# Learning By Doing, Worker Turnover and Productivity Dynamics*

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**Abstract**

Recent evidence based on longitudinal firm-level data suggests that within-firm productivity growth explains about 50 percent of total factor productivity growth in the manufacturing sector while net entry effects account for about 30 percent of total factor productivity growth. These two forces may be connected via learning by doing of young businesses. That is, the recent evidence also shows that young businesses that survive exhibit more rapid productivity growth than older incumbents. The idea that learning-by-doing is important and, in particular, important for young businesses is not novel to this paper. What is novel about this paper is that newly developed longitudinal employer-employee matched data are used to characterize and measure the nature of

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learning. In contrast to the exiting literature on learning, this paper shows that learning is not only affected by past output, but also by worker turnover within firms. The basic idea is that firms with high worker turnover will make learning-by-doing more difficult. Using this approach, I estimate that firms with historically lower rates of turnover "learn" faster than those with higher turnover given the same amount of past output.

Keywords: Learning by Doing, Worker Turnover, Productivity

JEL classification: D24, J24, O47

# 1 Introduction

Recent evidence based on microdata suggests that there is tremendous heterogeneity among establishments in their productivity levels even in a narrowly defined industry and that there are significant productivity enhancing effects from entry/exit behavior often referred to as "creative destruction". The productivity of new entrants is on average higher than that of exiting establishments. At the same time, within-plant productivity growth contributes greatly to aggregate productivity growth. In other words, continuing businesses get better with age.

Foster, Haltiwanger, and Krizan (2001 and 2002) find that across firms with different ages, new entrants' productivity is lower than that of incumbents on average but that it tends to grow faster than that of incumbents. They also show that the productivity of earlier entrants is higher than that of later entrants. Indeed, using retail trade industry data, they show firms that entered between 1987 and 1992 who made it to 1997 were more productive than firms who entered between 1992 and 1997. That is, earlier entrants, who had more time to learn, improved as they aged. However, contributions of within-plant productivity growth and creative destruction (entry/exit) behavior are different for the manufacturing and retail trade industries. For the manufacturing industry, within-plant productivity growth explains about 50% of industry-wide productivity growth, while creative destruction is the dominant contributor to overall productivity growth in the retail trade industry.

In past research, selection effects have been emphasized as a driving force behind the increase in the average cohort productivity over time. Jovanovic (1982) first introduced this idea in his seminal 1982 paper. In it, he incorporates time invariant employer heterogeneity with noise to explain the selection process and patterns of employer growth. Literature based on vintage capital models with embodied technology also stress the implications of selection effects for productivity (Caballero and Hammour (1996), and Mortensen and Pissarides (1994)). Some models try to incorporate stochastic idiosyncratic component in embodied technology to explain heterogeneity within cohorts (Campbell (1998) and Pissarides (2000)). In these models, overall productivity growth is driven by exogenous embodied technological progress and endogenous growth from the selection effects. Even though industry-wide productivity is a non-stationary process due to the selection process, plant level productivity is stationary. Also, models that emphasize selection effects mostly rely on static heterogeneity in productivity. That is, the selection criterion is based on the level of productivity but not on growth rate of the productivity. This is partly because there is no mechanism to induce productivity increases at the establishment level in the typical vintage model. But not many models try to explain productivity increases within a firm or an establishment. Moreover, rarely are explanations given for why some firms' productivity growth rates are consistently higher than those of others. This paper seeks to address this topic by exploring the sources of within-plant productivity growth.

There are a number of possible explanations for within-plant productivity growth. A plant can improve its productivity by adopting new technology. A plant which successfully adopts new technology will improve its productivity while others remain at the same level of productivity. Alternatively, if there is industry-wide technological progress, possibly with serial correlation, then one might observe productivity enhancement due to both creative destruction and within-plant. However, in this case, most plants within the same industry should show similar productivity dynamics.

The approach I will focus on is one suggested by Foster, Haltiwanger, and Krizan (2002): introducing the learning effects, and especially "learning by doing", that can generate productivity increase within a firm. If there is a learning effect, then it is not hard to imagine that the average productivity of new firms is lower than that of existing firms but that it is growing faster. But there is also a tremendous heterogeneity in the growth rates of the productivity across firms within the same cohort. If within-firm productivity growth is driven mostly by learning effects, then this heterogeneity must be due to different learning speed. This leads to the next question: why do some firms learn faster than others? One obvious but trivial answer is that those firms with more "doing" learn faster. Another possible answer is that even if two firms have the same amount of 'doing', one firm may convert more of its 'doing' into learning than the other. If only a fraction of the firm's doing is accumulated as "learning", and if this fraction depends on some observable statistics, then one can find a model that can generate a pattern consistent with recent findings.

Traditional models that incorporate learning by doing assume that the learning process is a function of cumulative gross activities such as output, investment, or employment. However, if there is no difference in two firms' initial productivity levels and these initial conditions do not change over time, then this assumption will eventually generate the same learning processes for two firms since their output (or employment) decisions will be identical. In any case, productivity levels are different only because firms are different in their ages or their inherent abilities. It is not possible that less productive firms in earlier periods can catch up with more productive firms in later periods. This happens if the initial productivity level does not change over time. However, this is not realistic since we often see the case where firms' relative performances within the cohort change dramatically.

One possible source of change in idiosyncratic productivity over time may be the different rate of accumulation in the learning process. Some firms may be slower to learn than others. It may be because some firms are less smarter than others, or they suffer from more interruptions than others, and thus might not convert as much of their "doing" to "learning". As Lucas (1993) points out, a firm's learning can be done by the management, the workforce, or the organization as a whole. If it is the workforce that is doing the learning, then high worker turnover (loss of experienced employees) may be the reason for failing to convert "doing" into "learning." In any case, as emphasized in Reichheld (1996), it is not companies but individuals that learn and their learning takes time. Given that there is tremendous heterogeneity in firms' gross job flows and that job flows are the lower bound of worker flows, assuming learning is simply a function of cumulative activities can miss very important heterogeneity.

The above arguments are closely related with the concepts of "general" and "firm-specific" investment in human capital. Purely general training received by a worker within a given firm is defined as investment which raises the potential productivity of the worker in other firms by as much as it is raised within the firm providing the training. Purely specific training raises the worker's productivity within the firm providing the training, but leaves his productivity unaffected in other firms. General capital is completely embodied in the worker, but the productivity of specific capital is jointly dependent on the productive characteristics embodied in the worker and the characteristics of other firm-specific inputs[1]. Becker (1993) provides the following discussion on the relationship between specific human capital and worker turnover:

> Turnover becomes important when costs are imposed on workers or firms, which are precisely the effects of specific training. Suppose a firm paid all the specific training costs of a worker who quit after completing the training. According to our earlier analysis, he would have been receiving the market wage and a new employee could be hired at the same wage. If the new employee were not given training, his marginal product would be less than that of the one who quit since presumably training raised the latter's productivity. Training could raise the new employee's productivity but would require additional expenditures by the firm. In other words, a firm is hurt by the departure of a trained employee because an equally profitable new employee could not be obtained.

In this paper, I develop a new measure of "learning" that incorporates both cumulative "doing" and worker turnover. Turnover functions as if it were a depreciation factor of "doing" and essentially decreases the magnitude of "learning." This measure can be constructed only if one has longitudinal and universal data on employment history and firm activity. I use two main data sets at Bureau of the Census to create this new measure. One is the Annual Survey of Manufactures (ASM) on manufacturing plants' business activities. The other is the Longitudinal Employer Household Dynamics (LEHD) data on employment history. Combining these two data sets, I generate a new measure of "learning" and argue that firms with historically lower rates of turnover "learn" faster than those with higher turnover given the same amount of past output.

The paper is organized as follows. In Section 2, I review related literature on learning by doing. Section 3 describes the data sets used in my analysis. In Section 4, I discuss the estimation methods, and in Section 5, I explain estimation results. Section 6 conclude.

[1] See Willis (1986).

## 2 Learning By Doing

"Learning by doing," the hypothesis that unit costs are a decreasing function of cumulative production, was early observed in aircraft industry by Wright (1936), who found that unit labor inputs in airframe production declined with the total number of airframes of the same type previously produced. Arrow (1962) argues that learning is the product of experience and that it can only take place through the attempt to solve a problem during activity. However, he uses cumulative gross investment as an index of experience instead of cumulated gross output. Given that new machines produced and put into use is capable of changing the environment in which production takes place, he argues that learning happens with continually new stimuli.

