Abstract

The long literatures on the determinants of wage rates at the individual level and on the empirical relation between productivity and wage rates intersect when attention is focused on longitudinally linked employer-employee data. We estimate separate statistical components of wage rates associated with the observable individual characteristics, unobservable individual heterogeneity and unobservable employer heterogeneity. We define general human capital as the portable components of the full-time, full-year wage rate. Within each employer in the linked sample, we create employer-aggregates of the general human capital. We then estimate the relation between sales per employee, general human capital, and employer wage heterogeneity using micro data for the employing firms. The results reveal direct statistical links between the productivity outcome (sales/worker) and general human capital, controlling for firm-specific wage rate heterogeneity, which can be interpreted as specific human capital or as part of a firm-specific compensation strategy.

Human Capital and Worker Productivity: Direct Evidence from Linked Employer-Employee Data

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1 Introduction

The motivation for this paper comes from an interview with Zvi Griliches in the *Journal of Economic Perspectives [12]*. Regarding the data infrastructure used by economists, Griliches spoke about the limitations of available data and the general lack of interest by economists in collecting and assimilating new data. Given the dramatic growth in the use of computing in the economy in recent times, the amount of data that can be harvested has grown dramatically and has subsequently led to changes in the way economists think about data collection and analysis. With respect to labor economics, a long standing problem has been the difficulty in tracking individuals over time, particularly in industries that face a high degree of employee turnover. Using available data in France, Abowd, Kramarz and coauthors ([3], [6], [5], [7], [8]) created longitudinally linked data and showed how they can be used to study the distribution of characteristics of workers within employers over time. The purpose of this paper is to show that such data can be used to estimate production functions that depend on the distribution of human capital within a firm. The remainder of the paper is

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organized as follows. In section 2, we outline an augmented production function that we use for estimation of firm-level production functions. The augmentation is based on firm-specific measures of human capital instead of the traditional labor quantity measures. These measures come from a decomposition of individual wages into observable and unobservable components. Section 3 provides a brief description of the French data sets used to estimate the model. The results from using the new data sets are presented in Section 4. Finally, section 5 provides some concluding remarks.

2 Augmented Production Function

The presence of human capital in the production function is one of Zvi Griliches' enduring contributions to economics [9]. To further consider the implications of that insight, we start with the basic production function in which the total labor input, as measured by the average general human capital embodied in each worker, as well as the total physical capital input, both enter as factors of production. Restating the production function in per worker terms and taking logarithms yields:

$$\log(s/l)_{jt} = \delta \log(k/l)_{jt} + \gamma \overline{hc}_{jt} + \upsilon_{jt}. \tag{1}$$

where the dependent variable, $\log(s/l)_{jt}$, is log real sales per employee in firm j at date t, $\overline{hc}_{jt} = \sum_{i=1}^{N_{jt}} hc_{it}/N_{jt}$ is the average human capital per worker, and $N_{jt} = \sum_{\forall(i,s)} \mathbf{1}\left(\mathrm{J}\left(i,s\right) = j, s = t\right)$ is the number of DADS-sampled employees at the firm present in period t. The first component on the right hand side, $\delta \log(k/l)_{jt}$, is the effect of the capital stock per employee in firm j at date t, the second component $\gamma \overline{hc}_{jt}$ is a measure of the average human capital of workers i employed at firm j at date t, and the final component υ_{jt} is the statistical residual orthogonal to all other effects in the model. See Hellerstein, Neumark and Troske. [11] for a different representation of the production function that also embodies the personal characteristics of the employees.

Individual compensation is represented by the following equation

$$y_{it} - \mu_y = (x_{it} - \mu_x)\beta + \theta_i + \psi_{\mathrm{J}(i,t)} + \varepsilon_{it}. \tag{2}$$

where the dependent variable is the log annualized real wage rate (see: [6]). The function $\mathrm{J}(i,t)$ on the subscript of ψ is a firm specific indicator which varies over time, defined as being the employer of person i at date t. The first component on the right hand side, $(x_{it} - \mu_x)\beta$, is the effect of measured time-varying characteristics, the second component θ_i is the person effect, the third component $\psi_{\mathrm{J}(i,t)}$ is the firm effect, and the fourth component ε_{it} is the statistical residual, assumed to be orthogonal to all other effects in the model. Abowd, Kramarz and Margolis ([6], AKM below) provide a thorough discussion of this specification. In the current application, general human capital is modeled as the part of the wage rate that is portable over time and employers [2]. We do not model firm-specific human capital. It may included in the component ψ, but many other firm-specific compensation policies, such as incentive pay or efficiency wages could also be reflected in this component. The firm-specific component of compensation is included in our estimated production functions but interpret its effect without reference to any of these theories. In the estimation of equation 2, we include in x_{it} a quartic in actual labor force experience, unrestricted time effects, and an indicator for living in the Paris metropolitan area, all of which are fully interacted with an indicator for sex of the worker.

