my total by the share of each type in the FSM total from the USPS data.

There is one noticeable problem with the capital data. There appears to be a time lag between the measurement of the labor and TPF activity in an operation and the capital measurement. This is evident in the introduction of the AFSM operation, where labor hours and TPF variables are positive for several quarters before the capital is reported (Roberts 2006, VI.6 provides some statistics on how common this problem is). One solution, which I use, is to delete a plant's data for the first year in which the AFSM is operating in the plant but this does not really fix the problem. If the pattern observed with the AFSM reflects the data collection methods then whenever there is an increase in investment in the plant the capital variables will not accurately measure the change in the right time periods. Shifting the capital variables backward in time is another solution adopted in USPS-T-12, but this is not a substitute for getting the information in the two data systems (MODS and PPAM/PEAS) correctly synched in time.

## V.C. Disaggregating FHP

One criticism which has been made of the model used in this paper concerns its ability to account for differences in the depth of sorting undertaken in the plant. The argument is, basically, since FHP is only measured once for a piece of mail when it enters the plant it cannot completely capture the "sorting output" of the plant. This seems to be viewed as a conceptual problem with the definition of output (see USPS-T-12, Section III.A.3). There is not a conceptual problem with the definition of output. I discuss this issue in detail in Roberts (2006, Section II.B, II.E, IV.A) and will just give a brief overview here. Ideally, we would like to define multiple categories of mail which represent different combinations of mailer processing and final depth of sort (i.e., collection mail sorted in the outgoing mail stream, barcoded mail sorted in the outgoing mail stream, incoming mail sorted to a carrier route, incoming mail sorted to a DPS level, etc.) and measure the volume of mail in each category. The plant's output is the set of categories and the number of pieces of mail it processes in each category. Each of the plant's outputs is always measured as the number of pieces of mail it processes. What the empirical model estimates is the relationship between the number of pieces of mail processed and labor hours. What the multiple categories do is allow this estimated relationship to vary for each category.[9]

The practical measurement issue is the number of categories that can be defined in the MODS data and the quality of the FHP data as they are disaggregated among finer and finer categories. In Roberts (2006) I showed that the MODS data could support the disaggregation of FHP into two categories, one that is a measure of the volume of mail handled in the outgoing sortation stage ($FHP_{OUT}$) and one that measures the volume of mail handled in the incoming sortation stage ($FHP_{IN}$). This is a potentially important distinction since outgoing mail will be sorted to 5 digits or coarser while incoming mail will be sorted to carrier route or DPS depending on shape and time period. They will also differ in how they have been sorted when they arrive at the plant.

[9] This can also be described in terms of the automobile analogy introduced in Roberts (2006, footnotes 9 and 13) to explain the separability and proportionality assumptions. The output of the automobile plant is the number of vehicles produced. If the plant produces two kinds of vehicles, cars and trucks, then the output of the plant is the number of vehicles in each of the two categories. By treating cars and trucks as two separate outputs, we could estimate a different elasticity of labor hours with respect to the number of cars and labor hours with respect to the number of trucks.

The point is that 1000 letters in $FHP_{OUT}$ will likely use a different bundle of labor hours to reach its final sortation in the plant than 1000 letters in $FHP_{IN}$. To capture this effect each output is allowed to have a different regression coefficient in each labor demand equation.

If all the mail volume observed in the outgoing sortation (and measured as $FHP_{OUT}$) arrived at the plant with the same level of preprocessing and left with the same level of final sortation and all mail volume observed in the incoming sortation (and measured as $FHP_{IN}$) arrived at the plant with the same level of preprocessing and left with the same depth of final sort, then measuring each plant's FHP in these two categories would be sufficient to account for all differences in the mix of outputs across plants and time. Of course, in practice each of these variables are themselves combinations of letter mail that is heterogeneous in its characteristics and thus place different demands on labor hours. For example, $FHP_{OUT}$ includes collection mail and presorted/barcoded mail and these require different amounts of labor input and use different operations in the sorting process. $FHP_{OUT}$ will also contain local mail that remains in the plant and uses inputs in the incoming sorting stage. Also, $FHP_{IN}$ contains some mail that will be sorted to the DPS level and some that will only be sorted to carrier route or coarser. As a result when I estimate that the elasticity of DBCS hours with respect to $FHP_{IN}$, is 1.11 (Roberts 2006, Table 4), this is an estimate of the average effect on labor hours of an increase in the bundle of mail types included in $FHP_{IN.}$ I cannot separate whether it is the effect of sorting to the carrier route or DPS level, only some average of the two.

Conceptually, the useful way to extend the measurement is to divide the mail volume into finer categories with the differences in the level of presorting and final sorting defining the categories. Each category becomes a separate output and the mail volume in that category is the quantity of that output produced in the plant.[10] Each output is allowed to have a different impact on labor use in each operation by allowing a different regression coefficient for each output in each labor demand equation. In other words, the estimating model is not generalized by scaling or replacing FHP with a variable that is bigger or smaller, but rather by disaggregating FHP into finer categories and allowing each category to have a different relationship with labor hours. Regardless of how many categories it is divided into, the total volume of mail in the plant is always the same. Measurement error arising from the weight to piece conversion aside, each piece of mail that enters the plant is counted once and only once. The measure of the total volume of mail in the plant is identical, whether it is divided into one or 50 categories for measuring labor response.

To pursue this issues empirically, I further divide $FHP_{OUT}$ into two categories based on whether or not the mail arrives at the plant with a barcode and is handled directly in a BCS operation or is first processed in an OCR/ISS/OSS operation. This distinguishes mail that arrives in the plant with a barcode and skips all the processing steps used to resolve the address and apply a barcode from mail that passes through these steps. This breakdown is based on the disaggregated (three-digit) MODS category in which the FHP count is assigned. Outgoing mail that receives its FHP count on a MPBCS machine or a DBCS machine operating in BCS mode is assigned to one

[10] This is just like dividing up the number of cars in a plant into the number of compacts and number of full-sized cars and dividing the number of trucks into the number of large trucks and number of small trucks.

category. I call the amount of mail in this category $FHP_{OUT}$ automated. All other mail is assigned to a second category $FHP_{OUT}$ nonautomated.

I perform a similar disaggregation for $FHP_{IN.}$ The first category, which is the larger group, contains the amount of mail that receives its FHP count in an incoming primary or secondary MPBCS or DBCS operation. This is mail that arrives sorted to at least some degree and with a barcode attached. The second category is mail that receives its FHP count in an incoming OCR/ISS operation. This should include presorted mail which does not have a barcode attached and thus is not automation ready. The labor demand models are expanded to include these four categories of FHP and a separate labor elasticity is estimated for each one.

## VI. Estimating Model for Letters, Flats, Priority, and Cancellation Operations[11]

### VI.A Letter sorting

The basic estimating model is explained in Roberts (2006, Section V). I specify labor demand equations for three letter-sorting operations: manual, BCS (which is an aggregate of MPBCS and DBCS operations), and OCR. The dependent variable is the log of labor hours in the operation. I aggregate the MPBCS and DBCS operations into a single input because the MPBCS operation is being phased out over time and is not used in all plants or time periods. It is very difficult to estimate a stable labor demand equation for this operation, but rather than ignore it, I chose to account for the labor hours used by aggregating them with the DBCS hours.

