The Properties of Diffusion of an Automated Technology and its Effects on Labor Demand and Productivity: Evidence from the US Postal Service

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August 22, 2012

Abstract

This paper sheds light on the technological change process at the micro level using data from the United States Postal Service. The data-set covers the period from 1999 to 2005 during which an automation technology was gradually introduced across most of the USPS mail sorting plants. For each plant, at the quarterly frequency, we observe output, labor hours, capital stock and capital utilization and use this information to model the production technology and the demand for labor. One of the questions the paper answers is whether there is evidence of a slow adjustment process from the old to the new technology. The main finding of the paper is that there is, indeed, not only slow adjustment, but also experience spillovers from one facility to another, rendering the transition faster for the later adopters. The other question addressed is what is the the effect of automation technology on labor demand and plant productivity. I find that total labor demand was reduced by more than fifty percent, labor productivity more than doubled and its dispersion across plants increased significantly.

JEL Classification Codes: L87, O14, O33
Keywords: Technical Change, Automation Technology, Capital Adjustment Cost, Learning by Doing, Knowledge Spillovers, Productivity Dispersion, US Postal Service

*I thank my advisor, Mark Roberts for guidance and sharing the data used in this paper and Herman Bierens, Geert Ridder, Mark Rysman for helpful discussions. I also want to thank Daniela Puggioni for proofreading this and earlier drafts. Correspondence: 303 Kern, Department of Economics, Pennsylvania State University, University Park, PA 16802. Email: fakos@psu.edu

1 Introduction

There are several questions of interest to economists related to technology change at the establishment level. One set of questions has to do with the characteristics of the firms that introduce new technologies and which changes new technology induces in the organization of the firm. Dunne (1994) finds that plant size is correlated with the probability of adopting computer technologies. Dunne et al. (2004) show that the increase in computer investment leads to higher labor productivity and wage dispersion.

Another set of questions is related to the adjustment process from the old to the new technology. New technology usually implies large capital investment and the question is how large are capital adjustment costs and what are their properties. Cooper and Haltiwanger (2006), using plant level data from the US Census, estimate a structural model of firm investment and show that the data are consistent with non-convex adjustment costs and that, during the adjustment period, firms have lower profits. The speed of adjustment is also of interest since slow adjustment means that productivity gains are realized after several years. Brynjolfsson and Hitt (2003) study the effects of computerization on productivity and find that the productivity gains associated with computerization are five times larger over longer periods than over a one year period. Moreover, it is particularly interesting to ask whether there are experience spillovers from early adopters to late adopters that make adjustment costs lower for the latter. Levin et al. (1992), looking at the introduction of optical scanners at grocery stores, find that a supermarket chain adopting optical scanners, rolls out the new equipment faster in all its stores the larger the number of competing chains that already adopted the new technology.

In this paper I will answer several of the aforementioned questions using a unique dataset from the US Postal Service (USPS). More specifically, I will use plant level data from the USPS sorting facilities which are manufacturing style plants with the sole purpose of

sorting mail. My focus will be at the process of sorting a particular category of mail, flat mail, which includes magazines, large envelopes, newspapers, catalogs and anything else too large to be a letter and too small to be a parcel. This is because in this particular subprocess new capital equipment with automation technology was introduced in 2000 which changed the nature of production completely. Labor productivity at least doubled, a large portion of the old equipment was retired and labor demand dropped by more than fifty percent. What makes this data-set unique is the fact that I am able to see the labor hours allocated to the four substitute sorting technologies, the most labor intensive manual sorting, the two medium labor intensive mechanized sorting methods and the new least labor intensive computerized sorting technology in each plant. This level of detail in conjunction with the high frequency (quarterly) of the observations allow me to observe the substitution patterns among technologies along the transition path and extract useful information about the characteristics of the adjustment process.

I model the transition as a slow adjustment, depending on experience in using the new technology, and I find that adjustment happens rapidly the first year after the introduction of the new technology at each plant and that the productivity gains from the new capital equipment are not fully realized until four years after adoption. Moreover, taking advantage of the slow deployment of the technology across the plants, I am able to study the experience spillovers from early adopters of the technology to the late adopters and I find that late adopters were able to incorporate the new technology in production faster and realized productivity gains in less time than early adopters. This rendered the adjustment cost of the late adopters sixty percent lower than that of the early ones. Furthermore, my results indicate that the productivity dispersion across plants increased significantly after the automation technology was fully incorporated in production. Since this paper is related to technology adjustment and my modeling approach can be thought as a model of

learning due to accumulated experience, the next section presents a review of the literature on learning by doing and technology adjustment. Section 3 provides an overview of the industry environment, section 4 describes the data, sections 5 and 6 present the estimation methodology and the econometric issues involved, section 7 discusses the results and section 8 concludes.

2 Literature Review

An empirical literature in industrial organization has developed to study learning in production processes. The definition of learning by doing is the productivity enhancement due to accumulated experience. Experience can take the form of cumulative output, at the firm/plant level, or the amount of time a process has been performed. Zimmerman (1982) uses data from the construction of nuclear power plants to study how the accumulated experience in construction affects construction costs and the accuracy of their forecasts. He finds that internal learning by the construction firms is significant, while spillovers between firms are marginally significant. Benkard (2000), using data from one aircraft manufacturing production line, investigates the presence of learning by doing and spillovers between different aircraft models. His results indicate that the learning rate (the decrease in costs due to doubling of experience) is 36%, there is evidence of spillovers, and experience depreciates with time - what he calls organizational forgetting. Jarmin (1994) estimates a structural model of oligopoly in the rayon industry to investigate whether there is heterogeneity in the ability of firms to learn and whether learning induces firms to behave strategically. His analysis supports an affirmative answer to both questions. Lieberman (1984), using data for 37 chemical products under the assumption of constant price cost margins, finds that cumulative industry output, as a proxy of industry-wide experience, explains much of the cost reductions, with the learning rates varying between

different industries. Thompson (2001), Thompson (2007) and Thornton and Thompson (2001) use data from wartime shipbuilding to investigate the properties of learning. They conclude that learning in each shipyard is significant, while learning spillovers between shipyards are moderate and there is no evidence of organizational forgetting. Irwin and Klenow (1994) estimate a structural model with data from the Dynamics Random Access Memory Manufacturing industry and find that there is significant firm level learning as well as learning spillovers between firms. Moreover, the spillovers between firms are not confined between US manufacturers but are equally important between US and Japanese firms. More recently, Levit et al. (2011), using detailed production data from an automobile manufacturing plant, explore the nature of the learning process. Their estimates show that learning is not incorporated in the assembly teams, but it is embedded in the organizational capital of the plant and most of it takes place after 8 weeks from the introduction of each new car model in the assembly line.

Another strand of the literature related to this paper is the one on the nature of capital adjustment cost and the effect of technology on the organization of the firm. Doms and Dunne (1998), using data form the US Census, observe that investment is lumpy, i.e occurs in spikes. Bresnahan et al. (2002), combining firm level economic and survey data, verify that Information Technology investment is complementary with organizational change and demand for high skilled labor, indicating that investment is associated with costly changes at the firm level. Bartel et al. (2007), using data from the valve manufacturing industry, find that firms that adopted Information Technology changed the scope of product line and increased their demand for skilled labor.

3 Background Information on Mail Sorting

In this section I outline the USPS mail sorting operations. Mail is collected from the local post offices and sent to a Processing and Distribution Center (PDC), which is a facility where the stamps are canceled and the mail is sorted by destination and which from now on I will refer to as plant. The working conditions at these plants are similar to those of an assembly line in manufacturing industries. After sorting is undertaken, mail is transported either to a post office for door to door distribution or to another plant for further processing.

Mail is classified in three categories: Letters, Flats and Parcels. Letters are approximately between 5 and 11 inches long, 3 and 6 inches wide, weighting no more than 3.5 ounces and being no more than a quarter of an inch thick. Utility bills and postcards fall in this category. Flats are approximately between 11 and 15 inches long, 6 and 12 inches wide, one quarter and 3 quarters of an inch thick and must be flexible. Magazines, catalogs, newspapers and large envelopes fall in this category. Inflexible mail or mail exceeding the dimensions of flats is classified as parcel. These three mail categories use different sorting equipment that are not substitutes in production and as a result the three corresponding sorting processes can be studied in isolation.

