WOMEN MAKE A FRACTION OF EVERY EURO EARNED BY MEN...

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Women Make a Fraction of Every Euro Earned by Men…

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Abstract – *This paper is about estimating gender wage discrimination using* firm-level *data, covering the 2002-2010 period, for the Belgian private economy. Compared to worker-level wage data, firm-level data present the advantage of containing an independent measure of productivity. Using the framework assembled by Hellerstein-Neumark, they permit separate estimations of gender-wage and gender-productivity gaps; and also — something crucial for the evaluation of gender wage discrimination — of the degree of (non) alignment of these two gaps. Results are essentially twofold. First, gender wage discrimination estimated using firm-level evidence is small compare to worker-level earnings-regression estimates. Second, in the case of Belgium's private economy during the 2000s, it is only statistically significant for female blue collars.*

Keywords: *gender wage discrimination, labour productivity, structural production function estimation, firm-level panel data*

JEL Classification: *J24, C52, D24*

Résumé – *Ce texte relate un effort d'estimation de la discrimination salariale selon le genre au moyen de* données de firmes *privées situées en Belgique, et couvrant la période 2002-2010. Par rapport aux données individuelles sur les salaires, les données de firme présentent l'avantage de contenir une mesure indépendante et directe de la productivité. En utilisant le cadre analytique d'Hellerstein-Neumark, ces données permettent des estimations distinctes des écarts salariaux et de productivité selon le genre, et aussi – chose cruciale s'agissant de discrimination salariale – du degré de (non-)alignement de ces écarts. Les résultats sont essentiellement de deux ordres. Un, la discrimination salariale selon le genre estimée au moyen des données de firmes est faible comparativement à celle traditionnellement obtenue au moyen de données salariales individuelles. Deux, pour le secteur privé belge, au cours des années 2000, elle n'est statistiquement significative que dans le cas des femmes travaillant sous contrat ouvrier.*

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1 INTRODUCTION

Evidence of substantial earning differences between men and women – often termed the gender wage gap – is a systematic and persistent social outcome in the labour markets of most developed economies. In 1999, the gross pay differential between women and men in the EU-27 was, on average, 16% (European Commission, 2007), while in the U.S. this figure amounted to 23.5% (Blau & Kahn, 2000). Belgian statistics (Institut pour l'égalité des Femmes et des Hommes, 2013) point at an annual gender wage gap of 23%. But women tend to work less hours: taking this into account implies that women earn about 10% less per hour of work than men.[1] Although historically decreasing the gender wage differential, and particularly the objective of further reducing its magnitude, remains a central political objective in governments' agendas both in Europe and in the U.S.

Gender wage differences correspond to what people commonly consider as gender wage discrimination. Strictly speaking however, from an economic point of view, gender wage discrimination requires more: it implies that equal labour services provided by equally-productive workers have a sustained wage difference. This question has motivated the emergence of diverse concepts and theories of wage discrimination. Starting with Becker (1957) several theoretical models have been proposed to describe the emergence and persistence of wage discrimination under diverse economic settings. The development of a theoretical literature on gender wage discrimination was also accompanied by an abundant empirical work, aimed at properly measuring the magnitude of gender wage discrimination and its determinants (Heckman, 1998). This paper belongs to the latter strain of the literature.

Among economists, the standard empirical approach to the measurement of gender wage discrimination consists of estimating earnings/wage equation using individual-level data; often by applying Oaxaca (1973) and Blinder (1973) decomposition methods.[2] Wage discrimination is measured as the average mark-up on some measure of individual compensation (hourly, monthly wages...), associated to the membership to the minority group, controlling for individual productivity-related characteristics (*i.e.* the effect of differing human capital endowments, diploma, labour-market experience…). In short, it amounts to systematically different remunerations among individuals with the same endowments. The main shortcoming of this approach is that its identification strategy relies on the assumption that individuals are homogeneous in any productivity-related characteristic not included in the set of variables describing individuals' endowment. What is almost invariably missing from most existing studies is an independent measure of productivity.