The effects of primary interest in this model are the following. At the individual level, we are interested in person effects, consisting of both observable and unobservable personal heterogeneity. At the business or firm level, we are interested in unobservable firm heterogeneity. Once we have estimated these primary effects, we can then compute firm-average person effects, which consist of both observable and unobservable heterogeneity, as well as the within-firm variance of person effects. This allows to conduct an analysis at the firm-level that accounts for the distribution of human capital within the firm and its level.

The person effect can be decomposed in the following manner

$$\theta_i = \alpha_i + u_i\eta, \tag{3}$$

which is an orthogonal decomposition into α, the unobserved part of the person effect, and $u_i\eta$, the effect due to non time-varying characteristics of the individual. Education is an important variable in u_i. The identification of η is discussed in [3] and [6] in detail. We summarize here. The estimated overall person effect θ is regressed on measurable personal characteristics that do not time vary, u_i. Hence, the unobserved component, α_i, is identified as the residual in this regression. In the empirical analysis in this paper we include in u_i indicators for sex of the worker fully interacted with indicators for eight levels of education. Alternative identification strategies, based on mixed-model estimation are discussed in Abowd and Kramarz [4] and identification strategies for fixed effects estimation of θ and ψ are discussed in Abowd, Creecy, and Kramarz [1].

The firm-average person effect is not the same as the firm effect, rather it captures the average individual heterogeneity in the firm:

$$\overline{\theta}_{jt} \equiv \overline{\alpha}_{jt} + \overline{u}_{jt}\eta = \frac{\sum_{\{(i,s)|\,\mathrm{J}(i,s)=j,s=t\}} \theta_i}{N_{jt}} \tag{4}$$

Substituting appropriately, the production function becomes

$$\log(s/l)_{jt} = \delta \log(k/l)_{jt} + \gamma_1 \overline{x\beta}_{jt} + \gamma_2 \overline{\theta}_{jt} + \gamma_3 \psi_j + \upsilon_{jt} \tag{5}$$

where the first component remains the capital-labor ratio, the second component represents the average measured characteristics of employees in firm j at time t aggregated according to their weights in the log wage equation, the third component is the average person effect in firm j at date t, the fourth component is the firm effect from the log wage equation, and the fifth component is the statistical residual. We have allowed for the possibility that the three components of human capital do not have the same effect on productivity. In the implementation below, we also include the variance of these components. The estimation of (5) is accomplished using ordinary least squares with and without fixed firm effects.

Although the basic theory stresses the stock of general human capital as the relevant input to production, it is easy to imagine production processes in which the distribution of the human capital input matters. Expressed differently, if only the stock of human capital matters, then a specification in which the labor input is expressed as the product of the average human capital per worker and the number of workers contains all the information required. We wish to consider specifications in which more moments of the distribution of general human capital affect output. We parameterize these extensions of the production function by introducing additional moments of the distribution into the list of inputs. If homogeneity of the labor input enhances productivity, then we would expect the second moment of the distribution of human capital to have a negative coefficient in the production function. On the other hand, if heterogeneity enhances productivity, then the variance of human capital should have a positive effect on productivity. These effects can be estimated using the augmented production function

$$\log(s/l)_{jt} = \delta \log(k/l)_{jt} + \gamma_1 \overline{x\beta}_{jt} + \gamma_2 \overline{\theta}_{jt} + \gamma_3 \psi_j + \gamma_4 var(x\beta)_{jt} + \gamma_5 var(\theta)_{jt} + \upsilon_{jt} \tag{6}$$

The estimation of (2) is discussed in AKM and Abowd, Creecy and Kramarz [1]. The basic statistical model is summarized here. Equation (2) can be represented in the following matrix notation

$$y = X\beta + D\theta + F\psi + \varepsilon \tag{7}$$

where all vectors and matrices have row dimensionality equal to the total number of observations. Data are sorted by person-ID and ordered chronologically for each person. D is the design matrix for the person effect, where the number of columns is equal to the number of unique person identifiers. F is the design matrix for the firm effect, where the number of columns is equal to the number of unique firm Identifiers times the number of effects per firm, one in this application.