When mail arrives at a plant letters and flats are weighed in bulk and, using an estimate for pieces per kilogram, the weight is converted to mail pieces. All pieces will be eventually sorted, so the number of sorted pieces is what I consider as the measure of output.

In this paper I will focus on the sorting of flats since the technological change occurred in this process. During the 1990's there where three flat sorting technologies available at the USPS plants. The first is manual sorting involving mainly human hands. The second is mechanized sorting employing FSM881 machines. Each machine is capable of processing either mail with a barcode, printed by the sender, which contains information on the destination zip code or mail with a hand-written destination address. The barcoded

mail are just fed in the machine which mechanically places them in the appropriate bin while the non-barcoded mail has to be fed first to an the operator who has to type the destination zip code on a keypad and then the machine places the mail at the appropriate bin. FSM881 machines can sort at most fourteen thousand flats per hour and have limited capability in the sense that they cannot process magazines that are poly-wrapped or flats that are flimsy enough that cannot stand on their own. The third technology involves FSM1000 that is manned by two employees that load the mail and four employees that type the zip codes. It can mechanically sort a wider range of barcoded or non-barcoded flats than the FSM881, at a rate of ten thousand per hour[1].

In 2000 a new sorting technology was gradually introduced in the plants in the form of the AFSM100 machines. The AFSM100 is capable of processing all kinds of flats either barcoded or non-barcoded mail using an image processing software that can read hand-written addresses and infer the proper sort location at a rate of twenty one thousand per hour. It is manned by three people who load the mail in the machine. If the address cannot be read by the machine, a photo of the mail is taken which then appears on the computer screen of an employee who reads the address and types the zip code on a keypad in order the mail to be processed without being rejected by the machine. One advantage of this capability is that the person who reads the address of the rejected mail does not have to be in the plant. The photo can be sent anywhere through the network so only few plants need to maintain personnel for this kind of job[2]. The adoption of the AFSM100 technology resulted in the substitution of capital for labor in such a degree that total labor demand decreased by more than fifty percent. FSM881 machines were retired completely and labor demand for both manual and mechanized(FSM881, FSM100, AFSM100) sorting fell more than fifty percent. However, the realization of the advantages of the AFSM100

[1]For more details on FSM881 and FSM1000 see USPS (1999)
[2]For more information on AFSM100 see USPS (2002)

machines was not immediate. Software configuration and design of the sorting process took time to be optimized. The optimal stock of spare parts took time to be achieved causing either unnecessary machine downtime or overstocking of spare parts. Machine manuals and handbooks were rewritten several times until they reached a sufficient quality[3].

In this paper I am going to study the diffusion of AFSM100 in the plants and its effect on labor demand and productivity. I model the adjustment process as a learning process and investigate its properties. In the next section the data-set used in this study is described in detail.

4 Data

The data I use is a panel consisting of quarterly observations of 225 plants for the years 1999-2005. Specifically, there are plant level observations for 28 quarters of the following variables. The capital stock of machinery for each of the three mechanized flat sorting technologies (FSM881, FSM1000 and AFSM100), the labor hours allocated to each of the four flat sorting processes (manual, FSM881, FSM1000, AFSM100) and the number of pieces of mail fed in the FSM881, FSM1000 and AFSM100 machines. Also, the total number of flats, letters and parcels sorted in each plant and two hourly labor wage rates, one for the mechanized operations and one for the manual operations are available. Furthermore, for each mail category, there are two extra variables measuring the outgoing and incoming mail sorted[4]. The distinction is important because incoming mail differs from the outgoing in the depth of sorting required and the different mix of the two in each plant is something that can affect the labor hours and capital services used in each plant. The data come

[3]For further details on the deployment of AFSM100 see Darragh (2007)

[4]Incoming is the mail coming from other plants and has to be sorted by five digit or even nine digit zip code in order to be distributed to the local post offices, while outgoing is the mail collected locally and has to be sorted (usually) at the 3 digit level in order to be sent to other plants.

from the USPS itself which uses them to monitor production.

The descriptive statistics that follow are intended to give the reader a rough idea of the effect of the new technology in the production process and the cyclicality of output.

Mail demand is very cyclical and consequently plant output is cyclical, too. The left panel of Figure 1 depicts the quarterly time series pattern in the aggregate number of flats sorted across all plants[5]. Observe that the time trend in output is slightly positive. The right panel of Figure 1 shows the output by quarter to stress more vividly the seasonality of output which will be also evident in the labor demand analysis that follows.

In this paragraph I delineate the pattern of adoption of the AFSM100 machines and its effect on labor demand. The introduction of AFSM100 in the plants started in the second quarter of 2000 or the sixth quarter in the quarterly time series. Mechanized sorting using AFSM100 gradually replaced FSM881 and FSM100 sorting with FSM881 being retired completely. Figure 2 shows the labor demand for the three mechanized sorting technologies. Observe that labor demand exhibits the same seasonality as output. However, during the deployment of the AFSM100 machines, from quarter 6 to approximately quarter 15, the seasonality pattern breaks since the transition process induces such significant labor reallocation between technologies that wipes out the cyclicality.

The main effect of the new technology in the production process is the reduction in labor demand. Figure 3 depicts the total labor demand for flats processing by all plants and it is evident that labor demand decreased by more than fifty percent which is attributed to the introduction of the AFSM100[6]. Figure 4 and Figure 5 depict aggregate demand for mechanized sorting and manual sorting, respectively, and we can observe that both

[5]Because some plants have few missing observations and consequently the time series for these plants are shorter, these plants were not included in the aggregation for figure 1 but were included in the estimation and the derivation of all the other statistics. I do so to make sure that missing values do not distort the series pattern of the aggregate output.

[6]Output during the same time remained constant if not increased slightly as you can see in Figure 1

decreased by more than fifty percent. This means that the adoption of the AFSM100 technology not only substituted for labor in mechanized sorting but also in manual sorting. This is because the new AFSM100 machines are able to process flats that are impossible to be processed by the FSM881 and FSM1000 equipment and thus a higher percentage of the total mail volume was processed on automatic equipment.

The deployment of AFSM100 machines in the plants did not happen in an instant. It took a little more than two years, from the second quarter of 2000 to the third quarter of 2002. Approximately half of the plants got their first AFSM100 machine in the first four quarters of the deployment with the remaining half of the plants acquired the technology in the next 6 quarters. Figure 6 presents the histogram of the quarter of introduction of AFSM100 in each plant. This heterogeneity in the time of introduction allows me to investigate whether the accumulated experience of the first adopters spilled over to the late adopters making it easier for them to make the transition to the production with the new technology.

Before proceeding to the model I would like to discuss the relationship between technology adoption and plant size. Of the 225 plants in the sample, 27 of the smallest plants never adopted the AFSM100 technology which is in line with the finding of Dunne (1994) that the probability of adopting computerized technology is positively correlated with size. Moreover, size is also correlated with the quarter of introduction. The largest plants were the first adopters with the smallest plants acquiring the technology towards the end of the deployment. Figure 7 presents the relationship between plant size, measured as the average quarterly flats output, and quarter of introduction. The plants that never got the AFSM100 machines are depicted as if they adopted the technology at quarter 28. The graph shows that the first 4 quarters of introduction the machines where deployed in plants of varying sizes while the following quarters the technology was introduced predominantly

in smaller plants.

5 Estimation Methodology

The purpose of this paper is to investigate the characteristics of the transition process from the old technology to the new and the effect of automation on labor productivity. I model the transition process as a learning process about the new technology. I assume that when a plant when first gets the AFSM100 machines it incorporates them in production but is unable to realize their full potential until it accumulates enough experience either by using them or by learning from other plants' experiences or both. In order to estimate the effect of experience on the transition from the old production technology to the new, I estimate the labor demand functions for each sorting technology, manual, FSM881, FSM1000 and AFSM100, assuming that labor demand depends on a measure of experience. I assume that each plant minimizes labor costs given capital stock of each technology, output of flats to be sorted and a state variable measuring experience. Each plant chooses the allocation of labor between the subprocesses and the utilization of capital.

