Firm-level Evidence on Gender Wage Discrimination in the Belgian Private Economy

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Abstract

In this paper we explore a matched employer-employee data set to investigate the presence of gender wage discrimination in the Belgian private economy labour market. Contrary to many existing papers, we analyse gender wage discrimination using an independent productivity measure. Using firm-level data, we are able to compare direct estimates of a gender productivity differential with those of a gender wage differential. We take advantage of the panel structure to identify gender-related differences from within-firm variation. Moreover, inspired by recent developments in the production function estimation literature, we address the problem of endogeneity of the gender mix using a structural production function estimator (Olley & Pakes, 1996; Levinsohn & Petrin, 2003) alongside IV-GMM methods where lagged value of labour inputs are used as instruments. Our results suggest that there is no gender wage discrimination inside private firms located in Belgium, on the contrary.

JEL Classification: J24, C52, D24

Keywords: gender wage discrimination; labour productivity; structural production function estimation; IV-GMM; firm-level panel data.

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1. Introduction

Evidence of substantial average earning differences between men and women — what is often termed the gender wage gap — is a systematic and persistent social outcome in the labour markets of most developed economies. This social outcome is often perceived as inequitable by a large section of the population and it is generally agreed that its causes are complex, difficult to disentangle and controversial (Cain, 1986). 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 and Kahn, 2000). Belgian statistics (Institut pour l'égalité des Femmes et des Hommes, 2006) suggest gross monthly gender wage differentials ranging from 30% for white-collar workers to 21% for blue-collar workers.[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. The gender wage differential provides a measure of what Cain (1986) considers the practical definition of gender discrimination. In Cain's conceptual framework gender discrimination, as measured by the gender wage differential, is an observed and quantified outcome that concerns individual members of a minority group, women, and that manifests itself by a lower pay with respect to the majority group, men. Strictly speaking however, from an economic point of view, gender wage *discrimination* requires more that wage differences between men and women. It implies that equal labour services provided by equally productive workers have a sustained price/wage difference.[2]

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. But the development of a theoretical literature on gender wage discrimination was accompanied by empirical work measuring some concept of gender wage discrimination. And this paper belongs to the latter strain of the literature.

[1] These are figures for the private sector. The gap in the public sector is only 5%.
[2] In this paper, we will refer to labour costs differences and assume that they are good proxies for wages.

1.1. Oaxaca-Blinder earnings decomposition

The standard empirical approach among economists to the measurement of gender wage discrimination consists of estimating earning equations and applying Oaxaca (1973) and Blinder (1973) decomposition methods.[3] 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. With Blinder-Oaxaca decomposition methods the difference in the average wage of the minority group relative to the majority group is explained by what Beblo *et al.* (2003) call the endowment effect (*i.e.* the effect of differing human capital endowments, diploma, experience but also ability) and the remuneration effect (*i.e.* different remunerations of the same endowments). And the remuneration effect has been traditionally interpreted as a measure of wage discrimination in the labour market.

The main shortcoming of this approach is that its identification strategy relies on the assumption that individuals are homogeneous in any productivity-related characteristic that is not included in the set of variables describing individuals' endowment. Two problems, one theoretical and another empirical, emerge. First, the researcher has to choose a set of potential individual productivity-related characteristics (diploma, experience, ability…). Second, he needs to find or create appropriate measures of those characteristics. While the second problem is becoming more manageable with the recent availability of rich individual-level data sets, the first problem can never be fully solved without using some measure of individual productivity. Furthermore, insofar has discrimination affects individual choices regarding human capital decisions or occupational choices, the measure of discrimination obtained from wage equations will likely understate discrimination (Altonji & Blank, 1999).