1. These are figures for the private sector. The gender wage gap in the public sector is only 5 %.
2. For a recent application of this decomposition method to individual, worker-level, Belgian data see Rycx and Tojerow (2002).

2 DATA & METHODOLOGY

By contrast, in this paper, we use firm-level data. More precisely, we use a panel (32,417 firm-year observations) that covers the same firms from 2002 to 2010. The data forming this panel come from Bel-first and the Crossroads Bank for Social Security (CBSS).[3] All monetary values are expressed in nominal terms. We augment it with information about the level and the structure of the workforce (total number of workers in full-time equivalent (FTE)[4]), share of male vs. female workers…) by aggregation of our CBSS worker-level panel data. Descriptive statistics are presented in Tables 1-2.

Table 1. Bel-first & CBSS 2002-2010: mean of main variables

Year	Labour prod.(fte$) [log of]	Gr. wage EUR (fte$) [log of]	Capital th. EUR [log of]	Labour(fte$) [log of]	Mat. [log of]	Share workers$				
						Fem.	Fem BC[a]	Male BC[a]	Fem WC[b]	Male WC[b]
2002	4.268	3.699	6.895	3.144	8.699	0.267	0.067	0.457	0.200	0.276
2003	4.264	3.690	6.981	3.191	8.743	0.269	0.067	0.454	0.202	0.277
2004	4.309	3.721	7.058	3.213	8.825	0.273	0.067	0.450	0.205	0.277
2005	4.319	3.749	7.151	3.242	8.871	0.272	0.068	0.449	0.204	0.280
2006	4.352	3.777	7.274	3.285	8.947	0.273	0.066	0.447	0.206	0.280
2007	4.409	3.802	7.376	3.318	9.033	0.270	0.064	0.449	0.207	0.281
2008	4.412	3.844	7.456	3.350	9.040	0.270	0.064	0.449	0.207	0.281
2009	4.394	3.872	7.498	3.338	8.891	0.273	0.061	0.441	0.211	0.286
2010	4.448	3.888	7.561	3.310	8.962	0.273	0.061	0.436	0.212	0.291
N	32,417									

$: Based on full-time equivalent, computed using quarterly working time.
a: Blue collar. b: While collar.

These data permit a distinct estimation of gender-productivity and gender-wage gaps via the estimation of, respectively, a production and a wage/pay functions; with both functions expanded by the specification of a labour-quality index à-la-Hellerstein *et al.* (1999) (HN henceforth).[5] Under proper assumptions (see Box 1) the econometric estimation of these functions delivers separate estimates of the relative marginal productivity and wage of women. And assessing the (non)-equality of these two estimates provides a direct test for gender wage discrimination.

One advantage of HN is that it does not rely on productivity proxies taken at the individual level, known to be difficult to measure with precision, but rather at a more aggregate level, for groups of workers inside firms. Compared to

3. https://belfirst.bvdinfo.com, https://www.ksz-bcss.fgov.be/en
4. Number of individuals in the firm as the sum of their working time (reported as a fraction of the full-time quarterly number of hours).
5. The key idea of HN is to impose a production function or a wage function with heterogeneous labour input where different types (e.g. men/women, young/old) diverge in terms of productivity and/or pay.

decompositions based on earning equations, it avoids identifying as gender discrimination wage differences that can be ascribed to gender productivity differences.

Table 2. Crossroads Bank for Social Security (CBSS) 2002-2010. Within firm gender wage ratio, by year

Year	Female/male ratio		
	All [fte$]	Blue collar [fte$]	White collar[fte$]
2002	0.879	0.886	0.784
2003	0.894	0.881	0.786
2004	0.893	0.881	0.790
2005	0.899	0.887	0.796
2006	0.908	0.890	0.801
2007	0.913	0.892	0.803
2008	0.909	0.899	0.803
2009	0.923	0.900	0.811
2010	0.928	0.898	0.817
Total	**0.906**	**0.891**	**0.799**
N	30,244	13,266	26,245

$: Based on full-time equivalent, computed using quarterly working time.