The normal equations for the least squares estimation are given by the following:

$$\begin{bmatrix} X'X & X'D & X'F \\ D'X & D'D & D'F \\ F'X & F'D & F'F \end{bmatrix} \begin{bmatrix} \beta \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} X'y \\ D'y \\ F'y \end{bmatrix} \tag{8}$$

The full least squares solution to the basic estimation problem solves these normal equations for all identified effects. See Abowd, Creecy, and Kramarz [1] for a description of the conjugate gradient algorithm used to solve (8).

Once the basic log wage function has been estimated, we form the firm-level estimates of the average person effect, $\overline{\theta}_{jt}$, the average unobservable component of the person effect, $\overline{\alpha}_{jt}$, the average time-varying characteristic effect, $\overline{x\beta}_{jt}$, the average non-time-varying characteristic effect, $\overline{u}_{jt}\eta$, and the firm effect ψ_j at the firm level using all available DADS-sampled workers at the firm over 10-year subperiods (1976-1986 and 1987-1996) and we restrict our attention to firms that had an average employment of at least 100 workers over the subperiod. Obviously, we would prefer to use shorter subperiods (ideally annual) but we are confronted with the problem that the DADS is a sample of the workers, not a universe. If the DADS were a universe (as, for example, the American data used in Abowd, Lengermann and McKinney [2]), then, there would be no sampling variation in the firm-level estimates constructed from the estimated solution to 2 because the computed statistics could be interpreted as summarizing the complete distribution of employees. Because the DADS is a sample, we have limited our attention to those firms for which sampling variability in the estimated within-firm moments of the general human capital distribution is small. The average number of employees used to compute the within firm moments of the general human capital distribution is 78. Had we used annual data, this number would have been 19. In the ten-year subperiods, sampling error in the within firm measures is not a problem but it clearly would have been a problem for annual calculations.

3 Description of the Data

The data set was created from the following two sources. The Déclarations Annuelles des Données Sociales (DADS), the French Employer Payroll records, cover a $\frac{1}{25th}$ sample of the private and semi-public sectors, with individuals and employing firms identified. The DADS is conducted on an annual basis and the years from 1976-1996 are used here. A total of 13,759,302 observations, which cover more than 1.5 million individuals, are used.

The Enquête Annuelle d'Entreprises (EAE), is a survey covering basic firm-level variables such as employment, sales, and capital stock. Sampling in the EAE, both by size and industry, is stratified. The EAE data cover slightly fewer years, 1978-1996, than are covered by the DADS data used in this study. The base EAE data have 1,516,123 enterprise-level observations.

We then created a matched DADS-EAE data set. For each of the two DADS subperiods, 1976-1986 and 1987-1996, we averaged all of person-level data from the DADS-sampled individuals associated with jobs at particular EAE firms. The resulting data set contains 317,191 observations from the EAE (including small firms), and 1,363,444 observations from the DADS (aggregated over firms within subperiods and including small firms). Data analysis in this paper is restricted to those firms with average employment of at least 100 during the subperiod. As a result, there are 74,903 observations in the final analysis sample. These firms cover all industries except the public sector, and each observation covers a firm in a specific subperiod. There are a total of 37,319 observations for the EAE subperiod 1978-1986, and a total of 37,854 observations for the EAE subperiod 1987-1996.

The EAE is an annual survey. The extract we used contains annual corrected design weights that allow the estimation of economy-wide totals from the EAE firms. In the analyses that follow we report most results using an unweighted sample of EAE enterprises that have employees in the DADS sample. We restrict our attention to larger enterprises because such businesses generally have enough DADS-sampled employees to get reliable estimates of the components of human capital whose estimation is described in the previous section. To focus our attention on larger firms we estimate average employment two ways. First, in each of the two subperiods, we construct the average EAE employment for the years in which the firm appears in the EAE. Using this employment measure, we estimate a long-term sampling weight based on the average employment over the period and the EAE design sampling probabilities, which depend on firm-size and industry. This weight is used in some of our analyses below but it does not affect any of the conclusions, so we do not produce all of the weighted results. When we use this weight, the estimates are representative of the population of medium to large enterprises (100-499 employees and 500+ employees, respectively) in the French economy, excluding the public sector. In unweighted analyses large firms (500+ employees) are over-represented.