Studies of narrowly-defined occupations and audit studies attempt to provide escape routes from these problems. They estimate gender wage differentials in specific occupations assuming that sector-specificity is sufficient to eliminate the heterogeneity in workers' productivity-related characteristics (Gunderson, 2006). In our view, this approach suffers from two drawbacks. First, assuming away the omitted-variable bias is never fully satisfactory from the methodological point of view. Second, the identification of gender discrimination is subject to sector- and occupation-specific biases, *e.g* presence of rents that allow employers to indulge in gender discrimination etc. Audit studies, *e.g*. Neumark (1996), directly test for employment rather than wage discrimination

[3] For a recent application of this decomposition method to individual, worker-level, panel data see Pfeifer & Sohr (2009). For an application to Belgian data see Rycx & Tojerow (2002).

by comparing the probability of being interviewed and the probability of being hired of essentially identical individuals aside from the membership to the minority group. Audit studies also face serious empirical challenges in ensuring that their methodological requirements are satisfied (*e.g.* guaranteeing a large number of testers, auditors homogeneity etc.). More importantly, audit studies do not identify employment discrimination occurring at the market level. Indeed, Heckman (1998) notes that «a well-designed audit study could uncover many individual firms that discriminate, while at the same time the marginal effect of discrimination on the wages of the employed workers could be zero».

1.2. Comparison of firm-level productivity and labour costs

In short, what is almost invariably missing from the above studies is an independent measure of productivity. Most use observable individual-level characteristics that are presumed to be proxies for productivity. By contrast, in this paper we use firm-level direct measures of gender productivity and wage differentials via, respectively, the estimation of a production function and a labour cost equation, both expanded by the specification of a labour-quality index à-la-Hellerstein & Neumark (1999) (HN henceforth).[4] Under proper assumptions (see Section 2) the comparison of these two estimates provides a direct test for gender wage discrimination.

One advantage of this setting is that it does not rely on productivity indicators taken at the individual level, which are known to be difficult to measure with precision, but rather at the aggregate level, namely, for groups of workers. Moreover, because this approach uses information about firms of all sectors of the economy it properly measures, and tests for, a concept of market-wide gender discrimination**:** situations where numerous equally productive workers systematically earn different wages. It addresses some of the main identification problems of the empirical methodologies briefly reviewed above. Of course, in spite of its power the gender discrimination test developed and implemented in this paper is not bullet-proof. However, compared to Oaxaca-Blinder decompositions based on earnings equations, it avoids identifying as gender discrimination wage differences that can be ascribed to gender productivity differences.

More specifically, we implement HN using a large data set that matches firm-level data, retrieved from Belfirst[5], with data from Belgian's Social Security register containing detailed information

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[4] The key idea of HN is to impose a production function or a labour cost function with heterogeneous labour input where different types (e.g. men/women, young/old) diverge in terms of productivity and/or cost.

[5] http://www.bvdep.com/en/bel-first.html

about the characteristics of the employees in those firms. We show the HN approach can be used to directly measure gender wage discrimination as the *gap* between a measure of women's compensation relative to men's (the gender wage differential)[6] and a measure of women's productivity relative to men's (the gender productivity differential).

HN's methodology has also been used to test other wage formation theories, most notably those investigating the relationship between wages and productivity along age profiles, *e.g.* Hellerstein *et al.* (1999), Vandenberghe & Waltenberg (2010), Vandenberghe (2011). But applications of the HN methodology also comprises the analysis of race, education and marital status, e.g. Hellerstein *et al*. (1999) or Crépon, Deniau & Pérez-Duarte (2002). In this paper, we focus exclusively on gender and the interaction between gender and the worker's blue- vs. white-collar labour market status. [7]

From the econometric standpoint, recent developments of HN's methodology have tried to improve the estimation of the production function by the adoption of alternative techniques to deal 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 henceforth) 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 (see Ackerberg, Caves & Frazer, 2006 for a recent review). One set of techniques follows the dynamic panel literature (Arellano & Bond, 1991; Aubert & Crépon, 2003; Blundell & Bond, 2000; van Ours & Stoeldraijer, 2011), which basically consists of using lagged values of labour inputs as instrumental variables (IV-GMM henceforth). A second set of techniques, initially advocated by Olley & Pakes (1996) or more recently by Levinsohn & Petrin (2003) (LP henceforth) are somewhat more structural in nature. They consists of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity...) to "control" for (or proxy) unobserved productivity shocks.

