The Role of Worker Ability and Learning in Explaining Wage Changes and Mobility Patterns of Firm and Occupation Switchers (Preliminary and Incomplete: Please do not Cite)

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Abstract

We offer a novel approach for testing for the role of learning about unobserved worker ability in determining between firm and occupation wage differentials and allocation of workers between firms and occupations. Under the learning hypothesis, future success, determined by placement in a high-wage firm or occupation, is the direct consequence of positive signals about unobserved productivity in the previous time periods. This means that workers who are successful later in their career are currently more productive per unit paid, compared to other workers who are unsuccessful later in their careers. Using firm-level production functions and a large longitudinal matched employer-employee dataset for France for the period between 1978 and 1996, we find some evidence in favor of the learning hypothesis. Specifically, unskilled blue-collar workers who move to better occupations within 2 or 7 years are more productive than similar workers who do not move to better occupations; the gap in productivity is about twice as large as the gap in wages, indicating that workers who succeed in the future are under-paid relative to their productivity. Movers to high-wage firms are more productive than workers who do not move to better paying firms; for these workers, relative wages understate relative productivity.

1 Introduction

This paper offers a new test of the theory that markets' gradual learning about workers' ability contributes to wage changes experienced by workers switching firms and occupations[1]. We test the learning theory by for the first time comparing the productivity and wages of workers who do and do not switch to high-wage sectors. Previous tests of the learning theory involved longitudinal data on workers' wages and sector affiliation which precludes productivity measurement; we use firm-level data and production functions to measure productivity.

According to the learning theory, markets are initially unsure about the true worker ability; if all workers appear the same, workers will be paid similar wages. As more information on workers' performance accumulates over time, some workers prove their high ability, move

[1]Industry, occupation, and firm switchers experience large changes in wages (Krueger and Summers, 1988, Gibbons and Katz, 1992, Goux and Maurin, 1999, Gibbons et al, 2005, Abowd et al, 1999, 2005).

to high wage sectors, and enjoy a wage increase[2]. In this case, the wage increase reflects markets' updated information about workers' ability, and does not represent a pure wage differential between high and low wage sectors.

Investigating the source of wage differentials between sectors, and the role of ability and learning in explaining these differentials is important. It is important to understand whether ability or pure wage differences between sectors, such as rent sharing or other differences in compensation, are the primary cause of these differentials[3]. Policies such as training and job search assistance depend on our understanding of the relative role of ability and luck in wage changes experienced by sector switchers.

Existing research testing the contribution of learning to sector mobility and wage differentials assumes access to data on workers' wages and longitudinal history of sector affiliation (Gibbons and Katz, 1992, Gibbons et al, 2005)[4]. Gibbons and Katz (1992) reject the hypothesis that unmeasured ability plays the dominant role in generating wage changes for industry switchers. Gibbons et al (2005) conclude that higher skilled workers are sorted to better sectors, but wage differentials between occupations are caused mainly by different payments for ability between sectors, self-selection based on ability, and not learning; and results for industry wage differentials are inconclusive, even though suggestive that unmeasured ability is not the only explanation of between sector wage differentials. Oyer (2007) finds evidence that markets learn about true research ability of economists and allocate economists between higher- and lower-ranked economics departments based on updated information about ability[5].

To test the learning theory, ideally we need to measure workers wages and productivity before the sector switch. If the theory is true, workers who switch to high wage sectors should be initially more productive than workers who do not, and the gap in wages should

[2]Better workers may be optimally matched to high wage sectors due to comparative advantage, for example, as in Gibbons et al (2005). For an example of a model with self-selection and comparative advantage see Heckman and Sedlacek (1985).

[3]Compensation policies may include long-term employment contracts between firms and workers with deferred compensation (Lazear, 1979), efficiency wages (Akerlof and Yellen, 1986), or training with and without prior sorting of more able workers to firms providing more training (for a model with prior sorting, see Neal, 1998). There is some evidence that differences in wages between firms, for example, are related to firms' market power, capital intensity, and rent sharing (Goux and Maurin, 1999, Abowd et al, 1999, 2005, Abowd and Lemieux, 1993, van Reenen, 1996).

[4]For evidence of the role of learning in generating wage dynamics see Farber and Gibbons, 1996, Altonji and Pierret, 2001, Lange, 2007, Chiappori et al, 1999.

[5]Oyer (2007) does not have information on economists' wages, and therefore, he cannot study wage differentials between economics departments.

be smaller than the productivity gap. No other theory of sector wage differentials offers this prediction which offers an opportunity to evaluate the importance of learning in generating wage differentials between firms and occupations. Our objectives in this paper are twofold: i) to test whether more productive workers are sorted to better paying sectors (this may be the case even without learning); and ii) to test whether learning contributes to sector wage differentials and assess its relative importance.

We use production functions with several types of workers to measure the relative productivity per wage unit between workers who do and do not move to high-wage firms and occupations in the near future. The method closely follows Hellerstein, Neumark, and Troske (1999) and Hellerstein and Neumark (2004). The statistical model allows for the correlation of the proportion of workers who move to high-wage sectors at the firm level with firm-level time-invariant characteristics and productivity shocks.

The data are a large matched employer-employee dataset for France for the period between 1978 and 1996. Our findings are consistent with learning playing a role in allocating workers between occupations: workers who move out of unskilled blue-collar occupations within the next 2 or 7 years are more productive per unit of wages paid than workers who stay in unskilled and services occupations. Workers who move to (or remain in) high wage firms are more productive per unit paid than workers who do not. The findings for firms and occupations imply that better, more productive workers are sorted into better paying firms and better occupations over their careers.

The next section describes the model, Section 3 presents the statistical model and assumptions required for the identification of the parameters of interest; Section 4 describes the data and implementation. Results are presented in Section 5, and Section 6 concludes.

2 A Model with Two Sectors and Learning

The model is related to Gibbons et al (2005), Gibbons and Katz (1992), Farber and Gibbons (1996), Lange (2007), Oyer (2007), and Jovanovic (1979). Instead of using individual data, however, we will use longitudinal matched employer-employee data and estimate payroll and production functions specifications at the firm level. Assume that the output of worker i in period t is given by:

$$\chi_{it} = \eta_i + \epsilon_{it}.$$

where $\eta_i \sim F_\eta$ and $\epsilon_{it} \sim F_\epsilon$, and ϵ_{it} is drawn independently from η_i. In the above equation, η_i measures the quality, or the level of skill of worker i, and ϵ_{it} is a random shock that causes worker output χ_{it} to diverge from worker skill η_i. Assume that all market participants observe worker-level output in each time period, but η_i is unobserved.

The prior distribution of worker skill is F_η, which coincides with the true overall distribution of skill in the economy. Each period, firms update their beliefs about worker skill η_i by computing the posterior distribution of skill for each worker based on previous output observations for individual workers. Firms set wages to equal the expected output for each worker.

To illustrate, suppose $\eta_i \sim N(m = 0, \sigma_\eta^2 = 4)$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2 = 4)$; the distributions do not need to be normal in general. Then in period one worker $i's$ output and wage equal to:

$$\begin{aligned} w_{i1} &= E(\eta_i) = m = 0 \\ \chi_{i1} &= \eta_i + \epsilon_{1i}, \end{aligned}$$

in period two output and wages equal to:

$$\begin{aligned} w_{i2} &= m_{1,i} = E(\eta_i|\chi_{i1}) = \frac{\frac{m}{\sigma_\eta^2} + \frac{1}{\sigma_\epsilon^2}(\eta_i + \epsilon_{i1})}{\frac{1}{\sigma_\eta^2} + \frac{1}{\sigma_\epsilon^2}} = \frac{\eta_i + \epsilon_{i1}}{2} \\ \chi_{i2} &= \eta_i + \epsilon_{2i}, \end{aligned}$$

and for any time period t,

$$
\begin{aligned}
w_{it} &= m_{t-1,i} = E(\eta_i|\chi_{i,1},...,\chi_{i,t-1}) = \\
&= \frac{\frac{m}{\sigma_\eta^2} + \frac{1}{\sigma_\epsilon^2}\left((t-1)\eta_i + \sum_{\tau=1}^{t-1}\epsilon_{i,\tau}\right)}{\frac{1}{\sigma_\eta^2} + \frac{1}{\sigma_\epsilon^2}} = \\
&= \frac{(t-1)\eta_i + \sum_{\tau=1}^{t-1}\epsilon_{i,\tau}}{t} \\
\chi_{it} &= \eta_i + \epsilon_{ti}.
\end{aligned}
$$

Assume that each firm in the economy employs exactly one worker. We assume that there are two sectors in the economy: "bad" (low-wage) and "good" (high-wage) sectors, and that initially workers are randomly distributed between the two sectors. For now assume that there are no true sector-specific effects, and that workers' output depends only on workers' ability (η) and the random error (ϵ), as outlined above. The top 50% of workers should be optimally matched to the top 50% of firms; firms are ranked based on the average gain in wages experienced by firm switchers.