We created a second estimate of long-term employment based on the number of years that an enterprise appeared in each of the two subperiods, the total number of DADS employees appearing in the firm and the sampling rate for the DADS. This long-run employment average was used to select firms with estimated average employment of at least 100 during each subperiod. We prefer this estimate for sample selection of the firms because it ensures an adequate number of actual DADS-sampled employees to compute our independent variables with reliability. There is too much sampling error in the firm-average characteristics of the workers to do the analysis using annual observations from the EAE.

Our analysis sample, therefore, contains only EAE enterprises that have substantial numbers of linked DADS-sampled employees. It excludes all small enterprises but contains essentially the universe of EAE firms with employment of 100 or more. Our results should be interpreted as applicable for medium (100-499 employees) and large (500+ employees) private French firms.

4 Descriptive Statistics and Results

Table 1 provides summary statistics for all the analysis variables contained in the final sample of observations for the combined subperiods and for each subperiod separately. All variables are measured in logarithms and the specification of the wage equation used to estimate the components of compensation is also in logarithms. Therefore, all of the firm level variables (log real sales per employee, log real average annual compensation, log real capital per employee, and the firm averages from the wage equation) can be interpreted as logarithmic. The firm variances are squares of variables measured on a logarithmic scale. All of the variables from the log wage equation ("log real average annual compensation" through "ψ in the wage equation" in Table 1) have a mean of zero in the job-level analysis file from which equation 2 was estimated. The nonzero mean in Table 1 indicates the difference between a firm-average of these variables and a job-average. These means are also affected by the composition favoring large firms. This table is presented unweighted because most of the results we discuss below are unweighted. None of the substantive conclusions are affected by weighting the analysis to make it representative of (medium to large) French firms.

Table 2 provides results from the unweighted ordinary least squares analysis of equation (1), both for the entire sample and for the two subperiods. The first two columns provide results for the entire sample. The parameter estimates on all included variables are positive and significant. In the overall estimates, the two person-specific components of the wage rate, interpreted here as representing general human capital, have the same magnitude relationship to productivity. The firm-effect, interpreted here as specific human capital, bargaining, or incentive compensation policies, has a coefficient of slightly lower magnitude than either the measured time-varying characteristics or the person effect; however, it is more variable (see the standard deviation in Table 1). All of the wage decomposition coefficients (general human capital and ψ) are substantially larger than the the coefficient attributed to the capital-labor ratio, although the capital-labor ratio is substantially more variable in this sample of firms. Because of its greater variability, a one standard deviation increase in $\log(k/l)$ has twice the estimated impact of a one standard deviation change in each of the wage components.

The interpretation of the person-specific components of general human capital is straightforward and completely in the spirit of the Griliches-style production function. The portable part of an individual's wage rate does appear to represent compensation for productivity-enhancing characteristics of the employee–general human capital. The coefficient on the firm-specific component of log wages is more difficult to interpret cleanly. A general human capital interpretation of this component implies that the productivity effect be portable in the labor market, but the method used to identify ψ in the log wage equation implies that it is not portable. Thus, we must use either a specific human capital interpretation or an optimal compensation contract (bargaining, incentive, or agency) interpretation. The specific human capital interpretation works as follows. The employee receives a share of the productivity enhancement due to the specific human capital. The greater is ψ, the greater is the specific human capital and, therefore, the large the associated increase in productivity. The optimal incentive contract interpretation requires more modeling. Basically, the argument is similar to an efficiency wage model. A higher ψ induces greater effort, which results in greater productivity. In either the specific human capital or the optimal compensation contract case, the positive association of the ψ component of log wages with productivity implies that the firm is getting something valuable in exchange for the quasi-rent associated with ψ. See Abowd and Kramarz [3] for more details of these theories.

The third and fourth columns of Table 2 provide results for the earlier subsample, while the fifth and six columns provide results for the later subsample. The parameter estimates obtained for both subsamples are similar to those found for the overall sample, although there is enough data to reject a simple test of homogeneity of the coefficients. In contrast to the earlier subsample, results for the later period indicate a greater importance of the measured personal characteristics effect and a relatively smaller importance of the firm effect. One possible explanation for this in the context of French labour markets is the decline of rents associated with highly-regulated product and labor markets.