In this paper, we follow these most recent applications of HN's methodology. We combine and

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[6] Our measure exploits labour costs data (that include gross wage and social security contributions) which are very good proxy of what employees get paid.

[7] Historically in Belgium, white collars (or "employees") were those performing work that requires predominantly mental rather than physical effort (presumably educated people thus), whereas the blue collars (or "workmen") were employed in manual/ unskilled labour. But that distinction has partially lost its relevance, particularly for the white-collar group that now encompasses a rather heterogeneous set of activities and levels of education. The distinction also largely recoups separate industrial relation arrangements (different rights and obligations in terms of notice period, access to unemployment insurance benefits…).

compare all the above-mentioned econometric techniques (FE, IV-GMM, OP-LP). Our main results about gender wage discrimination are all based on within-firm variation that we derive from the use of FE. To control for the potential endogeneity in labour input choice, in particular that of the share of women employed by firms, we combine FE with both IV-GMM techniques and the LP intermediate-goods proxy technique that we implement using information on firms' varying level of intermediate consumption. [8]

Our preferred estimates indicate that the cost of employing women[9] is 3 to 8 %-points lower than that of men, pointing at a wage differential of similar magnitude. But on average, women's collective contribution to a firm's value added (i.e. productivity) is estimated to be about 16 to 17 %-points lower than that of the group of male workers. The key result of the paper is thus that female workers they get paid 11 to 14 %-points more than what their (relative) productivity would imply. Our labour cost estimates are consistent with evidence obtained by the previous studies of the gender wage gap in the Belgian labour market (Rycx, & Tojerow, 2002; Meulders & Sissoko, 2002), in the sense that they systematically point at lower pay for women. But our work adds new key results to that evidence. Our direct estimates of gender productivity differences and show indeed that firm employing more women also generate significantly less value added *ceteris paribus*.

The rest of the paper is organised in the following way. In Section 2 we review the algebra underpinning the HN methodology and explain how it can be used to assess gender wage discrimination. Section 3 describes the data and presents summary statistics. In Section 4 we present, discuss and interpret the results of our preferred econometric specifications. Section 5 summarizes and concludes our analysis.

2 Econometric modelling and methodology

In order to estimate gender productivity profiles, following authors interested in understanding how workers' characteristics (age, race, marital status, education or gender) influence firms'

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8 It is calculated here as the differences between the firm's turnover (in nominal terms) and its net value-added. It reflects the value of goods and services consumed or used up as inputs in production by enterprises, including raw materials, services bought on the market.

9 And presumably their wage.

productivity, we consider a Cobb-Douglas production function (Hellerstein *et al.*, 1999; Aubert & Crépon, 2003, 2007; Dostie, 2006; van Ours & Stoeldraijer, 2011):

$$ln\ (Y_{it}\ /L_{it}\ )=lnA + \alpha\ ln\ QL_{it} + \beta\ lnK_{it} - lnL_{it} \qquad (1)$$

where: $Y_{it}\ /L_{it}$ is the average value added per worker (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 key variable in this production function is the quality of labour aggregate QL_{it}. Let F_{it} be the number of female workers in firm i at time t. We assume that male and female are substitutable with different marginal products. And each gender is assumed to be an input in quality of labour aggregate. The latter can be specified as:

$$QL_{it} = \mu_{iM}\ M_{it} + \mu_{iF}\ F_{it} = \mu_{iM}\ L_{it} + (\mu_{iF} - \mu_{iM})F_{it} \qquad (2)$$

where: $L_{it} \equiv F_{it} + M_{it}$ is the total number of workers in the firm, μ_{iM} the marginal productivity of men (i.e. reference) and μ_{iF} that of their female colleagues.