[11] I cannot estimate labor demand models for parcels because the MODS data does not provide the FHP count for parcels in the plant and thus it is not possible to construct a measure of the volume of parcels arriving in the plant.

The key explanatory variables are the log of $FHP_{IN}$ and $FHP_{OUT}$ for letters. The other control variables are capital stocks for all substitute or complementary operations in the plant, which includes MPBCS, DBCS, OCR, AFCS, and all other capital, a dummy variable indicating if the plant still used the MPBCS technology (all plants used DBCS in every year), year dummies to capture long-term changes in technology, relative wage for manual and automated operations, and a plant fixed effect. The capital stock in AFCS is used as a control because of the fact that the cancellation stage is being used to do some of the address recognition step and could thus be a substitute for hours in OCR or other downstream operations.

**VI.B Flat sorting**

The model for flat sorting operations is very similar. I estimate labor demands for three sorting operations in the period 2002-2005: manual, FSM1000, and AFSM. A labor demand for the FSM881 operation is not estimated because it was eliminated from all plants by 2005 and is not relevant for assessing labor response to volume changes in future years. Because of the importance of the AFSM operation and the fact that it was phased in over the 2001-2003 period, I require that the plants in the sample be using the AFSM technology but that the data not correspond to the first year of operation of the AFSM in the plant. This helps to standardize the mix of sorting operations in the sample of plants used for estimation.

The output variables in each equation are the log of $FHP_{IN}$ and $FHP_{OUT}$ for flats. The other independent variables are the capital stocks in FSM881, FSM1000, AFSM100, and other plant capital, dummies equal to one if the plant used the FSM881 or FSM1000 technologies in the time period, the relative wage for manual to automated operations, and year dummies. Notice that the capital stock and technology dummy for the FSM881 operation are included as control variables in the three labor demand equations. This is necessary because this technology was still in use in some plants in 2002-2004 and thus plays a role in generating some of the data that is being used in estimation.

**VI.C Priority Mail**

Priority mail is sorted with a combination of labor hours in manual and labor hours in the SPBS operation. However, not all plants that sort priority mail use the SPBS.[12] I estimate two different models for priority mail. The first model is applied to all plants that report labor hours in the SPBS operation for at least 12 of the 16 quarters from 2002-2005. In this case there are labor demands for both operations. The output variables are the log of $FHP_{IN}$ and $FHP_{OUT}$ for priority mail. The independent variables are the capital stock in the SPBS, the relative wage of manual to automated labor, and year dummies. The second model is estimated for the plants that use only the manual operation to sort priority mail. In this case, the capital stock variable is not relevant and is deleted and there is only a single labor demand equation to be estimated.

**VI.D Cancellation Operations**

The cancellation operation is different from the letter, flat, and priority categories

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[12] Priority mail is sorted on flat sorting machinery in a small number of plants. There were too few observations to estimate labor demand models for this operation and it is ignored.

because the volume of mail relevant to explaining the number of labor hours is not a single shape, but rather is a mix of letters and flats. It is also the case that letters and flats received in the incoming processing stage have already been cancelled and therefore have no impact on hours in cancellation. The relevant output for the labor demand in the cancellation operation is the volume of mail in the outgoing processing stage, which is measured as $FHP_{OUT}$ for letters and $FHP_{OUT}$ for flats. I estimate a single labor demand equation for total hours in this operation using the two $FHP_{OUT}$ variables as explanatory variables. The other control variables are the capital stock in the AFCS equipment, which is the primary capital variable used in cancellation, the capital stock in other plant equipment, the relative wage between cancellation and manual operations, and year dummies.

## VII. Econometric Methodology

Two important econometric issues are discussed in detail in Roberts (2002, Section V). First is the endogeneity of FHP which is caused, at least in part, by measurement error in the use of FHP as a measure of mail volume. I proposed the use of the instrumental variables (IV) estimator to deal with this problem and used the FHP variable for the other shape of mail as an appropriate IV. This was extended to deal with the endogeneity of $FHP_{IN}$ and $FHP_{OUT}$ in Roberts (2006). Second, is the use of plant fixed effects to control for unobserved differences across sorting plants. The use of fixed effects changes the type of variation in the data that is used to estimate the model parameters, reducing the importance of across-plant variation and increasing the importance of time-series variation within each plant. In particular, the role of quarter-to quarter variation in the level of FHP, which reflects variation in the seasonal activity of mailers, is the major source of data variation available to estimate the output elasticities. In Roberts (2006, Section V.E) I showed that including quarterly dummies in the estimating model makes a difference to the estimated elasticities because it changes the type of output variation - from quarterly variation in FHP for each plant to deviations in the quarterly FHP from the common quarterly mean. Because the quarterly variation is common across all plants, this eliminates much of the important exogenous output variation in the data and is not desirable.

In this paper I extend the methodology and show that there is another way to use the quarterly variation in the output data to estimate the model. In the estimating equations in Section VI above, the role of the instrumental variables is to measure variation in $FHP_{IN}$ and $FHP_{OUT}$ that is not the result of measurement errors in the FHP variables or otherwise correlated with the error term in the labor demand equations. Those errors represent random shocks to the technology in the plant that result in variation in labor hours. Any exogenous source of fluctuations in the demand for mail services will lead to fluctuations in the FHP variables that are not correlated with the error term and, as a result, will be useful as an instrumental variable. In short, variables that measure fluctuations in the demand for mail services will be good instrumental variables (IVs) because they will be correlated with FHP but not correlated with the technology shocks or output measurement errors captured by the error terms.

