Wages, Productivity, and Worker Characteristics: A French Perspective*

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Abstract

We investigate the relationship between wages, productivity, and worker characteristics using a new exhaustive matched employer–employee longitudinal dataset for France. Expanding on the methodology originally proposed by Hellerstein, Neumark and Troske (1999), we relax their hypotheses and provide a new method using cost for the employer. Interestingly, results for France stand in stark contrast with those found in the US: in manufacturing, we find no or little wage discrimination against women who appear to hold less productive jobs, while older workers are relatively overpaid, or equivalently, younger workers are underpaid. Robustness of these results across time periods, industries and identifying assumptions, are confirmed. (J24, J31, J7)
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1 Introduction

The paradigm of wage and marginal productivity equality is the most common way of understanding wage differences across occupations. Some of these differences are key issues in labor economics: gender wage gaps can be interpreted as wage discrimination, while differences according to seniority, experience or education could be caused by underlying differences in human capital. Even though there is a vast literature discussing the various situations in which such an equality may not hold there have so far been few empirical attempts to test whether differences in wages are due to differences in marginal productivity.[1]

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[1]Medoff and Abraham (1980) is one of the first attempts to link wages and measures of productivity given by managers' performance ratings.

A new approach was proposed by Hellerstein, Neumark, and Troske (1999) (hereafter HNT). As wages are readily observable the main difficulty in the comparison of wages and productivity across groups of workers lies in the measurement of productivity differences, and more drastically on the availability of information on the heterogeneity of the workforce in each firm. HNT use a matched employer–employee dataset to recover firm-level information on the workforce. Assuming perfect substitution among the different types of workers, they estimate a production function using shares in days worked by each type of worker as additional regressors. They thus derive relative marginal productivities between worker categories. Their main findings are that (1) wage rates of senior workers reflect higher productivity, and (2) lower wage rates for women do not completely reflect lower productivity.

Our paper starts off from HNT and expands on their methodology taking advantage of specific information in our data. We use a new unique dataset matching firm level data with employee characteristics in France. This data differs in three ways from the one used by HNT. First, it is an exhaustive file of all workers of most of the firms in the private sector. While the employee file provides less detailed information (such as education) it measures precisely instead of only estimating some sort of heterogeneity of the workforce. Second, and most importantly, this dataset provides us with the cost to the employer of each worker. Our alternative method of estimating the differences between marginal productivity and wages consists in using shares in total labor costs instead of days (our data also provides shares in hours worked, making little difference in the estimation). Last, this data is available over the period 1994-1997. We may therefore implement panel data estimation and try to remove some of the bias associated to OLS estimation of production function (Griliches and Mairesse, 1997).

Overall, our method leads to the conclusion that in France there is no or little gender wage discrimination. This is confirmed using the two-equation approach of HNT: women are less paid than men but appear also to hold less productive jobs. On the contrary, we observe a wage productivity gap increasing with age. The age profile of wages exhibits the usual increasing concave pattern while the age profile of productivity stops rising (and even decreases) after some experience level.[2] It is unclear whether old workers are overpaid or young underpaid or even if it is a mixture of both. However it is clear that for workers over 35, the increase in wages cannot be interpreted as reflecting human capital accumulation. This finding is consistent with the implementation in France of an early retirement policy that helped to remove older workers from the labor market. It may however point to one important policy issue in France. France has a pay-as-you-go pension system. Its funding is under strain due to, among other factors, the slowdown in the growth of the labor force and the increase in life expectancy. One of the possible solutions consists in raising the mandatory retirement age (Charpin et al., 2000), though it is the subject of a wide debate. The implementation of this policy may be problematic due to the poor performance of older workers in the labor market, already apparent in the popularity of early retirement plans and the decrease in the activity rates of older workers, and confirmed by our findings.

One other important result of this paper is that measured effects are heteroge-

[2] Hægeland and Klette (1999) report similar findings for Norway.

neous among worker groups. This is especially true for women. The low estimated productivity of jobs held by women is essentially due to unskilled women workers who are significantly overpaid, potentially because of the minimum wage. On the contrary jobs of skilled women are slightly more productive than those held by men.

The paper proceeds as follows: in section II we present the methodology used; section III describes the data and section IV our results. We conclude in section V.

2 Methodology

The traditional approach of estimating wage equations does not tell anything about workers productivity, and so far has not allowed labor economists to know whether wage differentials among different types of workers reflect marginal productivity differentials or not. Hellerstein et al. (1999) have thus adopted a new approach, based on the joint estimation of a wage equation and a production function that leads to direct comparisons of wage and productivity differentials. We briefly review the main ideas of their methodology (see HNT for more details), and examine what the availability of labor costs can bring in this framework.

2.1 Production function

For each plant, consider a Cobb-Douglas production function (a translogarithmic function does not change the results):

$$\log Q_i = \alpha \log L_i^* + \beta \log K_i + u_i$$

where Q_i is value-added output, L_i^* is a measure of human inputs, K_i is the capital stock and u_i is a scale factor and a disturbance parameter.

Let L_{ik} be the amount of hours worked by workers of type k in plant i and λ_{ik} their hourly productivity. Assuming perfect substitutability between worker types, the total amount of work L_i^* in plant i can be written as:

$$L_i^* = \sum_0^K \lambda_{ik} L_{ik} = \lambda_{i0} L_i + \sum_1^K (\lambda_{ik} - \lambda_{i0}) L_{ik}$$

where L_i is the sum of hours worked and λ_{i0} the productivity of the category of workers taken as reference.[3]

The previous equation can be written as

$$\log L_i^* = \log \lambda_{i0} + \log L_i + \log\left(1 + \sum_1^K (\frac{\lambda_{ik}}{\lambda_{i0}} - 1) P_{ik}\right) \quad (1)$$

where P_{ik} is the ratio of hours worked in plant i by worker k on the total amount of hours worked in plant i. The relative marginal products are assumed to be constant

[3] This specification is only one of many possible; it hinges on the assumption of perfect substitutability between different worker types. Modeling labor inputs with only a few characteristics is certainly reductive and simplistic, but little is known on interactions between different types of capital and different categories of workers and how they can be modeled, especially when the number of categories is important.

across firms,[4] thus the production function can be written:

$$\log Q_i = \alpha \log L_i + \alpha \log\left(1 + \sum_{1}^{K}(\frac{\lambda_k}{\lambda_0} - 1)P_{ik}\right) + \beta \log K_i + \varepsilon_i \tag{2}$$

Cross section data only are available to HNT and their model is estimated by (non linear) OLS, corresponding to the identifying assumption :

$$E(\varepsilon_i | K_i, L_i, P_{ik}, X_i) = E(\varepsilon_i | X_i), \tag{3}$$

where X_i includes all variables used as controls.

We will also mainly focus on this type of identifying assumption and our main results will be obtained by between estimation.

However the estimation of production functions through simple OLS may involve biases as explained at length in Griliches and Mairesse (1997) (GM). One main source of bias is the existence of simultaneity between unobserved terms and the quantities of inputs — part of the unobserved term is transmitted to inputs in the GM terminology. Shocks may be either permanent or transitory. Permanent shocks can be eliminated by performing estimations in the within dimension or in differences. One way to consistently estimate the parameters when transitory shocks are also present is the use of internal instrumental variables. Past values of explanatory variables can be used as instruments for the model in first differences (Arellano and Bond, 1991) but past values of the first differences of explanatory variables can also be used as instrument for the model in levels, although under more restrictive conditions (Arellano and Bover, 1995). These methods however may perform poorly as internal instrument may be very poor. Olley and Pakes (1996) illustrate another way to deal with the endogeneity issue. They make a distinction between flexible and quasi fixed inputs and suggest the use of control variables which are functions of firms' investment in order to free the error term from its correlation with explanatory variables.

All these methods dealing with the endogeneity issue require panel data. We will thus also estimate the model in the within and long differences dimension as well as through GMM methods, (levels instrumented by lagged first differences, as Arellano and Bover, 1995).

2.2 Earnings equation

Whereas standard methods consist of regressing individual wages on workers characteristics, HNT suggest regressing total wages at plant level on the composition of the workforce in each plant. This is valid if the conditions outlined below hold.

The equation at plant level can be written as:

$$\overline{w}_i = \sum_{k=0}^{K} w_{ik} \frac{L_{ik}}{L_i} = w_{i0} L_i \left(1 + \sum_{k=1}^{K}(\frac{w_{ik}}{w_{i0}} - 1)P_{ik}\right) \tag{4}$$

[4]This leads to a simple decomposition of the form $\lambda_{ik} = \lambda_k \exp u_i^P$, where u_i^P is a term accounting for possible differences in workers' productivity levels across firms.

where $\overline{w}_i$ is the average wage in plant i, w_{ik} the wage of workers of type k in plant i, w_{i0} the wage of workers in the reference category in plant i.[5] Taking logarithms, we then have

$$\log(\overline{w}_i) = \log\left(1 + \sum_1^K (\frac{w_k}{w_0} - 1)P_{ik}\right) + u_i^W. \quad (5)$$

The identifying hypothesis is

$$E(u_i^W | X_i, P_{ik}) = E(u_i^W | X_i)$$

Joint estimation of equations (2) and (5) is at the heart of the methodology in HNT. It gives us the shape of both relative marginal products and relative wages across workers' categories, which can be interesting on their own. Nevertheless the main interest lies in its ability to test the equality of relative wages and relative marginal productivities, using standard statistical tests.