As to the econometric methodology we adopt of a fully linearized Cobb-Douglas specification that allows us to estimate fixed effect models (FE hereafter) and thus to control for interfirm unobserved and time-invariant heterogeneity. We also implement econometric techniques to deal with the risk of endogeneity/simultaneity bias and the possibility of a strong correlation between the residual of the productivity and the labour cost equations (see Box 2).

Box 1. The Hellerstein-Neumark Methodology

Results presented here rest on the Hellerstein-Neumark approach to labour heterogeneity. To estimate productivity (and/or wage) profiles according to a given characteristic of the workforce (e.g.; age, gender or education attainment), following most authors in this area, we consider a Cobb-Douglas technology (Hellerstein *et al.*, 1999; van Ours & Stoeldraijer, 2011; Vandenberghe, 2011a,b):

$$ln Y_{it} = ln A + \alpha ln QL_{it} + \beta ln K_{it} \quad [1]$$

where: Y_{it} is the value added (productivity hereafter) in firm i at time t, QL_{it} is an aggregation of different types of workers, and K_{it} is the stock of capital.

The variable that reflects the heterogeneity of the workforce is *the quality of labour index* QL_{it}. Let L_{ijt} be the number of workers of type j (*e.g.* young / old; men/women; low/high educated) in firm i at time t, and μ_{ij} be their contribution to output. We assume that workers of various types are substitutable with different marginal products. As each type of worker *j* is assumed to be an input in quality of labour aggregate, the latter can be specified as:

$$QL_{it} = \Sigma_j \mu_{ij} L_{ijt} = \mu_{i0} L_{it} + \Sigma_{j>0} (\mu_{ij} - \mu_{i0}) L_{ijt} \quad [2]$$

where: $L_{it} \equiv \Sigma_j L_{ijt}$ is the total number of workers in the firm, μ_{i0} the marginal productivity of the reference category of workers (*e.g.* prime-age men) and μ_{ij} that of the other types of workers.

If we further assume that a worker has the same marginal product across firms, we can drop subscript *i* from the marginal productivity coefficients. After taking logarithms and doing some rearrangements equation (2) becomes:

$$ln\,QL_{it} = ln\,\mu_0 + ln\,L_{it} + ln\,(1 + \Sigma_{j>0} (\lambda_j - 1)\, S_{ijt}) \quad [3]$$

where $\lambda_j \equiv \mu_j/\mu_0$ is the relative marginal productivity of type *j* worker and $S_{ijt} \equiv L_{ijt}/L_{it}$ the share of type *j* workers over the total number of workers in firm *i* .

Since $ln\,(1 + x) \approx x$, we can linearize [3] by:

$$ln\,QL_{it} = ln\,\mu_0 + ln\,L_{it} + \Sigma_{j>0} (\lambda_k - 1)\, S_{jt} \quad [4$$

And the production function becomes:

$$ln\,Y_{it} = ln\,A + \alpha\,[ln\,\mu_0 + ln\,L_{it} + \Sigma_{j>0} (\lambda_j - 1)\, S_{ijt}] + \beta ln\,K_{it} \quad [5]$$