Consider the following cost function faced by each plant:

$$C(w, k, y, E) \tag{1}$$

where w is a vector of hourly wages for manual labor and labor used in automated sorting operations (w_m, w_a), k is a vector of the level of the stock for the different capital equipment (k_1, k_2, k_3, k_o), where k_1, k_2, k_3 correspond to the FSM881, FSM1000, AFSM100 machines and k_o is the level of the stock of other capital equipment[7] used in the plant such as forklifts, scales etc. Variable y is a vector of the log of incoming and outgoing flats to be

[7]Th capital stock in each category is deflated using national capital deflators in order to control for different vintages.

sorted $(y_{\text{in}}, y_{\text{out}})$ and E is a variable measuring experience. Depending on the specification of experience, E is either a scalar or a vector. The reason why I use capital stock in levels instead of logarithms is that each of these three capital stocks are not essential in production and often take the value of zero. I am not interested in the coefficients of the capital stock variables per se however, I want to control for the capital mix so I include their levels. I break output into incoming and outgoing flats because outgoing mail may involve different depths of sorting than incoming mail. Since plants are heterogeneous in the mix of outgoing and incoming mail, due to the way the plant network is set up, it is important to account for this heterogeneity. To the cost function correspond four labor demand functions, which represent the optimal labor allocations, given w, k and y. These labor functions are given by:

$$l_m(\tilde{w}, k, y, E) \quad l_1(\tilde{w}, k, y, E) \quad l_2(\tilde{w}, k, y, E) \quad l_3(\tilde{w}, k, y, E) \quad l(\tilde{w}, k, y, E) \tag{2}$$

where $\tilde{w} = \frac{w_a}{w_m}$ is the logarithm of the ratio of the wages in mechanized/automated and manual sorting, l_m, l_1, l_2, l_3 is the logarithm of labor hours used in manual, FSM881, FSM1000, AFSM100 sorting respectively and l is the logarithm of total labor hours allocated to flats sorting.

Total labor demand, equation l, will show how total labor adjusts, abstracting from substitution patterns between the four subprocesses (FSM881, FSM100, AFSM100 and manual sorting). Equations l_m, l_1, l_2, l_3 will show how experience affects individual technology processes and the substitution patterns between them.

I assume that the labor demand equation takes the form:

$$l_{it} = a_i + b_y y_{it} + b_k k_{it} + b_u \text{tech}_{it} + b_{\tilde{w}} \tilde{w}_{it} + b_e E_{it} + \epsilon_{it} \tag{3}$$

Parameters a_i are plant level fixed effects which control for plant level differences in organizational capital, building layout and staffing patterns not captured in wages. Parameters b_y are the incoming and outgoing output elasticities while parameter b_w is the relative wage elasticity. The variable tech is a vector $(\text{tech}_1, \text{tech}_2)'$ of dummy variables that take the value zero when the technologies FSM881 and FSM1000 respectively are idle which means that the machines are not sorting any mail during that quarter. This is because before either FSM881 or FSM1000 are retired they remain idle in the plant for some quarters. This extreme form of underutilization is a form of measurement error, and if not controlled for, will bias the capital coefficients of FSM881 and FSM1000. The coefficients of experience b_e capture the learning component of labor demand.

The basic specification of experience that I use takes the form of dummy variables corresponding to quarters since the introduction of AFSM100 in the plant. The quarter of introduction is defined as the first quarter where the plant reports positive labor hours and positive pieces fed in the AFSM100 operation. In other words, the dummy variable $Quarter1$ takes the value one in the first quarter of introduction of AFSM100, while the dummy variable $QuarterN$ takes the value one in the Nth quarter since the introduction. I chose dummy variables because it is a very flexible way to capture experience imposing minimal assumptions on the functional form of the effect of experience on labor demand. This specification captures solely own plant learning and ignores spillovers from other plants. I also estimate two additional specifications of the experience variables. One that takes the form of the logarithm of the number of quarters since the introduction, nq_{it}, and the other that takes the form of the logarithm of the cumulative labor hours used in the AFSM100 sorting operation since its introduction in the plant, i.e. $ce_{it} := \log\left(\sum_{j=0}^{t-1} L_{3ij}\right)$. The last two specifications assume constant learning rate and are estimated mainly in order to make the results comparable with the literature on learning by doing.

To capture spillovers between plants, I estimate the labor demand with 4 different specifications of experience. In the basic specification I create two sets of dummy variables $QuarterN$ corresponding to two cohorts of plants. The first cohort is comprised of the 95 plants that got their first AFSM100 machine the first year of deployment while the second cohort is comprised of the 102 plants that got the technology later. In this way I am able to test whether the coefficients of the dummy variables are the same between the two cohorts. In the next three specifications I add interaction terms between the dummy variables $QuarterN$ and a variable capturing aggregate experience. The three measures of aggregate experience I consider are NQ_t, defined as the logarithm of the number of quarters since the introduction of AFSM100 in the first plant, i.e. the second quarter of 2000, NY_t, defined as the logarithm of the number of years since the introduction of AFSM100 in the first plant and CE_{it} is the logarithm cumulative labor hours allocated to AFSM100 sorting by all other plants until the previous quarter i.e. $CE_{nt} := \log\left(\sum_{i\neq n}\sum_{j=0}^{t-1} L_{3ij}\right)$. I estimate the full set of specifications for the total labor demand while for the rest of the equations I estimate only the basic specification with and without spillovers.

Because the effect of automation technology on labor productivity is interesting, I plotted the quantiles of labor productivity among plants by quarter since the introduction of the new technology and the result can be seen in figure 8. Not only did productivity more than double after the introduction of AFSM100, but it also became more dispersed.

6 Econometric Issues

In this section I discuss three main econometric issues that arise from the estimating equations. I assume that the error ϵ_{it} encompasses optimization error from the plants and productivity shocks, such as machine breakdowns and accidents, that the plant manager cannot foresee when making allocation decisions. The first two have to do with the pres-

ence of measurement error in the output variables and the capital stock of AFSM100. The measurement error in output arises from the way the value is measured at the plant. When mail arrives at the plant to be sorted, it is weighed and then, using an estimate of the average weight of a flat, weight is transformed to pieces. The number of incoming and outgoing flats sorted is also estimated by converting weight to pieces. This classical measurement error biases the coefficients of output towards zero. To solve this problem I follow Roberts (2006)[8] and instrument ingoing and outgoing output with quarterly dummies, output of parcels, incoming and outgoing letters at the same plant. Quarterly dummies are expected to be correlated with y_{in} and y_{out}, due to the seasonality of output, but they are uncorrelated with the measurement error incorporated in ϵ. Output of parcels, incoming and outgoing output of letters are correlated with ingoing and outgoing flats, again because of seasonality and because plants with high flats output have high parcels and letters output and vice versa.

The capital stock of AFSM100 also suffers from measurement error. This can be easily detected from observations where labor hours and flats fed variables have positive values while, at the same time, capital stock is zero. Flats fed and labor hours are precisely measured and are consistent with each other. The most plausible explanation for measurement error is that the AFSM100 capital stock, especially in the first quarters of introduction, is reported with some lag. This measurement error is non classical because it tends to zero as the capital stock stabilizes after the full deployment of the new equipment, which implies that the measurement error is correlated with the value of the capital stock vari-

[8] Roberts (2006), using the same data-set, estimates long run labor demand elasticities. Since the goal there is the estimation of long run labor demand equations, the data corresponding to the phase-in of AFSM and the phase-out of FSM881 or FSM1000 are dropped. More specifically, the observations corresponding to the first year of introduction of the new technology or the last year before the retirement of an old technology are not used in the estimation. The focus of this paper, on the other hand, is on the transition from the old technology to the new, and those observations, not used in Roberts (2006), will provide most of the information in answering the question addressed here.