2.3 Cost equations—definition of markdown

The data set we use provides us cost variables which were not available to HNT. These variables allow us to proceed differently. We show here that we can directly estimate the differences in relative marginal products and relative wages using a single equation similar to (2) where the share of hours worked is replaced by the share in total cost.

As in HNT we define effective work in each plant by $L_i^* = \sum_0^K \lambda_{ik} L_{ik}$ but decompose it in the following way:

$$L_i^* = \sum_0^K \frac{\lambda_{ik}}{w_{ik}} w_{ik} L_{ik} \quad (6)$$

Let $\delta_{ik} = \lambda_{ik}/w_{ik}$ be the *markdown* (the bigger δ_{ik} is, the more important is the gap between productivity and wage of workers k in plant i; a higher markdown can be interpreted as a higher relative exploitation). Choosing the same reference category, we get:

$$\begin{aligned} L_i^* &= \delta_{i0} w_{i0} L_{i0} + \sum_1^K \delta_{ik} w_{ik} L_{ik} \\ &= \delta_{i0}\, \overline{w}_i L_i \left(1 + \sum_1^K (\frac{\delta_{ik}}{\delta_{i0}} - 1)\frac{w_{ik} L_{ik}}{\overline{w}_i L_i}\right) \end{aligned}$$

Expanding as before and taking logarithms, with $P_{ik}^w = (w_{ik} L_{ik})/(\overline{w}_i L_i)$ the share of total wages received by employees of type k in firm i, we get:

$$\log L_i^* = \log L_i + \log \overline{w}_i + \log \delta_{i0} + \log\left(1 + \sum_1^K (\frac{\delta_{ik}}{\delta_{i0}} - 1)P_{ik}^w\right)$$

[5] As for the production function, it is assumed that relative wages are constant across firms, so that $w_{ik} = w_k \exp u_i^W$.

We assume that relative markdown is equal across firms, so that it can be written $\delta_{ik} = \delta_k \exp u_i^\delta$. This hypothesis is less restrictive than the previous ones in the joint estimation of productivity and wages, as it does not require neither productivity nor wages to be equal across firms, but only their ratios (i.e. constancy of the markdown across firms).[6]

The production function is

$$\log Q_i = \beta logK_i + \alpha \log L_i + \alpha \log \overline{w}_i + \alpha \log \left(1 + \sum_1^K (\frac{\delta_k}{\delta_0} - 1) P_{ik}^w\right) + \varepsilon_i \qquad (7)$$

with $\varepsilon_i = u_i + \alpha u_i^\delta$.

Equation (7) bears an additional term from standard production function estimates, as average wage—potentially endogenous—is included as a regressor, and as the disturbance term contains u_i^δ. Clearly, a high value for u_i^δ (i.e. a larger markdown in the firm) leads to a small value in average labour costs. To tackle this endogeneity bias, several identifying assumptions are possible; we may want to examine three of particular interest:

$$E(\varepsilon_i | K_i, \overline{w}_i L_i, P_{ik}^w, X_i) = E(\varepsilon_i | X_i) \qquad (8a)$$

$$E(\varepsilon_i | K_i, L_i, P_{ik}^w, X_i) = E(\varepsilon_i | X_i) \qquad (8b)$$

$$E(\varepsilon_i | K_i, L_i, \overline{w}_i, P_{ik}^w, X_i) = E(\varepsilon_i | \overline{w}_i, X_i). \qquad (8c)$$

Assumption (8a) is quite natural, however it ignores the endogeneity problem. Assumption (8b) deals with this endogeneity by instrumenting the average wage bill with employment in the firm; the last assumption (8c) introduces the average wage $\overline{w}_i$ as a control variable. It relaxes the restriction in assumption (8a) that the coefficient of $\overline{w}_i$ and L_i should be equal. Estimating with these different assumptions leads to similar results:[7] between (8a) and (8b) the differences are negligible, while (8c) modifies some coefficients, principally those associated with skill levels.[8] We will thus concentrate on restriction (8a).

The cost variables could allow us to substitute for the wage equation (5) the direct estimate of the differences in relative mean earnings between worker types. However, due to the important dispersion in relative wages w_{ik}/w_{i0} at the firm level, it is uncertain whether this procedure leads to better estimates.

2.4 Simple vs. Extended model

By crossing the different types of variables (gender, qualification, age), we can classify the workforce in a great number of categories: young unskilled males, young unskilled females, and so on. In theory it could be possible to estimate relative productivities, wages and markdown for each category, though computational problems

[6]Indeed, this is compatible with the representation of productivity and earnings in which differences in product and wages are written $\psi_{ik} \exp u_i^P \lambda_k$ and $\psi_{ik} \exp u_i^w w_k$.

[7]See table A.2.

[8]This last result could be related to the fact that the average wage is also proxy for the average skill level in the firm, and so if the share of skilled workers is measured with error, the average wage will enter significantly the equation and will bias some coefficients.

will arise if the number of categories is too large. HNT could define 128 categories, but lack appropriate data and computational issues lead them to specify what we can call a *simple model* to reduce the dimensionality of the problem. This also allows simpler interpretations. We now present our approach to deal with this problem.

For clarity's sake, suppose there are only 4 categories: two for gender and two for age (M and W, Y and O), taking young men as a reference. Effective labor (in log) as previously used in equation (2) would be

$$\log L^* = \log L + \log(1 + \gamma_{MO} L_{MO}/L + \gamma_{WY} L_{WY}/L + \gamma_{WO} L_{WO}/L), \tag{9}$$

where γ stands for $\lambda/\lambda_0 - 1$. Since $\log(1+x) \approx x$ for x small, this equation can be rewritten as[9]

$$\log L^* = \log L + \gamma_{MO} L_{MO}/L + \gamma_{WY} L_{WY}/L + \gamma_{WO} L_{WO}/L \tag{10}$$

This specification will be called the *extended model*, as it includes all categories of workers.

To simplify this formula, it is sufficient to assume that the extended coefficients can be decomposed as sums of simpler coefficients: in other words, that there is a γ_O and a γ_W such that $\gamma_{MO} = \gamma_O$, $\gamma_{WY} = \gamma_W$ and $\gamma_{WO} = \gamma_O + \gamma_W$. Effective labor can thus be written in the *simple model* as :

$$\log L^* = \log L + \gamma_W L_W/L + \gamma_O L_O/L. \tag{11}$$

For example the estimated equation for the production function in the simple model will be, when skilled (Q_2) male workers between 35 and 49 are taken as the reference category:

$$\begin{aligned} \log Q_i = {} & \alpha \log L_i + \beta \log K_i + \alpha(\frac{\lambda_F}{\lambda_0} - 1) P_{iF} \\ & + \alpha(\frac{\lambda_{A_1}}{\lambda_0} - 1) P_{iA_1} + \alpha(\frac{\lambda_{A_2}}{\lambda_0} - 1) P_{iA_2} + \alpha(\frac{\lambda_{A_4}}{\lambda_0} - 1) P_{iA_4} \\ & + \alpha(\frac{\lambda_{Q_1}}{\lambda_0} - 1) P_{iQ_1} + \alpha(\frac{\lambda_{Q_3}}{\lambda_0} - 1) P_{iQ_3} + \varepsilon_i \end{aligned} \tag{12}$$

3 Description of the data

The dataset used is a matched set from two different sources, the Bénéfices Réels Normaux (BRN), an employer-level file, and the Déclarations Annuelles des Données Sociales (DADS), an employee-level file. It covers the period 1994–1997 and consists of 77,868 firms.

The BRN consists of firms' balance sheets and is collected by the Direction Générale des Impôts; it provides us with all useful information needed to estimate production functions: employment, capital stock, value-added, output, but also total wages. This file includes around 600,000 firms in the private non finacial non agricultural sectors each year and covers around 80% of total sales in the economy.

[9] Estimating the model with and without the approximation does not lead to sensibly different results; the γ coefficients are usually small and when large, corresponding shares are small.