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

$$ln\ QL_{it} = ln\ \mu_M + lnL_{it} + ln\ (1+ (\lambda_F - 1)\ SF_{it}) \qquad (3)$$

where $\lambda_F \equiv \mu_F/\mu_M$ is the relative marginal productivity of female k worker and $SF_{it} \equiv F_{it}/L_{it}$ the share of female workers over the firms' total workforce .

Since $ln(1+x) \approx x$ for small values of x, we can approximate (3) by:

$$ln\ QL_{it} = ln\ \mu_M + ln\ L_{it} + (\lambda_F - 1)\ SF_{it} \qquad (4)$$

And the production function becomes:

$$ln\ (Y_{it}\ /L_{it}\ )=lnA+ \alpha\ [ln\mu_M + ln\ L_{it} + (\lambda_F -1)\ SF_{it}] + \beta\ lnK_{it} - lnL_{it} \qquad (5)$$

Or, equivalently,

$ln\ (Y_{it}/L_{it})=B + (\alpha\text{-}1)l_{it} + \eta SF_{it} + \beta\ k_{it}$ (6)

where:

$B=lnA+\alpha\ ln\ \mu_M$
$\eta= \alpha\ (\lambda_F - 1)$
$\lambda_F=\mu_F/\mu_M$

….

$l_{it}=lnL_{it}$
$k_{it}=lnK_{it}$

Note first that (6) being loglinear in *SF* the coefficient η measures the percentage change in the firm's average labour productivity of a 1 unit (here 100 percentage points) change of female share of the employees of the firm; in other words the productivity differential characterizing women vis-à-vis men.

A similar approach can be applied to a firm's average (per employee) labour cost. If we assume that firms operate in the same labour market they pay the same wages to the same category of workers. We can thus drop subscript *i* from the remuneration coefficient. Let π_F stand for the remuneration of female workers (male being the reference). By definition, the overall average labour cost equals the sum of what is spent on male workers ($\pi_M\ M_{it}$) and female workers ($\pi_F\ F_{it}$) divided by total workforce

$$W_{it}/L_{it}= (\pi_M\ M_{it} +\pi_F\ F_{it})\ /L_{it}$$

or equivalently

$$W_{it}/L_{it} = \pi_M + (\pi_F - \pi_M)\ F_{it}/L_{it}= \pi_M\ (1+ (\pi_F/\pi_M - 1)\ F_{it}/L_{it} \qquad (7)$$

Taking the logarithm and using again $log(1+x)\approx x$, one can approximate this by:

$$ln(W_{it}/L_{it})= ln\ \pi_M+ (\Phi_F - 1)\ SF_{it} \qquad (8)$$

where the Greek letter $\Phi_F \equiv \pi_F/\ \pi_M$ denotes the relative remuneration of female with respect to male workers, and $SF_{it}= F_{it}/L_{it}$ is again the proportion/share of female workers over the total number of workers in firm *i* .

The logarithm of the average labour cost becomes:

$$ln\ (W_{it}/L_{it}) = B^w + \eta^w SF_{it} \qquad (9)$$

where:

$$B^w = ln\ \pi_M$$
$$\eta^{\boldsymbol{w}} = (\Phi_F - 1)$$
$$\Phi_F \equiv \pi_F / \pi_M$$

Like in the productivity equation (6) coefficient η^w captures the sensitivity of labour cost to marginal changes of the workforce gender structure (SF_{ik}); in other words, the labour cost differential characterizing women vis-à-vis men.

Formulating the key hypothesis test of this paper is now straightforward. The null hypothesis of no gender wage discrimination for female workers implies $\eta = \eta^w$. Any negative (or positive) gap between these two coefficients can be interpreted as a quantitative measure of the propensity of firms to pay women below (or above) their relative productivity. This is a test that can easily implemented if we adopt strictly equivalent econometric specifications[10] for the average productivity and average labour cost; in particular if we introduce firm size *(l)* and capital stock (*k*) in the labour cost equation (9).