Workers are re-matched to firms after each period based on the expected value of η_i, or based on $m_{t-1,i}$, which is the expected value of η_i given the history of output realizations $(\chi_{i,1},...,\chi_{i,t-1})$ up to period $(t-1)$. We assume further that if a worker has to move from the good sector to the bad sector, for example, her next period replacement will be a random draw from the set of workers in the good sector who are moving to the bad sector. A similar assumption is adopted for workers moving from the bad sector to the good sector. Based on these assumptions, we can derive expressions for firm-level output in each sector in each time period.

Consider a representative firm in the bad sector. The next step for us is to describe output of this representative firm in the bad sector in each time period and identify the parameters of interest that we will estimate in the empirical section of the paper. We continue to assume that there is only one worker per firm. Workers age simultaneously in this initial setup; workers start with zero experience and a random distribution between sectors and then gradually move between sectors as more information about individual skill becomes available.

For now we abstract from returns to experience and focus on the evolution of output based purely on learning.

The first step in describing firm's output in the bad sector is to acknowledge the fact that it is possible that the firm may have a different worker employed at different points in time. We denote firms using subscript j and workers, indexed by subscript i, will be indexed by time period within firms: for example, the worker in firm j in period t is $i(j,t)$. For now we omit subscript j and consider the output of a representative firm in the bad sector over time:

$$y_t = \eta_{i(t)} + \epsilon_{i(t)}. \tag{1}$$

To test the learning theory, we are interested in comparing output and wages of workers who will and will not move to the good (high-wage) sector in the next time period. Specifically, one of the parameters of interest in the first period is the wage differential between workers who do and do not move to the good sector in the second period. This wage differential is zero in the first period because we assumed that workers are randomly distributed in the first period between firms, and firms set wages equal to expected output in each period. The second parameter of interest is the difference in productivity between workers who move out of the bad sector in the second period and workers who stay in the bad sector in the second time period:

$$E(\eta_{i(1)} + \epsilon_{i(1)}|m_{1,i(1)} > 0) - E(\eta_{i(1)} + \epsilon_{i(1)}|m_{1,i(1)} < 0),$$

where we use the fact that, given $\eta_i \sim N(0,4)$ and $\epsilon_{it} \sim N(0,4)$, $m_{1,i}$ has a normal distribution with mean zero, and in a large sample of workers, workers with $\big(m_{1,i(1)} > 0\big)$ will move to the good sector in the second period, and workers with $\big(m_{1,i(1)} < 0\big)$ will stay in the bad sector.

For an arbitrary time period we are interested in comparing the difference in wages and productivity between good and bad workers, with bad workers being workers staying in the bad sector in the next time period. The parameters of interest that we seek to identify are the differences in wages:

$$E(m_{t-1,i(t)}|m_{t,i(t)} > 0) - E(m_{t-1,i(t)}|m_{t,i(t)} < 0),$$

and productivity:

$$E(\eta_{i(t)} + \epsilon_{i(t)}|m_{t,i(t)} > 0) - E(\eta_{i(t)} + \epsilon_{i(t)}|m_{t,i(1)} < 0), \tag{2}$$

using firm-level information for firms in the bad (low-wage) sector. Note that the exact nature of these population parameters will depend on the distributions of workers moving between sectors at any particular point in time, and on all past history of movements of workers between sectors, as described in detail in the next section.

The learning theory implies that the difference in current wages understates the difference in current productivity. Intuitively, a large positive signal in the current period increases the probability of moving to the good (high-wage) sector, and decreases the probability of staying in the bad sector. This positive current signal about productivity is not yet reflected in wages because wages are based on output in periods up to $(t-1)$. This means that the gap in wages understates the gap in productivity between good and bad workers.

Other theories of wage determination and of sector wage differentials do not imply the two hypotheses based on the learning model, tested in this paper: i) that workers who move to good sectors or stay in good sectors are more productive than other workers; and ii) that the positive gap in productivity between good and bad workers exceeds the gap in wages. The general human capital model cannot explain wage differentials between sectors without compensating wage differentials; and there is little evidence of compensating wage differentials at least between industries (Krueger and Summers, 1988). The specific human capital model, even with extensions allowing sorting of better workers to firms providing specific training, does not predict that the gap in productivity between good and bad workers is not equal to the gap in wages (Neal, 1998).

Search models with or without counter offers cannot explain the gap in productivity between workers moving between sectors because all workers are assumed to be identical in these models (Manning, 2000, Burdett and Mortensen, 1998, Burdett and Coles, 2003, Postel-Vinay and Robin, 2002a,b, Stevens, 2004). Queuing models do not generate clear cut predictions for wages and productivity and are not considered here. Pure rent sharing models would not be able to explain the gap between relative wages and productivity for good and bad workers (for tests of these models, see Abowd and Lemieux, 1993, van Reenen, 1996). Long-term deferred compensation and efficiency wage models cannot explain why productivity and wage differences arise before moving to high-wage sectors, if the only difference betweeen good and bad sectors is the effort-inducing compensation schemes in good sectors (Lazear, 1979, Akerlof and Yellen, 1986).

In this paper, we find support for the learning hypothesis; the evidence presented here, however, does not rule out other explanations of sector wage differentials. In fact, there is substantial evidence that rent sharing pays a role in generating wage differentials between firms (Abowd and Lemieux, 1993, van Reenen, 1996). The next section develops the empirical model and outlines the estimation strategy.

3 Empirical Model with Two Sectors and Learning

Consider a typical firm in the bad sector; we continue to omit the firm subscript j; we continue to assume that there is one worker per firm for simplicity. For now we continue to assume that wages and productivity are determined exclusively as described by the learning model and that there is no impact of experience or other person and firm characteristics on firms' and workers' productivity and wages. We are still considering one generation of workers which is ageing over time. Equations (1) can be written using the population parameters in equations (2):

$$y_t = \alpha_t^0 P_t^0 + \alpha_t^1 P_t^1 + v_t, \tag{3}$$

where

$$\begin{aligned} \alpha_t^1 &= E(\eta_{i(t)} + \epsilon_{i(t)} | m_{t,i(t)} > 0) \\ \alpha_t^0 &= E(\eta_{i(t)} + \epsilon_{i(t)} | m_{t,i(1)} < 0). \end{aligned}$$

The main parameters of interest, as in equation (2), are $(\alpha_t^1 - \alpha_t^0)$; using $(P_t^0 + P_t^1 = 1)$ we can rewrite equation (3) to focus on the main parameters of interest:

$$\begin{aligned} y_t &= \alpha_t^0 \left(1 - P_t^1\right) + \alpha_t^1 P_t^1 + v_t, \\ y_t &= \alpha_t^0 + \left(\alpha_t^1 - \alpha_t^0\right) P_t^1 + v_t, \\ y_t &= \alpha_t^0 + \tilde{\alpha}_t^1 P_t^1 + v_t. \end{aligned} \tag{4}$$

If the model in equation (4) represents the true data generating process, then equation (4) can be estimated and estimates of parameters $\tilde{\alpha}_t^1$ can be recovered using ordinary least squares because the data observations at the firm level represent independent and identically distributed observations and the following condition holds for the error term:

$$E(v_t|P_t^1) = 0; \tag{5}$$

since the errors v_t are correlated over time, estimation can be improved by taking this correlation into account[6].