It is available starting 1984 and firms are identified through a specific code SIREN that allows following firms over time. The real value added is defined as the sum of total employers' compensation cost and operating income divided by the value added price index at the two digit level available from National Accounts. The capital stock is constructed using fixed assets. This information is registered at its historical cost. To recover a capital stock in volume we proceeded to a correction which consists in deflating the initial measure by the investment price index at the date considered minus an estimated age of capital. This amounts to assuming that all the capital was bought all at once. The age of capital is calculated as the ratio of depreciated assets over fixed assets, multiplied by equipments' average length of life (assumed to be of 16 years). The dataset was constructed for several uses; a cost of capital variable was also computed although it is not directly used in the present study. This was done according to the Auerbach (1991) formula, and thus includes the debt ratio of the firm, its depreciation rate computed from depreciated assets, as well as interest expenses.

The BRN files were then merged and balanced over the period 1993-1997 using the SIREN code. This left us with a file of 295,118 firms. We then performed some cleaning over some of the main variables. We imposed that value added, employment, capital stock and total labor cost be positive at each date. We also imposed that the growth rate of value added, employment, and capital stock, the log and growth rate of value added per head, capital stock per head, average labor cost and cost of capital be between the first and the 99th percentile interval at each date. This cleaning strongly reduced the size of the sample to 112,812. Almost 62% of the firms were discarded. This was due mainly to the positive constraints on the variables and also to the computation and cleaning on the cost of capital.

The DADS is an exhaustive data set available since 1993, containing information about each employee of each firm. The data is made upon mandatory employer reports of the gross earnings of each employee subject to French payroll taxes. This file includes around 15 million workers each year. Workers can be followed only through two adjacent years. There is one file for the pair of years 1993-1994, one for 1994-1995 and so on, providing the information for the two corresponding years for each worker. The identifying code of workers changes from one file to the other. The files provide information on working days, working hours, wages and various characteristics of the employee (gender, age, occupation) for all firms in the private sector. It also includes the SIREN identifying code of the firm. Labor costs at the employee level were computed from wages by applying the payroll taxes rule. This is a complex rule that changed during the covered period, especially trough the introduction of a reduction in payroll taxes for low wage workers. Employees' information was then aggregated at the firm level into 24 groups, depending on gender (H for men, F for women), age, and skill level. Three classes of skill are distinguished, using the occupation classification: (Q3) highly skilled workers (engineers, technicians and managers, corresponding to the categories 20, 30 and 40 of the occupation classification), (Q2) skilled workers (skilled blue and white collars, corresponding to the categories 52, 54, and 62 to 65 of the classification), (Q1) unskilled workers which includes all other codes. We also distinguish four age groups: (A1) entry workers under 25, (A2) young workers, from 25 to 34, (A3) prime age workers, from 35 to

Table 1: Descriptive statistics—size of firms

	Manufacturing				Non-manufacturing			
Size	Nb. firms	(%)	Nb. of employees	(%)	Nb. firms	(%)	Nb. of employees	(%)
1 to 4	2,995	12.8	10,364	0.8	18,767	34.2	61,941	3.4
5 to 9	5,092	21.8	38,205	3.1	16,447	30.0	119,008	6.6
10 to 14	2,687	11.5	33,267	2.7	5,136	9.4	63,190	3.5
15 to 19	1,902	8.1	33,100	2.7	2,878	5.2	50,040	2.8
20 to 49	6,354	27.2	208,735	17.0	8,004	14.6	257,618	14.2
50 to 99	2,025	8.7	144,036	11.7	1,952	3.6	135,995	7.5
100 to 349	1,759	7.5	316,757	25.7	1,402	2.6	239,253	13.2
350 and over	524	2.2	446,107	36.3	306	0.6	885,662	48.9
All	*23,292*	*100*	*1,230,572*	*100*	*54,576*	*100*	*1,812,710*	*100*

NOTE.—Matched DADS-BRN dataset, INSEE.

49, and (A4) older workers over 50. Skilled prime age (between 35 and 49) men are taken as the reference category, since it is the largest category.

The two files were merged using the identifying SIREN code for the years 1993 to 1997. The quality of the match is not perfect. 9% of the firms in the BRN files do not appear in the DADS file. The reason for this remains unclear up to now, but the firms discarded are always small. The file at this stage has 102,403 firms. It covers all sectors in manufacturing, construction and non manufacturing. We restricted our study to manufacturing and non manufacturing sectors, dropping the construction sector for now. We were left with 23,292 firms in the manufacturing sectors and 54,576 in the non-manufacturing sectors.

Our employee file has some advantages over the Worker Establishment Characteristics Database (WECD) used by HNT. First, as it is exhaustive, we can directly measure the share of the various types of workers as opposed to HNT who have only access to estimates of the shares in each firm. Second, it contains wage information which allows us to measure the share of each worker type in total wage bill. Finally our data covers both manufacturing and non manufacturing sectors (excluding financial sectors). An important drawback of our file is that it does not provide a very rich description of the heterogeneity of the workforce. For example, HNT have information about education levels and marital status.

Tables 1 to 3 present some descriptive statistics in manufacturing and non manufacturing sectors. Average sizes are 52.72 and 33.19 in manufacturing and non manufacturing respectively.

4 Estimating and testing the model

We now present the results of our different estimates. We will begin by presenting the estimation of the "simple" model—equations (2), (5) and (7) with labor inputs as defined in (11). We will then examine crossed effects using the "extended" model. Results are obtained using OLS in the "between" dimension of the variables.

Table 2: Descriptive statistics—selected variables

Variables	Manufacturing Mean	Manufacturing StdDev	Non-manufacturing Mean	Non-manufacturing StdDev
Log output	7.777	1.346	6.875	1.185
Log capital	7.490	1.675	6.556	1.386
Log wages	5.251	0.264	5.160	0.303
Nb employees	52.72	238.3	33.19	1400
Categories				
(F) Women	0.270	0.229	0.412	0.312
(Q1) Unskilled	0.265	0.226	0.295	0.290
(Q2) Skilled	0.469	0.228	0.381	0.304
(Q3) Highly skilled	0.265	0.188	0.323	0.252
(A1) Entry (under 25)	0.081	0.088	0.099	0.116
(A2) Young (25 to 34)	0.323	0.164	0.331	0.200
(A3) Prime age (35 to 49)	0.428	0.169	0.411	0.217
(A4) Older (over 50)	0.167	0.140	0.158	0.175

NOTE.—Matched DADS-BRN dataset, INSEE.

4.1 Simple model

Estimating the simple model leads to the results in table 4. We use the two different methods presented above: an estimation with hours worked (for the columns labeled "Output" and "Wage") and a estimation with costs to the employer (for the "Markdown"). The λ/w column presents the ratio of the Output and Wage coefficients of the first two columns, and the last column (1) test the equality of this ratio and the markdown coefficients.

Average number of workers is used as labor input in the productivity equation, total wage bill as cost input in the markdown regression. The share of hours worked in each firm by each worker category is used in the productivity and earnings equations, while the share in the total wage bill is used in the markdown equation. Additional controls used include hours worked per day in all three equations, size of firms (5 categories), some type of sub-industry dummies (18 for manufacturing and 9 for non-manufacturing) and a proxy for firm's creation year (6 categories). The reference category of workers is unskilled entry (under 25) males.

On a methodological aside, the results obtained with HNT's methodology and the markdown approach are always qualitatively similar, though in a few cases the test $\lambda/w = 1$ and $\delta = 1$ does not lead to the same conclusion. Quantitatively the equality $\lambda/w = \delta$ is almost always rejected. However the differences in estimated coefficients are usually small and the rejection is probably due to the very large number of firms in the sample. Some differences can however be pointed out, for example for older workers the HNT's methodology leads to estimates closer to one than with the markdown approach.

There are two main results in these estimates: first, there is little or no wage discrimination against women—their jobs are less paid, but are also less productive, by almost the same amount—and second, there is an important gap between wages