$$ln\ (Y_{it}/L_{it}) = B + (\alpha\text{-}l)l_{it} + \boldsymbol{\eta}\ SF_{it} + \beta\ k_{it} + \gamma F_{it} + \varepsilon_{it} \qquad (10)$$

$$ln\ (W_{it}/L_{it}) = B^W + (\alpha^w\text{-}l)l_{it} + \boldsymbol{\eta}^{\boldsymbol{w}}\ SF_{it} + \beta^w\ k_{it} + \gamma^w F_{it} + \varepsilon^w{}_{it} \qquad (11)$$

What is more, if we take the *difference* between the logarithms of average productivity (*Y/L*) (10) and labour costs[11] (*W/L*) (11) we get a direct expression of the productivity-labour costs ratio[12] as a linear function of its workforce determinants.

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[10] Note that these include a residual term and a set of controls *F*. More of the justification of these in the data section below.

[11] Labour costs used in this paper, which were measured independently of net-value added, include the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. The summary statistics of the variables in the data set are presented in Table 1.

[12] Measured in %. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e., percentage) differences: i.e. *(Y-W)/W.*

$$Ratio_{it} \equiv ln\ (Y_{it}\ /L_{it}) \text{-}\ ln\ (W_{it}\ /L_{it}) = ln\ (Y_{it}) \text{-}\ ln\ (W_{it}) = \ B^G + \alpha^G l_{it} + \boldsymbol{\eta}^{\boldsymbol{G}} SF_{it} + \beta^G\ k_{it} + \gamma^G F_{it}\ + \varepsilon^G{}_{it} \quad (12)$$

where: $B^{\boldsymbol{G}}$= B -B^w; α^G=α-α^w ;$\boldsymbol{\eta}^{\boldsymbol{G}}$**=** $\boldsymbol{\eta}$**-**$\boldsymbol{\eta}^{\boldsymbol{w}}$; $\beta^{G=}$ β- β^w ;γ^G= γ-γ^w and $\varepsilon^G{}_{it}$ =ε_{it} -$\varepsilon^w{}_{it}$.. It is immediate to see that the coefficient η^G of equation (12) provides a direct estimate of the *gap* that may exist between the marginal productivity and the labour cost differentials characterizing women vis-à-vis men.

Note also the inclusion in (10)(11) and (12) of the vector of controls F_{it}. It comprises the firm's total amount of capital (in logs). In all the estimations presented hereafter F_{it} also contains region[13], year and sector[14] dummies. This allows for systematic and proportional productivity variation among firms along these dimensions. This assumption can be seen to expand the model by controlling for year and sector- specific productivity shocks, labour quality and intensity of efficiency wages differentials across sectors and other sources of systematic productivity differentials (Hellerstein *et al.*, 1999). More importantly, since the data set we used does not contain sector price deflators, the introduction of these dummies can control for asymmetric variation in the price of firms' outputs at sector level. An extension along the same dimensions is made with respect to the labour costs equation. Of course, the assumption of segmented labour markets, implemented by adding linearly to the labour costs equation the set of dummies, is valid as long there is proportional variation in wages by gender along those dimensions (Hellerstein *et al*., 1999).

It is also important to stress that we systematic include in F_{it} firm-level information on the (log of) average number of hours worked annually per employee; obtained by dividing the total number of hours reportedly worked annually by the number of employees (full-time or part-time ones indistinctively). There is evidence in our data that average hours worked is negatively correlated with the share of female work: something that reflects women's higher propensity to work part-time, but that crucially needs to be controlled for to properly capture the productivity (and labour costs) effect of changes in the share of female work.

But, as to proper identification of the causal link between the productivity and the gender composition of the workforce, the main challenge consists of dealing with the various constituents of the residual ε_{it} of productivity equation (12). We assume that the latter has a structure that comprises three elements

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13 NUTS1 Belgian regions : Wallonia, Flanders and Brussels.
14 NACE2 level.

$$\varepsilon_{it} = \theta_i + \omega_{it} + \sigma_{it} \qquad (13)$$

where: $cov(\theta_i, SF_{it}) \neq 0$, $cov(\omega_{it}, SF_{it}) \neq 0$ and $E(\sigma_{it})=0$

The first two terms reflect elements of the firm's productivity that are know by the managers (but not by the econometrician) and influence input choice. The first one is time-invariant θ_i and amounts to a firm fixed effect. The second one ω_{it} is time-varying. The third term is a purely unanticipated and random productivity shock σ_{it}.