In practice, we would like to allow for the presence of time-invariant firm effects that are possibly correlated with P_t^1 on the right hand side of equations (4) and for the possibility that there are shocks that are correlated with P_t^1. Firm-level heterogeneity in P_t^1 may arise due to different employee retention policies between firms, for example. And shocks to firms' productivity may lead to temporary fluctuations in employee retention and employment opportunities after separation, leading to the regression error in equations (4) to be correlated with P_t^1, the proportion of good workers.

Let us start by first ignoring the firm effects and allowing for a shock correlated with P_t^1. To illustrate the idea behind identification in this case, allow multiple workers per firm and assume that workers live just for one time period and at the end of the period it becomes clear if workers are good or bad (if they would be in the good sector if there was another

[6]To see equation (5), consider $E(v_t|P_t^1 = 1) = E(y_t - E(\eta_{i(t)} + \epsilon_{i(t)}|m_{t,i(t)} > 0)|m_{t,i(t)} > 0) = E(\eta_{i(t)} + \epsilon_{i(t)}|m_{t,i(t)} > 0) - E(\eta_{i(t)} + \epsilon_{i(t)}|m_{t,i(t)} > 0) = 0$. Similarly, $E(v_t|P_t^1 = 0) = 0$.

time period). In this case,

$$y_{jt} = \alpha_t^0 + \tilde{\alpha}^1 P_{jt}^1 + v_{jt} + \epsilon_{jt}, \tag{6}$$

where v_t is uncorrelated with P_{jt}^1, and ϵ_{jt} is a shock which is correlated with P_{jt}^1, and j indexes firms. We assume that the parameter $\tilde{\alpha}^1$ is unchanged over time, and that P_{jt}^1 at the firm level behave as a stationary process.

If future P_{jt}^1 can be predicted using the stationary process generating proportions of good workers at the firm level, then past proportions can be used as instruments in equation (6). Persistence in the proportion of good workers at the firm level in the bad sector (the sector we are considering at the moment) can be generated by persistence in firm-level recruitment practices. If there is a firm effect ψ_j in addition to the shock ϵ_{jt} in equation (6), then first differencing and then using previous proportions of good workers as instruments is a valid option; equation (6) can be estimated using GMM in first differences or, under additional assumptions, system GMM (Arellano and Bond, 1991, Arellano and Bover, 1995, Blundell and Bond, 2000).

The setup becomes somewhat more complicated when we allow multiple time periods, multiple workers per firm, and multiple generations working side-by-side within firms in the presence of shocks and firm-level heterogeneity. Some of the new complications arise because of the possible correlation between the current error term in equations (4) and the past proportions of good workers within the same generation. To see this, consider what happens if there are two consecutive generations of workers in firms working side-by-side, with each firm employing one worker from each generation; now generation age and the current time period do not coincide, and we need to introduce more notation. In addition, assume that workers work only for two periods, and the quality of workers is revealed at the end of the first and second periods:

$$\begin{aligned} y_{g2,1} &= \alpha_1^0 + \tilde{\alpha}_1^1 P_{g2,1}^1 + v_{g2,1} + \alpha_2^0 + \tilde{\alpha}_2^1 P_{g1,2}^1 + v_{g1,2}, \\ y_{g3,1} &= \alpha_1^0 + \tilde{\alpha}_1^1 P_{g3,1}^1 + v_{g3,1} + \alpha_2^0 + \tilde{\alpha}_2^1 P_{g2,2}^1 + v_{g2,2}, \end{aligned} \tag{7}$$

where $g1$, $g2$, and $g3$ denote generations of workers, and $(g2, 1)$ and $(g2, 2)$ are the first and the second years of generation two respectively. Using the same idea as with one age group above, we could use proportions of good workers (workers moving to the high-wage sector in the next time period) within the age group in past periods as instruments for similar proportions in the current time periods in the presence of productivity shocks. In particular, $P^1_{g2,1}$ could be used as an instrument for $P^1_{g3,1}$, and $P^1_{g1,2}$ could be used as an instrument for $P^1_{g2,2}$. Unfortunately, $P^1_{g2,1}$ may be correlated with $v_{g2,2}$, and we need to modify the model to account for this correlation.

For now let us consider equations (4) in more detail and explicitly specify the potential sources of correlation between the error term and past proportions of good workers. We are back to the one-generation, multiple period and gradual learning model with one worker per firm, as in the beginning of this section:

$$\begin{aligned} y_t &= \alpha^0_t + \tilde{\alpha}^1_t P^1_t + v_t \\ y_{t+1} &= \alpha^0_{t+1} + \tilde{\alpha}^1_{t+1} P^1_{t+1} + v_{t+1}. \end{aligned} \tag{8}$$

In equations (8), $E(v_{t+1}|P^1_t)$ may not zero because if $P^1_t = 1$, then the worker in period t is replaced by a worker from the good sector in period $(t+1)$, and if $P^1_t = 0$ then in our model, the worker stays with the firm for another period. The mean quality (productivity) of workers who will stay within the bad sector in period $(t+2)$ may differ between groups of workers with these two distinct past histories. The same statement applies to workers who will move to the good sector in period $(t+2)$. This may cause a correlation between v_{t+1} and P^1_t, and this is why past proportions of good workers may be invalid instruments in equations (7).

A solution to this problem is to allow coefficients α to differ between groups of workers by employment history. This solution has its limitations: the number of parameters increases dramatically with workers' age. Productivity equations in period t, allowing for conditioning on the full past worker history, are as follows:

$$y_t = \sum_{h(t)} \left(\alpha^0_{h(t)} P^0_{h(t)} + \alpha^1_{h(t)} P^1_{h(t)} \right) + \tilde{v}_t,$$

where $h(t)$ is a history of sector affiliation over $(t-1)$ time periods (e.g., the full history of sector affiliation in time period 3 is $\{00, 01, 10, 11\}$. Since it is impossible to allow for complete employment histories even for relatively moderate levels of experience, we assume that α-s differ only between groups of workers defined by at most the last year's sector affiliation. This assumption can be relaxed and tested by using a more disaggregated setup and comparing the resulting estimates to the estimates obtained under a more restrictive setup. It is easy to see that $E(\tilde{v}_t|P^1_{h(t-1)}) = 0$ for all $h(t-1)$, and past proportions can be used as instruments for future proportions of similarly aged workers in models with multiple generations of workers working side by side in firms.

If worker's output at the firm level (y_t) can be interpreted as the worker's value of the marginal product of labor, then we can use the learning theory developed above in a more general production context. For instance, it is not necessary to assume a linear production specification; a Cobb-Douglas functional form for the firm's total output will use most of the theoretical innovations developed above:

$$Q_{jt} = AK_{jt}^{\beta_1} L_{jt}^{\beta_2}, \tag{9}$$

$$L_{jt} = \sum_{i \in (jt)} (\eta_i + \epsilon_{it}), \tag{10}$$

where K is capital, A represents the firm's technology, Q is output, β_1 and β_2 are the Cobb-Douglas coefficients, and L is labor quality[7].

After taking logs, re-interpreting P^0 and P^1 as proportions of "bad" and "good" workers respectively, and v_t as the average deviation of $\sum_{i\in(jt)}(\eta_i + \epsilon_{it})$ from $(\alpha^0 P^0 + \alpha^1 P^1)$, and re-arranging equations (9) and (10), we have:

$$\begin{aligned} \ln Q_{jt} &= \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + \beta_2 \ln(\frac{1}{L}(\sum_{i\in(jt)} (\eta_i + \epsilon_{it}))), \qquad (11) \\ \ln Q_{jt} &= \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + \beta_2 \ln(\alpha^0 P^0 + \alpha^1 P^1 + v_t). \end{aligned}$$

[7]The marginal product of labor equals $y_{jt} = \frac{\partial Q}{\partial L}\frac{\partial L}{\partial L_i} = \beta_2 A K^{\beta_1} L^{\beta_2 - 1}(\eta_i + \epsilon_{it})$ if L_i is the set of all workers with the marginal product of labor $(\eta_i + \epsilon_{it})$. In the learning model, wages equal the expected value of the marginal product of labor (the expected value of y_{jt}, which is the expected value of η_i since $E(\epsilon_{it}) = 0$).