Table 3 provides results from an ordinary least squares regression weighted with the EAE sampling weights to be representative of French enterprises. As explained in section 3 the analysis sample includes only medium and large firms. The weights make the estimated coefficients representative of the population of medium and large French firms. The results are provided for the entire sample as well as for the two subperiods. Results for the entire sample are in the first and second columns. The parameter estimates are very similar to those obtained from the unweighted sample. Only the estimate for $\overline{x\beta}$, the effect of firm-average measured characteristics, is slightly reduced in the weighted estimates. Because of the overall similarity between Tables 2 and 3, we do not present weighted versions of the other analyses.

Table 4 replicates the results from the unweighted OLS analysis found in Table 2 except that the firm-average person effect $\bar{\theta}$ is broken down into its observable, $\overline{x\beta}$, and unobservable, $\bar{\alpha}$, components. Once again results are provided for the entire sample as well as for the two subsamples. The results are similar to Table 2. We note that although the coefficient on $\bar{\alpha}$, the the unobservable part of θ, is four times smaller than the coefficient on $\overline{u\eta}$, the observable component of θ, their standard deviations go in exactly the opposite direction so that a one standard deviation change in either component is about comparable.

Table 5 provides results from an unweighted OLS regression that includes the same effects as in Table 2 as well as the variances of measured characteristics, observed and unobserved person effects, and the residual from the wage equation. Variances are computed within firm for each subperiod. All the obtained parameter estimates are positive and significant with the exception of that for the variance of $u\eta$, the observed person effect, which is negative and significant. Holding the average level of a characteristic constant, the variance coefficient indicates whether homogeneity or heterogeneity of the characteristic is productivity enhancing. Taking account of the estimated coefficients and the standard deviations of all variables and, in particular those of the within-firm variances, heterogeneity of the residual variance is quantitatively the most important of these effects. Nevertheless, all of the firm variance effects are less important than the associated firm average effects for the components of the log wage rate. Firm average measured characteristics (time varying: $\overline{x\beta}$, and time invariant: $\overline{u\eta}$) are clearly the most important of the general human capital variables in this specification. It interesting to note that increasing the variance of time-invariant factors (in these data: sex and education) holding constant the mean value is productivity reducing. This suggests that homogeneous work forces of a constant observable quality are more productive than heterogeneous work forces of the same average quality. The opposite result holds for unobservable and time-varying components of general human capital. Another possible interpretation of these results is mis-specification of the production function. For example, a CES production function would not be linear in the logarithms. Table 8, discussed below, provides some basic evidence that the log linear functional form is reasonable; however, we cannot definitively rule out the mis-specification interpretation of Table 5.

Table 6 provides estimation results from a model with fixed firm effects. The specification in columns one and two of Table 6 (estimates of the overall effect of the firm-average person effect) is comparable to the specification in columns one and two of Tables 2. The specification in columns three and four of Table 6 (decomposition of $\bar{\theta}$ into its observable and unobservable components) is comparable to the specification in columns one and two of Table 4. All parameter estimates are positive and significant. The estimated effect of the measured characteristics and the natural log of capital per employee are similar across the two specifications. When $\bar{\theta}$ is broken down into observable and unobservable components, as shown in the third column, the observable component is of much greater importance, even taking account of its standard deviation.

Table 7 provides results comparable to Table 5 with fixed firm effects. Table 7 also provides results comparable to Table 6 (columns three and four) controlling for the variances of the human capital components. Compared to Table 5 results, most coefficients are similar except for the effect of unobservable person effects, which are less important–indicating that the Table 5 results may be upward biased. The effect of the variance of α is negative in

Table 7, indicating that heterogeneity is not productivity-enhancing once firm heterogeneity is controlled.

Finally, Table 8 provides a final unweighted specification with fixed firm effects. Additional regressors added in comparison with Table 6 (columns one and two) are interactions of log real capital per employee with average $x\beta$ and θ. None of these interactions is significant. Thus, Table 8 shows that the augmented production function shown in equation 1 is properly specified as log-linear.