Parameter θ_i. in (13) represents firm-specific characteristics that are unobservable in our case but driving the average productivity. For example the vintage of capital in use, the overall stock of human capital[15], firm-specific managerial skills, location-driven comparative advantages[16]. And these might be correlated with the gender structure of the firm's workforce, and resulting in *heterogeneity bias* with OLS results. Women for instance might be underrepresented among plants built a long time ago using older technology.[17] However, the panel structure of our data allows us to estimate models with firm fixed effects (FE). The results from the FE estimation (using first-differences in our case) can be interpreted as follows: a group (e.g. male or female) is estimated to be more (less) productive than another group if, within firms, a increase of that group's share in the overall workforce translate into productivity gains (loss). Algebraically, the estimated FE model corresponds to

$$\Delta ln\ (Y_{it}/L_{it}) = \Delta B + (\alpha\text{-}l)\ \Delta l_{it} + \boldsymbol{\eta}\ \Delta SF_{it} + \beta\ \Delta k_{it} + \gamma \Delta F_{it} + \Delta\varepsilon_{it} \qquad (14)$$

$$\Delta ln\ (W_{it}/L_{it}) = \Delta B^{W} + (\alpha^{w}\text{-}l)\ \Delta l_{it} + \boldsymbol{\eta}^{\boldsymbol{w}}\ \Delta SF_{it} + \beta^{w}\ \Delta k_{it} + \gamma^{w} \Delta F_{it} + \Delta\varepsilon^{w}_{it} \qquad (15)$$

$$\Delta Ratio_{it} = \Delta B^{G} + \alpha^{G} \Delta l_{it} + \boldsymbol{\eta}^{\boldsymbol{G}} \Delta SF_{it} + \beta^{G}\ \Delta k_{it} + \gamma^{G} \Delta F_{it} + \Delta\varepsilon^{G}_{it} \qquad (16)$$

where the Δ operator reflects to demeaning or (as will be the case with our analysis) first differences. With FE estimation the error terms becomes:

$$\Delta\varepsilon_{it} = \Delta\omega_{it} + \Delta\sigma_{it} \qquad (17)$$

15 At least the part of that stock that is not affected by short-term recruitments and separations.

16 Motorway/airport in the vicinity of logistic firms for instance.

17 According to Hellerstein *et al.* (1999), the US evidence is that technological innovation has reduced the proportion of (predominantly male) production worker employment.

where $cov(\Delta\omega_{it}, \Delta SF_{it}) \neq 0$ and $E(\Delta\sigma_{it})=0$

This said, the greatest econometric challenge is to go around endogeneity bias stemming from the likely presence of the time-varying productivity term ω_{it} (Griliches & Mairesse, 1995). The economics underlying that concern is intuitive. In the short run firms could be confronted to productivity deviations ω_{it} (say, a positive deviation due to a turnover spike, itself the consequence of a successful sale opportunity). Contrary to the econometrician, firms may know about ω_{it} (and similarly about $\Delta\omega_{it}$) and respond by expanding recruitment of temporary- or part-time staff. Assuming the latter is predominantly female, we should expect an increase of the share of female employment in periods of positive productivity deviations (and decrease during negative ones). This would generate spurious positive correlation between the share of female labour force and productivity of firms, even when resorting to FE.