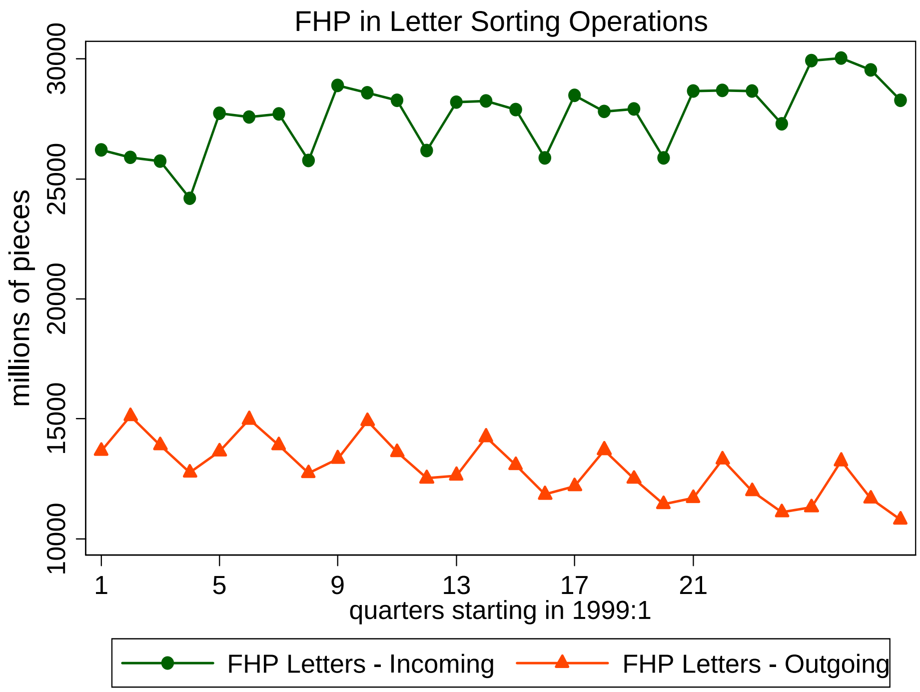
In Roberts (2002, 2006) I used the FHP variables for flats (letters) as IV's for the FHP letters (flats). The FHP variables for the other shape of mail are important because they reflect variation in the demand for mail services that can result from differences in the mix of business and household mailers in the plant's service areas, differences in population and its growth over time, and other sources of differences in demand across plants. In this paper I will augment these with an additional set of variables that also measure differences in mail processing demand across plants and time.[13] The most important addition to the set of IV's is a set of quarterly dummy variables. Figure 1 shows the total FHP for incoming and outgoing letters and flats by quarter for 1991:1 to 2005:4. There is an obvious quarterly cycle with FHP letters being low in the fourth quarter and $FHP_{OUT}$ being high in the second quarter. For flats, the high periods are the first and third quarters of each year. This quarterly variation is due to the actions of mailers and is a nice source of exogenous variation in FHP. The quarterly dummy variables satisfy the requirements for good IVs. In addition I will also include a set of variables that measure the number of destinating letters, flats, and parcels in the plant's service area. These variables are measured externally to the MODS data using ODIS and were first used by the USPS in R2005-1, T-12 and again in R2006-1, T-12 and are potentially useful measures of differences in mail demand across plants and time periods.

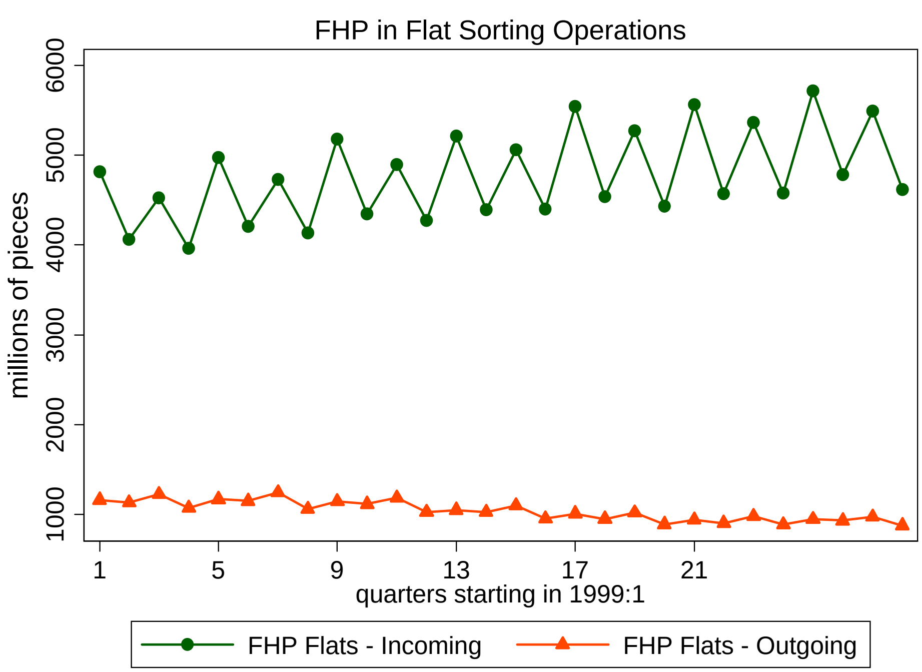
The final set of IVs used in the flat and letter sorting equations are $FHP_{IN}$ and $FHP_{OUT}$ for the other shape, a set of three quarterly dummy variables, and the number

[13] An increase in the number of IV's will lead to an increase in efficiency or decrease in the standard errors of the estimates if the instruments are strongly correlated with the endogenous variables. On the other hand, including variables that are only weakly correlated with the endogenous variable can lead to increased bias in small samples. See the references in Roberts (2002), Section V. For this application we would like a set of IVs that are strongly correlated with the FHP variables. Below we will show that the FHP for the other shape and the quarterly dummies satisfy this requirement.

Figure 1

## Quarterly FHP 1999:1 to 2005:4
(Sum over 304 mail processing plants)



of destinating letters, flats, and parcels in the plant's service area. Because of the importance of the quarterly dummies and the fact that they were not used in my previous studies, I will provide estimates for the models both with and without the quarterly dummies in the set of IVs. In the case of Priority Mail, I will use $FHP_{IN}$ and $FHP_{OUT}$ for both letters and flats in the set of IVs, as well the quarterly dummies and destinating letters, flats, and parcels.[14] Finally, for the cancellation operations the set of IVs has to be altered. Since the endogenous variables are $FHP_{OUT}$ for letters and flats, it is not appropriate to use $FHP_{IN}$ for the same shape as an IV because the factors that lead to measurement error in the outgoing variable could lead to the same type of measurement error in the incoming variable of the same shape. Instead, in this case I use only the quarterly dummies and destination letters, flats, and parcels as IVs.

## VIII. Empirical Estimates of Labor Demand Equations

### VIII.A The Significance of the Instrumental Variables

Before estimating the labor demand models it is important to check the relevance of the instrumental variables. We can empirically test if the IVs are correlated with $FHP_{IN}$ and $FHP_{OUT}$ for letters by regressing $FHP_{IN}$ and $FHP_{OUT}$ on the IVs. These regressions are estimated using the fixed-effects estimators with plant-level intercepts, year dummies, capital stock variables for letter operations, the relative wage for automated and manual letter operations, and the three sets of IVs. Table 2 reports the

[14] The FHP variables for Priority Mail are both appropriate IVs for the letters and flats equations. I did not use them because the set of plants that sort Priority Mail is smaller than the set that sort letters and flats and many observations would be lost in those equations by requiring that the FHP variable for Priority Mail be available to use as an IV.

Table 2

## Hypothesis Tests for Relevance of Instrumental Variables

F-statistic (P-value)

| Instrumental Variable Group | Endogenous Variable | | | |
|---|---|---|---|---|
| | Letters | | Flats | |
| | $\log(FHP_{IN})$ | $\log(FHP_{OUT})$ | $\log(FHP_{IN})$ | $\log(FHP_{OUT})$ |
| $\log(FHP_{IN})=\log(FHP_{OUT})=0$ | 24.43 * (.000) | 65.04 * (.000) | 33.65 * (.000) | 82.19 * (.000) |
| Destinating Letter, Flats, Parcels =0 | 11.69 * (.000) | 0.26 (.851) | 0.46 (.707) | 1.87 (.132) |
| Quarterly Dummies =0 | 226.70 * (.000) | 913.70 * (.000) | 772.38 * (.000) | 82.11 * (.000) |

* Reject the hypothesis that the IV group has no effect on the endogenous variable using a one-percent significance level.