able. From the data, I can identify the lag of reporting by counting the number of quarters between the first positive labor observation and the first positive capital stock observation. Descriptive statistics for the lags are displayed in Table 1 and show that only ten percent of the plants have zero lag with the median lag being four quarters. The extent of the measurement error is large and I will attempt to reduce it. I correct the capital stock series by shifting it forward in time to match the quarter with the first positive labor hours observation and then repeating the last observation at the end of the series. Repeating the last observation at the end of the series should not bias the estimates much because, after the full deployment of the new technology, the capital stock becomes fairly stable in each plant. However, the measurement error will be still present but I hope I will reduce its variance. To show that the capital stabilizes and that repeating the last observation in the end of the series should not bias the results a lot, I calculate summary statistics for the percentage difference of the largest to the smallest capital stock observation for each plant for the first 5 observations and the last 5 observations. The reason I chose to compare the last 5 observations to the first 5 observations of AFSM100 capital stock in each plant is that ninety percent of the plants have at most 5 lags. Let t_1 be the first quarter in which AFSM100 is introduced in a plant and $\bar{T}$ the quarter of the last observation. Define:

$$\xi_1 \equiv \left(\max_{t_i, t_j \in \mathbb{T}_1} \left[\frac{k_{3t_i}}{k_{3t_j}} \right] - 1 \right) \cdot 100, \quad \mathbb{T}_1 \equiv \{t_1, t_1+1, t_1+2, t_1+3, t_1+4\}$$
$$\xi_2 \equiv \left(\max_{t_i, t_j \in \mathbb{T}_2} \left[\frac{k_{3t_i}}{k_{3t_j}} \right] - 1 \right) \cdot 100, \quad \mathbb{T}_2 \equiv \{\bar{T}, \bar{T}-1, \bar{T}-2, \bar{T}-3, \bar{T}-4\}$$

The statistics of the distributions of ξ_1 and ξ_2 are presented in table 2 and show that the mean of ξ_1 is 25 times higher than the mean of ξ_2 and the median plant's largest AFSM100 capital stock value is only 15% higher than the smallest value in the last five observations.

This is evidence that the AFSM100 capital stock stabilizes in the last periods so replicating the last observation in the end of the corrected series should be a good approximation of the true capital stock series.

The last econometric issue has to do with possible endogeneity of the tech right hand side dummy variables in the regression that take the value zero when the corresponding capital is idle in that quarter. In most plants, if the capital stock of FSM881 or FSM1000 becomes idle in one quarter, it remains idle ever after which means that the tech dummy variable reflects the decision to retire the corresponding technology. The decision to retire a technology can be correlated with the error ϵ_{it} but I do not expect this correlation to be significant because the decision of whether to retire a technology or not will be mainly affected by state variables such as the capital stock of AFSM100 and the level of experience and less by the transitory productivity shock.

In all the estimates that follow the standard errors are estimated using the block bootstrap from 200 samples and are robust to arbitrary form of heteroskedasticity and autocorrelation of the shocks.

7 Results

In this section I discuss the estimation results beginning with the estimates from the basic experience specification presented in Table 3. The total labor demand experience coefficients are significant and show that the learning/adjustment rate is very fast in the first year, slows down after the fourth quarter, but stops only after the sixteenth quarter, or four years, after the introduction of the technology when the gains from automation are fully realized. For example the coefficient of $Quarter1$ (-0.106) means that the total labor demand with respect to the pre AFSM100 era, not explained by the capital stock, is 90% and the coefficient of $Quarter4$ (-0.305) means that the total labor demand is 74% of the

pre AFSM1000 era, implying a 26% reduction in a year. In the second, third and fourth year the total labor reduction due to experience is is 4%, 7% and 6% respectively.

This slow reduction in total labor demand is due to the gradual substitution of the old technology with the new one as showed by the demand equations l_m, l_1, l_2 and l_3. Manual labor demand (l_m) drops 60% in the first year but, due to the magnitude of the standard errors, it is not evident when growth stops exactly, being somewhere between the tenth and the sixteenth quarter. The most dramatic drop occurs in labor demand for FSM881, which is 97% in the first year, meaning that the FSM881 is actually retired by the end of the fourth quarter[9]. The substitution of FSM1000 by AFSM100 happens in a longer span of time. The reduction in labor demand for FSM1000 in the first year is 30% while in the second, third and fourth year is 16%, 30% and 33% respectively.

Labor demand for AFSM100 exhibits a different pattern[10]. In the initial quarters, labor demand increases with experience until quarter seven, when it is 500% higher than the demand in the first quarter, and 25% higher than in the second quarter, showing the degree of underutilization of the AFSM100 machines in the first couple of quarters. From the eighth quarter on, demand starts decreasing and stabilizes around quarter sixteen when it is 10% lower than its peak at quarter seven. This is probably because experience increases the efficiency of the AFSM100 use, driving demand down.

7.1 Experience Externalities Between Plants

Here I describe the estimation results of the specification that allows for experience spillovers between plants. The results are presented in Table 4. The plants are divided in two co-

[9]The reason why there are not estimates for late quarters for l_1 is that there are not enough observations due to the retirement of the old capital.

[10]Note that all the quarters are not separately identified from the fixed effects in the l_3 equation because the observations for l_3 begin with the introduction of the AFSM100 to the plants. This is why the dummy variables begin from $Quarter2$ meaning that all the coefficients characterize the labor demand with relative to the demand in first quarter of introduction.

horts: the early and late adopters. In the end of the table the Wald test statistic for the hypothesis that the coefficients of the variables $QuarterN$ are equal in the two cohorts[11] is reported. The pattern of the effect of experience on total labor demand is similar for the two cohorts and consistent with the results of the basic specification without spillovers. However, the magnitudes are different, with late adopters realizing faster reduction in total labor use in the first year than early adopters. More specifically, the drop in total labor demand in the first two quarters with respect to the pre AFSM100 era for the early adopters is 17% while it is 25% for the late adopters. The test for equality of the coefficients in the two cohorts is rejected at 5% significance level. Figure 9 depicts the labor demand reduction due to experience, separately for the two cohorts. Recall that the reference level of labor demand is the labor demand before the introduction of AFSM100 since all the dummies for the observations before the introduction of AFSM100 have the value zero.[12]. From the graph it is easy to see that the learning is steeper for the second cohort in the first quarters. This large gap between late and early adopters stems from the difference in how fast these two cohorts substitute the old FSM881 and FSM1000 technology with the new AFSM100 technology.

This pattern is also evident from equations l_1 and l_2, where the labor demand for FSM881 in the first two quarters drops 56% in the early adopting plants while it drops 98% in the late adopting plants, indicating that the latter actually retired the FSM881 technology in just two quarters while the former did so only after the sixth quarter. The labor demand for FSM1000 in the first two quarters drops 10% in the early adopting plants while it drops 43% in the late adopting plants. In both equations, l_1 and l_2, the Wald test for equality of the coefficients of the two cohorts is rejected at 5% significance

[11] In parenthesis is the degrees of freedom of the asymptotic χ^2 distribution of the test statistic.

[12] If L is the pre AFSM100 labor demand and the coefficient of QuarterN is b_e then $\log \frac{L'}{L} = b_e \Rightarrow \frac{L'}{L} = exp(b_e)$

level. The estimates for l_3 indicate that the new AFSM100 machines where fully utilized from the second quarter in the late adopting plants. On the contrary, early adopters did not fully utilize AFSM100 machines until the seventh quarter. Again, the hypothesis of equal coefficients in the two cohorts is rejected at 5% significance level.

The estimation of the manual labor demand does not exhibit the same strong spillover pattern as l, l_1, l_2 and l_3 labor demands. The standard errors are quite large and any direct comparison of the two cohorts does not reveal statistically significant differences. The hypothesis that the two cohorts have the same coefficients cannot be rejected at 10% significance level, implying that firm level experience did not render the substitution of manual labor with AFSM100 faster in the late adopting plants. Another explanation for this pattern may be the presence of labor market frictions at the plant level that do not allow immediate layoffs or hours reduction in the manual sorting. If this is the case any between plant spillovers, even if they are present, will not be identified from the data. Moreover, workers in manual sorting have different skills than workers in mechanized sorting and cannot be reallocated between technologies immediately.

From the estimates of the total labor demand specification with between-plant experience spillovers I also calculate the adjustment cost of the technology change. I define the cost of adjustment as the total labor employed during the adjustment process on top of the long run labor requirement. In other words, if the labor required by a plant after it has completely incorporated the AFSM100 technology, lets say at period T, is L_T, while the labor required during the adjustment process is $L_t, t < T$, then the adjustment cost in terms of labor is given by:

$$Adj = \sum_{t<T} \left(\frac{L_t}{L_T} - 1 \right) = \sum_{t<T} \left[exp\left(\text{Quarter}_t - \text{Quarter}_T\right) - 1 \right]$$

I assume that the long run labor requirement is achieved in quarter 20 for the first cohort

and in quarter 17 for the second cohort. The adjustment cost for cohort 1 is $3.26 * L_T$ with standard error[13] .18 while the adjustment cost for cohort 2 is $1.28 * L_T$ with standard error 0.25 which is 60% less than the first cohort. The Wald test for the null hypothesis that the adjustment costs are the same for both cohorts is rejected at 5% significance level with test statistic 12.4. This result shows a remarkable spillover for the second cohort, which is able to capitalize the experience accumulated by the early adopters.