Table 3: Descriptive statistics—by worker categories

Category			Manufacturing				Non-manufacturing			
			Hours worked			Cost	Hours worked			Cost
			Mean (%)	Std	Percentage of zeros	(per hour)	Mean (%)	Std	Percentage of zeros	(per hour)
Men	Age 1	Unskilled	2.3	4.2	34.5	71.5	2.0	4.5	55.2	66.7
	Age 2		6.2	8.7	29.3	83.5	4.7	9.1	51.9	80.0
	Age 3		5.5	8.3	34.4	92.6	3.7	8.2	58.9	90.4
	Age 4		1.9	4.1	55.7	95.1	1.2	4.5	77.0	94.7
	Age 1	Skilled	3.0	5.3	31.6	76.9	2.7	5.7	51.7	73.2
	Age 2		12.9	12.8	15.5	95.0	10.1	13.9	38.9	86.6
	Age 3		14.8	13.9	15.7	108.2	11.0	15.7	41.7	98.5
	Age 4		4.5	6.9	38.5	112.9	3.1	7.2	63.9	105.4
	Age 1	Highly	0.6	1.8	64.8	91.5	0.6	2.1	78.2	93.2
	Age 2	skilled	5.0	7.8	35.6	144.7	4.6	8.8	53.2	135.1
	Age 3		10.4	10.7	18.2	194.9	10.0	13.1	36.2	180.5
	Age 4		5.8	7.8	29.3	233.2	5.2	9.7	52.8	214.7
Women	Age 1	Unskilled	1.1	3.4	62.5	66.4	3.0	7.3	61.5	62.3
	Age 2		3.2	6.8	54.4	71.6	6.0	12.0	55.7	66.9
	Age 3		4.7	8.8	48.1	76.1	6.5	12.9	52.9	70.2
	Age 4		1.6	4.2	62.6	78.1	2.6	7.8	70.0	73.0
	Age 1	Skilled	0.9	2.2	53.5	72.9	1.0	2.9	67.0	71.8
	Age 2		3.8	6.0	37.0	85.9	3.7	7.0	54.0	85.7
	Age 3		5.2	7.3	30.4	94.1	4.9	8.7	49.3	98.3
	Age 4		1.8	4.3	58.1	99.3	1.7	5.2	73.9	100.4
	Age 1	Highly	0.2	1.0	80.1	93.4	0.7	3.0	81.6	85.4
	Age 2	skilled	1.3	3.6	64.8	133.0	4.0	10.9	66.2	115.8
	Age 3		2.2	4.9	56.4	157.2	5.1	11.2	57.8	138.0
	Age 4		1.2	3.8	68.9	175.6	2.2	6.8	74.0	154.3

NOTE.—Average percentage of workers in each category, which read as in the previous table (Age 1: under 25, Age 2: between 25 and 34, Age 3: between 35 and 49, Age 4: over 50); see text for details. The "percentage of zeros" column is the percentage of firms with no workers in the category. Cost is total cost for each category in the sectors considered, divided by the number of hour worked (in French Francs of 1994).

and productivity in the jobs occupied by older workers—though the wage profile rises with age, the productivity profile only exhibits a small hump.[10] This is in stark contrast with HNT, who found a large wage discrimination against women but no difference between the wage and productivity profiles by age.

The difference in relative marginal product and relative wages between men and women is only of 3% in manufacturing and below 2% in non-manufacturing sectors, with a standard error of 1% and 0.6% respectively. Similarly, as measured by the markdown equation, the difference is of only 2.8% and 1.4% respectively. Thus it appears that there is a significant but qualitatively small discrimination against women. In relative productivity and wages however the differences are significant

[10]These results are robust to various subsamples, specifications and identifying assumptions. See appendix A.

Table 4: Simple model estimates

Variable	Manufacturing					Non-manufacturing				
	Output λ	Wage w	λ/w	Markdown δ	(1)	Output λ	Wages w	λ/w	Markdown δ	(1)
Log Capital	0.176			0.117		0.155			0.107	
	(0.003)			(0.002)		(0.002)			(0.001)	
Log Labor/Cost	0.820			0.886		0.796			0.853	
	(0.005)			(0.003)		(0.003)			(0.002)	
(F) Female	0.888	0.862	1.030	1.028	–	0.931	0.915	1.017	1.014	**
	(0.014)	(0.008)	(0.011)	(0.010)		(0.008)	(0.006)	(0.006)	(0.005)	
(Q1) Unskilled	0.835	0.852	0.979	0.989	***	0.973	0.972	1.001	1.023	***
	(0.012)	(0.008)	(0.010)	(0.010)		(0.009)	(0.006)	(0.006)	(0.006)	
(Q3) Highly skilled	1.571	1.475	1.065	1.077	***	1.248	1.337	0.933	0.917	***
	(0.016)	(0.011)	(0.007)	(0.008)		(0.010)	(0.007)	(0.005)	(0.006)	
(A1) Entry age (<25)	0.906	0.786	1.153	1.139	**	0.846	0.778	1.087	1.097	***
	(0.030)	(0.020)	(0.025)	(0.023)		(0.017)	(0.012)	(0.016)	(0.014)	
(A2) Young ($25 \leq$ age < 35)	1.109	0.969	1.144	1.135	***	1.100	0.969	1.135	1.121	***
	(0.017)	(0.011)	(0.011)	(0.011)		(0.010)	(0.007)	(0.007)	(0.006)	
(A4) Older ($50 \leq$ age)	1.011	1.105	0.915	0.923	–	0.901	1.031	0.874	0.898	***
	(0.022)	(0.014)	(0.013)	(0.010)		(0.012)	(0.009)	(0.008)	(0.006)	

NOTE.—Linear regressions in manufacturing (23,292 firms) and non-manufacturing (54,576 firms) on the means over 4 years. Average number of workers is used as Labor input and total wage bill as Cost input in the markdown regression; hours worked are used in the output and wage regressions, costs for the employer in the markdown regression. Controls used are size of firms (5 categories), some type of sub-industry dummies (18 for manufacturing and 9 for non-manufacturing), average number of hours worked per day, and age of firm (6 categories). Reference category is skilled males between 35 and 49. See text and table 3 for the exact definitions of the categories. Column (1) shows the results of the test $\lambda/w = \delta$, with the p-values represented as follows: *** below 1%, ** between 1 and 5%, * between 5 and 10%, – over 10%. Standard errors robust to heteroskedasticity are shown in parentheses.

and important: women are less paid and hold less productive jobs.

Women are measured to be 11% less productive than men in manufacturing, and 7% in non-manufacturing sectors. This estimate is robust to the measurement of labor inputs, whether by hours or by number of days worked. This difference in productivity is slightly sensitive to the presence of the average number of hours worked per day in the firm; if it is absent the gap increases to 15% in manufacturing and to 13% in non-manufacturing sectors. Thus it appears that the smaller productivity for women is not caused by the failure to take into account part-time characteristics of the jobs. The main explanation relies on the fact that we only measure the productivity of the jobs occupied, and thus if women are placed in less productive jobs they will seem to have a lower productivity.

Women are also less paid than men: 14% in manufacturing and 9% in non-manufacturing sectors. This is not a surprise, for a large number of studies have tried to measure and decompose this wage gap. The approach found here and in HNT is new, so we may need to compare our findings in this area with others. In Meurs and Ponthieux (2000), the unexplained wage gap (in the Oaxaca and Blinder methodology) once controls for hours worked and for other observable characteristics are included is only of 4.2% (p. 145). If we exclude the part explained by "other characteristics" (such as education, experience, social and occupational category, tenure, type of job contract, number of children, marital status) for which we only imperfectly control, the unexplained wage gap is of 16%. Our estimate of wage differential lies in between the unexplained and the partially explained wage gaps, so we are quite confident in its validity.

We can compare these results to the ones in HNT: in the US women are 15% less productive than men (as measured by HNT) but 45% less paid than men, strongly different from the 35% found in the Census of Population in the same article and the 20% gap found in Altonji and Blank (1999) when several controls included. Hægeland and Klette (1999) show that in Norway too women are less productive than men (17%) but are also less paid (18%).

The difference in the patterns of productivity and wages with age is the other important result: older workers are relatively overpaid when compared to younger ones when productivity is taken into account.[11] Markdown (relative to the reference category of prime age workers) declines with age form 1.14 to 0.92 in manufacturing and from 1.10 to 0.90 in non-manufacturing. HNT's methodology leads to similar conclusions, though the numerical values are a little higher. Young workers are measured to be 20% more productive than entry age ones in manufacturing, while for prime age and older workers, the productivity is only 10% greater in manufacturing. Thus it is an increase followed by a stagnation or a decrease in productivity with age. On the contrary, wages increase steadily for each age category. Hence the difference between relative marginal product and wages increases with age, and is significant for workers over 35, in both sectors.

In the US, as measured by HNT, older workers are 19% more productive in the US than entry workers (with a standard error of 15%) and are also paid as much: in France the result on productivity is drastically different, as older workers are between 10% to 20% *less* productive than younger workers (with a standard error of only 3%). Also, wage increase is lower in the US, where workers aged over 55 are only paid 18% more, compared to 36% in France. It might be possible that this different wage schedule is attributable to the "marriage premium" variable used to estimate the equations in the US, as there is a positive correlation between age and an "ever married" indicator.

4.2 Discussion about productivity and age

Of particular concern in the productivity equation is the stagnation or decrease of marginal relative product with age. Using a slightly different method, Ilmakunnas, Maliranta, and Vainiomäki (1999) show that in Finland total factor productivity of a plant declines as the mean age of the workforce rises over 40, all other things equal—a result indeed compatible with our own. Theories of human capital explain the increase in wages with age (or tenure) with the concepts of firm specific and general human capital, arguing that more seasoned and experienced workers are more productive. In France we can therefore argue that productivity and experience are not related for workers over 35, hence human capital models are of little use in explaining wage formation with respect to productivity for those workers.[12] Several explanations can be found. The first reason is possible mismeasurement of productivity. Vintage or generation specific effects might also be a clue, as older

[11] As this is only relative to the reference category, an alternative interpretation is that young men are underpaid and older workers are paid "just fine".