We can further take α^0 outside of the last term because α^0 is not separately identified, and re-arrange equation (11) as follows:

$$\ln Q_{jt} = \tilde{\beta}_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + \beta_2 \ln(1 + \left(\frac{\alpha^1}{\alpha^0} - 1\right) P^1 + \frac{v_t}{\alpha^0}). \tag{12}$$

In equation (12), we estimate the relative marginal product between "good" and "bad" workers which serves the same purpose as estimating $(\alpha^1 - \alpha^0)$. If the term in $\left(\frac{\alpha^1}{\alpha^0} P^1 + \frac{v_t}{\alpha^0}\right)$ is not very large (and we do not suppose that "bad" and "good" workers would differ in productivity by a factor greater than 2), then we can write:

$$\ln Q_{jt} = \tilde{\beta}_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + \beta_2 \left(\frac{\alpha^1}{\alpha^0} - 1\right) P^1 + \mathring{v}_t + \epsilon_{jt}. \tag{13}$$

The same ideas about estimation as the ones considered for the linear production function in the earlier parts of this section apply, and we can estimate equation (13) using first differencing (if there are time-invariant firm effects) and lagged values of P^1 as instruments; in a model with multiple generations of workers working side by side, additional controls for previous history of sector affiliation may be necessary, as discussed above. In practice, we also control for other worker characteristics such as, depending on specification, age, proportion of female workers, and occupation.

The equations estimated using nonlinear least squares in the current version of the Results section are as follows; for firms as sectors (firms are ranked by the magnitude of the firm effect in the logged wage equation with person, firm effects and worker characteristics on the right hand side - see Abowd et al, 2002):

$$\begin{aligned} \ln Q_{jt} &= \tilde{\beta}_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + & (14) \\ &\quad \beta_2 \ln((1 + \left(\frac{\alpha^1}{\alpha^0} - 1\right) P^1)(1 + (\alpha_f - 1) P^f) & \\ &\quad (1 + \sum_{i=1}^{3} (\alpha_{oi} - 1) P^{oi})(1 + \sum_{i=1}^{3} (\alpha_{ai} - 1) P^{ai})) + \epsilon_{jt}, & (15) \end{aligned}$$

where P^f is the proportion of female workers, P^{oi} are proportions by occupation (managerial and supervisory, services, skilled blue-collar, and unskilled blue-collar), and P^{ai} are 4 age groups (≤25, 26-35, 36-50, 51+). This specification assumes the same differentials between good and bad workers for all age groups and work histories of sector affiliation. As explained in Hellerstein, Neumark, and Troske (1999), this specification also assumes the same proportions of female workers, for example, within other cells (by occupation, age, etc) as well as the same relative marginal products between female and male workers in all other cells.

We also estimate equations for sectors defined as occupations:

$$\begin{aligned}\ln Q_{jt} &= \tilde{\beta}_0 + \beta_1 \ln K_{jt} + \beta_2 \ln L_{jt} + && (16)\\ &\beta_2 \ln((1 + (\alpha^{ug} - 1)\, P^{ug} + \left(\alpha^{ub} - 1\right) P^{ub} + \\ &(\alpha^{u} - 1)\, P^{u} + (\alpha^{m} - 1)\, P^{m} + (\alpha^{s} - 1)\, P^{s}) && (17)\\ &(1 + (\alpha_f - 1)P^f)(1 + \sum_{i=1}^{3}(\alpha_{ai} - 1)P^{ai})) + \epsilon_{jt},\end{aligned}$$

where P^m and P^s are proportions of workers in managerial and services occupations respectively, and P^{ug} is the proportion among unskilled workers who will be in managerial or skilled occupations in the future, P^{ub} - unskilled who will remain in unskilled or services occupations, and P^u is the proportion among unskilled for whom future occupation status is unknown.

The next sections present a brief data description and the Results section describes the parameters obtained after estimating equations (14) and (16).

4 Data and Implementation

The data for this project require information on firm's inputs and output as well as information on the firm-level composition of employment by sex, occupation, age, future firm quality, and future occupation. The data are matched employer-employee data for France, with a longitudinal workers' employment history file with information on workers demographic characteristics and salaries matched to a firm-level survey with information on firms' production inputs and outputs. The match between the two files, the worker history file with identifiers by worker, firm identifiers and year of employment, and firm-level file with identifiers by firm and year, is conducted using firm identifiers and year.

The source of information on the firm level composition of employment by sex, birth cohort, and occupation is “Déclarations annuelles des salaires“ (DADS) administered by INSEE (Institut National de la Statistique et des Etudes Economiques) in the years between 1976 and 1996, with the exception of 1981, 1983, and 1990. The data are a 1/25 subset of all workers in the French economy, with the exclusion of civil servants. The sample includes all workers born in October of even-numbered years, and the data are from mandatory reports provided by employers. Self-employed workers are included in the data, but we cannot identify them.

For each worker-year record the following information is available: the identity of the employing firm (the data are aggregated to the level of the firm from establishment-level data), full-time status, the number of days paid, a measure of annualized compensation, occupation, the industry of the employing firm, workers' age and sex. Each record is identified by a person identifier, firm identifier, and year. The full data set with observations identified by person, firm, and year of employment contains 15,424,755 observations, with 1,142,736 firms and 1,951,334 workers. Since the data for firms is available only starting in 1978, the DADS sample excluding 1978 and 1979 contains 13,949,578 observations, and information on 1,076,340 unique firms and 1,853,134 unique workers (Table 1).

The source of firm-level information is the annual survey “Enquête annuelle d'entreprises“ (EAE) available for the years between 1978 and 1996. Employer-level information includes the firm identifier, the four digit industrial affiliation, employment, capital, and sales by year. The sampling frame for this data set is described in INSEE documents, and larger firms were sampled with a larger probability than smaller firms. An approximate sample weight was constructed for the data to be representative by firm size (the weight was not used in the current set of estimations). Two-digit industry capital and value added deflators were available separately from INSEE for the period under investigation. The deflators were obtained from the INSEE macroeconomic time series data (Banque de données macroéconomiques).

Information on the composition of workers at the firm/year level by sex, occupation, age, firm quality, future occupation in DADS was merged with information on firm-level inputs and outputs by year and firm identifier. The estimating sample was further reduced due to some firms missing information on sales, capital, and/or employment. Finally, the sample of firms was further restricted to firms with at least two matched workers. Table 2 contains the description of the merged sample of workers and its comparison to DADS for 1978-1996 four time intervals: 1978-1980, 1982-1985, 1986-1989, 1991-1993, and 1994-1996.

From Table 2, the sample with at least two matched workers per firm contains slightly less than half of all observations in DADS for 1978-1996, slightly better paid workers and more full-time workers than in the full sample. The total number of observations is larger in 1986-1989 because this time interval contains four years of data compared to all other time intervals with three years of data. After taking this into account, the number of worker-year observations has been increasing over time which reflects population growth and changes in workforce participation. The sample is reasonably well-representative by age and residence in Ile-de-France.

Table 2 describes the sample of firm-year observations with at least two matched workers per firm/year compared to the full EAE sample. The sample of firms contains about 30% of all firm-year observations in the full EAE dataset: 504,858 out of 1,516,123. The most important difference is that the firms in the sample are larger by all available measures: they are larger in terms of employment, sales, and capital, and there are about 22 percent of all firms in the sample with over 150 employees compared to the full EAE dataset which has only about 11% of such firms. There are about 75% of firms with 3 and more matched employees from DADS, and 35% of firms with 6 or more matched workers.