F-statistics for the hypotheses that each set of instruments is statistically significant. The statistics in column 1 show that all three sets of IVs are significantly correlated with $\log(FHP_{IN})$ for letters and thus satisfy the first condition for an instrument. In the second column, both the FHP variables for flats and the quarterly dummies are statistically significant. The quarterly dummies are particularly important as an exogenous source of variation in $FHP_{OUT}$. The group of variables measuring destinating letters, flats, and parcels are jointly not statistically significant, indicating, at best, that they are weak instruments. Given the importance of the other two groups, however, it is unlikely that including them would lead to the small sample biases that arise when there are large numbers of weak instruments.

The last two columns of Table 2 report the same statistics for the FHP flats variables. The FHP variables for letters and the quarterly dummies are always significantly correlated with them. The destinating letters, flats, and parcels are not statistically significant. These latter variables should pick up quarterly variation in mailer activities but the statistical tests show they do not contribute much once the quarterly dummies are controlled for. Nonetheless, I will continue to use these three groups of variables as IVs in all the regression models.

**VIII.B Coefficient Estimates for Letter-Sorting Operations Using Two Outputs**

Table 3 reports the full set of coefficient estimates for the three letter-sorting operations. In general, the capital coefficients and the technology dummy variable for the use of MPBCS are not statistically significant. In particular, there is no significant evidence that the DBCS capital is leading to a reduction in manual labor use. This is

Table 3

## Labor Demand Coefficients: Letter Sorting Operations

FE/IV estimator
(standard errors in parentheses)

| | Manual | OCR | Aggregate BCS |
|---|---|---|---|
| log ($FHP_{IN}$) | 1.423 (.094) * | .800 (.188) * | .788 (.063) * |
| log ($FHP_{OUT}$) | .494 (.041) * | .293 (.079) * | .258 (.027) * |
| Capital MPBCS | .0012 (.012) | .068 (.022) * | .019 (.008) |
| Capital DBCS | -.005 (.006) | -.026 (.011) | -.007 (.004) |
| Capital OCR | .022 (.007) * | .021 (.012) | .007 (.004) |
| Capital AFCS | -.055 (.068) | .125 (.125) | -.072 (.045) |
| Capital Other | .003 (.004) | .006 (.007) | .005 (.002) |
| Tech MPBCS | .008 (.018) | -.073 (.034) | -.013 (.012) |
| Relative Wage | .431 (.041) * | -.263 (.078) * | -.307 (.027) * |
| Dummy 2003 | -.154 (.007) * | -.055 (.013) * | .004 (.004) |
| Dummy 2004 | -.275 (.008) * | -.172 (.017) * | -.017 (.006) * |
| Dummy 2005 | -.383 (.012) * | -.255 (.025) * | -.017 (.008) |
| Intercept | -4.960 (.329) * | -3.188 (.673) * | -1.165 (.218) * |
| | | | |
| $R^2$ | .878 | .795 | .961 |
| Sample size | 4220 | 3879 | 4220 |
| Hausman Test Statistic (p-value) | 197.3 (.000) | 7.40 (.001) | 80.25 (.000) |

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

Instrumental variables used are log($FHP_{IN}$ ) and log($FHP_{OUT}$) for flats, log of destinating letters, flats, and parcels, and three quarterly dummy variables.

likely due to the fact that the technology is well diffused across plants by the start of the sample in 2002 and the substitution of DBCS capital for labor is largely finished by that time.[15] The relative wage variable has the correct sign, higher wages in automated operations lead to an increase in manual labor and a reduction in labor in automated operations. The time dummies indicate a general downward trend in the hours in manual and OCR operations and no significant change in aggregate BCS hours.

Focusing on the FHP coefficients, they vary across sorting operations and between $FHP_{IN}$ and $FHP_{OUT}$.[16] In manual operations a one percent increase in FHP in the incoming sorting stage raises total manual labor use by 1.424 percent. Similarly, a one percent increase in FHP in the outgoing sorting stage raises total manual labor use by .493 percent. A one percent increase in total mail volume in the plant means that both $FHP_{IN}$ and $FHP_{OUT}$ increase by one percent. This will lead to a change in total manual labor hours of 1.917 (=1.424+.493) percent. On average across the observations, manual sorting hours will rise more rapidly in percentage terms than the increase in letter volume. This implies diminishing returns to this sorting operation as mail volume rises. Overall, all three letter-sorting operations show evidence of

[15] I also estimated the model using the same group of plants and all the years from 1999-2005. In this sample the capital coefficients are generally statistically significant and show the expected pattern, increasing the use of labor in the own operation and reducing it in substitute operations. This was also the pattern seen in Roberts (2006) using data for 1999-2004. Both the reduction in sample size and the reduction in the time-series variation in the capital stocks as the DBCS technology was diffused would contribute to a reduction in the capital coefficients estimated using the 2002-2005 data.

[16] The Hausman test statistic reported in the last row of the table, refers to a test of the hypothesis that the FHP variables are exogenous in the labor demand equations. The large value of the test statistic, or low p-value, implies that the hypothesis is rejected indicating it is necessary to use the IV estimator. The exogeneity of the FHP variables will be rejected in virtually all the labor demand equations reported below.

diminishing returns. The effect of a 1 percent increase in both types of FHP on labor use in each operation is given in the third line of Table 4. The effect on labor use in the operation is 1.093 percent (s.e. = .147) in OCR and 1.046 percent (s.e.=.050) in BCS. Neither estimate is statistically different than one.

It is also possible to construct an aggregate elasticity for each of the two outputs as well as for the whole letter-sorting operations. Roberts (2002, Section II.D equations 3-5) shows that each of these aggregates can be written as a weighted sum of the elasticities for the manual, OCR, and BCS operations where the weights are the share of total hours in each of the three operations.[17] The elasticity of total labor hours in letter sorting with respect to an increase in incoming mail volume is a weighted sum of the elasticities in the first row of Table 4. This sum, which is reported in column 4, equals 1.017 meaning that if the incoming mail volume increased by one percent, the total use of manhours in letter sorting operations would increase by 1.017 percent. Similarly, a one percent increase in outgoing mail volume will raise total manhours by .345 percent. Finally, if both incoming and outgoing mail rise by one percent, the use of labor in letter sorting would increase by 1.361 percent. This elasticity implies that labor use rises more rapidly than mail volume or that there is rising marginal cost for letter sorting operations.

The remainder of Table 4 summarizes the estimated output elasticities for a number of alternative models or subsets of the data. Each panel changes one aspect of the model or data and each one can be compared with the top panel. In panel B, the

[17] When aggregating the three operations I will weight by the aggregate hours shares observed in 2005. The shares are: .358 for manual, .077 for OCR, and .565 for BCS.