[12] Little is known on the accurate measurement of labor productivity for individual workers, and it is hard to define for each worker in a firm what is precisely her contribution to output (excepting piece rate contracts).

workers could be selected into less productive jobs (age-biased technological change, see Friedberg (2001) for example). Another explanation lies in the selectivity in the skill levels. Good unskilled young workers can climb up through the skill categories and proceed to higher skilled jobs as they grow older. Thus the unskilled categories at older ages will contain less successful workers; instead of finding an increase of productivity with age we will measure a higher effect of skill on productivity. By estimating the equations without the skill categories, we will get an upper bound of the "true" productivity of older workers; omitted variables will be a concern here. If we exclude the skill categories from the equations, measured productivity is much higher (around 30% in manufacturing) for older workers, with a slight decrease for workers aged over 35.

Nevertheless relative earnings always rise more with age than relative productivity, so that markdown always declines with age. Does this fact reveal an inefficiency in the labor market?

On one hand, if the wedge between wage and productivity is caused by laws protecting older workers, such as increasing adjustment costs with age (i.e. firing costs), then older workers are overpaid.[13] In search models of the type studied by Burdett and Mortensen (1998), friction in the labor market and monopsony powers cause the probability of having a high wage to be increasing with age. Hence younger workers are more underpaid than older workers.[14]

On the other hand, the difference between wages and productivity can also be observed in models of perfect competition. In the Lazear (1979) model of implicit contracts, younger workers are paid below their productivity and older ones above it, with neutrality over the lifecycle. In Harris and Holmstrom (1982), workers receive a downward rigid wage below their marginal product, the difference being a premium against the risk carried by their unknown true ability. As information is gathered by the firm and the worker, this premium decreases and wages increase. In this model of symmetric imperfect information, younger workers are thus underpaid relatively to older workers, though it is debatable if this is an inefficiency.

Our methodology does not allow in itself to distinguish between these models. Nevertheless, the comparison with the results of HNT in the US, where wages and productivity do not differ with age, could be of some help. One major difference between the two labor markets lies in the firing costs (although to our knowledge there is no available estimate of the firing costs in the US, it is a common widely accepted view that these costs are lower in the US than in continental Europe—Abowd and Kramarz (2000) show the importance of those costs in France). Notice also that the changes in firm ownership in the US in the 70's and 80's which have not happened as such in France—the so-called "raiders" studied by Caves and Krepps (1993)—may have produced a lasting change in the wage structure of firms as raiders get rid of unproductive and overpaid workers.

[13]In these models the important variable is experience rather than age. However in France legislation protects both high-seniority workers and older ones (see Goux and Maurin 2000). Abowd and Kramarz (2000) nevertheless estimate that severance pay depends more on age (555FF per year) than on seniority (only 221FF p.a.).

[14]With risk averse agents, the wage contract offered by firms may even be increasing, as in a preliminary manuscript by Burdett and Coles.

4.3 Extended model estimates

So far we have considered that the term of labor input can be written in a condensed way, so that we can discuss for example the relative marginal product of women compared to men. This requires that relative coefficients across a group are equal along all other characteristics. Due to the lack of data (and a very large number of categories), HNT were unable to adequately test this hypothesis. Working with a smaller number of categories and more data, we can estimate an extended model where all 24 categories appear. We will also be able to test the equality of relative coefficients across groups.

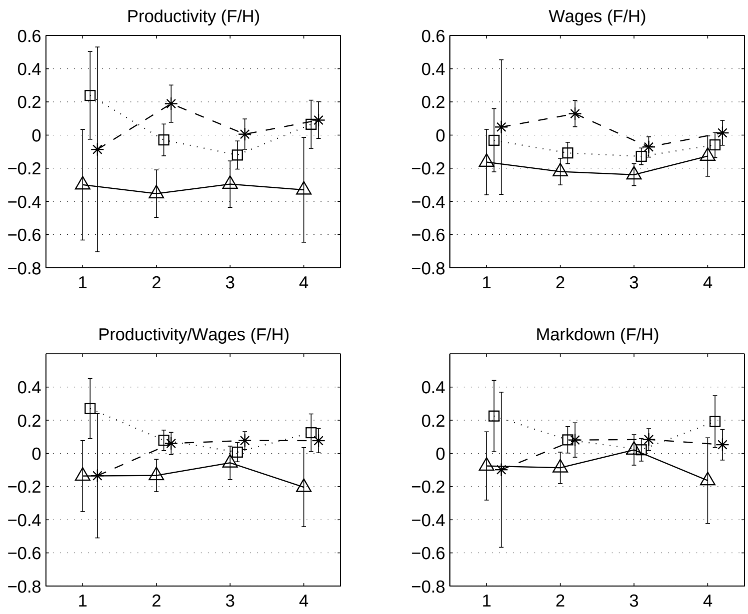
Table A.1 in the appendix presents the results of this section. The setup is very similar to the one before, except for the larger number of coefficients estimated. The left and right panels are for manufacturing and non-manufacturing sectors respectively. The results are however hard to interpret, because of the high number of categories, but also and most of all because of the existence of an unique reference category (skilled males between 35 and 49). If we only compare productivity and wages for each category (or markdown) we see that the the result of the previous section is confirmed: only older workers seem to be favored, relative to the reference category—but what does this really mean? To analyze in more detail these results, we will concentrate on the two most important issues we have found so far: gender and age related differentials. The advantage of this method is that it allows us to get rid of the hypothesis of constancy of relative characteristics across groups.

To assess the wage discrimination issue we calculate for each Age–Skill pair the ratios of women's over men's productivity, earnings and markdown. This is done in figure 1, where each line corresponds to a skill level and plots the relative productivity (or wages, or markdown) between men and women, at different ages.

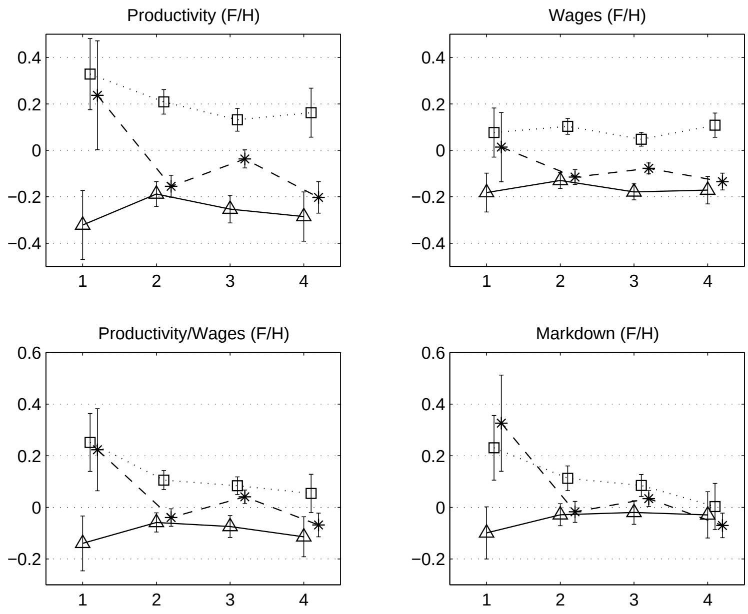
If marginal products (or wages, or markdown) of men relative to women were constant across skills and ages, then the plotted lines would be identical and constant. However, as can be seen in the figure, the lines are approximately constant (particularly in manufacturing) but are not identical. Hence, in manufacturing, relative products, wages and markdown between men and women are different between skills but do not vary with age. This implies that the gender gap can be parameterized by only a skill level effect. Skilled and highly skilled women are approximately as productive as men, while only unskilled women are less productive. Women's earnings are below those of men except for highly skilled women who are as paid as men. Finally, the ratios of productivity over earnings (or, equivalently, markdown) are significantly greater than one for skilled and highly skilled women (with a point estimate over 7% with a s.e. around 2%), while unskilled women are relatively favored (with a -4.5% markdown with s.e. of 2%).

In non-manufacturing sectors the results are less clear cut. Skilled women (Q2) are 20% more productive but only 10% more paid than men, and appear to be discriminated against, whereas for both unskilled and highly skilled women markdown is not significant except for highly skilled women under 25 years.