Table 3 presents the distribution of workers in the sample compared to DADS and the distribution of firms in the sample compared to EAE by industry. The industry classification in Table 3 is a NAP40 classification with 38 industries. The codes were changed after 1983, but a cross-walk between time intervals provided by INSEE was used to make NAP40 codes consistent between all years in the data. Compared to all workers in DADS, the sample contains fewer workers in construction and homebuilding, services to individuals, financial and non-profit services, and a larger fraction of workers in manufacturing, in particular in trucks and auto industries, electrical materials and electronics. There is a larger fraction of workers employed in firms providing services to firms in the sample compared to DADS. Compared to the full sample in EAE, the sample of firms used in estimating equation contains fewer firms in construction and home building and in financial services, and a larger fraction of firms in non-food wholesaling, food retailing, and transportation services. Table 4 describes the average proportions of workers by cohort and time period, sex, and occupation in the full worker history file DADS and in the estimating sample.

5 Results

Table 5 displays descriptive statistics for workers who are currently employed in a blue-collar unskilled occupation, and who will find a better occupation (skilled blue-collar or managerial and supervisory occupation) within 2 or 7 years. About 18 percent of unskilled workers will transition to a better occupation within two years, and 50% will transition to a better occupation within seven years.

Firms' quartile of the firm effect was determined from fixed firm effects in log wage equations with a quartic in experience, time dummies, fixed firm and person effects on the right hand side (see Abowd et al, 2002). Table 5 shows that unskilled workers employed in high wage firms have a somewhat higher probability to transition to a better firm: 17.55% of unskilled workers move to a better occupation within 2 years in the bottom quartile of firm effects; the corresponding proportion is 20.33% in the top quartile (for workers finding a better job within seven years the proportions are 48.16% and 52.73% respectively). The firm-level average proportions of workers with better occupations are as follows: 3.8% for better occupations within two years, and 11.2% for better occupations within seven years (Table 5).

The production functions and payroll equations with productivity and relative wages comparisons between unskilled workers who will and will not move to better occupations within 2 or 7 years are presented in Table 6. Workers who will be successful in the future are more productive than workers who will not be successful in the future: the productivity gap is 0.588 and 0.421 for 7 and 2 years respectively, and the Wald test rejects the hypothesis that this difference equals to zero. The gap in relative wages is .307 and .236 for 7 and 2 years, and this difference is also distinct from zero. The results indicate that unskilled workers who will find better occupations are more productive than workers who will not find better occupations within 2 and 7 years, and that the productivity gap exceeds the gap in relative wages by about 0.251 and 0.236 for specifications with 7 and 2 years respectively. This implies that workers who will succeed in the future are more productive per unit of wages paid than workers who will not succeed. This evidence supports the learning hypothesis and the hypothesis that more productive workers are sorted into better occupations over their careers.

The estimates in Table 6 do not indicate a divergence between relative productivity and wages between managerial and services occupations (even though there is a divergence for these occupations and the reference category - skilled blue-collar occupations). In the specification with 7 years, the relative productivity between managerial and services occupations is 2.682/1.976=1.36, and wages 1.646/1.129=1.46; and in specifications with 2 years: relative productivity - 2.736/1.840=1.49, and wages - 1.713/1.137=1.51. For females, relative wages appear to exceed relative productivity, compared to male workers. Wages tend to increase with age while productivity declines. The sum of the coefficients with logged employment and capital in the production function is close to one (but is slightly less than one); the production technology is close to exhibiting constant returns to scale.

Table 7 contains the average proportions at the firm level for workers whose maximum firm effects will be in the 1st - 4th quartile within three years, and Table 8 presents the production functions and payroll equations for firms in the top and bottom firm effect quartile. For firms in the top quartile, workers can either stay in the same quartile within the next three years or move down. The results in the top panel in Table 8 indicate that workers who stay in the fourth quartile are more productive than workers who move down, and that wages do not reflect the full magnitude of the productivity gap: the gap in productivity is 26% and the gap in wages is 6% between the fourth and third quartiles.

In Table 8, workers in the bottom quartile of firm effects can either stay in the same quartile or move up. Moving up to the fourth quartile in the future is associated with a large positive productivity differential (2.8/1.6=1.75), and a large but smaller wage differential (1.9/1.3=1.5). The results in Table 8 are consistent with the learning hypothesis for sorting of workers between firms: better workers are sorted into better firms, and before sorting actually happens, workers who are sorted into better firms are more productive per unit of wages than workers who do not move to better firms.

Table 9 presents wage growth analysis for male workers who are unskilled in 1978, and who will and will not find a better occupation within seven years. One of the concerns about our results is that the productivity gap which was found to be larger than the wage gap between workers successful and unsuccessful in the future may reflect wage compression between high and low skilled workers if higher skilled workers within unskilled workers are more likely to move to better occupations. It is true that within the unskilled category, workers with more education have a higher probability to move to better occupations (results available from the authors). But the unskilled category consists mainly of lower-educated workers, and any bias from wage compression should not be significant.

Table 9 shows that the gap in wages opens up with time for workers aged 25 or less and for workers aged 36-50 in 1978. Workers aged 25 or less who will succeed ("Good") are initially equally compensated as "Bad" workers; the gap opens up and grows to 15 percent within 18 years. The gap grows from 14% to 20% for workers aged 36-50. The results show that at least for younger workers (25 or less), there is little evidence that there are observed time-invariant differences between eventually successful and unsuccessful workers (these differences, if observed, would be reflected in relative wages); our results in Table 7 showed a productivity gap between successful and unsuccessful workers; the wage patterns in Table 9 appear to support the prediction of the learning hypothesis that wages will gradually move towards reflecting actual initially unobserved productivity.

6 Conclusion

We propose a new method for testing the learning hypothesis and the hypothesis that better workers are gradually sorted into better occupations based on the gradually revealed time-invariant productive ability using relative wages and productivity in firm-level production functions and log payroll equations. We compare the relative productivity between unskilled workers who will and will not move to a better occupation within 2 and 7 years, and for workers who will and will not move to a high-wage firm within three years. We use a large French employer-employee dataset for the years between 1978 and 1996 matched to information about workers in DADS. We find that there are productivity gaps for specifications analyzing future occupations and future firm quality, and that these productivity gaps exceed the corresponding gaps in relative wages. For occupations, unskilled workers who move to better occupations are about 20% more productive per unit of wages paid than unskilled workers who do not move to better occupations; the wage gap between these two groups of workers widens with time. A similar gap in relative productivity and relative wages was found for workers who move to the lowest firm quality quartile within three years while currently employed in a top firm quality quartile, and for workers currently employed in the bottom quartile who will move to the top quartile within three years. These observations are consistent with better workers sorted into better firms and occupations over time, and with the learning hypothesis: part of productive ability is not reflected in wages initially, but this ability plays a role in the determination of the future sector, with sectors defined by firms and occupations.