5 Conclusion

The traditional production function approach in the literature, which aggregates labor components by observables like age, sex and education, does not easily permit the analyst to study the effects of unobservable heterogeneity in the work force. Such unobservable heterogeneity is known to be a feature of wage outcomes and to be associated with both the individual and the employer. We identify this heterogeneity by using a full wage decomposition of the sources of general human, which includes measures of experience, education, and unobserved abilities. After computing this wage decomposition for a sample of workers in the French economy, we relate the components to measured labor productivity, using firm-level augmented production functions. Measured and unmeasured individual heterogeneity matter. Increasing any of the components of general human capital, is associated with increases in labor productivity. But so is an increase in the firm-specific component of log wages, which does not have an unambiguous interpretation in terms of specific human capital or optimal compensation contracts. Increasing the variability of time-varying measured components within a firm is also associated with increased labor productivity. However, increased variability for most unmeasured components is associated with decreased labor productivity, at least once we control for firm-specific heterogeneity in the production function.

So it seems, not surprisingly, that "... if you go down to the micro level [in enterprises] you are going to control for heterogeneity. But in fact the heterogeneity just changes. ... There are very few enterprises or anything which are single dimensional." (Griliches, p. 185, [12])

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Table 1 - Descriptive Statistics						
	All Periods		1976-1986		1987-1996	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Log real sales per employee	5.5181	0.8248	5.4456	0.7677	5.5900	0.8719
Log real compensation	0.0860	0.5160	0.0754	0.4520	0.0964	0.5723
Firm average $x\beta$ from wage equation	0.0717	0.2385	0.0743	0.2126	0.0691	0.2616
Firm average θ from wage equation	-0.0114	0.2999	-0.0340	0.3182	0.0111	0.2787
Firm average α (part of θ due to unobservables)	0.0027	0.2749	-0.0068	0.2921	0.0121	0.2562
Firm average $u\eta$ (part of θ due to observables)	-0.0141	0.0836	-0.0272	0.0821	-0.0010	0.0830
Ψ from wage equation	0.0290	0.3710	0.0381	0.3476	0.0199	0.3926
Firm variance of $x\beta$ from wage equation	0.0834	0.0601	0.0811	0.0563	0.0857	0.0636
Firm variance of θ from wage equation	0.1590	0.1885	0.1666	0.1959	0.1514	0.1806
Firm variance of α (unobservables)	0.1456	0.1811	0.1499	0.1855	0.1413	0.1766
Firm variance of $u\eta$ (observables)	0.0149	0.0215	0.0152	0.0219	0.0146	0.0210
Firm variance of residual from wage equation	0.2636	0.4042	0.2389	0.3588	0.2882	0.4433
Log real capital per employee	3.4895	1.6171	3.3963	1.5543	3.5820	1.6721

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903. Two subperiods (i.e., at most two observations per firm) with 37,319 for years 1976-1986 and 37,584 for years 1987-1996. The mean (resp., standard deviation) is the unweighted mean (resp., standard deviation) of the firm-level observations. Variances are computed within firm and period.

Table 2 - Results: Unweighted Ordinary Least Squares Analysis of Log Real Sales per Employee						
	All Periods		1976-1986		1987-1996	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept	4.7921	0.0061	4.7951	0.0083	4.8085	0.0089
Firm average $x\beta$ from wage equation	0.5678	0.0113	0.4082	0.0167	0.6889	0.0153
Firm average θ from wage equation	0.5893	0.0091	0.6065	0.0120	0.5640	0.0141
Ψ from wage equation	0.3415	0.0075	0.4227	0.0111	0.2768	0.0102
Log real capital per employee	0.1955	0.0016	0.1839	0.0023	0.2016	0.0023
Adjusted R-squared	0.2916		0.2604		0.3157	
Root mean squared error	0.6942		0.6603		0.7213	
F-test for constant parameters	116.9233					

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903. Two subperiods (i.e., at most two observations per firm) with 37,319 for years 1976-1986 and 37,584 for years 1987-1996. The F-test has 5 and 74,893 degrees of freedom.

Table 3 - Results: Weighted Ordinary Least Squares Analysis of Log Real Sales per Employee

	All Periods		1976-1986		1987-1996	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept	4.8366	0.0066	4.8264	0.0089	4.8594	0.0098
Firm average $x\beta$ from wage equation	0.4175	0.0116	0.2487	0.0174	0.5463	0.0156
Firm average θ from wage equation	0.5596	0.0092	0.5848	0.0122	0.5310	0.0141
Ψ from wage equation	0.3472	0.0074	0.4308	0.0111	0.2834	0.0101
Log real capital per employee	0.1915	0.0018	0.1844	0.0024	0.1950	0.0026
Adjusted R-squared	0.2316		0.2188		0.2440	
Root mean squared error	0.1388		0.1314		0.1450	
F-test for constant parameters	91.9135					

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903. Two subperiods (i.e. at most two observations per firm) with 37,319 for years 1976-1986 and 37,584 for years 1987-1996. Weighted by the ex post survey sampling weight, corrected for the match with DADS, in the Enquete Annuelle d'Entreprises. The F-test has 5 and 74,893 degrees of freedom.