Table 4

## Output Elasticities of Labor Demand by Letter Sorting Operation

(standard errors in parentheses)

| Elasticity with respect to a change in: | Manual Labor | OCR | Aggregate BCS | | Total Letters |
|---|---|---|---|---|---|
| **A. Base Model: 304 plants, 2002-2005** | | | | | |
| $FHP_{IN}$ | 1.423 (.094) | .800 (.188) | .788 (.063) | | 1.016 (.051) |
| $FHP_{OUT}$ | .494 (.041) | .293 (.079) | .258 (.027) | | .345 (.022) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.916 (.075) | 1.093 (.147) | 1.046 (.050) | | 1.361 (.041) |
| **B. Eliminate quarterly dummy variables as IV** | | | | | |
| $FHP_{IN}$ | .911 (.110) | .783 (.227) | .930 (.080) | | .912 (.062) |
| $FHP_{OUT}$ | .609 (.077) | .420 (.153) | .202 (.056) | | .364 (.044) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.520 (.075) | 1.204 (.241) | 1.132 (.091) | | 1.276 (.061) |
| **C. Disaggregate BCS operation** | | | | | |
| | | | MPBCS | DBCS | |
| $FHP_{IN}$ | 1.423 (.094) | .800 (.188) | .985 (.422) | .761 (.071) | 1.013 (.056) |
| $FHP_{OUT}$ | .494 (.041) | .293 (.079) | .552 (.186) | .222 (.031) | .342 (.025) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.916 (.075) | 1.093 (.148) | 1.537 (.335) | .983 (.056) | 1.356 (.044) |
| **D. Reduced Sample: 237 plants** | | | | | |
| $FHP_{IN}$ | 1.444 (.116) | 1.064 (.180) | .707 (.072) | | .999 (.060) |
| $FHP_{OUT}$ | .503 (.048) | .249 (.074) | .287 (.030) | | .362 (.025) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.947 (.091) | 1.314 (.140) | .995 (.056) | | 1.360 (.047) |
| **E. Expanded Time Period: 1999-2005** | | | | | |
| $FHP_{IN}$ | 1.424 (.076) | .854 (.169) | .567 (.062) | | .896 (.046) |
| $FHP_{OUT}$ | .460 (.037) | .250 (.082) | .320 (.030) | | .365 (.022) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.884 (.061) | 1.104 (.131) | .887 (.050) | | 1.261 (.037) |

only change that is made is to eliminate the use of the quarterly dummies as IVs. The main effect is to lower the elasticity for manual incoming to .911 and raise the elasticity for BCS incoming to .930. This arises because there is a strong cyclical pattern in $FHP_{IN}$ and the quarterly dummies pick up some of this variation that was missed by the other instruments. Because the coefficients move in offsetting directions, the impact on the overall elasticity for labor is less substantial than for the individual components. The overall elasticity for letters falls slightly to 1.276.

Panel C of the table dissagregates the BCS operation into separate MPBCS and DBCS operations. In general, the estimates for the MPBCS operation are not very precisely estimated while the DBCS coefficients have relatively small standard errors. The combined BCS operation is dominated by the hours used in the DBCS operation and thus the coefficients for DBCS are very similar to the aggregate BCS coefficients reported in the top panel. Disaggregating the BCS operation into these two components has no effect on the aggregate elasticities by output in column 4.

Panel D of Table 4 checks the sensitivity of the results to a reduction in the sample of plants that are used to estimate the model. The base group of plants is reduced from 304 to 237 plants to try to achieve a more homogeneous mix of plants.

There is very little effect of reducing the sample in this way.

Panel E of the table applies the base model to the data from 1999-2005. The estimates for manual labor and OCR are virtually unchanged from the estimates using only the 2002-2005 data in panel A. The incoming elasticity for the BCS operation is slightly lower, .567 instead of .788, while the outgoing elasticity is slightly higher and the total elasticity for the operation declines to .887 from 1.046. The reduction in the BCS elasticity contributes to a slight decline in the overall letters elasticity to 1.261.

The estimates in Table 4 are very consistent across a number of alternative specifications. They indicate that a one percent increase in FHP for letters leads to between a 1.26 and 1.36 percent increase in total manhours in the manual, OCR, and BCS operations. While the individual output coefficients may vary across specifications, the aggregate effect is very consistent and indicates diminishing returns or rising marginal cost for letter processing.

One other way to judge the robustness of these results is to compare them with the findings I reported using earlier generations of this empirical model. In Roberts (2002) I use a single output model and report estimates of the overall letter elasticity using 1994-1999 data that vary from .951 to 1.026 depending on various assumptions made. In Roberts (2006) I estimated the same two output model used here and found overall estimates of .990, .890 for $FHP_{IN}$ and .100 for $FHP_{OUT}$ using data for 1999-2004. The current estimates are higher. Using the base model, the elasticity for $FHP_{IN}$ rises to 1.016 and $FHP_{OUT}$ rises to .345. The reason for this is a substantial increase in the elasticities for manual sorting with respect to incoming and outgoing FHP. They rise from .869 and .045, respectively, in the earlier study to 1.423 and .494 in the current study. Tracing the source of this change back farther, the rise in coefficients seen in the current study is caused by a combination of two factors: the change in the sample of years, from 1999-2004 to 2002-2005, and a simultaneous change in the set of IVs, specifically, including the quarterly dummies and destinating letters, flats, and parcels.

If only the change in time period size is made, the comparison of Panels A and E in Table 4 show the current estimates are not greatly affected. If only the quarterly dummies are dropped as IVs, the comparison of Panels A and B show that the elasticities for manual sorting drop and for BCS sorting rise, but the aggregate is unaffected. However, if the time period is expanded to 1999-2005 and only the FHP flat variables are used as IVs then the manual labor elasticities drop to .861 (s.e.=.089) for incoming and .159 (s.e.=.054) for outgoing, which are very similar to the estimates in Roberts (2006, Table 4, column 1). Which set is more appropriate? Given the evidence reported in Table 2, it is appropriate to include the quarterly dummies in the set of IVs. They are highly correlated with the FHP variables and are a good source of exogenous variation in demand for mail services. In Roberts (2006) I did not include quarterly dummies in the set of instruments. The current instruments and, thus the estimates for manual sorting in Table 3, have a stronger justification than the ones used in the earlier paper and I think are more appropriate as a basis for cost allocation in this rate case.

Overall, one strong conclusion that can be drawn from the estimates presented in Tables 3 and 4 is that there is no evidence that the elasticity of labor use with respect to mail volume is less than one in letter sorting. All of the estimates reported in Table 4 indicate that an expansion of total mail volume in the plant results in a larger proportional expansion in total labor hours. While the earlier studies I estimated indicated an overall elasticity closer to one, they also would not support the conclusion that the labor elasticity in letter sorting is less than one.

### VIII.C Letter Sorting Operations with Additional Outputs.

While it is possible to define many categories for output based on different combinations of mailer preparation and final depth of sorting in the plant, the disaggregation of total plant FHP into incoming and outgoing stages captures the two categories of output with the most substantial difference in the mix of labor hours used in sorting. What is gained by this disaggregation in the labor demand models? We can get an idea by comparing the results for the model using $FHP_{IN}$ and $FHP_{OUT}$, reported in Panel A of Table 4 (which are reproduced in Panel A of Table 5), with the results using a single output measure, $FHP_{TOTAL} = FHP_{IN} + FHP_{OUT}$, that are reported in Panel B of Table 5. The comparison reveals that the disaggregation into two outputs has no effect on the total elasticity in each of the three sorting operations or on the estimate of the aggregate labor elasticity in letter sorting. The two output model gives an estimate of this equal to 1.361 while the single output model gives 1.296. If the focus is on the effect of a total increase in plant FHP it matters little whether FHP is treated as a single output or disaggregated into two.