Finally, in Table 5 the estimation results for the total labor demand with interaction of plant-level and firm-level experience are presented. The test statistic of the hypothesis that the interaction terms are all zero is reported in the end of the table. All three specifications have significant estimates of the interaction terms between the firm-level experience (NQ, NY, CE) and the dummy variables of the first three quarters after the introduction of AFSM100 and show that firm-level experience is mainly important during the very first quarters after introduction in each plant. This is consistent with the results from Table 4, which show that the main difference between early and late adopters is that the latter adjust much faster in the first two quarters. Note also that the interaction terms in the last quarters are significant in all specifications, probably because the early adopters, mainly large plants, realize larger productivity gains from the automation technology in the long run with respect to the smaller plants that got the AFSM100 machines later.

7.2 Parsimonious Specification

For reasons of comparability with the learning literature, tables 6 and 7 present estimates of the total labor demand equation with experience measured as nq, the logarithm of quarters since introduction, and ce, the logarithm of cumulative plant labor allocated to AFSM100. The learning/adjustment rate is calculated[14] as $1 - 2^{b_e}$ and represents the decrease in labor

[13] The standard error is calculated using the delta method.

[14] $\log \frac{L'}{L} = b_e \log \frac{2E}{E} = b_e \log(2) \Rightarrow \frac{L'}{L} = 2^{b_e}$

demand caused by the doubling of experience. The standard error corresponding to the learning rate is calculated using the delta method. The learning rates of 6.4% and 3.2%, respectively, are quite low but are the average rate between a high learning rate in the first four quarters and a zero rate in the last quarters.

8 Conclusion

In this paper I used plant level data from the USPS sorting facilities in combination with a model of slow adjustment in production due to learning from experience to investigate the process of technology change. The main finding of the paper is that incorporating the new technology in the plants involves significant adjustment costs and it takes approximately three years for the plants to realize the full potential of the new capital equipment. In addition, spillovers between plants are very important and, more specifically, plants that adopt the technology later face adjustment costs approximately 60% lower than plants that adopted the same technology earlier. Moreover, graphical analysis indicates that the productivity dispersion across plants increased significantly because of the automation technology.

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A Tables and Figures

Figure 1: Flats output in all plants

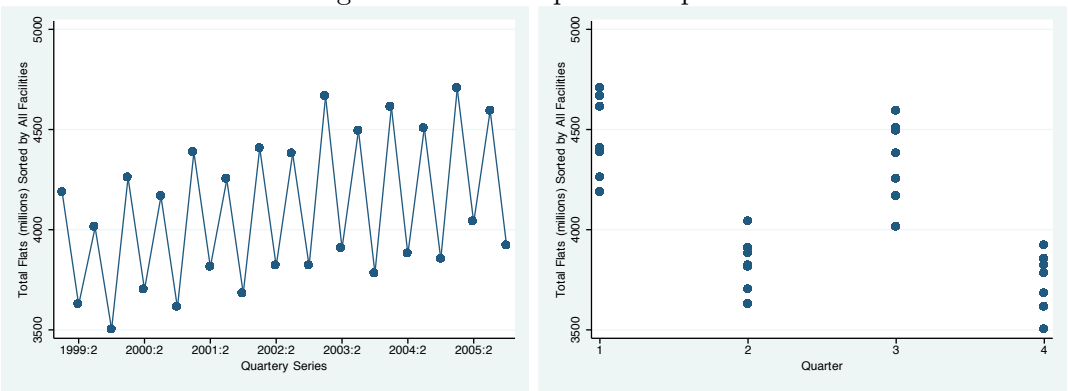

Figure 2: Labor allocation in the three mechanized sorting technologies

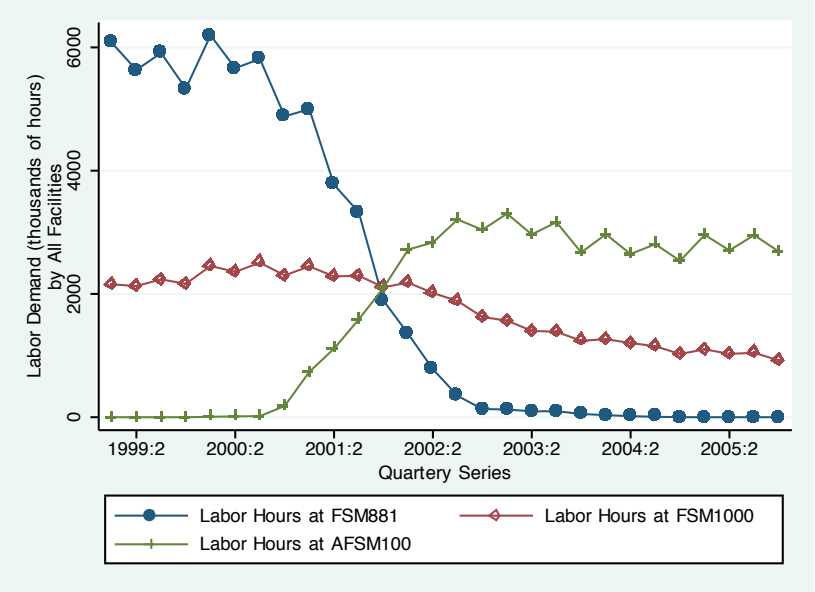

Figure 3: Total Labor Demand by all Plants

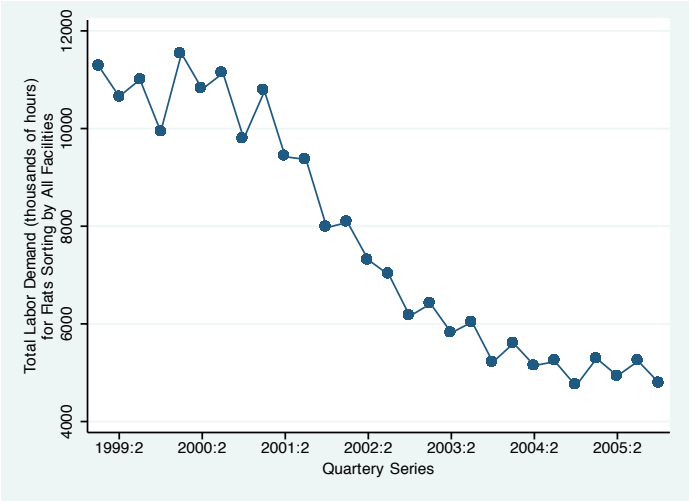

Figure 4: Labor Demand for Mechanized Sorting (FSM881, FSM1000, AFSM100) by all Plants