Or, equivalently, if $j = 0,1,\ldots N$ with $j = 0$ being the reference group (*e.g.* prime-age male workers)

$$y_{it} = B + \alpha l_{it} + \eta_1 S_{i1t} + \ldots\ \eta_N S_{iNt} + \beta k_{it} \quad [6]$$

where:

$$B = ln\,A + \alpha ln\,\mu_0\,;\ \lambda_j = \mu_j/\mu_0 \qquad j - = 1\ldots N$$

$$\eta_1 = \alpha(\lambda_1 - 1)\ \ldots.\ \eta_N = \alpha(\lambda_N - 1)$$

$$y_{it} = ln\,Y_{it}\,;\ l_{it} = ln\,L_{it}\,;\ k_{it} = ln\,K_{it}$$

Note first that [6], being loglinear in *S*, has coefficients that can be directly interpreted as the percentage change in the firm's average labour productivity of a 1 unit (here 100 percentage points) change of the considered type of workers' share among the employees of the firm. Note also that, strictly speaking, to obtain a type *j* worker's relative marginal productivity, (*i.e.* λ_j), coefficients η_j should be divided by α, and 1 needs to be added to the result.

A similar approach can be applied to a firm's labour cost leading to a very similar equation

$$w_{it} = B^w + \alpha^W l_{it} + \eta^W{}_1 S_{ij1t} + \ldots + \eta^W{}_N S_{iN\,t} + \beta^w k_{it} \quad [7]$$

where $\eta^w{}_1 = \alpha(\Phi_1 - 1)\ \ldots.\ \eta^w{}_N = \alpha(\Phi_N - 1)$ *containing the* relative marginal labour cost (*i.e.* Φ_j),

The key hypothesis test can now be easily formulated. Assuming spot labour markets and cost-minimizing firms the null hypothesis of alignment of productivity and labour cost ratio for type *k* worker implies $\lambda_j = \Phi_j$. Any negative (or positive) difference between these two coefficients is a measure of the degree of misalignment of relative marginal productivity and labour cost.

3 ECONOMETRIC ANALYSIS

Our main econometric results are reported in Tables 3-6. We present results of the estimation of productivity and wage under five alternative econometric strategies. The first strategy is the standard OLS using total variation (A). Then FE where parameters are estimated using only within-firm variation (B) – Box 2. Unobserved heterogeneity bias might be present since our sample covers all sectors of the Belgian private economy and the list of controls included in our models is limited. Even if the introduction of the set of dummies (namely year, NACE5 industry) in F_{it} can account for part of this heterogeneity bias, FE is still the most powerful way out. We also estimate the FE model via non-linear least-squares (thus relaxing the assumption that the HN quality index amounts to simple sum of shares) and allowing for correlation among productivity and wage equation residuals (NL-FE-SUR) (C). The last model (D) combines the FE and the LP intermediate proxy idea (Box 2). All models control for the age structure of the workforce (mean and interquartile dispersion) the blue-collar vs white collar composition, the industry to which the firm belongs (5-digit NACE 5) and the overall state of the economy when firms were observed through year fixed effects.

Box 2. Coping with the risk of unobserved firm-level heterogeneity and endogeneity/simultaneity

From the econometric standpoint, recent implementations of HN's methodology have tried to improve the estimation of the production function by the adoption of econometric techniques dealing with potential heterogeneity bias (unobserved time-invariant determinants of firms' productivity that are correlated with labour inputs) and simultaneity bias (endogeneity in input choices in the short run that includes firm's gender mix). A standard solution to the heterogeneity bias is to resort to fixed-effect analysis (FE); be it via first-differencing or mean-centring of panel data. As to the endogeneity bias, the past 15 years has seen the introduction of new identification techniques. Initially advocated by Olley and Pakes (1996) or more recently by Levinsohn and Petrin (2003) (LP), they consist of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity...) to "control" for (or proxy) unobserved idiosyncratic productivity shocks that are potentially correlated with firms' overall level of labour inputs, and in particular their gender mix.

In this paper, we follow these most recent applications of HN's methodology, that we implement econometrically by combining fixed effects with the LP strategy (LP-FE) using information on firms' varying level of intermediate consumption.[6] We implement HN using a large data set that matches firm-level data, retrieved from Bel-first, with worker-level data from Belgian's Social Security register containing detailed information about the characteristics of the employees in those firms (gender, blue vs white collar status); in particular their working time. We also allow for non-linearities in the specification of the labour quality index – Box 1, equ. [3]) (NL-FE). Following the seminal paper of Hellerstein and Neumark (1999) on

6. Raw materials & consumables.

estimating gender-wage discrimination using firm-level data, we also implement (LP-FE and NL-FE) in combination with seemingly-unrelated methods (SUR) that are aimed at controlling for potential correlation between productivity and wage equation residuals.