Rapping (1965) uses Liberty shipbuilding data during World War II and takes a production function approach to show that cumulated output has a significant effect on productivity advances during wartime. Sheshinski (1967), working under the assumption of disembodied technical progress and using a constant elasticity of substitution (CES) production function, shows with cross-sectional US and international data on manufacturing industry that efficiency growth is correlated with the level of cumulated investment (and output).

Early research on the topic of "learning by doing" is in many aspects limited. One obvious problem lies in the data. Studies on the aircraft industry use military production data. Sheshinski (1967) uses aggregate (two digit) and state level U.S. manufacturing data. Therefore, sample sizes are quite small. Since data are not longitudinal, it is not possible to identify firm births or to calculate cumulated gross investment (output). He uses gross book value of capital stock as an index for learning. Cross country data are two digit aggregate manufacturing data over ten years. However, imposing homogeneous production technology across countries is also very restrictive.

Bahk and Gort (1993) use U.S. Census Bureau's Longitudinal Research Database (LRD),[2] which is plant level, longitudinal data on the U.S. manufacturing industry. One can identify a plant's birth so that calculation of cumulated gross activity is easily done, and sample size increases significantly to 2,150 plants over a 14-year

[2] LRD consists of Census of Manufactures (CM) and Annual Survey of Manufactures. See Section 3 for detailed descriptions on LRD.

period. Production function estimation can be done by as detailed as four digit SIC. Bahk and Gort try to decompose "learning by doing" into organizational learning, capital learning, and manual task learning. They estimate effects of firm specific learning-by-doing while controlling for variation of general human capital with the average wage rate. Since identifying birth is possible with LRD, they focus only on new plants and their histories following birth. However, a sample of only new plants may not be representative and estimating production function with this sample may result in sample selection bias. Later I explain an alternative way to utilize the entire LRD, including not only new plants but also continuing plants. Bahk and Gort find that plant-specific learning effect is important, but in estimating production functions with learning as one of their arguments, they do not try to correct the endogeneity problem of production function. I use a recently developed estimation technique which can solve this problem, albeit under some restrictive assumptions.

However, as Argote *et al*. (1990) and Benkard (2000) point out, traditional learning models, which define experience simply as cumulative past output (or investment) as follows,

$$E_t = E_{t-1} + q_{t-1}, \tag{1}$$

assume that recent production and more-distant past production are equally important in determining a firm's current efficiency. For example, the conventional literature assumes that production during the Henry Ford era in the early 20th century is as important as production last year for current production. Argote *et al*. allow a possibility of depreciation of knowledge and use a new definition of experience as follows

$$E_t = \delta E_{t-1} + q_{t-1}. \tag{2}$$

This specification allows for the possibility that learning does not persist. Argote *et al*. (1990) find with wartime Liberty ship production data that learning depreciates quickly. Benkard (2000), using production data for the Lockheed L-1011 TriStar, find evidence supporting organizational forgetting, a hypothesis that a firm's stock of production experience depreciates over time. However, "depreciation" or "forgetting" are very abstract concepts[3]. Moreover, their implicit assumption that there is a constant rate of depreciation or organizational forgetting over time is quite restrictive.

[3] Although Benkard (2000) does not explicitly explore the sources of forgetting, he suggests that turnover and layoffs may lead to losses of experience.

In this paper, I adopt the idea of depreciating learning but, instead of estimating a depreciation rate or forgetting rate, I explicitly measure a variable which, I believe, is a main source of depreciation of learning, and test whether "learning," defined in this fashion can explain a firm's productivity variation better than the traditional measure. The measure I use in defining "learning" is the worker turnover rate, and more specifically, the separation rate. The index for "learning" is defined as follows

$$E_t = (1 - sr_{t-1})\,(E_{t-1} + q_{t-1}) \tag{3}$$

where $sr_{t-1}$ is the separation rate[4]. The reason why I use turnover as a source of depreciation of learning is explained below.

The actual meaning of "learning" is one thing, the previous literature on learning by doing has not been very clear. It is implicitly assumed that a firm itself is the one who is doing the "learning." Hence, if two firms are identical in their past gross activities, then they should be identical in their levels of "learning." However, as Lucas (1993) points out, a firm's learning can be done by the management, the workforce, or the organization as a whole. Which part dominates a firm's learning is an empirical question and may depend on industry characteristics, etc. If it is the management or the organization, then the usual assumption that only focuses on gross activity may not be too misleading. However, if it is the workforce that does the learning, then heterogeneity in worker flows among firms is very important determinant in the learning process. "Learning" from the firm's perspective is just the sum of each individual worker's "learning." High turnover (i.e. the loss of experienced employees) will make it harder for a firm to convert its "doing" into "learning." Only when a firm can retain its experienced workers, or those who have accumulated important knowledge from their past production activities, can it fully convert its "doing" into a stock of "learning." In any case, as emphasized in Reichheld (1996), it is not companies but individuals that do learn and their learning takes time. Given that there is tremendous heterogeneity in firms' worker flows and turnover patterns, assuming that learning is simply a function of cumulative activities can miss very important heterogeneity that can explain variation of productivity among firms within an industry.

A firm's "learning", in this sense, might be thought of as the sum of each worker's

[4] A formal definition of separation will be provided in Section 3.

"human capital" within that firm. As is well known, human capital can be decomposed into "general" and "firm-specific" human capital. What is lost from failing to retain experienced workers should be "firm-specific" human capital, since the same level of "general" human capital is easy to get with the same amount of compensation to new workers. New workers accumulate "firm-specific" human capital during the production process. This point is well understood by Bahk and Gort (1993), who use the average wage rate to control for general human capital when they try to identify firm-specific learning by doing. I also try to separate effects of the "general" and "specific" learning. However, instead of using the wage rate to proxy for human capital, I use new estimates of human capital developed by Abowd, Lengermann, and McKinney (2002)[5].

# 3 Data

In this study, I use two main datasets of the U.S. Census Bureau. One is the Longitudinal Research Database (LRD), which contains annual data on U.S. manufacturing establishments collected in the Census of Manufactures (CM) and the Annual Survey of Manufactures (ASM). The U.S. Census Bureau conducts the CM in years ending in "2" and "7" and the ASM in each of the 4 years between the CMs. The ASM is based on a sample drawn from the census universe of approximately 300,000~400,000 establishments. The ASM sample is updated every 5 years. The design of the ASM assures that large establishments are included with certainty and that small establishments are rotated out of the panel at the end of the five-year period. Both the CM and ASM collect data on output, input, identification and classification variables. Information on factors of production such as employment, payrolls, supplementary labor costs, worker hours, cost of fuels and electricity, cost of materials, capital expenditures, inventories and on outputs, such as value of shipments and value added, are available. The basic unit of observation in the LRD is the "establishment", which is defined as a "single physical location" engaged in one of the categories of industrial activity in the Standard Industrial Classification (SIC) system. Information from the LRD is rich enough to estimate production functions. However, with the LRD, while one can generate gross job flows data by establishments, one cannot generate the worker flows data that is crucial to constructing an important measure

[5] The estimation method of Abowd, Lengermann, and McKinney is discussed in Section 3.

of "learning." For this, we need a dataset that stores complete work history for each individual worker.

The other main dataset used here was developed by the Longitudinal Employer-Household Dynamics Program (LEHD) at the Census Bureau. This data set integrates information from state unemployment insurance (UI) data, ES202 data and Census Bureau economic and demographic data in a manner that permits the construction of longitudinal information on workforce composition at the firm level. This data set is both universal and longitudinal[6].

Every state in the U.S., through its Employment Security Agency, collects quarterly employment and earnings information to manage its unemployment compensation program. This database enables LEHD to construct quarterly longitudinal data on employees. The data are frequent, longitudinal, and potentially universal. The sample size is large and information is more accurate than survey based data. Since it is universal, movements of individuals to different employers and their consequences for earnings can be tracked. It is also possible to construct longitudinal data using the employer as the unit of analysis. This UI wage record is linked to Census Bureau data. The individual can be integrated with administrative data at the Census Bureau containing information such as date of birth, place of birth, and gender for almost all the workers in the data. LEHD staff have exploited the longitudinal and universal nature of the dataset to estimate jointly fixed worker and firm effects using the "human capital" model which will be discussed below.