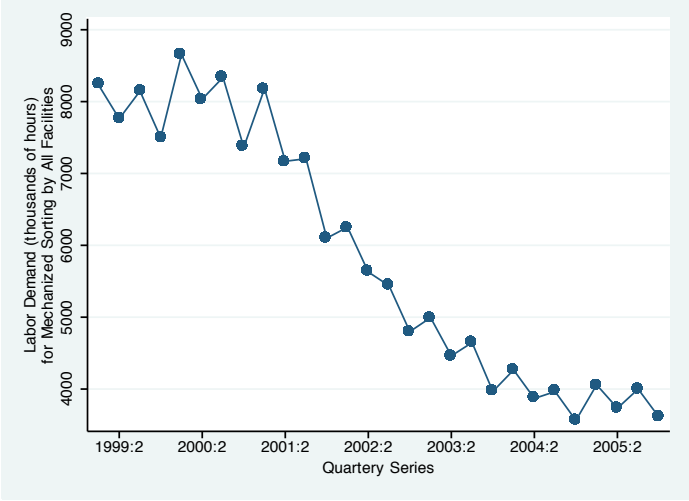

Figure 5: Labor Demand for Manual Sorting by all Plants

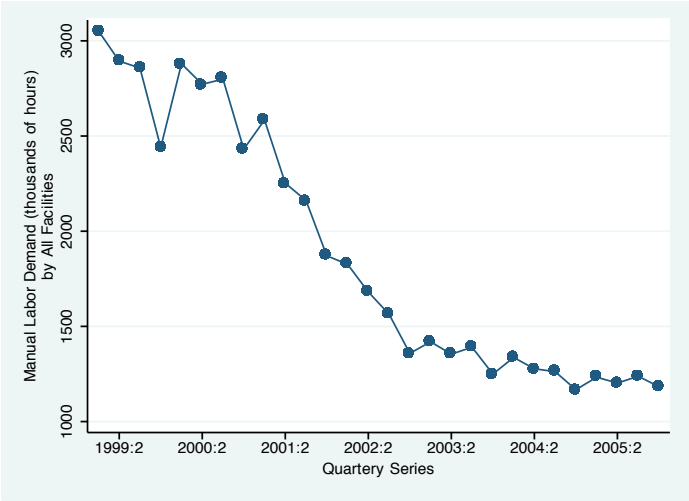

Figure 6: Deployment of AFSM100

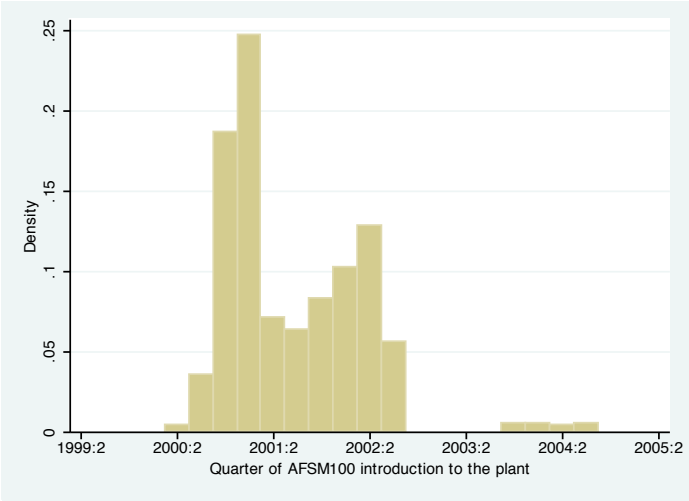

Figure 7: AFSM100 adoption by plant size

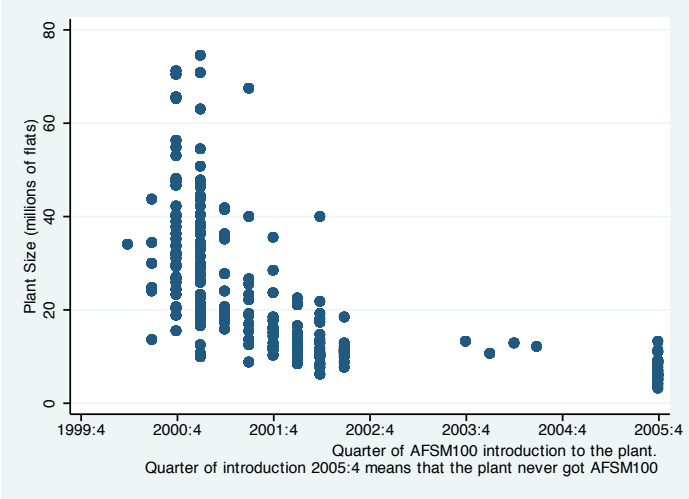

Figure 8: Quantiles of Productivity among plants by quarter since introduction of the new technology

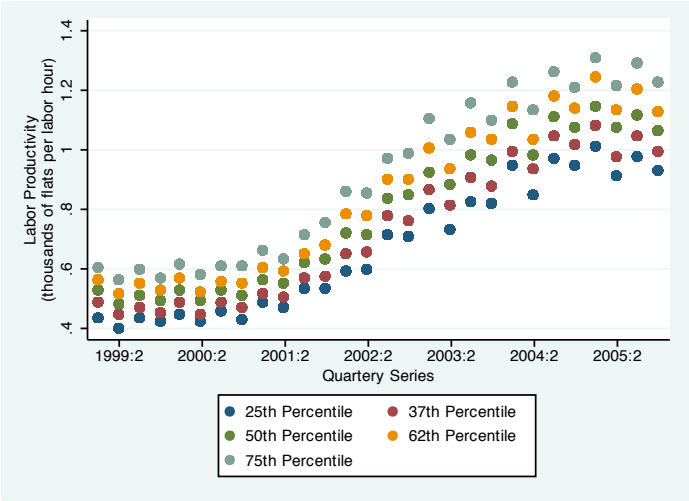

Table 1: Distribution of *Lag*

Percentile (%)	1	5	10	25	50	75	90	95	99	Mean	SD
Lag	0	0	0	3	4	5	5	6	8	3.4	1.8

Number of Plants: 225

Table 2: Percentiles of ξ_1, ξ_2, Ξ

Percentile (%)	1	5	10	25	50	75	90	95	Mean	SD
ξ_1	6.6	9.1	11.1	17.4	164	392	581	800	516	2095
ξ_2	4.4	7.6	11.3	13.7	15.2	19	38.2	57.7	21.3	21.2

Table 3: Labor Demands - Basic Experience Specification

	Total Labor - l		Manual - l_m		FSM881 - l_1		FSM1000 - l_2		AFSM100 - l_3	
Ind. Var.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.
y_{in}	0.371***	0.027	0.339***	0.089	0.300	0.308	0.360**	0.169	0.472***	0.089
y_{out}	0.367***	0.064	0.459*	0.232	1.505***	0.604	0.301	0.338	0.269**	0.211
$tech_1$	0.226***	0.016	0.101	0.083			0.126*	0.070	-0.231***	0.042
$tech_2$	0.009	0.019	-0.746***	0.107	-1.180***	0.404			0.004	0.048
k_1	0.089***	0.032	0.013	0.123	1.648***	0.352	-0.432***	0.147	-0.075	0.067
k_2	-0.054*	0.030	-0.305**	0.132	-1.575***	0.471	0.471***	0.177	-0.249***	0.065
k_3	0.007	0.005	0.007	0.020	0.004	0.106	0.004	0.027	0.055**	0.028
k_o	0.001	0.004	-0.006	0.022	0.019	0.037	0.011	0.014	0.007	0.012
$\tilde{w}$	-0.166***	0.065	0.372	0.230	-0.408	0.508	-0.146*	0.277	0.181	0.135
constant	1.932***	0.078	1.065***	0.301	1.296	0.800	0.753**	0.382	-0.833***	0.312
Quarter 1	-0.106***	0.010	-0.127***	0.048	-0.507***	0.100	-0.065	0.043		
Quarter 2	-0.236***	0.015	-0.432***	0.074	-2.393***	0.205	-0.296***	0.079	1.443***	0.109
Quarter 3	-0.279***	0.017	-0.564***	0.091	-2.768***	0.252	-0.337***	0.087	1.551***	0.113
Quarter 4	-0.305***	0.017	-0.501***	0.089	-3.526***	0.263	-0.365***	0.091	1.642***	0.112
Quarter 5	-0.312***	0.022	-0.563***	0.099	-4.287***	0.373	-0.457***	0.141	1.644***	0.118
Quarter 6	-0.320***	0.023	-0.579***	0.104	-4.775***	0.374	-0.491***	0.142	1.669***	0.120
Quarter 7	-0.326***	0.024	-0.620***	0.117	-5.503***	0.411	-0.417***	0.115	1.672***	0.120
Quarter 8	-0.344***	0.024	-0.608***	0.110	-6.467***	0.419	-0.545***	0.125	1.668***	0.121
Quarter 9	-0.358***	0.024	-0.648***	0.121	-7.038***	0.420	-0.561***	0.122	1.664***	0.120
Quarter 10	-0.365***	0.025	-0.727***	0.133	-7.415***	0.356	-0.691***	0.155	1.632***	0.120
Quarter 11	-0.384***	0.025	-0.685***	0.122	-7.422***	0.367	-0.788***	0.151	1.614***	0.120
Quarter 12	-0.410***	0.025	-0.663***	0.127	-7.403***	0.406	-0.895***	0.169	1.587***	0.121
Quarter 13	-0.423***	0.026	-0.662***	0.119	-7.592***	0.462	-0.882***	0.154	1.584***	0.122
Quarter 14	-0.430***	0.026	-0.665***	0.123	-7.647***	0.546	-0.914***	0.163	1.583***	0.123
Quarter 15	-0.450***	0.027	-0.674***	0.124	-7.591***	0.521	-1.082***	0.180	1.572***	0.125
Quarter 16	-0.475***	0.027	-0.688***	0.122	-7.890***	0.476	-1.297***	0.222	1.568***	0.127
Quarter 17	-0.488***	0.027	-0.742***	0.121			-1.232***	0.207	1.567***	0.127
Quarter 18	-0.492***	0.028	-0.781***	0.127			-1.225***	0.200	1.564***	0.129
Quarter 19	-0.495***	0.028	-0.773***	0.144			-1.191***	0.194	1.559***	0.128
Quarter 20	-0.507***	0.030	-0.725***	0.143			-1.302***	0.226	1.577***	0.129
Quarter 21	-0.527***	0.035	-0.778***	0.200			-1.526***	0.263	1.573***	0.135
Quarter 22	-0.489***	0.048	-0.293	0.411			-2.159*	1.182	1.653***	0.146
R^2	0.867		0.301		0.683		0.404		0.749	