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Table 1. Descriptive Statistics for Workers

Time Interval	Variable	DADS		Sample	
		Mean	SD	Mean	SD
1978-1980	Age	34.539	12.227	36.088	12.203
	Logged compensation	4.007	0.837	4.189	0.676
	Ile-de-France	0.285	0.451	0.247	0.431
	Observations	2,322,435		919,394	
1982, 1984, 1985	Age	34.997	11.718	35.530	11.529
	Logged compensation	4.046	0.907	4.160	0.863
	Ile-de-France	0.281	0.449	0.287	0.452
	Observations	2,224,398		994,606	
1986-1989	Age	35.018	11.381	35.106	11.217
	Logged compensation	4.030	0.966	4.141	0.945
	Ile-de-France	0.280	0.449	0.299	0.458
	Observations	3,368,644		1,402,544	
1991-1993	Age	35.337	11.329	34.814	11.181
	Logged compensation	3.986	1.118	4.100	1.131
	Ile-de-France	0.272	0.445	0.286	0.452
	Observations	2,986,837		1,235,914	
1994-1996	Age	35.848	11.191	35.254	11.032
	Logged compensation	3.880	1.245	4.016	1.201
	Ile-de-France	0.257	0.437	0.272	0.445
	Observations	3,047,264		1,251,219	
Unique Firms		1,076,340		105,157	
Unique Workers		1,853,134		1,060,641	
Total Observations		13,949,578		5,803,677	

Notes: 1) Data source: DADS, 1978-1996
2) The sample contains all worker-year observations employed in firm/years (504,858 obs.)
used in constructing labor inputs in the estimated the production function
(or workers employed in firms in years with matched firm-level information from EAE,
firms with at least two matched workers to the firm, valid capital, employment, and sales)
3) Logged real annualized compensation (1980 FF) includes employer and employee taxes
4) Observation counts refer to worker-year observations

Table 2. Firm-Level Variables

Variable	Period	EAE			Sample		
		Mean	SD	Obs	Mean	SD	Obs
Logged Employment	1978-1981	3.965	0.946	173,344	4.487	1.077	75,580
	1982-1985	3.863	0.975	201,406	4.414	1.095	82,762
	1986-1989	3.772	1.023	293,200	4.356	1.044	116,916
	1990-1993	3.901	0.888	202,750	4.201	0.968	119,263
	1994-1996	3.933	0.916	187,519	4.250	0.987	110,337
Logged Real Capital	1978-1981	8.012	1.594	115,121	8.307	1.619	75,580
	1982-1985	7.695	1.891	132,482	8.020	1.933	82,762
	1986-1989	7.617	1.971	214,337	8.089	1.972	116,916
	1990-1993	7.643	1.826	279,710	8.196	1.794	119,263
	1994-1996	7.756	1.854	284,738	8.369	1.855	110,337
Logged Real Sales	1978-1981	9.581	1.254	173,730	10.222	1.259	75,580
	1982-1985	9.570	1.331	198,313	10.201	1.356	82,762
	1986-1989	9.659	1.306	267,804	10.225	1.355	116,916
	1990-1993	9.732	1.259	203,607	10.033	1.319	119,263
	1994-1996	9.785	1.304	188,315	10.101	1.365	110,337
Firm Size	<21	6.9			2.1		
(employees)	21-75	69.8			56.4		
	76-150	12.2			20.0		
	151-350	6.8			13.0		
	351+	4.4			8.5		
	Total	100.0			100.0		
Percent of workers matched per firm					0.082		
Distribution of the number of matched workers per firm	2				26.35		
	3				18.42		
	4				12.13		
	5				8.07		
	6+				35.03		
	Total				100.00		
The total number of firm/years				1,516,123			504,858

Notes: 1) The sample is a subset of firms in EAE with at least 2 matched workers and valid observations for employment, capital, and sales

2) Capital is measured as the book value of capital in the beginning of the period

3) Data source: EAE, France 1978-1996

Table 3. The Composition of Workers and Firms by Industry

Industry	EAE	Sample of Firms	DADS	Sample of Workers
Agriculture	0.50	0.04	0.02	0.01
Milk and Meat	1.79	2.37	0.95	1.84
Other Agriculture and Food	2.61	3.51	2.37	2.91
Mining	0.01	0.01	0.07	0.15
Oil and Natural Gas Production	0.09	0.09	0.20	0.44
Electricity, Natural Gas Distribution, Water	0.24	0.21	0.84	1.90
Steel, Ferrous Metals	0.28	0.40	0.68	1.29
Non-Ferrous Metals	0.17	0.23	0.29	0.62
Construction Materials	1.70	1.48	0.82	1.12
Glass	0.23	0.30	0.34	0.64
Chemical and Artificial Fibers	0.44	0.58	0.69	1.40
Pharmaceuticals	1.11	1.55	1.10	2.22
Metal Working and Foundry	5.18	4.89	2.50	3.23
Mechanical Construction	4.71	4.86	2.63	3.79
Electrical Materials and Electronics	2.58	3.00	3.04	5.71
Trucks and Automotive	0.89	1.20	2.19	4.52
Shipbuilding, Aerospace, Arms	0.27	0.36	0.76	1.53
Textile and Apparel	4.51	4.81	2.56	3.52
Leather and Shoes	0.88	0.93	0.51	0.74
Lumber and Furniture	3.46	3.09	1.69	1.85
Paper and Carton	0.89	1.15	0.63	1.15
Printing and Publishing	2.58	2.37	1.51	1.87
Rubber and Plastics	1.68	1.89	1.18	2.06
Construction and Home Building	13.65	10.55	8.17	6.95
Food Wholesaling	3.85	3.48	1.50	1.69
Non-Food Wholesaling	9.17	10.21	4.31	5.15
Food Retailing	3.73	4.85	3.73	5.68
Non-Food Retailing	4.18	3.82	4.72	3.85
Automotive Sales and Repairs	3.75	4.12	1.97	1.56
Restaurants and Tourism	2.18	2.70	4.61	2.36
Transportation Services	5.57	6.73	4.65	6.46
Postal/Telecommunications	0.05	0.04	0.64	0.57
Services to Firms	10.64	10.06	13.42	16.59
Services to Individuals	3.45	3.19	11.91	3.83
Real Estate and Leasing	0.92	0.90	0.61	0.71
Insurance	0.17	0.00	0.91	0.02
Financial Services	1.67	0.01	2.17	0.01
Non-Profit Services	0.24	0.05	9.11	0.06
Total	100.00	100.00	100.00	100.00

Notes: Data Source EAE and DADS, France 1978-1996
The sample of firms includes firms with at least two matched workers and valid observations for capital, sales, and employment. The sample of workers includes all workers observed working in the sample of firms. The proportions are out of the total number of firm-years and worker-years.

Table 4. The Composition of Firm-Level Employment by Occupation, Sex, and Age

		DADS: Mean Firm-Level Proportions					Sample of Firms				
Category	Labor Input	1978-1981	1982-1985	1986-1989	1990-1993	1994-1996	1978-1981	1982-1985	1986-1989	1990-1993	1994-1996
Cohort	1912-1920	4.16					4.17				
		[58-81]					[58-81]				
	1922-1928	9.92	6.51	2.86			11.78	6.95	2.33		
		[50-59]	[54-63]	[58-67]			[50-59]	[54-63]	[58-67]		
	1930-1932	6.60	5.82	4.37	1.88		7.46	6.54	4.56	1.65	
		[46-51]	[50-55]	[54-59]	[58-63]		[46-51]	[50-55]	[54-59]	[58-63]	
	1934-1936	6.62	6.14	5.26	3.92	2.21	7.25	6.59	5.54	4.04	2.08
		[42-47]	[46-51]	[50-55]	[54-59]	[58-62]	[42-47]	[46-51]	[50-55]	[54-59]	[58-62]
	1938-1940	6.54	6.18	5.63	4.83	3.99	6.95	6.62	5.84	5.06	4.15
		[38-43]	[42-47]	[46-51]	[50-55]	[54-58]	[38-43]	[42-47]	[46-51]	[50-55]	[54-58]
	1942-1944	7.71	7.33	6.82	6.18	5.65	8.01	7.78	7.15	6.39	5.91
		[34-39]	[38-43]	[42-47]	[46-51]	[50-54]	[34-39]	[38-43]	[42-47]	[46-51]	[50-54]
	1946-1948	10.93	10.09	9.51	8.86	8.36	11.24	10.94	10.13	9.19	8.71
		[30-35]	[34-39]	[38-43]	[42-47]	[46-50]	[30-35]	[34-39]	[38-43]	[42-47]	[46-50]
	1950-1952	12.91	11.21	10.38	9.78	9.41	12.66	11.82	11.02	10.23	9.90
		[26-31]	[30-35]	[34-39]	[38-43]	[42-46]	[26-31]	[30-35]	[34-39]	[38-43]	[42-46]
	1954-1956	14.59	12.09	10.78	9.85	9.50	13.67	12.51	11.40	10.40	10.03
		[22-27]	[26-31]	[30-35]	[34-39]	[38-42]	[22-27]	[26-31]	[30-35]	[34-39]	[38-42]
	1958-1960	15.61	14.76	12.89	11.22	10.69	13.77	14.59	13.24	11.75	11.26
		[18-23]	[22-27]	[26-31]	[30-35]	[34-38]	[18-23]	[22-27]	[26-31]	[30-35]	[34-38]
	1932-1968	4.42	18.87	27.98	27.48	25.31	3.03	14.84	26.40	27.97	26.66
		[16-19]	[16-23]	[18-27]	[22-31]	[26-34]	[16-19]	[16-23]	[18-27]	[22-31]	[26-34]
	1970-1980			3.34	15.26	24.01			2.26	12.90	20.78
				[16-19]	[16-23]	[16-26]			[16-19]	[16-23]	[16-26]
Sex	Proportion female	38.33	40.93	42.18	44.20	44.40	31.59	34.05	34.64	33.66	33.08
Occupation	Managerial and Professional	5.70	7.28	8.90	11.20	12.17	4.29	6.53	8.17	9.49	10.44
	Lower-Level Supervisory	12.74	14.68	15.95	16.35	16.46	14.16	15.95	16.73	16.91	17.19
	Service	29.10	31.03	31.46	31.62	31.44	18.64	23.07	24.24	20.57	19.88
	Skilled Laborers	30.63	27.03	25.36	22.95	21.69	36.69	30.81	29.19	31.17	31.09
	Unskilled Laborers	21.82	19.98	18.33	17.87	18.23	26.22	23.64	21.67	21.86	21.40