Similarly, to assess the effect of age, we calculate for each Gender–Skill pair the ratio of productivity (or wages, or markdown) for each age category A1, A2 and A4 over productivity (resp. wages, markdown) for age category A3. Figure 2 plots the results, where each line corresponds to a skill level and a gender, and each point

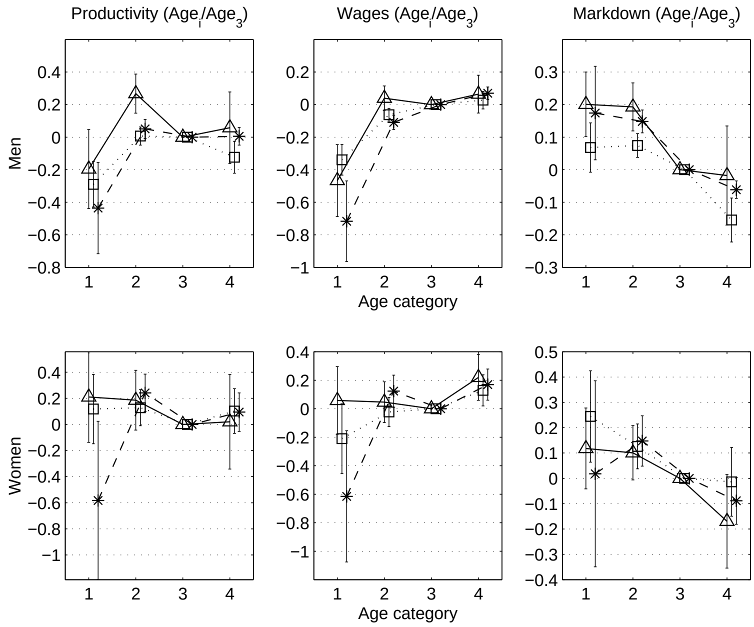


(a) Manufacturing

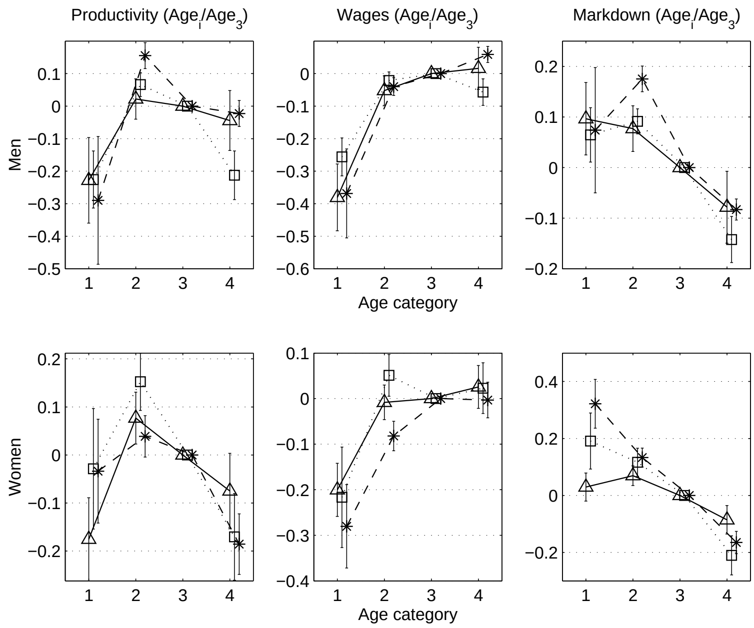


(b) Non-manufacturing

Figure 1: Women compared to men: (log) relative ratios of women over men's productivity, wages, productivity/wages ratio, and markdown (left to right, top to bottom). △ is Q1 (unskilled), □ is Q2 and ❋ is Q3 (highly skilled). The x-axis is age category.



(a) Manufacturing



(b) Non-manufacturing

Figure 2: Age effect: (log) relative ratios of workers' productivity, wages, and markdown over reference category (Age 3) ones' (left to right, top row men, bottom row women). △ is Q1 (unskilled), □ is Q2 and ✱ is Q3 (highly skilled). The x-axis is age category.

represents the relative product, wages or markdown of a given age compared to the entry workers of the same gender and skill. The most notable result is that there is not a strong heterogeneity in the wages, productivity and markdown age profiles among the different gender–skill pairs. A formal statistical test would reject the constancy of relative markdown for the different categories but the general pattern is the same: the markdown sharply decline with age. The order of magnitude of this decline is the same as what was found in the simple model : 15% for entry age and young workers and -10% for older workers, relative to workers between 35 and 49, for manufacturing.[15]

As a summary, the extended model offers the possibility of more subtle effects, the cost being less precise estimates. The robust result is the relative overpaying of older workers (or equivalently, the relative underpaying of younger ones). The gender gap is significant and positive in skilled categories and negative in unskilled ones.

4.4 Assessing the robustness along the time dimension

One concern in our earlier estimation procedures is the possible endogenous selection of employees into firms, e.g. women could be excluded from high productivity firms and thus end up in low productivity firms. This would bias women's estimated productivity downward. The availability of data along the time dimension could allow us in principle to estimate more robust specifications. The identification of production functions is a complex task, as Griliches and Mairesse (1997) document. Estimating in first (or long) differences or within firms removes firm specific effects but may introduce other biases. General Method of Moments procedures are the consensus, though the difficulty lies in the selection of identifying moment conditions. Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998*b*) are examples of the type of restrictions one can introduce. Blundell and Bond (1998*a*) provide a framework to estimate production functions using GMM in the case of autocorrelated transitory shocks.

Table 5 presents the results of the estimation of the markdown equation in long differences, within firms and with several GMM-type procedures to large firms, as well as the production function in manufacturing for comparison purposes. We only present GMM results corresponding to the system estimator of Arellano and Bover (1995); other estimators either led to imprecise results or were rejected by the Sargan overindentifying restriction tests. We only consider the sample of the largest firms (above 100 employees), as only large firms exhibit the necessary variability in the share of labor inputs to be acceptable instruments. Moreover, if smaller firms are included, the Sargan overindentifying restriction tests reject all identifying restrictions.

One difficulty is the short length of time periods available; with only four time periods the number of identifying restrictions is fairly limited. This may explain the low precision of the estimates. Weak instruments in this context can lead to biased finite-sample estimators.

Overall these estimates stand in agreement with the previous section. Long

[15] For non-manufacturing firms, the results are more heterogeneous.

Table 5: Markdown Long differences, within and GMM estimates

	Manufacturing					Non-manufacturing			
Variable	L. diff.[a]	Within[a]	Within[b]	GMM[b]	Production[b]	L. diff.[c]	Within[c]	Within[d]	GMM[d]
Log Capital	0.070 (0.006)	0.042 (0.004)	0.008 (0.015)	0.137 (0.050)	0.203 (0.057)	0.080 (0.004)	0.043 (0.002)	0.040 (0.012)	0.134 (0.032)
Log Cost	0.847 (0.009)	0.848 (0.005)	0.904 (0.019)	0.940 (0.068)	0.925 (0.081)	0.718 (0.005)	0.695 (0.003)	0.824 (0.017)	0.929 (0.046)
(F) Female	0.966 (0.029)	0.971 (0.017)	1.006 (0.093)	1.108 (0.259)	0.907 (0.340)	0.965 (0.013)	0.970 (0.008)	0.766 (0.094)	0.978 (0.147)
(Q1) Unskilled	1.036 (0.015)	1.029 (0.008)	1.027 (0.032)	0.714 (0.105)	0.756 (0.113)	1.022 (0.011)	1.036 (0.006)	1.070 (0.050)	1.261 (0.168)
(Q3) High Skill	0.921 (0.015)	0.948 (0.009)	1.064 (0.045)	0.841 (0.152)	1.395 (0.160)	0.947 (0.010)	0.989 (0.006)	1.075 (0.072)	1.014 (0.140)
(A1) Entry age	1.013 (0.021)	1.067 (0.013)	1.306 (0.099)	1.616 (0.226)	1.684 (0.231)	1.030 (0.012)	1.115 (0.007)	1.282 (0.078)	1.031 (0.178)
(A2) Young	0.998 (0.015)	1.030 (0.009)	1.120 (0.066)	1.421 (0.131)	1.273 (0.148)	1.016 (0.007)	1.061 (0.005)	1.282 (0.077)	1.416 (0.154)
(A4) Older	0.955 (0.014)	0.940 (0.009)	0.951 (0.074)	0.557 (0.194)	1.053 (0.256)	0.962 (0.008)	0.927 (0.005)	0.814 (0.075)	0.956 (0.184)

NOTE.—Estimates of the markdown equation on the full sample(a: 23292 manufacturing, c: 54576 non-manufacturing) and on firms over 100 employees (b: 2281, d: 1705 respectively), linear specification of the model. "L. diff." is the model in long differences, estimated in 1997-1994 differences, while the "Within" model is the four year panel where firm means have been subtracted. GMM estimation is a Chamberlain type estimator equivalent to the Arellano and Bover (1995) estimator, and the Sargan test of over-identifying restrictions is not rejected. Controls used in this last case are as in table 4. The column labeled "Production" is the estimate of the production function in manufacturing by system estimator GMM for comparison purposes.

differences and within coefficient estimates are quite similar. As is common in this type of estimation, the coefficient of capital is very low.