Three asterisks mean significance at 1%, two at 5% and one at 10%.

Table 4: Total Labor Demand - Basic Experience Specification with Spillovers

		Total Labor - l		Manual - l_m		FSM881 - l_1		FSM1000 - l_2		AFSM100 - l_3	
Cohort	Ind. Var.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.
First	Quarter 1	-0.063***	0.015	-0.201**	0.090	-0.140**	0.072	-0.037	0.046		
	Quarter 2	-0.182***	0.022	-0.506***	0.109	-0.829***	0.139	-0.101**	0.046	1.591***	0.136
	Quarter 3	-0.236***	0.024	-0.621***	0.124	-1.353***	0.186	-0.130**	0.055	1.791***	0.142
	Quarter 4	-0.299***	0.022	-0.547***	0.115	-2.449***	0.284	-0.180***	0.069	1.981***	0.140
	Quarter 5	-0.321***	0.034	-0.678***	0.147	-3.194***	0.379	-0.219**	0.113	2.080***	0.144
	Quarter 6	-0.310***	0.036	-0.667***	0.143	-3.676***	0.380	-0.278**	0.123	2.153***	0.149
	Quarter 7	-0.323***	0.037	-0.702***	0.150	-4.534***	0.411	-0.357***	0.136	2.180***	0.151
	Quarter 8	-0.348***	0.040	-0.677***	0.152	-5.883***	0.512	-0.493***	0.146	2.180***	0.152
	Quarter 9	-0.361***	0.040	-0.761***	0.182	-6.487***	0.460	-0.575***	0.153	2.172***	0.153
	Quarter 10	-0.357***	0.041	-0.788***	0.193	-7.112***	0.435	-0.623***	0.159	2.146***	0.157
	Quarter 11	-0.396***	0.039	-0.772***	0.176	-6.892***	0.413	-0.817***	0.184	2.103***	0.155
	Quarter 12	-0.447***	0.039	-0.802***	0.200	-6.760***	0.405	-0.905***	0.177	2.046***	0.155
	Quarter 13	-0.457***	0.042	-0.765***	0.175	-6.964***	0.424	-0.930***	0.183	2.031***	0.158
	Quarter 14	-0.458***	0.043	-0.766***	0.190	-7.343***	0.535	-0.914***	0.166	2.026***	0.158
	Quarter 15	-0.497***	0.042	-0.713***	0.180	-7.227***	0.414	-1.008***	0.175	1.994***	0.158
	Quarter 16	-0.531***	0.041	-0.755***	0.174	-7.327***	0.441	-1.333***	0.259	1.982***	0.158
	Quarter 17	-0.538***	0.043	-0.823***	0.181			-1.272***	0.223	1.985***	0.158
	Quarter 18	-0.529***	0.045	-0.850***	0.188			-1.300***	0.241	1.988***	0.159
	Quarter 19	-0.528***	0.043	-0.794***	0.189			-1.248***	0.223	1.990***	0.157
	Quarter 20	-0.528***	0.043	-0.796***	0.191			-1.305***	0.257	2.009***	0.159
	Quarter 21	-0.550***	0.045	-0.855***	0.239			-1.529***	0.317	2.016***	0.162
	Quarter 22	-0.512***	0.055	-0.367	0.369			-2.162*	1.244	2.085***	0.161
Second	Quarter 1	-0.145***	0.015	-0.054	0.050	-0.701***	0.111	-0.078**	0.075		
	Quarter 2	-0.298***	0.021	-0.366***	0.081	-3.928***	0.269	-0.557***	0.171	1.334***	0.177
	Quarter 3	-0.337***	0.026	-0.558***	0.111	-4.824***	0.356	-0.637***	0.193	1.363***	0.182
	Quarter 4	-0.332***	0.026	-0.505***	0.106	-5.521***	0.456	-0.673***	0.195	1.362***	0.180
	Quarter 5	-0.335***	0.028	-0.499***	0.117	-5.929***	0.427	-0.858***	0.260	1.346***	0.181
	Quarter 6	-0.367***	0.029	-0.538***	0.129	-6.382***	0.420	-0.881***	0.255	1.347***	0.183
	Quarter 7	-0.371***	0.030	-0.581***	0.140	-7.133***	0.433	-0.637***	0.165	1.341***	0.186
	Quarter 8	-0.384***	0.030	-0.582***	0.129	-7.322***	0.432	-0.771***	0.199	1.337***	0.185
	Quarter 9	-0.401***	0.030	-0.584***	0.128	-7.680***	0.458	-0.711***	0.162	1.332***	0.187
	Quarter 10	-0.421***	0.032	-0.731***	0.164	-7.149***	0.339	-0.944***	0.225	1.310***	0.189
	Quarter 11	-0.424***	0.033	-0.658***	0.152	-7.441***	0.408	-0.924***	0.189	1.310***	0.195
	Quarter 12	-0.425***	0.033	-0.588***	0.143	-7.920***	0.661	-1.059***	0.254	1.309***	0.193
	Quarter 13	-0.440***	0.033	-0.612***	0.149	-8.226***	0.454	-1.008***	0.212	1.300***	0.193
	Quarter 14	-0.452***	0.035	-0.617***	0.145	-7.504***	1.484	-1.110***	0.256	1.298***	0.195
	Quarter 15	-0.450***	0.037	-0.688***	0.149			-1.382***	0.309	1.311***	0.202
	Quarter 16	-0.450***	0.040	-0.652***	0.163			-1.413***	0.344	1.317***	0.202
	Quarter 17	-0.451***	0.044	-0.702***	0.177			-1.311***	0.299	1.325***	0.204
	Quarter 18	-0.463***	0.042	-0.786***	0.184			-1.107***	0.275	1.337***	0.206
	Quarter 19	-0.447***	0.054	-1.122***	0.377			-0.935***	0.207	1.314***	0.206

Three asterisks mean significance at 1%, two at 5% and one at 10%.

(Table Continued)

		Total Labor - l		Manual - l_m		FSM881 - l_1		FSM1000 - l_2		AFSM100 - l_3	
Cohort	Ind. Var.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.
	y_{in}	0.362***	0.026	0.344***	0.094	0.382	0.271	0.424**	0.182	0.533***	0.088
	y_{out}	0.371***	0.060	0.428*	0.251	0.697	0.530	0.161	0.363	0.175	0.203
	$tech_1$	0.202***	0.018	0.115	0.084			0.030	0.084	-0.202***	0.032
	$tech_2$	0.010	0.022	-0.740***	0.101	-0.329	0.278			-0.034	0.043
Both	k_1	0.080***	0.029	-0.004	0.115	1.446***	0.303	-0.390***	0.131	-0.018	0.065
	k_2	-0.062*	0.034	-0.334**	0.153	-0.380	0.387	0.481**	0.205	-0.151***	0.054
	k_3	0.008	0.007	0.014	0.026	-0.047	0.086	0.000	0.030	0.026	0.018
	k_o	0.001	0.004	-0.003	0.022	-0.018	0.031	0.006	0.015	-0.001	0.011
	$\tilde{w}$	-0.164***	0.062	0.362	0.225	-0.254	0.445	-0.121	0.321	0.089**	0.133
	constant	1.976***	0.074	1.079***	0.323	1.126	0.734	0.849*	0.467	-0.901***	0.309
	R^2	0.866		0.290		0.795		0.274		0.699	
	$\chi^2(r)$	80.4(19)		20.9(19)		192.9(14)		46.7(19)		124.7(18)	

Three asterisks mean significance at 1%, two at 5% and one at 10%.