Tables 3-4 present the results where we only consider female workers against male workers. In Tables 5-6 we go beyond the simple distinction between men and women and consider the interaction of status (blue-collar/white collar) and gender. Referring to the HN modelling, this means estimating them with $j = 0,1,2,3$ categories of workers, where the reference category in our case corresponds to blue-collar men. Note that the white vs. blue-collar female/male comparison is a way to somehow compensate for the lack of information on the level of education (which is one shortcoming of our data). Reported values in the upper parts of Tables 3-4 correspond to the productivity and wage coefficients. In the lower part of Tables 3-4 and in Tables 5-6 we report the implied values of marginal productivity (λ) and marginal wage (θ); and a series of crucial hypothesis tests: *i)* whether marginal productivity or wage is statistically difference from that of the reference category (i.e.; men in Tables 3-4 or blue-collar men in Tables 5-6); and *ii)* whether marginal productivity and pay are aligned. It is the latter test that is crucial to determine the presence or absence of gender wage discrimination.

In Table 3, OLS (A) suggest that a typical female worker is only paid 77.6%-points of the sum received by male workers. But the main interest firm-level data is that the separately deliver estimates of women's relative productivity. And the first column of Table 3 suggests it is only .79 (of the male reference). The difference between this productivity gap and the above wage gap is positive, but not statistically significant. Thus, OLS results support the idea of no wage discrimination in the Belgian private economy.

Turning to FE estimates (B), we have that our parameters – including the implied marginal productivity and wage reported at the bottom of the Table – are solely estimated by the within-firm variation. As one would expect in the presence of gender employment *segregation* – i.e. the propensity of women to concentrate in firms that are intrinsically less productive – FE estimation reduces the magnitude women' productivity handicap vis-à-vis men. At the bottom of Column 1 in the right-hand part of Table 3 we see that women's relative marginal productivity is estimated to be .907 of that of men (compared to .776 with OLS). Simultaneously, their relative marginal pay is estimated to be .85 (compared to .79 with OLS) of the male equivalent. This hints at slightly larger .05 gender wage gap. However, the latter gap remains not statistically significant.

Table 4 contains the results delivered by our preferred models. These control simultaneously for firm unobserved heterogeneity (i.e. firm fixed effects FE) and either *i)* the possibility of non-linearities in the HN labour-quality index (NL-FE) or *ii)* a simultaneity bias à-la-Levinsohn-Petrin (LP-FE). Both models also allow for some correlation between the productivity and wage equations residuals (SUR). In short these methods deliver results that are qualitatively like those on display in Table 3: within firms, women appear significantly less productive than their male peers, with a relative marginal productivity of .82 to .91. Simultaneously, they wage turns out to be only .78. to .849 of the male equivalent. Both methods point as gender wage discrimination ranging from .036 to .064. But again, none of these values are statistically significant.

Tables 5-6 report the results, replicating these 4 estimations when gender is combined with the blue vs white-collar status. OLS results (A) in Table 5 about marginal productivity suggest that female blue collars produce .77 as much as their male blue collar peers (the ref. group). White-collar women appear .35 more productive than the ref. group, whereas white-collar males show a .548 productivity advantage. A similar hierarchy is visible in terms of wages. But we now observe a statistically-significant misalignment of productivity and wage for blue-collar female workers, of about .18. This result is confirmed when resorting to within-firm-only variance (FE) (B). This is supportive of gender wage discrimination against blue-collar female workers. In the case of white-collar female workers, the corresponding OLS estimate (.044) is not statistically significant, and the FE estimate (.095) is only significant at the 5% threshold. Turning to our preferred models (Table 6), we get the confirmation that marginal productivity and wage are aligned for white-collar women. This is supportive of the absence of gender wage discrimination. However, for blue-collar women, we find confirmation of the evidence delivered by OLS and FE; women forming that category get paid below their marginal productivity in the range of .19 to .25; something which is consistent with gender wage discrimination.