What the single output model provides is an estimate of the effect of a one percent increase in total plant FHP. The gain in moving to the two output model is that it provides separate estimates of the labor response to a one-percent increase in incoming mail volume (1.016) and a one-percent increase in outgoing mail volume (.345). Each output is allowed to have its own effect on labor use in each operation.

In this section I report results for two further disaggregations of FHP. Estimates of the labor demand elasticities for the disaggregation of $FHP_{OUT}$ are reported in Panel C of Table 5. The $FHP_{IN}$ variable is not affected and the elasticity estimates for each

Table 5

## Output Elasticities for Disaggregated FHP categories for Letters

(standard errors in parentheses)

| Elasticity with respect to a change in: | Manual Labor | OCR | Aggregate BCS | Total Letters |
|---|---|---|---|---|
| **A. Base Model: 304 plants, 2002-2005** | | | | |
| $FHP_{IN}$ | 1.423 (.094) * | .800 (.188) * | .788 (.063) * | 1.016 |
| $FHP_{OUT}$ | .494 (.041) * | .293 (.079) * | .258 (.027) * | .345 |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.916 (.075) * | 1.093 (.147) * | 1.046 (.050) * | 1.361 |
| **B. Aggregate FHP into a Single Output** | | | | |
| $FHP_{TOTAL}$ | 1.837 (.057) | 1.058 (.108) | .986 (.037) | 1.296 |
| **C. Disaggregate $FHP_{OUT}$** | | | | |
| $FHP_{IN}$ | 1.307 (.134)* | .710 (.231) * | .809 (.077) * | .981 |
| $FHP_{OUT}$ nonautomated | .371 (.040) * | .147 (.076) | .207 (.023) * | .261 |
| $FHP_{OUT}$ automated | .147 (.067) | .222 (.128) | -.012 (.039) | .063 |
| All 3 categories | 1.825 (.094) * | 1.079 (.171) * | 1.005 (.054) * | 1.304 |
| **D. Disaggregate $FHP_{OUT}$ and $FHP_{IN}$** | | | | |
| $FHP_{IN}$ nonautomated | -.315 (.198) | -.079 (.155) | .077 (.064) | -.075 |
| $FHP_{IN}$ automated | 2.316 (.585) * | 1.035 (.453) | .644 (.191) * | 1.273 |
| $FHP_{OUT}$ nonautomated | .335 (.080) * | .124 (.078) | .209 (.026) * | .248 |
| $FHP_{OUT}$ automated | .020 (.162) | .153 (.154) | .004 (.053) | .021 |
| All 4 categories | 2.357 (.307) * | 1.232 (.243) * | .934 (.100) * | 1.466 |

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

operation are very similar to the base model estimates in Panel A. The elasticity for $FHP_{OUT}$ is now divided among the two new variables. For manual sorting, a one percent increase in nonautomated, outgoing FHP increases labor hours by .371 percent, while a similar increase for automated, outgoing FHP increases labor hours by .147 percent and the coefficient is not statistically different from zero. This effect is quite reasonable. Mail that is first processed in a BCS operation is more likely to be able to be handled in automated operations throughout its stay in the plant and thus have little impact on the use of manual hours. It is also the case that the sum of these two coefficients (.518) is very similar to the elasticity for $FHP_{OUT}$ in Panel A (.494). As was seen when we went from one to two outputs, the further disaggregation does not change the estimated total effect greatly, but just allocates it across more categories. A similar pattern is seen for the OCR and BCS operations summarized in Panel C. Finally, the estimates in the final column of Panel C show that an increase in the volume of mail that is not automation-ready has a larger impact on labor use, the elasticity equals .261, than a similar increase in automation-ready mail, where the elasticity equals .063.

It is also useful to note that the disaggregation of $FHP_{OUT}$ has little effect on the overall elasticity for each sorting operation or for the total labor elasticity in the plant. The latter estimate changes from 1.361 to 1.304. There is one cost of this disaggregation, however, and that is a loss of precision in the estimates. The standard errors of the elasticities tend to be larger, particularly for automated $FHP_{OUT}$, than the estimates in Panel A. Of the six $FHP_{OUT}$ elasticities in Panel C, only two are statistically different than zero. This contributes to an overall increase in the standard errors for the sum in each operation. This loss of precision is not surprising. More coefficients are being estimated and the two new variables are likely to be correlated so that precisely estimating their individual effects can be difficult.

As a final exercise to see how far this process can be taken, I also disaggregate the incoming FHP into two categories. The elasticities are reported in Panel D. None of the three elasticities for incoming, nonautomation FHP are statistically different than zero. For the other category, two of the three coefficients are statistically significant but the standard errors are much larger than the ones for $FHP_{IN}$ in either Panel A or C. The two significant coefficients are in the manual and BCS categories which is reasonable. We would not expect any effect of this output in the OCR operation, however, the estimated coefficient is large, 1.035, but statistically insignificant. Overall the set of output coefficients in Panel D do tend to be larger and statistically significant in the categories where it is expected, manual and BCS for nonautomated outgoing mail and automated incoming mail, but the precision of the estimates is substantially less than in the more aggregated models. The conclusion I draw is that the disaggregation of the FHP variables to finer levels than $FHP_{IN}$ and $FHP_{OUT}$ does not produce elasticity estimates with sufficient precision to be useful in measuring cost differences across categories of mail. Pursuing further disaggregations of FHP to try to correct for increasingly subtle differences in the depth of sorting or preprocessing in the output bundle is not a good use of this data set.

### VIII.D Coefficient Estimates for Flat Sorting Operations

The full set of coefficient estimates for the three flat sorting operations are reported in Table 6. For the manual labor demand reported in column 1, the capital coefficients are statistically significant and indicate that automated and manual hours are substitutes. The use of the FSM1000 technology reduces the demand for manual

Table 6

## Labor Demand Coefficients: Flat Sorting Operations

FE/IV estimator
(standard errors in parentheses)

| | Manual | FSM1000 | AFSM |
|---|---|---|---|
| log ($FHP_{IN}$) | .168 (.170) | .712 (.281) | .394 (.039) * |
| log ($FHP_{OUT}$) | .422 (.288) | .969 (.470) | .450 (.067) * |
| Capital FSM881 | -.268 (.095) * | .129 (.146) | .071 (.022) * |
| Capital FSM1000 | -.325 (.073) * | .373 (.115) * | .043 (.017) |
| Capital AFSM | -.181 (.036) * | .116 (.056) | -.034 (.008) * |
| Capital Other | .012 (.013) | -.020 (.020) | .001 (.003) |
| TECH FSM881 | .043 (.060) | .253 (.096) * | -.089 (.014) * |
| TECH FSM1000 | -.910 (.059) * | n.a. | -.066 (.014) * |
| Relative Wage | .724 (.175) * | -.531 (.296) | -.268 (.040) * |
| Dummy 2003 | .051 (.074) | -.284 (.117) | .074 (.017) * |
| Dummy 2004 | .016 (.086) | -.577 (.136) * | -.013 (.020) |
| Dummy 2005 | .016 (.100) | -.834 (.159) * | .035 (.023) |
| Intercept | 1.320 (.370) * | -1.526 (.663) | .909 (.086) * |
| | | | |
| $R^2$ | .079 | .333 | .856 |
| Sample size | 2860 | 2325 | 2904 |
| Hausman Test Statistic (p-value) | 4.35 (.013) | 16.12 (.000) | 60.27 (.000) |

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

Instrumental variables used are log($FHP_{IN}$) and log($FHP_{OUT}$) for letters, destinating flats, letters, and parcels and three quarterly dummy variables.

labor (all plants in the sample use the AFSM) and the relative wage has the expected sign.