Table 4 - Results: Unweighted Ordinary Least Squares with θ Decomposed of Log Real Sales per Employee						
	All Periods		1976-1986		1987-1996	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept	4.8018	0.0061	4.8113	0.0083	4.8066	0.0089
Firm average $x\beta$ from wage equation	0.6209	0.0113	0.4582	0.0168	0.7348	0.0153
Firm average α (part of θ due to unobservables)	0.4006	0.0105	0.4349	0.0140	0.3871	0.0159
Firm average $u\eta$ (part of θ due to observables)	1.6527	0.0311	1.5665	0.0431	1.5888	0.0457
Ψ from wage equation	0.2550	0.0078	0.3315	0.0117	0.2039	0.0106
Log real capital per employee	0.1967	0.0016	0.1865	0.0023	0.2025	0.0023
Adjusted R-squared	0.3035		0.2709		0.3256	
Root mean squared error	0.6884		0.6556		0.7160	
F-test for constant parameters	393.7589					

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903. Two subperiods (i.e. at most two observations per firm) with 37,319 for years 1976-1986 and 37,584 for years 1987-1996. The F-test has 5 and 74,893 degrees of freedom.

Table 5 - Results: Unweighted Ordinary Least Squares Analysis of Log Real Sales per Employee

	Parameter Estimate	Standard Error
Intercept	4.7233	0.0079
Firm average $x\beta$ from wage equation	0.7574	0.0132
Firm average α (part of θ due to unobservables)	0.4217	0.0105
Firm average $u\eta$ (part of θ due to observables)	1.5754	0.0357
Ψ from wage equation	0.3008	0.0081
Firm variance of $x\beta$ from wage equation	0.2400	0.0469
Firm variance of α (unobservables)	0.1846	0.0153
Firm variance of $u\eta$ (observables)	-0.6864	0.1336
Firm variance of residual from wage equation	0.1160	0.0075
Log real capital per employee	0.1965	0.0016
Adjusted R-squared	0.3088	

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903.

Table 6 - Results: Unweighted Least Squares Analysis with Fixed Firm Effects of Log Real Sales per Employee

	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Firm average $x\beta$ from wage equation	0.3874	0.0260	0.3845	0.0258
Firm average θ from wage equation	0.1937	0.0229		
Firm average α (part of θ due to unobservables)			0.0795	0.0246
Firm average $u\eta$ (part of θ due to observables)			1.0884	0.0766
Log real capital per employee	0.1317	0.0035	0.1271	0.0035
Adjusted R-squared (includes firm effects)	0.9744		0.9747	
Firm variance of $x\beta$ from wage equation				

Table 7 - Results: Unweighted Least Squares Analysis with Fixed Firm Effects of Log Real Sales per Employee

	Parameter Estimate	Standard Error
Firm average $x\beta$ from wage equation	0.4192	0.0279
Firm average α (part of θ due to unobservables)	0.0571	0.0249
Firm average $u\eta$ (part of θ due to observables)	1.2187	0.0836
Firm variance of $x\beta$ from wage equation	0.3233	0.0743
Firm variance of α (unobservables)	-0.0999	0.0271
Firm variance of $u\eta$ (observables)	-0.9590	0.2347
Log real capital per employee	0.1250	0.0035
Adjusted R-squared (includes firm effects)	0.9744	

Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903.

Table 8 - Results: Unweighted Least Squares Analysis with Fixed Firm Effects of Log Real Sales per Employee		
	Parameter Estimate	Standard Error
Firm average $x\beta$ from wage equation	0.4505	0.0432
Firm average θ from wage equation	0.1548	0.0408
Log real capital per employee	0.1326	0.0036
Log real capital per employee x (firm average $x\beta$)	-0.0187	0.0102
Log real capital per employee x (firm average θ)	0.0111	0.0091
Adjusted R-squared (includes firm effects)	0.9744	
Source: DADS (1976-1996), EAE (various years between 1978 and 1996). Number of observations: 74,903.		