From an econometric point of view, it is worth stressing the dramatic reduction of the female blue-collar productivity handicap from OLS to FE (Table 5). It means that the concentration of low-educated women in intrinsically less productive firms is a major source of underestimation of their relative productivity. The various estimates of wage are also affected by the within/FE transformation, although to a lesser extent.

As to the simultaneity bias, its magnitude can be evaluated by comparing the results of the two models in Table 6. Based on Belgian evidence summarized in Meulders & Sissoko (2002), we were convinced that, if anything, the presence of simultaneity bias would lead to an overestimation of female productivity with methods that do not explicitly account for that particular bias. Since in Belgium temporary contract employment is asymmetrically concentrated in female employment, we should expect that, if temporary employment is one, or the main, labour-adjustment variable to unobserved changes in firms' economic environments, the share of female employment should increase in periods of positive productivity changes and decrease in periods of negative productivity changes. This would generate a positive correlation between the share of females in the workforce and firms' productivity, thereby leading OLS or NL-FE to underestimate the gender productivity differential.[7] But our results invalidate this prediction: LP-FE model (D) estimates are much in line with those of NL-FE.

7. In absolute value.

Table 3. Firm-level estimation of the gender wage gap (2002-2010). Estimation of Productivity, wage and gross profit Equations – OLS & Fixed effects(FE)

	OLS (A)			FE (B)		
	Productivity (η)	**Wage** (η^W)	**Profit** ($\eta^P = \eta - \eta^W$)	**Productivity** (η)	**Wage** (η^W)	**Profit** ($\eta^P = \eta - \eta^W$)
Share female	–0.1711***	–0.2267***	0.0556***	–0.0618*	–0.1504***	0.0887***
	(0.0160)	**(0.0058)**	(0.0153)	(0.0253)	(0.0067)	(0.0255)
Nobs	32,417					
R^2	.5	.7	.37	.83	.95	.76
Control var.	Mean age, p25 age p75age share blue collars, NACE5 & year FE			Mean age, p25 age p75age share blue collars, NACE5 & year FE		
	Implied marginal productivity and wage (ref = male)					
	All female					
λ *(marginal prod)*	0.790***			0.907*		
Prob $\lambda = 1$	0.000			0.015		
Φ *(marginal wage)*		0.776***			0.850***	
Prob $\Phi = 1$		0.000			0.000	
$\lambda - \Phi$ *(alignment)*			0.014			0.057
Prob $\lambda = \Phi$			0.440			0.135

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4. Firm-level estimation of the gender wage gap (2002-2010). Estimation of productivity and wage equations – Non-linear FE + SUR[a], Levinsohn-Petrin & FE +SUR[b]

	NL-FE [SUR][a] (C)	LP-FE[SUR][b] (D)
η *(share female)* [productivity equ.]	–0.0874*	–0.1149**
	(0.0353)	(0.0412)
η^W *(share female)* [wage equ.]	–0.1509***	–0.2133***
	(0.0062)	(0.0091)
Nobs	32,417	17,258
Control var.	Mean age, p25 age p75age share blue collars, **firm** & year FE	
	Implied marginal productivity and wage (ref = male)	
	All female	
λ *(marginal prod)*	0.913*	0.819**
Prob $\lambda = 1$	0.013	0.005
Φ *(marginal wage)*	0.849***	0.783***
Prob $\Phi = 1$	0.000	0.000
λ-Φ *(alignment)*	0.064	0.036
Prob $\lambda = \Phi$	0.072	0.581

a=: estimated using (non-linear) seemingly (un)related regression.
b=: estimated using seemingly (un)related regression.
Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5. Firm-level estimation of the gender wage gap (2002-2010): blue vs withe-collar breakdown. Estimation of productivity, wage and gross profit equations – OLS & Fixed effects(FE)