It is the important to note at this point that the units of observation in the two data sets are not identical. While the LRD is at the establishment level (Permanent Plant Number: PPN), the business level identifiers on UI files are State Employer Identification Numbers (SEINs), which do not necessarily match the establishment level identifiers. Although one can impute establishment level data, the establishment level, identifiers (SEINUNITs) are still different from those in the LRD. To solve this problem, we need a common identifier for both data sources. Fortunately, there are two supplementary sources to enable successful match. One is the Census Bureau's Business Register, previously known as the Standard Statistical Establishment List (SSEL). The other is ES202 data available from each state. The variables I use are the Employer Identification Number (EIN)[7] as well as the county code that identifies

[6]For the desciption of LEHD data, see Abowd et. al. (2002).

[7]An EIN entity is an administrative unit that the IRS has assigned a unique identifier for use in

geographic information. Since the LRD and the Business Register have common establishment level identifiers (Census File Number: CFN), one can match by this to get information on the EIN and county. The UI data and the ES202 data also share the state level employer identifiers (SEINs and SEINUNITs), so one can match the UI data with the ES202 data using SEIN to get information on the EIN, and county.

Some caution is warranted when the EIN is used as a business identifier. The EIN is a unique business identifier for single units. However, when more than one establishment are under common ownership (multi-units), then those establishments may have the same EIN. In any case, the EIN is an identifier of more aggregated business units than establishments. This is also the case for LEHD data sources. Hence, we have to deal with at least some level of aggregation before matching. Rather than using only the EIN, I use the EIN/county combination for the level of aggregation in the following analysis. This unit, I believe, is closer to the concept of "establishment" than the EIN only.

As is mentioned in the previous section, I want to control for the effect of general human capital on a firm's efficiency. By general human capital, I mean the concept defined in Abowd, Kramarz and Margolis (1999) and in Abowd, Lengermann, and McKinney (2002). The core estimation model used is:

$$w_{ijt} = \theta_i + x_{it}\beta + \psi_j + \varepsilon_{ijt}. \tag{4}$$

The dependent variable is the log wage rate of individual $i$ working for employer $j$ at time $t$. The first component is a time invariant person effect, the second is the contribution of time varying observable individual characteristics, the third is the firm effect and the fourth component is the statistical residual, orthogonal to all other effects in the model. Human capital is defined as the sum of the fixed worker effect and the experience component and denoted by "$h$" (i.e. $h_{it} = \theta_i + x_{it}\beta$). This human capital measure is merged with the UI data before I calculate worker flows and aggregate up to the EIN/County.

Variables used from the LRD are constructed as follows. Real output is the total value of shipments less inventory investment (finished goods and work-in-progress) deflated by four digit SIC output deflator. Real material costs are the sum of the costs of materials, parts, resales, fuels, electricity, and contract work deflated by four digit

tax reporting.

materials deflator. Production hours worked is the total man-hours of production workers. Non-production worker is the number of non-production workers employed during the pay period including the 12th of March. Industry level deflators are available from the NBER/CES Productivity Database constructed by Bartelsman, Becker, and Gray.

Initial establishment equipment and structure capital stocks are the reported book values of machine and building assets deflated by the ratio of book to real values for the corresponding two digit industry published by the BEA. In the following years, I use the perpetual inventory method[8] to construct capital stock series. However, it is possible that an establishment is sampled in some years but not in other years. Whenever the previous year's real capital stock values are not available, I re-initialize real capital stock values in that year, and re-apply the perpetual inventory method.

Worker turnover rates and specifically separation rates are derived from the UI data of the LEHD. While the LRD variables are annual, the earnings history of the UI data is quarterly. Hence, I have to develop a measure comparable to the annual LRD variables. In this study, a separation occurs in year $t$ when there is no valid UI wage record for at least two consecutive quarters in year $t$ for worker $i$ who has valid wage record for at least two consecutive quarters in year $t-1$. If this measure is used, then it will not be heavily affected by changes of short period temporary employment. For the formal definitions, see the Appendix.

The final dataset I use is smaller than the LRD or the UI data for several reasons. The LRD and the UI data both have limitations in their data coverage. First, while the LRD covers all states, LEHD does not have the UI datasets of all states and therefore, estimates of human capital are only available for 7 states.[9] Second, the UI data are available mostly for 1990s while the LRD covers 1980s and 1970s. Third, the LRD only covers the manufacturing sector, while the UI data covers all sectors. Hence, the sample size of matched dataset is smaller compared to each of two main datasets. However, there is another sample selection restriction other than those mentioned above. Learning by doing hypothesis requires that one be

[8] Perpetual inventory method is as follows

$$K_t = (1 - \delta_t)\, K_{t-1} + I_t$$

where $\delta_t$ is four digit industry depreciation rate, $K_{t-1}$ real capital stock (equipment or structure) of the previous year, and $I_t$ real investments.

[9] Due to these reasons, only 7 states are used in this study.

able to calculate cumulated gross output (or investment). Given that the UI data are mostly available for the 1990s and one can calculate cumulative activity only for those identifiable businesses whose year of birth is during 1990s, the learning by doing hypothesis restricts the sample to include only new businesses with consecutive years of reports. This requirement is very demanding and reduces our sample size significantly. Therefore the final matched dataset has at most 7,370 observations and 3,351 businesses with the mean age of only 2.2 years.

Figure 1 shows age distribution of the sample by ownership type. The number of observations declines rapidly with age and falls more quickly for single-units than for multi-units. Two thirds of observations are younger than 3. This highly concentrated distribution might be due to either the sampling nature of ASM or to exits of young businesses. Given the short average age of businesses in the sample, the estimation that I conduct relies more heavily on cross-sectional variations rather than on time series variation. Figure 2 shows turnover patterns of young businesses. There is a persistence in turnover rates and a significant heterogeneity among businesses. One can also see many observation off the 45 degree line. Figure 3 suggests that persistence in productivity is stronger than in the turnover rate. Figure 4 and Figure 5 show that "learning" indices are extremely persistent. However, there are some differences between two measures. By construction, the traditional measure is non-decreasing in age. Meanwhile, the new measure can decrease in age if the turnover rate is very high relative to production. We can see this happening when we find below-diagonal observations. Even though the new measure is still very persistent, it is less persistent than the traditional measure since the new measure has additional variations resulting from turnover behavior. The main reason why even the new measure of learning shows such a high persistence is that "learning" is a state variable that is accumulated. Thus, the variation in learning is not as volatile as that in turnover.

# 4 Estimation

There are at least two ways to estimate learning by doing using the production function approach. To illustrate the differences of these two, consider the following simple Cobb-Douglas production function with an index of "experience" or "learning" incorporated as in equation (5) .

$$Y_{i,t} = AK_{i,t}^{\alpha}L_{i,t}^{\beta}E_{i,t}^{\gamma} \tag{5}$$

The first way that has been adopted in previous literature, such as Argote, *et al.* (1990), Bahk and Gort (1993), and Benkard (2000), is to estimate equation (5) directly to determine the coefficient of "learning" together with elasticities of usual input variables. The second approach, as in Levinsohn and Petropoulos (2001) and Pavcnik (2002), which I take here involves a two step procedure. In the first step, productivity measure is generated ignoring variables other than usual input variables. In the second step, the effects of learning on firm productivity is estimated.

There are trade-offs between the two approaches. As is emphasized in the previous section, our final sample is quite small due to reasons already mentioned. This small sample, which is mostly composed of young businesses, may not be representative. Hence, estimation using this non-representative sample may result in sample selection bias. On the other hand, the first step estimation using the entire LRD, which is supposed to be representative, can avoid this problem. However, this approach implicitly assumes that input variables and those variables not included in the first step but used as regressors in the second step, are orthogonal to each other. But this assumption is very unrealistic if one considers that the "learning" variable is just cumulative past output. Therefore, there must be an "omitted" variable bias in the second approach.

## 4.1 Productivity Estimation

There are two different methods to derive the productivity measure. One is the index number approach, such as cost-share based method. No estimation is involved in this approach. One can calculate the productivity measure using existing statistics. The other approach is econometric and is based on production function estimation. An easy but inconsistent method is using simple OLS. Another consistent approach used here is based on the work by Levinsohn and Petrin (2003), which, in turn, is based on Olley and Pakes (1996).