Notes: Source: DADS 1978-1996
The column proportions within categories defined by occupation and cohort do not always sum to 100%
Age ranges for the cohort-year cell are in square brackets.

Table 5. Descriptive Statistics for the Proportion of Workers in a Good Occupation within 2 and 7 Years
(for workers currently employed in unskilled occupations)

Unskilled, good occupation within 2 years (year<95)			Unskilled, good occupation within 7 years (year<90)		
Variable	Worker Count	Percent	Variable	Worker Count	Percent
Good	492,349	18.34	Good	987,217	50.54
Bad	1,715,319	63.90	Bad	766,671	39.25
Unknown	476,517	17.75	Unknown	199,462	10.21
Total	2,684,185	100	Total	1,953,350	100
Firm Effects Quartile:	Proportion "Good"		Firm Effects Quartile:	Proportion "Good"	
1st quartile	17.55		1st quartile	48.16	
2nd quartile	19.03		2nd quartile	50.87	
3rd quartile	19.24		3rd quartile	52.51	
4th quartile	20.33		4th quartile	52.73	
Firm Effects Quartile:	Proportion "Bad"		Firm Effects Quartile:	Proportion "Bad"	
1st quartile	61.44		1st quartile	40.54	
2nd quartile	62.95		2nd quartile	39.06	
3rd quartile	66.05		3rd quartile	38.97	
4th quartile	62.09		4th quartile	37.16	
Firm-level Proportion "Good"					
Firms	Mean	SE	Firms	Mean	SE
560,570	0.038	0.129	352,775	0.112	0.214

Source: DADS 1978-1994 for worker counts and means by firm effect quartile, EAE for other lines
Tabulations for unskilled workers
Good occupations include all skilled blue-collar, managerial, lower-level supervisory
and technical occupations (PCS codes starting with 2, 3, 4, and codes 62-65)
Bad occupations - blue collar unskilled, services, and apprentices (all other codes)
The firm effects are fixed effects in logged wage equations with a quartic in experience, time dummies,
and person and firm fixed effects.

Table 6. Nonlinear Least Squares Results for Future Occupations: Production Functions and Payroll Equations

Production Function			Log Payroll Equation	
Variable	Coefficient	SE	Coefficient	SE
Good occupations within 7 years, 1978-1989				
Constant	5.507	0.025	3.767	0.013
Log Capital	0.202	0.002		
Log Employment	0.744	0.002		
Proportion Good	1.181	0.039	0.979	0.015
Proportion Bad	0.623	0.030	0.672	0.013
Proportion Unknown	0.593	0.087	0.767	0.037
Managerial	2.682	0.059	1.646	0.016
Services Occupations	1.976	0.051	1.129	0.014
Female	0.623	0.012	0.790	0.007
Age 26-35	0.972	0.029	1.147	0.018
Age 36-50	0.882	0.024	1.207	0.016
Age 51+	0.566	0.027	1.116	0.020
Observations	52,161			
Adjusted R-squared	0.846		0.903	
(1) Good: productivity-wages	0.202	0.000		
(2) Bad: productivity-wages	-0.049	0.127		
(3) The difference between (1) and (2)	0.251	0.000		
(4) Productivity: Good-Bad	0.558	0.000		
(5) Wages: Good - Bad	0.307	0.000		
Good occupations within 2 years, 1978-1994				
Constant	5.458	0.022	3.724	0.011
Log Capital	0.199	0.002		
Log Employment	0.755	0.003		
Proportion Good	1.245	0.053	1.034	0.020
Proportion Bad	0.824	0.022	0.798	0.009
Proportion Unknown	0.593	0.050	0.796	0.022
Managerial	2.736	0.048	1.713	0.013
Services Occupations	1.840	0.039	1.137	0.011
Female	0.657	0.010	0.807	0.005
Age 26-35	0.984	0.024	1.148	0.014
Age 36-50	0.845	0.019	1.888	0.013
Age 51+	0.618	0.023	1.147	0.016
Observations	74,271			
Adjusted R-squared	0.850		0.909	
(1) Good: productivity-wages	0.211	0.000		
(2) Bad: productivity-wages	0.026	0.288		
(3) The difference between (1) and (2)	0.185	0.002		
(4) Productivity: Good-Bad	0.421	0.000		
(5) Wages: Good - Bad	0.236	0.000		

Source: EAE merged with DADS, 1978-1994, at least more than 10 workers matched per firm
(the proportion in unskilled occupations equals Good+Bad+Unknown)
Proportion Good - all skilled blue-collar, managerial, lower-level supervisory and technical occupations (PCS codes starting with 2, 3, 4, and codes 62-65)
Proportion Bad - blue collar unskilled, services, and apprentices (all other codes)
Dependent variable in the production function is logged sales
In lines (1)-(3), p-values for the Wald (null =0) tests are reported in the column "SE"
Method: nonlinear least squares, payroll equation and production function estimated as a system
Other controls: industry indicators (NAP40), year dummies
Reference group - skilled blue-collar, male, less than or equal to 25 years old

Table 7. Mean Firm-Level Proportions by Future Firm Effect

Variable	Proportion	Standard Deviation
Firm Effects Proportion 1	0.202	0.377
Firm Effects Proportion 2	0.164	0.343
Firm Effects Proportion 3	0.120	0.299
Firm Effects Proportion 4	0.204	0.377
Unknown	0.311	0.438

Source: EAE merged with DADS, 1978-1993, at more than 5 workers matched per firm
Firm Effects Proprotion1-4 - proportion of workers based on the maximum firm effect quartile within the next three years
Firm effects are fixed effects in log wage equations at individual level with a quartic in experience, time dummies, firm and worker fixed effects
These proportions are based on 3,837,886 firm-year observations

Table 8. Nonlinear Least Squares Results for Future Firm Effects: Production Functions and Payroll Equations