The output coefficients, however, are small, .168 and .422 for incoming and outgoing FHP, respectively, and not statistically different than zero. While this gives an overall elasticity for manual labor of .590 (s.e.=.201), which is reported in the first column of Table 7 under Panel A, the use of manual hours is not closely tied to changes in the volume of flats. In the MODS data there is clear evidence that the introduction and expansion of the AFSM technology has reduced the overall use of manual flat sorting and the decline in manual hours is particularly large for the outgoing stage where it appears that manual sorting has been eliminated in some plants. The implication is that the role of manual processing has changed significantly over the 2002-2005 period as a result of the introduction of the AFSM and that it now plays a much smaller, if not insignificant, role in handling the quarter-to-quarter fluctuation in flats mail volume. It is also the case that if manual sorting of outgoing flats is being phased out of some plants and consolidated in others then the labor elasticity is not being estimated from a relatively homogeneous group of plants. This may help explain the insignificant coefficients.

In contrast, the automated operations, FSM881 and AFSM, show a larger and more statistically significant response to fluctuations in flats volume. As shown in Panel A of Table 7, the incoming and outgoing elasticities for FSM881 hours are larger, although not very precisely estimated, and give an overall output elasticity of 1.681 (s.e. = .334). The AFSM has the most precisely estimated output elasticities and the overall elasticity for an expansion of both incoming and outgoing FHP is .844 (s.e.=.047). It is clear from the raw data that, as the AFSM operation has increased in importance, it is

Table 7

## Output Elasticities of Labor Demand by Flat Sorting Operation

(standard errors in paretheses)

| Elasticity with respect to a change in: | Manual Labor | FSM1000 | AFSM | Total Flats |
|---|---|---|---|---|
| **A. Base Model: Use AFSM technology, 2002-2005** | | | | |
| $FHP_{IN}$ | .168 (.170) | .712 (.281) | .394 (.039) | .403 (.076) |
| $FHP_{OUT}$ | .422 (.288) | .969 (.470) | .450 (.067) | .551 (.127) |
| $FHP_{IN}$ and $FHP_{OUT}$ | .590 (.201) | 1.681 (.334) | .844 (.047) | .954 (.090) |
| | | | | |
| **B. Eliminate quarterly dummy variables as IV** | | | | |
| $FHP_{IN}$ | -.140 (.289) | .177 (.504) | .448 (.073) | .242 (.134) |
| $FHP_{OUT}$ | .415 (.313) | 2.042 (.529) | .605 (.079) | .857 (.142) |
| $FHP_{IN}$ and $FHP_{OUT}$ | .275 (.361) | 2.219 (.595) | 1.054 (.091) | 1.098 (.162) |
| | | | | |
| **C. Single Output** | | | | |
| $FHP_{TOTAL}$ | .396 (.125) | 1.270 (.214) | .654 (.027) | .717 (.057) |
| | | | | |
| **D. Plants that do not use AFSM, 1999-2005** (a) | | | | |
| | Manual | FSM1000 | FSM881 | |
| $FHP_{IN}$ | .726 (.099) | .214 (.114) | .994 (.167) | .767 (.094) |
| $FHP_{OUT}$ | .169 (.154) | .364 (.200) | .219 (.278) | .233 (.156) |
| $FHP_{IN}$ and $FHP_{OUT}$ | .895 (.135) | .578 (.162) | 1.213 (.232) | 1.000 (.130) |

(a) the operations are aggregated using hours shares in 1999. The shares are .286 for manual, .192 for FSM1000 and .521 for FSM881.

also the operation where manhours respond most clearly to the quarterly fluctuations in FHP. Essentially, the response of manhours to the quarterly fluctuations in mail volume has shifted over time from the manual operation to the AFSM operation as the latter has grown in importance. This is consistent with both the level and precision of the estimated output elasticities in Panel A.

Aggregating across these operations produces an elasticity for incoming flats of .403 and for outgoing flats of .551.[18] The overall flats elasticity is the sum of these two, .954. Even though the individual components are not very precisely estimated, the overall flats elasticity does not indicate that there are significant increasing returns in flat sorting.

The remaining panels of Table 7 report estimates for alternative model specifications. Panel B deletes the quarterly dummies from the set of IV. This has a substantial effect on the estimates for the FSM1000, although the standard errors are so large that the estimates are useless. More interestingly, there is an increase in the magnitude of the elasticities for the AFSM as well as an increase in their standard errors. The latter likely reflects the loss of the information contained in the quarterly fluctuations, particularly in $FHP_{IN.}$ The overall flats elasticity rises to 1.098 but again the underlying components are not precisely estimated. Panel C reports elasticity estimates for a single output model. Given the large difference in the level of incoming and outgoing FHP (see the bottom panel of Figure 1) I would expect this model to be dominated by the data variation in $FHP_{IN}$ but the estimates are not really similar to those

[18] The hours shares that are used to weight over the three sorting operations are the shares of total hours in 2005. The shares are: .254 for manual, .208 for FSM1000, and .537 for AFSM

in the top row of Panel A. The one consistent element is that the elasticity for AFSM always has the smallest standard error and this reflects the fact that this operation is the main one used to handle the quarterly variation in FHP.

Finally, I report one additional set of estimates to try to more fully understand the role of manual flat sorting. As seen in Panel A, the manual elasticities are small and not statistically different than zero. There was an indication of this in the results reported in Roberts (2006) using data for 1999-2004, but the estimated responses are even smaller using this sample which requires the plants to be using the AFSM technology. As an alternative, I estimated a model for flats using only the subset of the data that is not affected by the AFSM operation. The bottom panel of Table 7 reports estimates for the subset of plants and time periods where the AFSM technology was not used. This includes most plants for the years 1999-2001 and a group of 65 plants for the years 2002-2005. These plants use only the manual, FSM881, and FSM1000 operations. The main point to notice is that the manual elasticities are much larger, .726 for incoming, .169 for outgoing, and .895 overall, and the latter is statistically significant. Prior to the introduction of the AFSM, manual hours played a much larger role in responding to fluctuations in mail volume.

The comparison of the top and bottom panels in Table 7 demonstrates two points: the importance of modeling the plant as an integrated whole rather than focusing on sorting operations separately and the need to use information on the volume of mail in the plant. The introduction of the AFSM technology greatly alters the relationship between the volume of flats and the hours in manual sorting. If there has been no change to the technology of manual flat sorting, a change in the relationship between manual hours and pieces handled would not be observed, but there can still be a substantial change in the link between manual hours and volume. Without using information on the volume of flats processed in the plant and also correcting for the presence and use of the alternative automated technology it would be impossible to see this.