In the following, I will assume that firms have access to the following production technology:

$$q_{i,t} = \beta_0 + \beta_k k_{i,t} + \beta_p l^p_{i,t} + \beta_n l^n_{i,t} + \beta_m m_{i,t} + \omega_{i,t} + \eta_{i,t} \tag{6}$$

where $q_{i,t}$ is the log of gross output from establishment $i$ in year $t$, $k_{it}$ the log of its capital stock at the end of year $t$, $l^p_{i,t}$ the log of its production hours worked, $l^n_{i,t}$ the log of its non-production workers, $m_{i,t}$ the log of its materials input, $\omega_{i,t}$ a transmitted component of its productivity shock that is assumed to be serially correlated, and $\eta_{i,t}$ is either measurement error or a shock to productivity that is not forecastable during the period in which variable inputs are adjusted. The difference between two error terms is that $\omega_{i,t}$ is a state variable in the firm's decision problem, while $\eta_{i,t}$ has no impact on the firm's decision. It is assumed that labor and intermediate inputs are variable factors but that capital stocks are fixed factors. I estimate equation (6) by four-digit industry.

### 4.1.1 Index number approach

The first method of estimating productivity, the an index number method using cost-shares, does not involve any regressions at all. Cost shares are four-digit industry level variables and averaged by the current and the previous year's shares. Based on the assumption of constant returns to scale and Shephard's lemma, one can calculate elasticities of inputs using cost shares. To do this, I have to first calculate four-digit industry level total costs as follows:

$$TC_{j,t} = pe_{j,t} \times KE_{j,t} + ps_{j,t} \times KS_{j,t} + PAY_{j,t} + MATCOST_{j,t}$$

where $pe_{j,t}$ is the rental price of equipment for industry $j$ in year $t$, $KE_{j,t}$ its equipment stock, $ps_{j,t}$ rental price of structure, $KS_{j,t}$ structure stock, $PAY_{j,t}$ total payroll, and $MATCOST_{j,t}$ total materials costs[10]. Then cost shares of, say, equipment stock are

[10] BLS has two digit industry level data on the following variables. Capital income ($EQKY$ and $STKY$), real productive capital stock ($EQPK$ and $STPK$), and the ratio of capital input to productive capital stock ($EQKC$ and $STKC$, 1987=100). I calculate rental prices $pe$ and $ps$ as

$$\begin{aligned} pe &= \frac{EQKY}{EQPK \times EQKC} \times 100 \\ ps &= \frac{STKY}{STPK \times STKC} \times 100. \end{aligned}$$

calculated as

$$\alpha ke_{j,t} = \left( \frac{pe_{j,t} \times KE_{j,t}}{TC_{j,t}} + \frac{pe_{j,t-1} \times KE_{j,t-1}}{TC_{j,t-1}} \right) \times 0.5$$

where $\alpha ke_{j,t}$ is industry $j$'s equipment share in year $t$. Other cost shares are calculated in the same manner. With cost shares calculated, total factor productivity (in logs) is obtained by

$$prod_{i,j,t} = q_{i,t} - \alpha ke_{j,t} \times ke_{i,t} - \alpha ks_{j,t} \times ks_{i,t} - \alpha l_{j,t} \times l_{i,t} - \alpha m_{j,t} \times m_{i,t}$$

where $ke_{i,t}$ is the log of equipment capital stock for plant $i$ in year $t$, $ks_{i,t}$ its log of structure capital stock, $l_{i,t}$ its log of total employment, and $m_{i,t}$ its materials.

#### 4.1.2 OLS method

One can obtain the productivity measure by running simple OLS regression on equation (6) allowing the coefficients to vary across four-digit industries. The productivity measure is defined as

$$prod_{i,t} = q_{i,t} - \widehat{\beta}_k k_{i,t} - \widehat{\beta}_p l^p_{i,t} - \widehat{\beta}_n l^n_{i,t} - \widehat{\beta}_m m_{i,t}. \tag{7}$$

However, estimates from this method will be inconsistent since input variables (at least variable inputs, such as labor and materials) respond to the unobserved productivity shock, $\omega_{i,t}$. To avoid this endogeneity problem, we apply a method developed by Levinsohn-Petrin.

#### 4.1.3 Levinsohn-Petrin method

The Levinsohn-Petrin method is based on Olley and Pakes (1996) in that it uses an observable variable to control for an unobservable state variable. The Levinsohn-Petrin method also draws upon Hall and Horowitz (1996) in using a bootstrap version of the covariance matrix instead of the asymptotic value of covariance. It consists of two stages. In the first stage, coefficients on variable factors are estimated, and in the second stage, the coefficient on capital stock is estimated.

Industry level input variables are in the NBER-CES Manufacturing Industry Database constructed by Bartelsman, Becker, and Gray.

**First stage.** The idea behind this method is that unobserved productivity shocks can be controlled for if there is a stable relationship between the shock and intermediate inputs, such as materials or energy inputs. In the following, it is assumed that I use materials to control for unobserved productivity. Then the materials demand function is given as

$$m_{i,t} = m\left(\omega_{i,t}, k_{i,t}\right). \tag{8}$$

Assume that this function is monotonic in $\omega_{i,t}$ for every $k_{i,t}$[11]. Inverting the input demand equation $(8)$, we get

$$\omega_{i,t} = \omega\left(m_{i,t}, k_{i,t}\right) \tag{9}$$

From (6) and (9), we have

$$q_{i,t} = \beta_p l_{i,t}^p + \beta_n l_{i,t}^n + \phi\left(m_{i,t}, k_{i,t}\right) + \eta_{i,t} \tag{10}$$

where

$$\phi\left(\cdot\right) = \beta_0 + \beta_k k_{i,t} + \beta_m m_{i,t} + \omega\left(m_{i,t}, k_{i,t}\right). \tag{11}$$

As Olley and Pakes (1996) and Levinsohn and Petropoulos (2001), I project $q_{i,t}$ on $l_{i,t}^p$, $l_{i,t}^n$ and a polynomial expansion of materials and capital stocks to get consistent estimates of $\beta_p$ and $\beta_n$, say $\widehat{\beta}_p$ and $\widehat{\beta}_n$. Note that, from this regression, one can also estimate $\phi$.

**Second Stage Estimation.** Assume that $\omega_{i,t}$ is serially correlated Then let

$$\begin{aligned} \xi_{i,t} &= \omega_{i,t} - E\left[\omega_{i,t}|\omega_{i,t-1}\right] \\ \eta_{i,t}^* &= \xi_{i,t} + \eta_{i,t}. \end{aligned}$$

The important thing to note is that $\eta_{i,t}^*$ is not orthogonal to variable factors such as labor and materials inputs. However, unlike the original error term $\omega_{i,t} + \eta_{i,t}$, which is serially correlated, $\eta_{i,t}^*$ is orthogonal to the state variables. This distinction is important since one can construct orthogonality conditions using the state variables

[11] This assumption is the most critical in this approach. Syverson (2001) has a nice critique on this assumption. The key criticism relies on the assumption that there is only one unobserved state variable. If there are more than one unobserved state variables, such as, input prices, then the invertibility may not hold unless we have information on other unobserved state variables.

and $\eta^*_{i,t}$.

To identify the coefficients on capital stocks, I employ the following moment conditions:

$$\begin{aligned}
E\left(\xi_{i,t}+\eta_{i,t}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|m_{i,t-1}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|m_{i,t-2}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|k_{i,t}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|k_{i,t-1}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|l^p_{i,t-1}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|l^p_{i,t-2}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|l^n_{i,t-1}\right) &= 0 \\
E\left(\xi_{i,t}+\eta_{i,t}|l^n_{i,t-2}\right) &= 0
\end{aligned}$$

Note the following relationship

$$q_{i,t}-\beta_p l^p_{i,t}-\beta_n l^n_{i,t}=\phi\left(m_{i,t},k_{i,t}\right)+\eta_{i,t}. \tag{12}$$

Define new variables

$$\begin{aligned}
Q_{i,t} &= q_{i,t}-\beta_p l^p_{i,t}-\beta_n l^n_{i,t} \\
\widehat{Q}_{i,t} &= q_{i,t}-\widehat{\beta}_p l^p_{i,t}-\widehat{\beta}_n l^n_{i,t}
\end{aligned}$$

and note the following relationship from (6), (11), and (12)

$$\begin{aligned}
Q_{i,t} &= \phi_t\left(m_{i,t},k_{i,t}\right)+\eta_{i,t} \\
&= \beta_0+\beta_k k_{i,t}+\beta_m m_{i,t}+\omega_{i,t}+\eta_{i,t} \qquad (13)\\
\phi_{i,t-1} &= \beta_0+\beta_k k_{i,t-1}+\beta_m m_{i,t-1}+\omega_{t-1} \qquad (14)
\end{aligned}$$