5 Conclusion

A recently constructed dataset representing almost 90 thousand French firms over 4 years has allowed us to study their output, the composition and earnings of the workforce. The availability of cost variables and the exhaustivity of the sources allow for increased precision and for a new method of estimating the wage-productivity differential expanding on the work of Hellerstein et al. (1999) for several kinds of worker groups. We define markdown as the ratio of marginal productivity on wages which can be directly estimated with our method. Two main results can be drawn from our study.

First, the markdown for senior workers is significantly lower than for younger ones: in other words, wages rise more quickly than productivity. The excess of wages is observable across industries and age and size of firm in the manufacturing sector, and in a lesser way in non-manufacturing sectors. This finding is consistent with the results of Hægeland and Klette (1999) and Ilmakunnas et al. (1999), while it is in sharp contrast with the US, as reported by Hellerstein et al. (1999). This result challenges the interpretation that experience in wage equations reflects human capital accumulation.

Second, women's and men's markdowns are significantly different but of a small order of magnitude: women's relative wages are slightly below the measured relative productivity of the jobs they hold. This too is in sharp contrast with the results of

Hellerstein et al.. However, jobs held by women are 15% less productive than those held by men: gender discrimination in France is more one of job allocation than in wage determination.

Examining the heterogeneity of these effects among worker groups, we find important differences along the skill dimension in gender markdown gaps. The markdown for low-skilled women is lower than for men while for medium- and highly-skilled women it is the opposite: jobs of low-skilled women seem to be "overpaid" compared to low-skilled men, while jobs held by highly-skilled women are more productive than those of men, the wage being approximately equal. Possible reasons include the existence of a minimum wage or measurement errors specific to this category of workers, though we have not investigated this matter further.

References

Abowd, John M., and Kramarz, Francis. "The Costs of Hiring and Separations." (2000). Mimeo.

Altonji, Joseph G., and Blank, Rebecca M. "Race and Gender in the Labor Market." In *Handbook of Labor Economics*, edited by Orley Ashenfelter and David Card, Amsterdam: North Holland, 1999, vol. 3C. 3143–259.

Arellano, Manuel, and Bond, Stephen R. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* 58 (1991): 277–97.

Arellano, Manuell, and Bover, Olympia. "Another Look at the Instrumental-Variable Estimation of Error-Components Models." *Journal of Econometrics* 68 (1995): 29–51.

Auerbach, Alan J. "Taxation, Corporate Financial Policy and the Cost of Capital." *Journal of Economic Literature* 21 (September 1991): 905–40.

Blundell, Richard W., and Bond, Stephen R. "GMM Estimation with Persistent Panel Data: An Application to Production Functions." Working Paper Series W99/4, The Institute for Fiscal Studies (1998). (*a*)

———. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87 (1998): 115–43. (*b*)

Burdett, Kenneth, and Mortensen, Dale T. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review* 39 (May 1998): 257–73.

Caves, Richard E., and Krepps, Matthew B. "Fat: The Displacement of Non-Production Workers from U.S. Manufacturing Industries." *Brookings Papers on Economic Activity, Microeconomics* 1993 (1993): 227–73.

Charpin, Jean-Michel, et al. *...* Paris: Rapport du Plan, 2000.

Friedberg, Leora. "The Impact of Technological Change on Older Workers: Evidence from Data on Computer Use." Working Paper 8297, NBER (2001).

Goux, Dominique, and Maurin, Éric. "Labor Market Institutions and Job Stability. A Firm Level Analysis for Layoff Risk for High and Low-Seniority Workers." Working Paper 2000-29, CREST (2000).

Griliches, Zvi, and Mairesse, Jacques. "Production Functions: The Search for Identification." Working paper 9730, CREST (1997).

Hægeland, Torbjørn, and Klette, Tor Jacob. "Do Higher Wages Reflect Higher Productivity? Education, Gender and Experience Premiums in a Matched Plant-Worker Data Set." In *The Creation and Analysis of Employer-Employee Matched Data*, edited by J. Haltiwanger, J. Lane, J. R. Spletzer, J. Theeuwes, and K. Troske, Amsterdam: North Holland, 1999.

Harris, Milton, and Holmstrom, Bengt. "A Theory of Wage Dynamics." *Review of Economic Studies* 49 (1982): 315–33.

Hellerstein, Judith K.; Neumark, David; and Troske, Kenneth R. "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations." *Journal of Labor Economics* 17 (1999): 409–46.

Ilmakunnas, Pekka; Maliranta, Mika; and Vainiomäki, Jari. "The Roles of Employer and Employee Characteristics for Plant Productivity." Working Paper W-223, Helsinki School of Economics and Business Administration (1999).

Lazear, Edward P. "Why Is There Mandatory Retirement?" *Journal of Political Economy* 87 (December 1979): 1261–84.

Medoff, James L., and Abraham, Katharine G. "Experience, Performance, and Earnings." *Quarterly Journal of Economics* 95 (December 1980): 703–36.

Meurs, Dominique, and Ponthieux, Sophie. "Une mesure de la discrimination dans l'écart de salaire entre hommes et femmes." *Économie et Statistique* 337-338 (2000): 135–58.

Olley, G. Steven, and Pakes, Ariel. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (November 1996): 1263–97.

A Robustness results

To assess the validity of our results and their robustness, we proceed to the estimation of the different equations on several types of sub-samples and with different specifications. The results are shown on table A.2: we ran the regressions of the markdown coefficients on firms over 20 employees, over 50 and over 100, on each sector of the 2-digit SIC, on the age of the firm (before and after 1980). We also report the effect of the identifying assumption for the markdown equation used on the whole sample.

The main impression in these regressions is that the markdown estimates are fairly robust to the sample used, with only a few exceptions. Women are significantly discriminated against only in the equipment goods sector (8% with a s.e. of 2%) and in the consumption goods sector (with a 5% markdown). In the agroalimentary sector women seem to be favored, but this is due to an estimated relative productivity well below that of men; the peculiar structure of this sector (in particular the high proportion of unskilled women) may explain this estimate.

The coefficients on age categories are also remarkably robust. For all sub-samples except for the one on firms over 50 employees in non-manufacturing sectors, markdown declines for all age categories, and is almost always lower for older workers than for younger workers. The influence of the age of the firm is not clear. In older firms the proportion of older workers is higher, and it might be possible that older unproductive workers are selected into less productive firms, hence introducing a negative correlation between the unobserved firm productivity and the share of older unproductive workers.

Last, the effect of the identifying assumption used to estimate the markdown equation is small. Using assumptions (8a) and (8b) the estimates are indeed exactly equal, while only slight differences are observed using (8c).