	OLS (A)			FE (B)		
	Productivity (η)	Wage (η^W)	Profit ($\eta^P = \eta - \eta^W$)	Productivity (η)	Wage (η^W)	Profit ($\eta^P = \eta - \eta^W$)
Control var.	Mean age, p25 age p75age share blue collars, firm & year FE					
Implied marginal productivity and wage (ref = blue-collar male)						
Blue-collar Female						
λ *(marginal prod)*	0.772***			1.077		
Prob $\lambda = 1$	0.000			0.257		
Φ *(marginal wage)*		0.818***			0.818***	
Prob $\Phi = 1$		0.000			0.000	
$\lambda - \Phi$ *(alignment)*			0.186**			0.187**
Prob $\lambda = \Phi$			0.001			0.007
White-collar Female						
λ *(marginal prod)*	1.352***			1.218***		
Prob $\lambda = 1$	0.000			0.000		
Φ *(marginal wage)*		1.182***			1.182***	
Prob $\Phi = 1$		0.000			0.000	
$\lambda - \Phi$ *(alignment)*			0.044			0.095*
Prob $\lambda = \Phi$			0.249			0.042

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Firm-level estimation of the gender wage gap (2002-2010): blue vs withe-collar breakdown. Estimation of productivity, and wage equations – Non-linear FE + SUR[a], Levinsohn-Petrin & FE +SUR[b]

	NL-FE [SUR][a] (C)	LP-FE [SUR][b] (D)
Control var.	Mean age, p25 age p75age share blue collars, firm & year FE	
Implied marginal productivity and wage (ref = blue-collar male)		
Blue-collar Female		
λ *(marginal prod)*	1.059	1.029
Prob $\lambda = 1$	0.351	0.825
Φ *(marginal wage)*	0.866***	0.777***
Prob $\Phi = 1$	0.000	0.000
$\lambda - \Phi$ *(alignment)*	0.194**	0.251*
Prob $\lambda = \Phi$	0.002	0.042

	While-collar Female	
λ (marginal prod)	1.215***	1.192**
Prob $\lambda = 1$	0.000	0.010
Φ (marginal wage)	1.148***	1.125***
Prob $\Phi = 1$	0.000	0.000
λ – Φ (alignment)	0.067	0.080
Prob $\lambda = \Phi$	0.119	0.195

a=: estimated using (non-linear) seemingly (un)related regression.

b=: estimated using seemingly (un)related regression.

standard errors in parentheses,

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 CONCLUSION

In this paper — in contrast with so many other papers using *individual* earnings decomposition methods — we use *firm-level* data to test for the presence of gender wage discrimination. Our results are essentially fourfold. First, our firm-level analysis is consistent with evidence obtained by the previous studies of the gender wage gap in the Belgian labour market (Rycx & Tojerow, 2002; Meulders & Sissoko, 2002; Garnero, Kampelmann & Rycx, 2014), in the sense that it systematically points at lower pay for women. We estimate here that, within private for-profit firms located in Belgium, during the year 2000s, female workers made only 78 to 84.9 cents for every euro earned by men. Second, separately we can estimate gender productivity gaps. And these show that female workers achieve a marginal productivity that is only .82 to .91 of the male equivalent. Third, the difference between the wage and the productivity gaps points at gender wage discrimination in the range of 3.6 to 6.4%-points; which is much less than traditional estimates delivered by individual-level wage regressions. What is more, none of these differences are statistically significant at the 5% threshold. Fourth, a closer examination of our data reveals that this conclusion is essentially true for (broadly defined) white-collar women. For the now relatively smaller category of blue-collar women, there is still evidence of wages being significantly inferior to productivity.

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