If $\omega_{i,t}$ is assumed to follow, say, an $AR(1)$ process, then we would have

$$\omega_{i,t}=\rho_0+\rho\omega_{i,t-1},$$

and one can then derive the following expression:

$$
\begin{aligned}
Q_{i,t} &= (\beta_0 + \rho_0 - \rho\beta_0) + \beta_k k_{i,t} + \beta_m m_{i,t} && (15)\\
&\quad + \rho \left[\phi_{i,t-1} - \beta_k k_{i,t-1} - \beta_m m_{i,t-1}\right] + \xi_{i,t} + \eta_{i,t} && (16)
\end{aligned}
$$

Since the true values of $Q_{i,t}$ and $\phi_{i,t-1}$ are not observed, I use predicted values, $\widehat{Q}_{i,t}$ and $\widehat{\phi}_{t-1}$ to form the following equation.

$$
\begin{aligned}
\widehat{Q}_{i,t} &= (\beta_0 + \rho_0 - \rho\beta_0) + \beta_k k_{i,t} + \beta_m m_{i,t} \\
&\quad + \rho \left[\phi_{i,t-1} - \beta_k k_{i,t-1} - \beta_m m_{i,t-1}\right] + \widehat{\xi_{i,t} + \eta_{i,t}} && (17)
\end{aligned}
$$

Let $Z_{i,t} = \left\{1, m_{i,t-1}, m_{i,t-2}, k_{i,t}, k_{i,t-1}, l^p_{i,t-1}, l^p_{i,t-2}, l^n_{i,t-1}, l^n_{i,t-2}\right\}$. The estimator for $\beta = (\beta_k, \beta_m, \rho)$ can be obtained by minimizing the the following criterion function[12]:

$$\widehat{\beta} = \arg\min_{\beta} Q(\beta) = \widehat{\xi + \eta}' \times W \times \widehat{\xi + \eta} \tag{18}$$

where $W$ is a positive definite matrix. GMM can then be used to get estimates.

The productivity measure can thus be obtained as in Levinsohn and Petropoulos (2001):

$$prod_{i,t} = \widehat{\phi}_{i,t} - \widehat{\beta}_k k_{i,t} - \widehat{\beta}_m m_{i,t}. \tag{19}$$

There is a slight difference in the definitions of productivity definitions in equation (7) and (19). The former is an estimate for both the persistent and the transitory components of the productivity shock $\omega_{i,t} + \eta_{i,t}$, while the latter is an estimate for only the persistent component of the productivity shock, $\omega_{i,t}$, which is supposed to be known to firm's manager.

## 4.2 Estimation of Learning Effects

The equation estimated to see the effects of learning on productivity is

$$prod_{i,j,t} = \gamma_0 + \gamma_j + \gamma_v v_i + \gamma_{tr} t + \gamma_h h_{i,t} + \gamma_{eo} e^o_{i,t} + \gamma_{en} e^n_{i,t} + u_{i,t} \tag{20}$$

where $\gamma_j$ is a four digit industry effect, $v_i$ is the vintage of a firm $i$, $t$ is a time trend to capture industry-wide technological progress, $h_{i,t}$ is a human capital measure, $e^o_{i,t}$

[12] $\beta_0$ and $\rho_0$ are not separately identified.

is a conventional learning measure, and $e^n_{i,t}$ a new measure of turnover-interacted "learning." This new measure of "learning", $e^n_{i,t}$ (in logs), can be defined as follows

$$\begin{aligned} e^n_{i,t} &= \log\left(E_{i,t}\right) \\ \text{where } E_{i,t} &= \left(1 - sr_{i,t-1}\right)\left(E_{i,t-1} + q_{i,t-1}\right). \end{aligned}$$

I include both the traditional and the new measure of learning in equation (20) to see whether either one is dominating the other in explaining productivity variation.

# 5 Results

I use five different dependent variables obtained by methods described in Section 4 to estimate equation (20). I use calendar year, vintage, and human capital ($h$) as control variables. Table 1 shows correlation coefficients of these three productivity measures. The index measure is highly correlated with OLS measures but not with the Levinsohn-Petrin measure. The reason might be that while the index measure and the OLS measure capture both the permanent and the transitory components of the productivity shock, the Levinsohn-Petrin measure captures only the persistent component. On the other hand, the two learning measures are highly colinear and the correlation coefficient between them is 0.98. Thus, we expect one will dominate the other in affecting productivity variation.

Estimation results are reported in Table 2 through Table 10. Tables 2-4 show results using the index number productivity measure as a dependent variable, Tables 5-7 show results using the OLS productivity measure, and Tables 8-10 show results based on the Levinsohn-Petrin productivity measure. The first table in each case presents the results when only the traditional measure of learning (learn1) is used as an independent variable. The second table presents the cases when only the new measure (learn2) is used as an independent variable. The third table shows the results when both the traditional and new measures are used in regressions to see which measure dominates in explaining productivity variation.

In Table 2, one can see that the traditional measure of learning is highly significant and that workforce quality (measured by the human capital estimate) is also very significant with expected signs. In Table 3, where learning is measured in a new way, learning and workforce quality are still highly significant with slightly higher $R^2$

values. In Table 4, where both measures of learning are used in a horse race, one finds the striking result that the new measure of "learning" is consistently significant and positive while the traditional measure is always insignificant. Moreover, the traditional measure has the wrong sign. The elasticity of productivity with respect to learning is around 4%. Given the new measure of learning, the high value of the traditional measure means high turnover rates in the past. So, given the same level learning as measured using the new method, a firm with lower past production rates and turnover rates is more productive than that with higher cumulative output but with higher past turnover. In other words, given the same amount of past output, those firms with lower past turnover rates, and hence lower values of the new measure of learning, are more likely to have higher productivity. Human capital also positively contributes to businesses' efficiency. According to Table 4, given the same workforce quality (measured by "general" human capital), losing workers with accumulated experience during the production process will result in lower productivity even if a firm hires workers with the same level of "general" human capital. This occurs because lost specific human capital cannot be replaced by new workers. The time trend and vintage show negative and positive effects, respectively, but neither is significant.

Tables 5-7 show results based on OLS methods. Again, both learning measures and human capital are highly significant in Table 5 and Table 6. However, in Table 7, where both learning measures are used in estimation, the traditional measure is significant with the wrong sign. The new measure, meanwhile, is highly significant and has the expected sign. The elasticity of productivity with respect to the new measure of learning is generally higher than that using an index number method. The effects of the time trend and vintage are more significant. Human capital's contribution is very significant, with a higher coefficient estimate on that variable.

Tables 8-10 use productivity measures based on the Levinsohn-Petrin method. The results are very similar to the other two cases. In Table 10, the new measure of turnover-interacted learning is always significant at least at the 90% significance level, while the traditional measure is always insignificant. However, human capital is now insignificant in every case. One can also observe that the elasticity of productivity with respect to new learning measure is smaller compared to the other methods. For example, it is around 2% instead of 4%.

Bahk and Gort (1993) did not use their learning variable - the traditional measure

- together with firm's age (which is just the difference between a time trend and its vintage) since those variables highly correlated with each other. However, in this paper, when I use the learning variable together with a trend and a vintage, the learning variable is still highly significant. This supports the idea in Arrow (1962) that not just a calendar time but some economic variable can explain productivity variation.

# 6 Conclusion

The learning by doing hypothesis has been documented extensively in the literature both theoretically or empirically. Since Wright (1936), it has been convention to measure "learning" with cumulative output (or investment). Some authors questioned this "persistent" or "permanent" learning measure and proposed "depreciating" or "forgetting" learning instead. They try to estimate effects of learning given this idea.

In this study, I suggest a new measure of learning. This new measure is similar to the traditional one in that it is also based on past business activity. However, it is based on "depreciating" learning where depreciation rate is not estimated but generated. Based on the production function approach, I estimate the effects of both the traditional learning measure and this new measure. Estimation results using several different methods consistently show that the new measure dominates the conventional one in explaining productivity variation.

# A Appendix

This Appendix describes concepts used to construct the turnover measure.

## A.1 Individual concepts

### A.1.1 Quarterly variables

In the following, $t$ refers to the sequential quarter.