Table A.1: Extended model estimates

Variable			Manufacturing					Non-manufacturing				
			Output λ	Wages w	λ/w	Markdown δ	(1)	Output λ	Wages w	λ/w	Markdown δ	(1)
Men	Age 1	Unskilled	0.926 (0.057)	0.777 (0.038)	1.191 (0.054)	1.221 (0.053)	$**$	1.028 (0.044)	0.889 (0.029)	1.156 (0.035)	1.198 (0.038)	$***$
	Age 2		0.987 (0.034)	0.846 (0.022)	1.166 (0.026)	1.185 (0.025)	$***$	1.170 (0.025)	1.018 (0.016)	1.148 (0.017)	1.155 (0.018)	$*$
	Age 3		0.782 (0.037)	0.834 (0.022)	0.938 (0.031)	0.973 (0.027)	$***$	1.155 (0.027)	1.085 (0.018)	1.065 (0.017)	1.064 (0.019)	-
	Age 4		0.823 (0.074)	0.886 (0.042)	0.929 (0.062)	0.949 (0.059)	-	1.106 (0.043)	1.103 (0.030)	1.002 (0.028)	0.981 (0.031)	$***$
	Age 1	Skilled	0.752 (0.052)	0.714 (0.034)	1.052 (0.047)	1.117 (0.040)	$***$	0.802 (0.035)	0.778 (0.023)	1.031 (0.032)	1.088 (0.029)	$***$
	Age 2		1.026 (0.028)	0.953 (0.018)	1.076 (0.020)	1.086 (0.020)	$*$	1.078 (0.020)	0.989 (0.013)	1.090 (0.013)	1.098 (0.013)	$***$
	Age 3		—	—	—	—		—	—	—	—	
	Age 4		0.907 (0.044)	1.044 (0.028)	0.869 (0.029)	0.849 (0.029)	$*$	0.820 (0.030)	0.956 (0.019)	0.857 (0.022)	0.869 (0.020)	$*$
	Age 1	Highly	0.922 (0.132)	0.692 (0.088)	1.333 (0.122)	1.267 (0.091)	-	0.930 (0.091)	0.954 (0.065)	0.974 (0.061)	0.984 (0.061)	-
	Age 2	skilled	1.561 (0.037)	1.321 (0.024)	1.182 (0.018)	1.161 (0.021)	$***$	1.464 (0.025)	1.337 (0.016)	1.095 (0.012)	1.058 (0.014)	$***$
	Age 3		1.489 (0.030)	1.477 (0.021)	1.009 (0.013)	0.967 (0.016)	$***$	1.255 (0.019)	1.392 (0.013)	0.902 (0.009)	0.875 (0.010)	$***$
	Age 4		1.497 (0.037)	1.582 (0.027)	0.946 (0.014)	0.895 (0.017)	$***$	1.228 (0.024)	1.476 (0.017)	0.831 (0.011)	0.796 (0.011)	$***$
Women	Age 1	Unskilled	0.667 (0.106)	0.627 (0.072)	1.064 (0.101)	1.155 (0.078)	$***$	0.753 (0.032)	0.723 (0.021)	1.042 (0.030)	1.104 (0.025)	$***$
	Age 2		0.671 (0.050)	0.635 (0.032)	1.057 (0.051)	1.131 (0.038)	$***$	0.974 (0.021)	0.881 (0.014)	1.105 (0.017)	1.134 (0.016)	$***$
	Age 3		0.562 (0.040)	0.609 (0.024)	0.923 (0.045)	1.043 (0.031)	$***$	0.903 (0.020)	0.889 (0.013)	1.016 (0.016)	1.056 (0.014)	$***$
	Age 4		0.571 (0.083)	0.754 (0.046)	0.757 (0.080)	0.853 (0.062)	$***$	0.839 (0.030)	0.912 (0.019)	0.919 (0.024)	0.965 (0.022)	$***$
	Age 1	Skilled	0.975 (0.119)	0.685 (0.080)	1.422 (0.124)	1.401 (0.115)	-	1.103 (0.065)	0.849 (0.045)	1.299 (0.058)	1.341 (0.061)	$**$
	Age 2		0.995 (0.050)	0.833 (0.033)	1.194 (0.038)	1.209 (0.039)	-	1.322 (0.030)	1.108 (0.020)	1.193 (0.019)	1.218 (0.023)	$***$
	Age 3		0.878 (0.041)	0.853 (0.027)	1.030 (0.032)	1.050 (0.030)	$**$	1.137 (0.026)	1.054 (0.017)	1.078 (0.017)	1.075 (0.019)	-
	Age 4		0.973 (0.067)	0.971 (0.041)	1.003 (0.055)	1.004 (0.060)	-	0.960 (0.039)	1.078 (0.026)	0.890 (0.025)	0.864 (0.027)	$***$
	Age 1	Highly	0.840 (0.247)	0.737 (0.166)	1.139 (0.194)	1.228 (0.207)	-	1.171 (0.062)	0.969 (0.044)	1.208 (0.049)	1.291 (0.055)	$***$
	Age 2	skilled	1.901 (0.098)	1.533 (0.061)	1.240 (0.036)	1.228 (0.054)	-	1.258 (0.025)	1.179 (0.017)	1.067 (0.015)	1.047 (0.017)	$***$
	Age 3		1.498 (0.067)	1.359 (0.046)	1.103 (0.029)	1.062 (0.031)	$***$	1.211 (0.022)	1.280 (0.015)	0.946 (0.012)	0.906 (0.013)	$***$
	Age 4		1.645 (0.089)	1.607 (0.064)	1.024 (0.037)	0.929 (0.041)	$***$	1.007 (0.030)	1.277 (0.022)	0.789 (0.016)	0.762 (0.015)	$***$

NOTE.—Linear between estimation, robust standard errors. Controls used and tests are as in table 4. The variables are the share of each demographic category, either in number of hours worked (output and wages equations) or in total employer costs (markdown equation). Reference category is skilled men in age category 3 (between 35 and 49).

Table A.2: Sensibility to sub-samples—Markdown coefficients

Sub-sample	N.Obs.	F	Q1	Q3	A1	A2	A4
Manufacturing							
Over 20 employees	10,653	1.023	1.009	1.176	1.269	1.207	0.910
		(0.013)	(0.013)	(0.016)	(0.045)	(0.021)	(0.022)
Over 50 employees	4,302	1.026	0.998	1.189	1.302	1.277	0.959
		(0.024)	(0.025)	(0.028)	(0.092)	(0.046)	(0.056)
Over 100 employees	2,281	0.997	0.985	1.140	1.441	1.400	1.117
		(0.036)	(0.036)	(0.040)	(0.152)	(0.074)	(0.103)
Agroalimentary (U2)	2,955	0.841	0.917	0.934	1.058	1.071	0.952
		(0.036)	(0.033)	(0.034)	(0.054)	(0.035)	(0.044)
Intermediate goods (U4)	7,261	1.008	1.014	1.075	1.179	1.129	0.920
		(0.021)	(0.016)	(0.018)	(0.047)	(0.020)	(0.018)
Equipment goods (U5)	5,834	1.083	1.036	1.058	1.195	1.128	0.922
		(0.019)	(0.019)	(0.013)	(0.045)	(0.018)	(0.017)
Consumption goods (U6)	7,242	1.055	1.032	1.134	1.172	1.160	0.926
		(0.014)	(0.016)	(0.015)	(0.036)	(0.018)	(0.018)
Created before 1980	12,319	1.027	0.959	1.084	1.149	1.174	0.911
		(0.014)	(0.014)	(0.013)	(0.037)	(0.017)	(0.015)
after 1981	10,973	1.031	1.017	1.069	1.136	1.109	0.941
		(0.013)	(0.013)	(0.011)	(0.029)	(0.014)	(0.014)
Assumption (8a)	23,292	1.028	0.989	1.077	1.139	1.135	0.923
		(0.010)	(0.010)	(0.008)	(0.023)	(0.011)	(0.010)
(8b)	23,292	1.026	0.985	1.095	1.134	1.138	0.923
		(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(8c)	23,292	1.054	1.016	1.017	1.184	1.148	0.907
		(0.010)	(0.010)	(0.009)	(0.023)	(0.011)	(0.011)
Year 1994	23,292	1.016	1.009	1.057	1.179	1.120	0.913
		(0.011)	(0.010)	(0.009)	(0.020)	(0.011)	(0.011)
1995	23,292	1.028	0.986	1.055	1.162	1.124	0.907
		(0.011)	(0.010)	(0.009)	(0.022)	(0.011)	(0.011)
1996	23,292	1.018	0.988	1.050	1.141	1.153	0.905
		(0.011)	(0.010)	(0.009)	(0.022)	(0.011)	(0.011)
1997	23,292	1.010	1.002	1.055	1.149	1.146	0.902
		(0.011)	(0.010)	(0.010)	(0.023)	(0.012)	(0.011)
Non-manufacturing							
Over 20 employees	11,635	0.992	1.104	1.086	1.150	1.146	0.857
		(0.013)	(0.014)	(0.017)	(0.056)	(0.023)	(0.023)
Over 50 employees	3,648	0.970	1.146	1.114	0.847	1.229	0.875
		(0.026)	(0.030)	(0.036)	(0.150)	(0.064)	(0.070)
Over 100 employees	1,705	1.013	1.280	1.166	0.551	1.305	0.871
		(0.036)	(0.047)	(0.056)	(0.240)	(0.133)	(0.167)
Retail and non retail trade (U8)	32,761	1.026	1.013	0.916	1.197	1.130	0.893
		(0.007)	(0.009)	(0.008)	(0.020)	(0.008)	(0.008)
of which: Drugstores	5,226	1.017	0.938	0.859	1.165	1.084	0.861
		(0.019)	(0.042)	(0.033)	(0.052)	(0.018)	(0.028)
Transport. and comm. (U9)	5,319	1.062	1.046	1.015	1.088	1.157	0.877
		(0.020)	(0.039)	(0.019)	(0.075)	(0.022)	(0.024)
Services (U10)	16,496	0.963	1.030	0.860	0.978	1.082	0.932
		(0.009)	(0.009)	(0.009)	(0.020)	(0.011)	(0.011)
Created before 1980	24,942	1.005	1.027	0.913	1.118	1.172	0.878
		(0.008)	(0.010)	(0.009)	(0.025)	(0.010)	(0.009)
after 1981	29,634	1.017	1.021	0.923	1.094	1.091	0.922
		(0.007)	(0.008)	(0.007)	(0.017)	(0.008)	(0.008)
Assumption (8a)	54,576	1.014	1.023	0.917	1.097	1.121	0.898
		(0.005)	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)
(8b)	54,576	1.010	1.023	0.927	1.095	1.124	0.897
		(0.005)	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)
(8c)	54,576	1.020	1.023	0.894	1.120	1.128	0.893
		(0.005)	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)

Note.—Regressions on some sub-samples and with different assumptions. Linear specification, markdown equation. N.Obs is the number of firms in the sub-sample. Controls used are as in table 4. Standard errors are robust to heteroskedasticity. The lines labeled "Assumption" refer to the equations labeled as such in the article, concerning the treatment of the log of mean wage in each firm in the markdown equation.