Overall, the labor demand elasticities in the individual operations, particularly the manual and FSM1000 operations, are sensitive to the data sample that is used and are often not very precisely estimated. The introduction of the AFSM technology had a major impact on the use of labor in these other sorting operations and the estimated elasticities reflect this. In the plants and time periods where the AFSM operation was in operation, the elasticities for manual labor are small and not statistically significant. In contrast, in the plants and time periods where the AFSM technology was not deployed, the elasticity of manual labor use to a change in incoming and outgoing FHP is .895. Given that the AFSM technology was deployed over the 2001-2003 period, much of the sample data used to estimate these equations may reflect a period of transition where all operations, not just AFSM, are adjusting. I believe more time is going to be needed before we can observe a stable relationship in the data for these operations. At this point I do not recommend using these data or estimates to construct cost allocations for flat sorting.

**VIII.E Coefficient Estimates for Priority Mail**

As was the case with flat sorting, there are two different mixes of technologies in the plants that sort Priority Mail. One group of plants uses only manual operations while the other uses manual and SPBS. I estimate the labor demand equations separately for each group of plants and the coefficients are reported in Table 8. For the plants that

Table 8

## Labor Demand Coefficients: Priority Mail

FE/IV estimator
(standard errors in parentheses)

| | Plants only use Manual | Plants use SPBS | |
|---|---|---|---|
| | | Manual | SPBS |
| log ($FHP_{IN}$) | .487 (.132) * | .393 (.176) | .277 (.221) |
| log ($FHP_{OUT}$) | .697 (.190) * | .804 (.168) * | .254 (.204) |
| Capital SPBS | n.a. | -.0003 (.0001) * | .00004 (.0001) |
| Relative Wage | -.082 (.335) | .758 (.279) * | -.630 (.337) |
| Dummy 2003 | -.009 (.056) | .130 (.054) | -.110 (.064) |
| Dummy 2004 | .047 (.062) | .034 (.049) | -.068 (.059) |
| Dummy 2005 | .004 (.063) | -.033 (.049) | -.152 (.059) |
| Intercept | 2.168 (.155) * | 1.636 (.107) * | 1.203 (.131) * |
| | | | |
| $R^2$ | .658 | .431 | .262 |
| Sample size | 1217 | 1154 | 1159 |
| Hausman Test Statistic (p-value) | 19.53 (.000) | 33.50 (.000) | 1.11 (.331) |

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

Instrumental variables used are log($FHP_{IN}$ ) and log($FHP_{OUT}$) for letters and for flats, destinating flats, letters, and parcels, and three quarterly dummy variables.

just use manual sorting, reported in column 1, the output elasticities are .487 and .697 for incoming and outgoing FHP, respectively. Both estimates are statistically significant. The overall elasticity for output is reported in Panel A of Table 9 and is 1.184 for this group of plants. This elasticity does decline to .833 if the two FHP variables are aggregated into a single output, although the size of the standard errors makes it hard to distinguish the two cases.

For the plants that also use the SPBS operation, the output elasticities in the first two rows of Table 8 are not statistically significant in three of the four cases. Only the coefficient on outgoing FHP in the manual operation is large and statistically significant. The overall elasticity for manual labor, reported in Panel B of Table 9, is is 1.197 for this group of plants. The SPBS operation has a lower elasticity (.531) than the manual operation and this results in a slightly lower overall elasticity, equal to 1.033, for plants that use both technologies.[19]

Overall, Priority Mail is characterized by an elasticity with respect to total volume that is not statistically different than one.

**VIII.F Coefficient Estimates for Cancellation Operations**

Tables 10 and 11 report the output elasticities for the cancellation operation. In this case the output variables are $FHP_{OUT}$ for letters and flats. I report the results for two time periods, 2002-2005 and 1999-2005, as a way of checking the robustness of the estimates. The elasticity for outgoing letters is .701 and .802 in the two time periods

[19] The share of manual hours in these plants in 2005 is .753 and the share of hours in the SPBS operation is .247. These are the weights used to construct the overall elasticity for Priority Mail.

and the standard error is small. The elasticity for outgoing flats is .217 and .142 depending on the time period and it is not as precisely estimated. The overall hours elasticity from an expansion of both outputs is .918 or .943 depending on the time period and neither estimate is significantly different than one. Both estimates are substantially higher than the .5 estimated advocated in USPS-T-12.

Table 9

## Output Elasticities of Labor Demand for Priority Mail

(standard errors in parentheses)

| Elasticity with respect to a change in: | Manual Labor | SPBS | Total Priority |
|---|---|---|---|
| | | | |
| **A. Plants only use manual** | | | |
| $FHP_{IN}$ | .487 (.132) | | .487 (.132) |
| $FHP_{OUT}$ | .697 (.190) | | .697 (.190) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.184 (.142) | | 1.184 (.142) |
| | | | |
| **B. Plants use manual and SPBS** | | | |
| $FHP_{IN}$ | .393 (.176) | .277 (.221) | .364 (.143) |
| $FHP_{OUT}$ | .804 (.168) | .254 (.204) | .668 (.162) |
| $FHP_{IN}$ and $FHP_{OUT}$ | 1.197 (.167) | .531 (.200) | 1.033 (.135) |
| | | | |
| **C. Single Output -manual only** | | | |
| $FHP_{TOTAL}$ | .833 (.088) | | .833 (.088) |
| | | | |
| **D. Single Output -manual and SPBS** | | | |
| $FHP_{TOTAL}$ | 1.293 (.224) | .556 (.189) | 1.110 |

Table 10

## Labor Demand Coefficients: Cancellation Operations

FE/IV estimator
(standard errors in parentheses)

| | 2002-2005 data | 1999-2005 data |
|---|---|---|
| log ($FHP_{OUT}$) for letters | .701 (.047) * | .802 (.050) * |
| log ($FHP_{OUT}$) for flats | .217 (.079) * | .142 (.076) * |
| Capital AFCS | .245 (.088) * | -.092 (.049) * |
| Capital Other | .014 (.005) * | .018 (.002) * |
| Relative Wage | .174 (.066) * | -.149 (.056) |
| Dummy 2003 | -.034 (.009) | -.002 (.011) |
| Dummy 2004 | -.030 (.011) | .003 (.013) |
| Dummy 2005 | -.002 (.013) | .037 (.014) |
| Intercept | -1.175 (.162) * | -1.347 (.168) |
| | | |
| $R^2$ | .773 | .748 |
| Sample size | 4067 | 7226 |
| Hausman Test Statistic (p-value) | 76.37 (.000) | 101.79 (.000) |

Instrumental variables used are the logarithm of destinating flats, letters, and parcels, and three quarterly dummy variables

Table 11

## Output Elasticities of Labor Demand for Cancellation Operations

(standard errors in parentheses)

| Elasticity with respect to a change in: | Labor |
|---|---|
| | **2002-2005 data** |
| $FHP_{OUT}$ Letters | .701 (.047) |
| $FHP_{OUT}$ Flats | .217 (.079) |
| $FHP_{OUT}$ for Letters and Flats | .918 (.074) |
| | |
| | **1999-2005 data** |
| $FHP_{OUT}$ for Letters | .802 (.050) |
| $FHP_{OUT}$ for Flats | .142 (.076) |
| $FHP_{OUT}$ for Letters and Flats | .944 (.071) |