**Flow employment** $(m)$: individual $i$ employed (matched to a job) at some time during period $t$ at employer $j$

$$m_{i,j,t} = \begin{cases} 1, & \text{if } i \text{ has positive earnings at employer } j \text{ during period } t \\ 0, & \text{otherwise} \end{cases} \tag{21}$$

**Beginning of quarter employment** $(b)$: individual $i$ employed at the end of $t-1$, beginning of $t$

$$b_{i,j,t} = \begin{cases} 1, & \text{if } m_{i,j,t-1} = m_{i,j,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

### A.1.2 Annual variables

In the following $t$ refers to the year and $q$ refers to the quarter. Let $b_{i,j,t,q}$ refer to beginning-of-quarter employment status. Then there is a one-to-one mapping between this definition and the one defined in equation (22) using sequential quarters.

**Flow employment** $(emp)$: individual $i$ employed at some time during year $t$ at employer $j$

$$emp_{i,j,t} = \begin{cases} 1, & \text{if } b_{i,j,t,2} = 1 \text{ or } b_{i,j,t,3} = 1 \text{ or } b_{i,j,t,4} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

This definition of annual employment requires some attachment of employer-employee relationship. More specifically, it requires at least two consecutive positive earnings record during a year. Given our emphasis on the learning by doing process, this attachment requirement should not be a very restrictive condition.

**Separations** $(s)$: individual $i$ separated from $j$ during year $t$

$$s_{i,j,t} = \begin{cases} 1, & \text{if } emp_{i,j,t-1} = 1 \text{ and } emp_{i,j,t} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

## A.2 Employer concepts

**Annual employment** (number of jobs) for employer $j$ during year $t$

$$EMP_{j,t} = \sum_i emp_{i,j,t} \tag{25}$$

**Annual separations** for employer $j$ during year $t$

$$S_{j,t} = \sum_i s_{i,j,t} \tag{26}$$

**Annual separation rate** for employer $j$ during year $t$

$$SR_{j,t} = \frac{S_{j,t}}{EMP_{j,t}} \tag{27}$$

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<Table 1> Correlations of productivity measures

| | Index | OLS | L-P |
|---|---|---|---|
| Index | 1.000 | 0.741 | 0.218 |
| OLS | | 1.000 | 0.437 |
| L-P | | | 1.000 |

<Table 2> Estimation Results

| model | learn1 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0253** | | | | 0.5347 | 7,370 |
| | (0.0028) | | | | | |
| 2 | **0.0257** | -0.0022 | | | 0.5347 | 7,370 |
| | (0.0029) | (0.0032) | | | | |
| 3 | **0.0262** | | 0.0050 | | 0.5348 | 7,370 |
| | (0.0029) | | (0.0033) | | | |
| 4 | **0.0226** | | | **0.0475** | 0.5311 | 7,075 |
| | (0.0030) | | | (0.0164) | | |
| 5 | **0.0299** | **-0.0113** | **0.0131** | | 0.5352 | 7,370 |
| | (0.0033) | (0.0045) | (0.0046) | | | |
| 6 | **0.0232** | -0.0030 | | **0.0458** | 0.5312 | 7,075 |
| | (0.0031) | (0.0034) | | (0.0166) | | |
| 7 | **0.0233** | | 0.0036 | **0.0491** | 0.5312 | 7,075 |
| | (0.0031) | | (0.0035) | (0.0165) | | |
| 8 | **0.0268** | **-0.0108** | **0.0113** | **0.0464** | 0.5316 | 7,075 |
| | (0.0035) | (0.0048) | (0.0049) | (0.0166) | | |

* Dependent Variable: TFP by cost share based index number
** Standard errors are in parentheses

<Table 3> Estimation Results

| model | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0257** | | | | 0.5356 | 7,343 |
| | (0.0027) | | | | | |
| 2 | **0.0258** | -0.0012 | | | 0.5356 | 7,343 |
| | (0.0028) | (0.0032) | | | | |
| 3 | **0.0262** | | 0.0039 | | 0.5357 | 7,343 |
| | (0.0028) | | (0.0032) | | | |
| 4 | **0.0230** | | | **0.0473** | 0.5321 | 7,049 |
| | (0.0029) | | | (0.0165) | | |
| 5 | **0.0280** | **-0.0070** | **0.0087** | | 0.5359 | 7,343 |
| | (0.0030) | (0.0043) | (0.0044) | | | |
| 6 | **0.0233** | -0.0020 | | **0.0463** | 0.5321 | 7,049 |
| | (0.0030) | (0.0034) | | (0.0166) | | |
| 7 | **0.0234** | | 0.0026 | **0.0486** | 0.5321 | 7,049 |
| | (0.0030) | | (0.0034) | (0.0166) | | |
| 8 | **0.0250** | **-0.0068** | **0.0073** | **0.0475** | 0.5323 | 7,049 |
| | (0.0032) | (0.0046) | (0.0046) | (0.0166) | | |

* Dependent Variable: TFP by cost share based index number
** Standard errors are in parentheses

<Table 4> Estimation Results

| model | learn1 | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|---|
| 1 | -0.0171 | **0.0416** | | | | 0.5357 | 7,343 |
| | (0.0126) | (0.0120) | | | | | |
| 2 | -0.0169 | **0.0415** | -0.0001 | | | 0.5357 | 7,343 |
| | (0.0130) | (0.0123) | (0.0033) | | | | |
| 3 | -0.0149 | **0.0401** | | 0.0032 | | 0.5358 | 7,343 |
| | (0.0128) | (0.0121) | | (0.0033) | | | |
| 4 | -0.0181 | **0.0398** | | | **0.0480** | 0.5322 | 7,049 |
| | (0.0130) | (0.0124) | | | (0.0165) | | |
| 5 | -0.0061 | **0.0334** | -0.0060 | 0.0077 | | 0.5359 | 7,343 |
| | (0.0148) | (0.0134) | (0.0050) | (0.0050) | | | |
| 6 | -0.0173 | **0.0392** | -0.0008 | | **0.0475** | 0.5322 | 7,049 |
| | (0.0134) | (0.0127) | (0.0035) | | (0.0166) | | |
| 7 | -0.0169 | **0.0390** | | 0.0019 | **0.0488** | 0.5323 | 7,049 |
| | (0.0132) | (0.0125) | | (0.0035) | (0.0166) | | |
| 8 | -0.0093 | **0.0333** | -0.0052 | 0.0058 | **0.0479** | 0.5323 | 7,049 |
| | (0.0152) | (0.0138) | (0.0053) | (0.0053) | (0.0166) | | |

* Dependent Variable: TFP by cost share based index number
** Standard errors are in parentheses

<Table 5> Estimation Results

| model | learn1 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0210** | | | | 0.5376 | 7,134 |
| | (0.0027) | | | | | |
| 2 | **0.0184** | **0.0124** | | | 0.5388 | 7,134 |
| | (0.0027) | (0.0030) | | | | |
| 3 | **0.0240** | | **0.0161** | | 0.5395 | 7,134 |
| | (0.0027) | | (0.0030) | | | |
| 4 | **0.0177** | | | **0.0624** | 0.5343 | 6,858 |
| | (0.0028) | | | (0.0155) | | |
| 5 | **0.0231** | 0.0026 | **0.0143** | | 0.5395 | 7,134 |
| | (0.0031) | (0.0042) | (0.0043) | | | |
| 6 | **0.0150** | **0.0131** | | **0.0706** | 0.5356 | 6,858 |
| | (0.0029) | (0.0031) | | (0.0156) | | |
| 7 | **0.0206** | | **0.0163** | **0.0696** | 0.5362 | 6,858 |
| | (0.0029) | | (0.0032) | (0.0155) | | |
| 8 | **0.0194** | 0.0037 | **0.0136** | **0.0707** | 0.5363 | 6,858 |
| | (0.0032) | (0.0044) | (0.0045) | (0.0156) | | |