Production Function			Log Payroll Equation	
Variable	Coefficient	SE	Coefficient	SE
Current firm is in the top quartile of firm effects				
Constant	5.168	0.046	3.566	0.023
Log Capital	0.185	0.003		
Log Employment	0.754	0.005		
Firm Effects Proportion 1	1.072	0.087	0.927	0.032
Firm Effects Proportion 2	0.795	0.071	0.899	0.030
Firm Effects Proportion 3	0.945	0.066	0.986	0.027
Firm Effects Proportion 4	1.224	0.053	1.046	0.018
Skilled Blue-Collar	1.317	0.051	1.151	0.017
Managerial	3.561	0.113	1.928	0.023
Services Occupations	2.451	0.090	1.397	0.021
Female	0.897	0.022	0.894	0.009
Age 26-35	1.028	0.037	1.133	0.019
Age 36-50	0.983	0.033	1.216	0.018
Age 51+	0.732	0.037	1.104	0.021
Observations	28,501			
Adjusted R-squared	0.843		0.926	
Current firm is in the bottom quartile of firm effects				
Constant	4.913	0.055	3.376	0.034
Log Capital	0.260	0.003		
Log Employment	0.640	0.005		
Firm Effects Proportion 1	1.652	0.114	1.279	0.036
Firm Effects Proportion 2	1.447	0.128	1.186	0.045
Firm Effects Proportion 3	1.417	0.143	1.205	0.052
Firm Effects Proportion 4	2.797	0.217	1.858	0.064
Skilled Blue-Collar	1.088	0.043	1.167	0.021
Managerial	2.155	0.072	1.556	0.025
Services Occupations	1.919	0.068	1.341	0.022
Female	0.661	0.019	0.764	0.010
Age 26-35	1.002	0.044	1.027	0.023
Age 36-50	0.860	0.038	1.075	0.022
Age 51+	0.747	0.046	1.053	0.028
Observations		21,567		
Adjusted R-squared		0.780	0.810	

Source: EAE merged with DADS, 1978-1993, at more than 5 workers matched per firm
Firm Effects Proprotion1-4 - proportion of workers based on the maximum firm effect quartile within the next three years
Firm effects are fixed effects in log wage equations at individual level with a quartic in experience, time dummies, firm and worker fixed effects
Reference group: unskilled male worker less than or equal to 25 years old with and unknown maximum quartile of the firm effect within the next three years

Table 9. Comparing Mean Wages and Wage Growth for Workers Who Will and Will Not Find a Good Occupation Within 7 Years in 1978

Mean Wage, Male, <=25 years old, Unskilled in 1978						Mean Wage Male, 36-50, Unskilled in 1978				
Year	Bad	SE	Good	SE	Good/Bad	Bad	SE	Good	SE	Good/Bad
1978	52.34	67.87	48.26	50.12	0.922	64.13	27.97	72.83	30.91	1.136
1979	54.09	23.55	53.90	27.87	0.996	66.77	20.38	76.05	34.56	1.139
1980	57.62	24.39	58.31	42.05	1.012	67.86	22.63	77.49	39.27	1.142
1982	62.34	29.44	64.48	33.59	1.034	98.95	481.73	85.07	206.22	0.860
1984	65.81	32.08	69.56	28.25	1.057	70.01	21.93	82.33	34.62	1.176
1985	67.37	40.92	73.56	110.78	1.092	71.77	29.63	82.55	33.69	1.150
1986	68.62	25.39	79.15	152.79	1.153	74.13	37.56	84.31	39.50	1.137
1987	70.33	27.19	78.39	67.25	1.115	74.09	30.79	89.20	156.63	1.204
1988	72.12	39.79	79.24	40.29	1.099	74.00	25.25	88.61	60.20	1.197
1989	72.91	27.73	81.97	41.44	1.124	75.49	29.09	88.57	56.83	1.173
1991	75.91	29.10	86.16	57.44	1.135	75.90	31.81	90.41	56.88	1.191
1992	78.74	38.74	88.68	55.66	1.126	76.70	24.58	90.35	89.63	1.178
1993	80.31	51.55	93.69	158.31	1.167	75.28	27.90	100.28	333.91	1.332
1994	80.62	42.82	90.65	49.82	1.124	75.94	44.44	88.05	43.85	1.159
1995	81.02	46.70	92.81	63.95	1.146	72.95	46.49	88.09	73.80	1.208
1996	80.78	45.64	93.24	59.82	1.154	72.54	49.32	87.32	56.08	1.204
1996/1978	1.543		1.932			1.131		1.199		

Source: DADS, Bad - still in unskilled or services occupations within 7 years, Good - moves to a better occupation within 7 years
Year 1978, Unskilled workers in 1978
For males 36-50, the counts are: 1,079 bad, 2,377 good
For males <=25, the counts are: 2,621 bad, 9,727 good

Table A1. System GMM Production Functions

Dependent Variable: Log Sales		
Variable	Coefficient	SE
Equation 1: balanced 1978-1996, >600 workers in each year		
Lagged Log Real Sales	0.794	0.004
Log Capital	0.159	0.007
Lagged Log Capital	-0.072	0.006
Log Employment	0.783	0.016
Lagged Log Employment	-0.711	0.016
Observations (firms, years)	6,012 (334, 18)	
Hansen Test	chi2(257)=266.91, p-value=.322	
Test for 2nd order serial correlation	z=1.04, p-value=.301	
Instruments: lags 2-5 of log sales, employment, lags 2-7 of log capital		
Equation 2: balanced 1978-1996, >300 workers in each year		
Lagged Log Real Sales	0.764	0.012
Log Capital	0.197	0.024
Lagged Log Capital	-0.130	0.020
Log Employment	0.600	0.045
Lagged Log Employment	-0.432	0.045
Observations (firms, years)	13,914 (773, 18)	
Hansen Test	chi2(174)=269.38, p-value=0.000	
Test for 2nd order serial correlation	z=1.40, p-value=.162	
Instruments: lags 2-3 of log sales, employment, lags 2-5 of log capital		
Equation 3: balanced 1978-1996, >100 workers in each year		
Lagged Log Real Sales	0.703	0.013
Log Capital	0.219	0.026
Lagged Log Capital	-0.157	0.020
Log Employment	0.611	0.058
Lagged Log Employment	-0.420	0.057
Observations (firms, years)	40,608 (2,256, 18)	
Hansen Test	chi2(145)=410.85, p-value=0.000	
Test for 2nd order serial correlation	z=3.43, p-value=0.001	
Instruments: lags 2-3 of log sales, employment, lags 2-3 of log capital		
Equation 4: balanced 1978-1996, >50 workers in each year		
Lagged Log Real Sales	0.704	0.012
Log Capital	0.194	0.023
Lagged Log Capital	-0.131	0.017
Log Employment	0.568	0.057
Lagged Log Employment	-0.377	0.054
Observations (firms, years)	60,624 (3,368, 18)	
Hansen Test	chi2(145)=615.76, p-value=0.000	
Test for 2nd order serial correlation	z=5.17, p-value=0.000	
Instruments: lags 2-3 of log sales, employment, lags 2-3 of log capital		

Source: EAE, 1978-1996
Time dummies are included in all specifications
Two-step standard errors are reported (which may be unreliable)
software used: xtabond2 in STATA
(similar results were obtained using DPD98 GAUSS program)

Table A2. The Relationship Between Firm Effects in the Log Wage Equation and Firm Effects in Firm-Level Productivity Equations (Method: OLS)

Dependent Variable: Firm Effect from Log Wage Equation		
Variable	Coefficient	SE
Constant	-0.497	0.011
TFP	0.081	0.002
R-squared	0.04	
Firms	57,237	

Source: DADS and EAE, 1978-1996
i) Firm effects in the log wage equation are fixed effects in log wage equations at individual level with the quartic in experience, time dummies, firm and worker fixed effects (see Abowd, Creecy, and Kramarz, 2002, for the estimated equation and details)
ii) TFP is the fixed firm effect (in LSDV regressions, the average of the residual at the firm level) in log sales specifications with log capital, log employment, proportions of workers by the quartile of the time-invariant worker effect in the log wage equation, proportion in high-skilled occupations (PCS codes starting with 2, 3, and 4), proportion female, proportions by four age groups, and time dummies

Firm-level equation (LSDV):

Dependent Variable: Log Sales		
Variable	Coefficient	SE
Age 26-35	0.943	0.006
Age 36-50	0.898	0.007
Age 51+	0.850	0.009
2nd quartile of person effects	1.038	0.008
3rd quartile of person effects	1.077	0.008
4th quartile of person effects	1.104	0.008
Female	0.932	0.007
High-Skilled Occupations	1.048	0.006
Constant	0.010	0.001
Log Capital	0.069	0.001
Log Employment	0.638	0.002
Observations		

This equation includes time dummies