Figure 9: Comparing Total Labor Demand Adjustment between the 2 cohorts

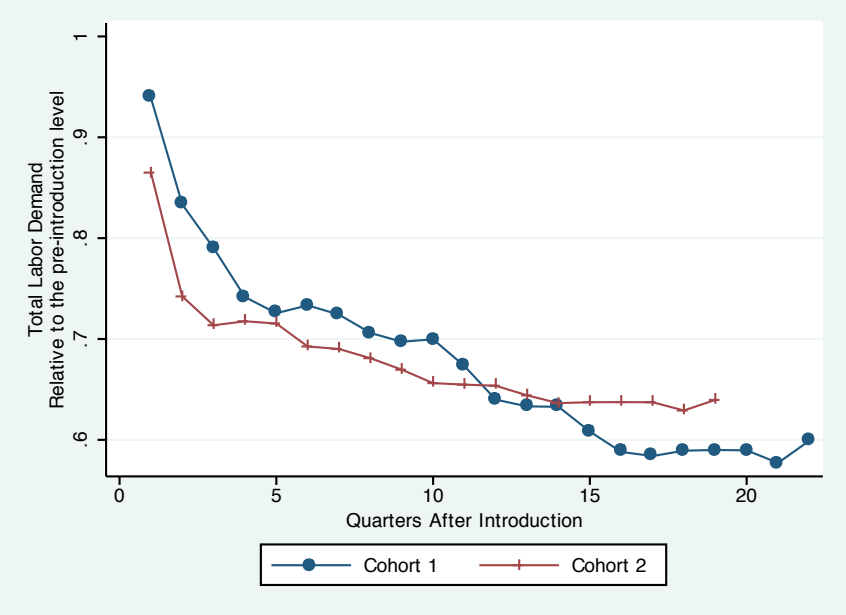

Table 5: Total Labor Demand - Experience Specification with Interactions of Firm-Level and Plant-Level Experience

	E = NQ		E = NY		E = CE	
Ind. Var.	Estim.	S.E.	Estim.	S.E.	Estim.	S.E.
y_{in}	0.372***	0.027	0.373***	0.033	0.372***	0.028
y_{out}	0.370***	0.060	0.365***	0.060	0.371***	0.064
$tech_1$	0.198***	0.018	0.210***	0.017	0.202***	0.017
$tech_2$	0.013	0.022	0.013	0.020	0.013	0.022
k_1	0.077***	0.029	0.077***	0.031	0.076**	0.034
k_2	-0.071**	0.031	-0.072**	0.034	-0.071**	0.034
k_3	0.009	0.007	0.009	0.008	0.009	0.007
k_o	0.001	0.004	0.002***	0.004	0.001	0.004
$\tilde{w}$	-0.165***	0.062	-0.166***	0.066	-0.163***	0.065
constant	1.949***	0.077	1.939***	0.090	1.942***	0.082
Quarter 1	0.031	0.034	-0.074***	0.014	0.003	0.031
Quarter 2	-0.020	0.071	-0.193***	0.027	-0.082	0.073
Quarter 3	-0.022	0.092	-0.219***	0.043	-0.018	0.114
Quarter 4	-0.135	0.098	-0.287***	0.045	-0.086**	0.129
Quarter 5	-0.227*	0.135	-0.325***	0.055	-0.211	0.195
Quarter 6	-0.098	0.169	-0.287***	0.073	0.025	0.262
Quarter 7	-0.130	0.197	-0.308***	0.100	0.044*	0.351
Quarter 8	-0.122*	0.231	-0.318***	0.104	0.131	0.422
Quarter 9	-0.082	0.259	-0.293***	0.097	0.191	0.520
Quarter 10	0.064	0.318	-0.245**	0.129	0.507	0.627
Quarter 11	-0.193	0.346	-0.428***	0.151	0.104	0.756
Quarter 12	-0.668*	0.374	-0.678***	0.157	-0.923**	0.882
Quarter 13	-0.787**	0.390	-0.689***	0.139	-1.279	0.909
Quarter 14	-0.882**	0.433	-0.730***	0.166	-1.563	1.023
Quarter 15	-1.219***	0.472	-1.044***	0.211	-2.384**	1.166
Quarter 16	-1.882***	0.599	-1.270***	0.276	-4.064***	1.369
Quarter 17	-2.458***	0.779	-1.480***	0.306	-5.532***	1.961
Quarter 18	-3.163***	1.139	-1.449***	0.304	-7.339***	2.655
Quarter 19	-3.844***	1.385	-1.407**	0.663	-8.998***	3.537
E*Quarter 1	-0.084***	0.020	-0.078***	0.024	-0.017***	0.005
E*Quarter 2	-0.123***	0.038	-0.078**	0.034	-0.022**	0.009
E*Quarter 3	-0.136***	0.045	-0.084*	0.048	-0.033***	0.013
E*Quarter 4	-0.087*	0.046	-0.033	0.050	-0.027*	0.015
E*Quarter 5	-0.048	0.056	-0.006*	0.044	-0.013	0.020
E*Quarter 6	-0.106	0.067	-0.050	0.054	-0.039	0.027
E*Quarter 7	-0.092	0.076	-0.034	0.073	-0.041	0.035
E*Quarter 8	-0.100	0.087	-0.039	0.073	-0.051	0.042
E*Quarter 9	-0.119	0.094	-0.069	0.064	-0.058	0.051
E*Quarter 10	-0.174	0.115	-0.106**	0.083	-0.090	0.061
E*Quarter 11	-0.083**	0.123	0.011	0.096	-0.051	0.073
E*Quarter 12	0.080	0.130	0.161***	0.097	0.047	0.084
E*Quarter 13	0.115	0.132	0.155**	0.081	0.079	0.086
E*Quarter 14	0.144	0.144	0.170*	0.093	0.105	0.096
E*Quarter 15	0.249	0.155	0.341***	0.119	0.180***	0.109
E*Quarter 16	0.461**	0.197	0.461***	0.160	0.336***	0.128
E*Quarter 17	0.645***	0.255	0.578***	0.179	0.471***	0.184
E*Quarter 18	0.868**	0.369	0.538***	0.169	0.638***	0.248
E*Quarter 19	1.078**	0.446	0.494	0.369	0.790**	0.329
R^2	0.870		0.869		0.870	
$\chi^2(r)$	75.0(19)		75.8(19)		74.6(19)	

Three asterisks mean significance at 1%, two at 5% and one at 10%.

Table 6: Total Labor Demand - Linear Specification with nq experience measure

y_{in}	0.353***	0.033
y_{out}	0.381***	0.084
$tech_1$	0.133***	0.021
$tech_2$	0.0171	0.025
k_1	0.155***	0.034
k_2	0.021	0.027
k_3	-0.008	0.005
k_o	-0.002	0.007
$\tilde{w}$	-0.169***	0.056
nq	-0.096***	0.014
constant	1.868***	0.102
Adjust. Rate	6.4%	0.9%
R^2	0.857	

Three asterisks mean significance at 1%, two at 5% and one at 10%.

Table 7: Total Labor Demand - Linear Specification with ce_{it} experience measure

Ind. Var.	Estim	S.E.
y_{in}	0.335***	0.038
y_{out}	0.468***	0.085
$tech_1$	0.132***	0.018
$tech_2$	0.031	0.024
k_1	0.185***	0.038
k_2	0.0217	0.027
k_3	-0.008	0.005
k_o	-0.004	0.007
$\tilde{w}$	-0.157***	0.058
ce	-0.047***	0.006
constant	1.823***	0.100
Adjust. Rate	3.2%	0.4%
R^2	0.835	

Three asterisks mean significance at 1%, two at 5% and one at 10%.