* Dependent Variable: TFP by OLS

** Standard errors are in parentheses

<Table 6> Estimation Results

| model | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0219** | | | | 0.5394 | 7,117 |
| | (0.0026) | | | | | |
| 2 | **0.0199** | **0.0129** | | | 0.5407 | 7,117 |
| | (0.0026) | (0.0029) | | | | |
| 3 | **0.0242** | | **0.0152** | | 0.5411 | 7,117 |
| | (0.0026) | | (0.0030) | | | |
| 4 | **0.0187** | | | **0.0616** | 0.5362 | 6,841 |
| | (0.0027) | | | (0.0156) | | |
| 5 | **0.0228** | 0.0052 | **0.0116** | | 0.5413 | 7,117 |
| | (0.0028) | (0.0040) | (0.0041) | | | |
| 6 | **0.0167** | **0.0134** | | **0.0690** | 0.5376 | 6,841 |
| | (0.0028) | (0.0031) | | (0.0156) | | |
| 7 | **0.0210** | | **0.0156** | **0.0690** | 0.5379 | 6,841 |
| | (0.0028) | | (0.0032) | (0.0156) | | |
| 8 | **0.0195** | 0.0058 | **0.0115** | **0.0703** | 0.5381 | 6,841 |
| | (0.0030) | (0.0042) | (0.0043) | (0.0156) | | |

* Dependent Variable: TFP by OLS

** Standard errors are in parentheses

<Table 7> Estimation Results

| model | learn1 | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|---|
| 1 | **-0.0250** | **0.0454** | | | | 0.5397 | 7,117 |
| | (0.0119) | (0.0114) | | | | | |
| 2 | **-0.0412** | **0.0580** | **0.0155** | | | 0.5415 | 7,117 |
| | (0.0122) | (0.0116) | (0.0030) | | | | |
| 3 | -0.0156 | **0.0386** | | **0.0146** | | 0.5413 | 7,117 |
| | (0.0120) | (0.0115) | | (0.0030) | | | |
| 4 | **-0.0286** | **0.0454** | | | **0.0627** | 0.5366 | 6,841 |
| | (0.0122) | (0.0117) | | | (0.0156) | | |
| 5 | **-0.0317** | **0.0509** | **0.0105** | 0.0067 | | 0.5416 | 7,117 |
| | (0.0139) | (0.0127) | (0.0046) | (0.0046) | | | |
| 6 | **-0.0455** | **0.0587** | **0.0164** | | **0.0724** | 0.5385 | 6,841 |
| | (0.0126) | (0.0120) | (0.0032) | | (0.0156) | | |
| 7 | -0.0195 | **0.0390** | | **0.0148** | **0.0694** | 0.5381 | 6,841 |
| | (0.0124) | (0.0118) | | (0.0032) | (0.0156) | | |
| 8 | **-0.0379** | **0.0530** | **0.0123** | 0.0055 | **0.0724** | 0.5386 | 6,841 |
| | (0.0143) | (0.0130) | (0.0048) | (0.0049) | (0.0156) | | |

* Dependent Variable: TFP by OLS
** Standard errors are in parentheses

<Table 8> Estimation Results

| model | learn1 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0140** | | | | 0.9197 | 7,134 |
| | (0.0017) | | | | | |
| 2 | **0.0139** | 0.0002 | | | 0.9197 | 7,134 |
| | (0.0017) | (0.0019) | | | | |
| 3 | **0.0147** | | **0.0043** | | 0.9198 | 7,134 |
| | (0.0017) | | (0.0019) | | | |
| 4 | **0.0128** | | | 0.0131 | 0.9221 | 6,858 |
| | (0.0018) | | | (0.0096) | | |
| 5 | **0.0166** | -0.0055 | **0.0083** | | 0.9199 | 7,134 |
| | (0.0019) | (0.0026) | (0.0027) | | | |
| 6 | **0.0127** | 0.0002 | | 0.0132 | 0.9221 | 6,858 |
| | (0.0018) | (0.0019) | | (0.0097) | | |
| 7 | **0.0136** | | 0.0046 | 0.0151 | 0.9221 | 6,858 |
| | (0.0018) | | (0.0020) | (0.0096) | | |
| 8 | **0.0155** | -0.0058 | **0.0087** | 0.0133 | 0.9222 | 6,858 |
| | (0.0020) | (0.0027) | (0.0028) | (0.0097) | | |

* Dependent Variable: TFP by Levinsohn and Petrin
** Standard errors are in parentheses

<Table 9> Estimation Results

| model | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|
| 1 | **0.0141** | | | | 0.9198 | 7,117 |
| | (0.0016) | | | | | |
| 2 | **0.0139** | 0.0009 | | | 0.9198 | 7,117 |
| | (0.0016) | (0.0019) | | | | |
| 3 | **0.0146** | | **0.0039** | | 0.9199 | 7,117 |
| | (0.0016) | | (0.0019) | | | |
| 4 | **0.0130** | | | 0.0121 | 0.9222 | 6,841 |
| | (0.0017) | | | (0.0097) | | |
| 5 | **0.0154** | -0.0031 | **0.0061** | | 0.9199 | 7,117 |
| | (0.0018) | (0.0025) | (0.0026) | | | |
| 6 | **0.0129** | 0.0009 | | 0.0126 | 0.9222 | 6,841 |
| | (0.0017) | (0.0019) | | (0.0097) | | |
| 7 | **0.0136** | | **0.0043** | 0.0141 | 0.9222 | 6,841 |
| | (0.0017) | | (0.0020) | (0.0097) | | |
| 8 | **0.0145** | -0.0036 | **0.0067** | 0.0134 | 0.9222 | 6,841 |
| | (0.0018) | (0.0026) | (0.0027) | (0.0097) | | |

* Dependent Variable: TFP by Levinsohn and Petrin
** Standard errors are in parentheses

<Table 10> Estimation Results

| model | learn1 | learn2 | trend | vintage | h | R-Squared | N |
|---|---|---|---|---|---|---|---|
| 1 | -0.0090 | **0.0225** | | | | 0.9198 | 7,117 |
| | (0.0075) | (0.0072) | | | | | |
| 2 | -0.0106 | **0.0238** | 0.0016 | | | 0.9199 | 7,117 |
| | (0.0078) | (0.0074) | (0.0019) | | | | |
| 3 | -0.0066 | **0.0208** | | 0.0037 | | 0.9199 | 7,117 |
| | (0.0076) | (0.0073) | | (0.0019) | | | |
| 4 | -0.0112 | **0.0235** | | | 0.0125 | 0.9222 | 6,841 |
| | (0.0076) | (0.0073) | | | (0.0097) | | |
| 5 | -0.0025 | **0.0177** | -0.0027 | 0.0057 | | 0.9199 | 7,117 |
| | (0.0088) | (0.0080) | (0.0029) | (0.0029) | | | |
| 6 | -0.0130 | **0.0249** | 0.0017 | | 0.0135 | 0.9222 | 6,841 |
| | (0.0079) | (0.0075) | (0.0020) | | (0.0097) | | |
| 7 | -0.0088 | **0.0218** | | 0.0039 | 0.0143 | 0.9222 | 6,841 |
| | (0.0077) | (0.0073) | | (0.0020) | (0.0097) | | |
| 8 | -0.0047 | **0.0187** | -0.0027 | **0.0060** | 0.0136 | 0.9222 | 6,841 |
| | (0.0089) | (0.0081) | (0.0030) | (0.0030) | (0.0097) | | |

* Dependent Variable: TFP by Levinsohn and Petrin
** Standard errors are in parentheses

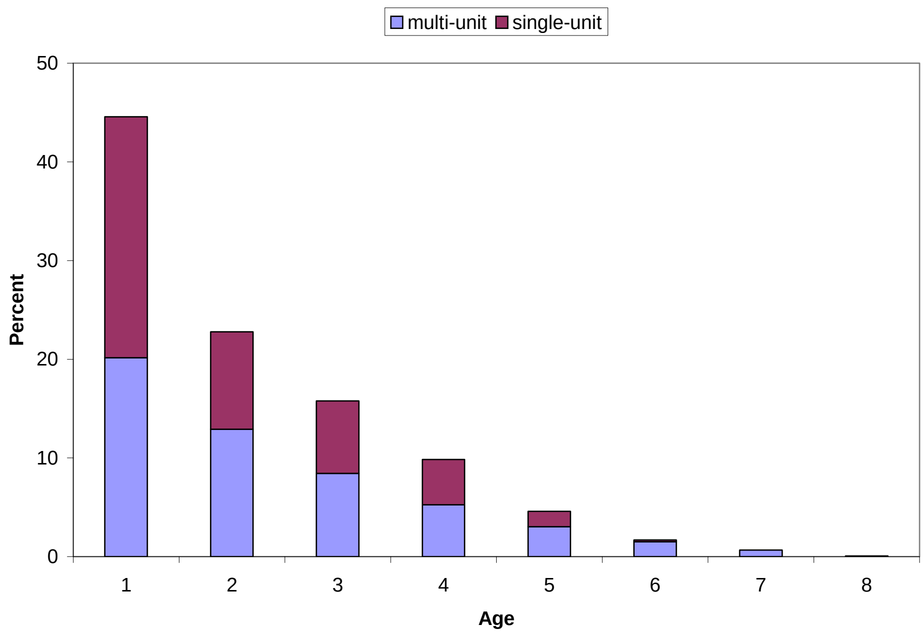


Figure 1: Age Distribution by Ownership Type

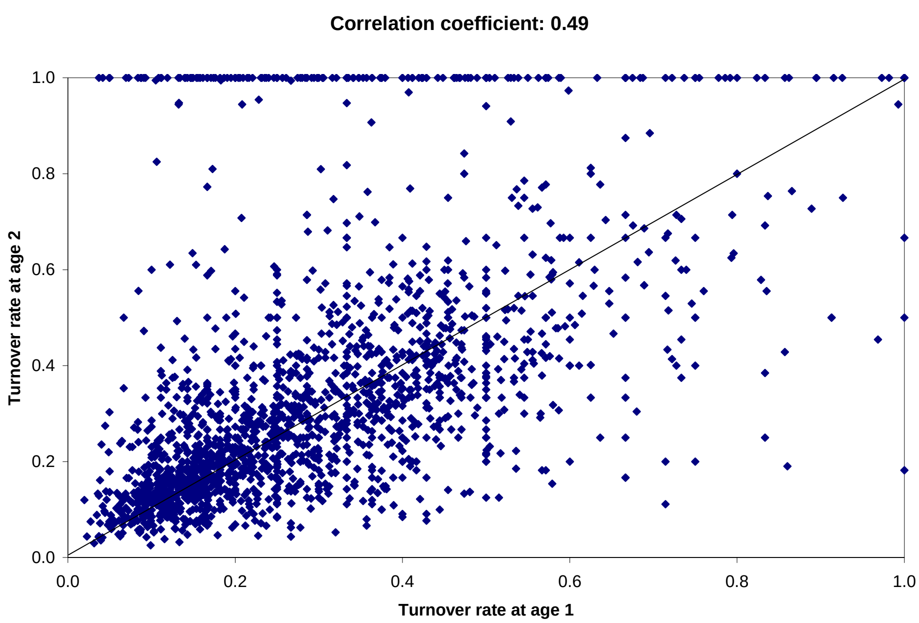


Figure 2: Persistence and Heterogeneity of Turnover

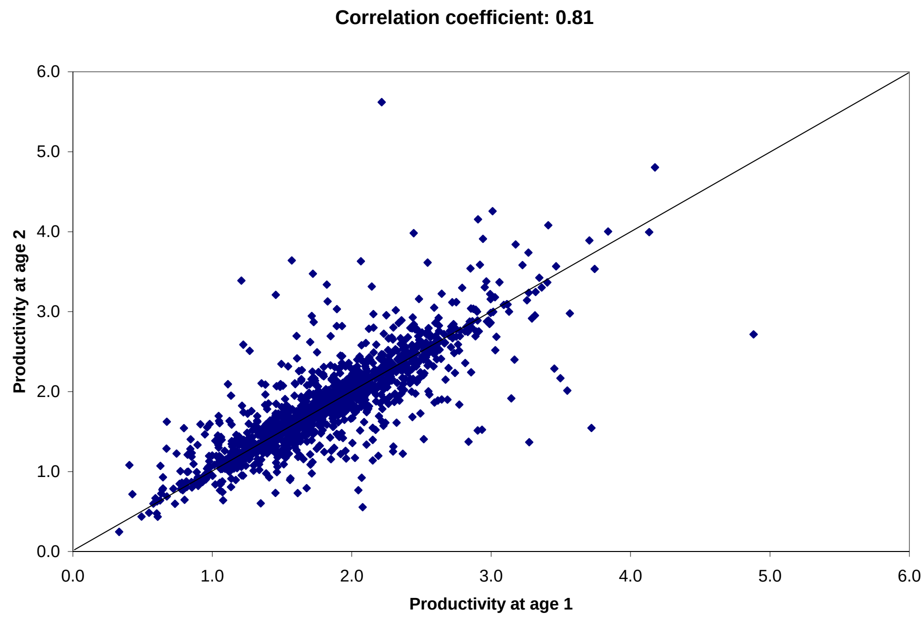


Figure 3: Persistence and Heterogeneity of Productivity (Index Number)

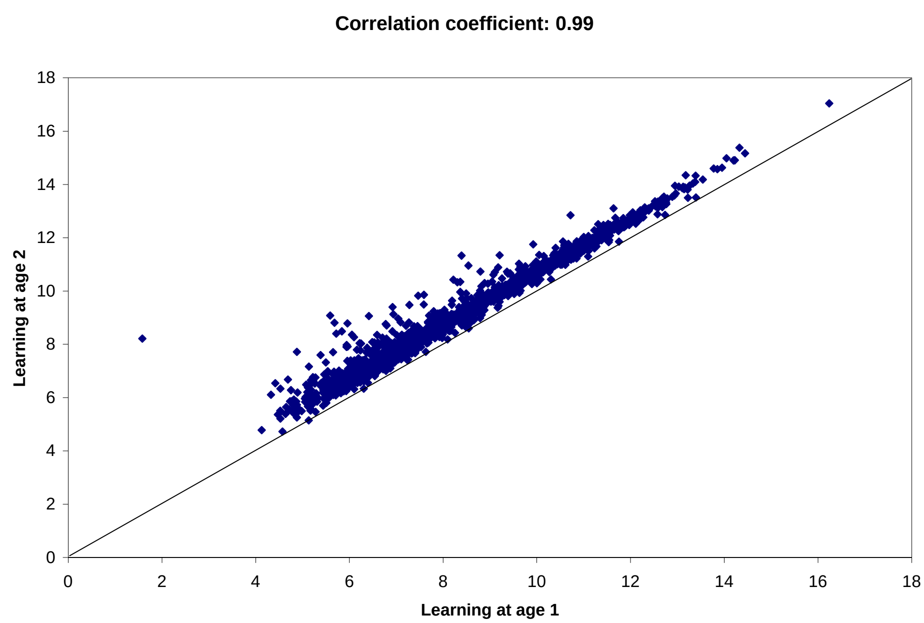


Figure 4: Persistence and Heterogeneity of Learning (Traditional Measure)

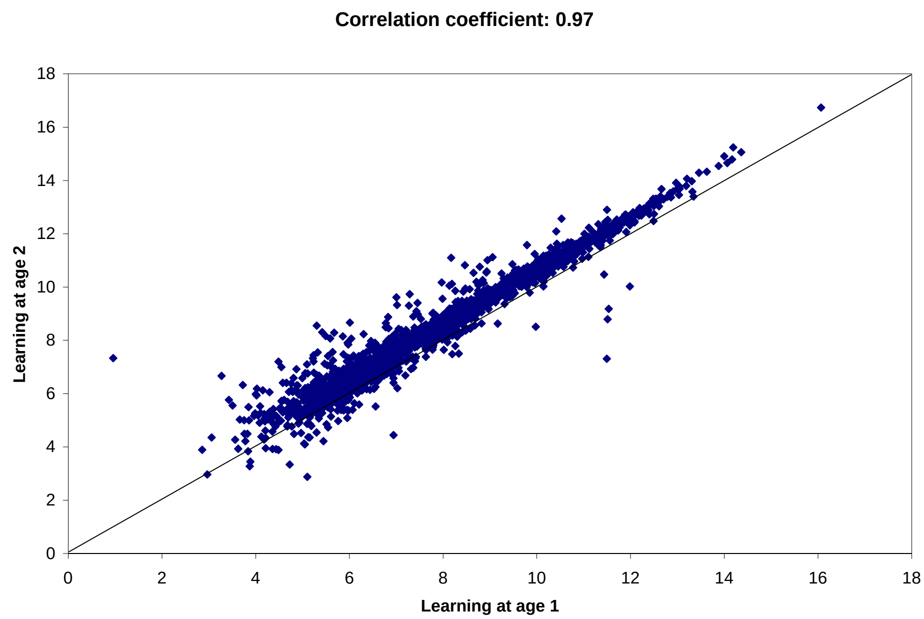


Figure 5: Persistence and Heterogeneity of Learning (New Measure)