To account for the presence of this endogeneity bias we first estimate the relevant parameters of our model using IV-GMM. This is a strategy regularly used in the production function literature with labour heterogeneity (Aubert & Crépon, 2003, 2007; van Ours & Stoeldraijer, 2011). Our choice is to instrument the potentially endogenous first differences of female share (ΔSF_{it}) with the second differences (ΔSF_{it} - ΔSF_{it-1}) and lagged second differences (ΔSF_{it-1}- ΔSF_{it-2}) *i.e.* past changes of the annual variations of the gender mix. The key assumptions are that these past changes are *i)* uncorrelated with year-to-year changes of the productivity term $\Delta\omega_{it}$, but *ii)* still reasonably correlated with year-to-year changes of the female share ΔSF_{it}.

An alternative to IV-GMM that seems promising and relevant, given the content of our data, it to adopt the more structural approach initiated by Olley & Pakes (1998) (OP hereafter) and further developed by Levinsohn & Petrin (2003). The essence of the OP approach is to use some function of a firm's investment to control for time-varying unobserved productivity ω_{it}. The drawback of this method is that only observations with positive investment levels can be used in the estimation. Many firms indeed report no investment in short panels. LP overcome this problem by using material inputs (raw materials, electricity,...) instead of investment in the estimation of unobserved productivity. Firms can swiftly (and also at a relatively low cost) respond to productivity developments ω_{it} by adapting the volume of the intermediate inputs they buy on the market. Whenever information of intermediate inputs is available in a data set — which happens to be the case with ours — they can be used to proxy short-term productivity deviations.

Following OP, LP assume that the demand for intermediate inputs (int_{it}) is a function of the time-varying unobserved productivity level ω_{it} as well as the current level of capital:

$$int_{it} = f(\omega_{it}, k_{it}) \qquad (18)$$

LP further assume that this function is monotonic in ω_{it} and k_{it}, meaning that it can be inverted to deliver an expression of ω_{it} as a function of int_{it} and k_{it}. In the LP framework, equation (13) thus becomes:

$$\varepsilon_{it} = \theta_i + f^{1}(int_{it}, k_{it}) + \sigma_{it} \qquad (19)$$

And LP argue that $\omega_{it}=f^{1}(int_{it}, k_{it})$ that can be approximated by a 3rd order polynomial expansion in int_{it} and k_{it}.. We use this strategy here to cope with the endogeneity bias. However, unlike LP or OP, we do this in combination with first differences (FD) to account for firm fixed effects θ_i.

In a sense, we stick to what has traditionally been done in the dynamic panel literature underpinning the IV-GMM strategy discussed above. We also believe that explicitly accounting for firm fixed effects increases the chance of verifying the key monotonicity assumption required by the LP approach in order be able to invert out ω_{it} , and completely remove the endogeneity problem. In the standard LP framework, the firm fixed effects are *de facto* part of ω_{it}.[18] The evidence with firm panel data is that these can be large and explain a large proportion (>50%) of the total productivity variation. This means that, in the LP intermediate good function $int_{ii}=f(\omega_{it}, k_{it})$, the term ω_{it} can vary a lot when switching from one firm to another and, most importantly, in a way that is not related to the consumption of intermediate goods. In other words, firms with similar values of int_{ii} (and k_{it}) are characterized by very different values of ω_{it}. This is something that invalidates the LP assumption of a one-to-one (monotonic) relationship.

Algebraically, our strategy simply consists of implementing LP to variables (the initial ones + those generated to form the LP polynomial expansion term[19]) that have been first-differenced. Justification is straightforward. First-differencing means that one deals with an expression for residuals equals to

$$\Delta\varepsilon_{it} = \Delta\big(f^{1}(int_{it}, k_{it})\big) + \Delta\sigma_{it} \qquad (20)$$

If one assumes, like LP, that the inverse demand function $f^{1}(.)$ can be proxied by a 3rd order

[18] LP assume that the error term has only two composents : ω_{it} and a random term σ_{it}.
[19] $int_{it}, int^{2}_{it}, int^{3}_{it}, k_{it}, k^{2}_{it}, k^{3}_{it}, int^{2}_{it}{*}k_{it}, int_{it}{*}k^{2}_{it}\ldots$

polynomial expansion in int_{it} and $k_{it,}$, that expression becomes

$$\Delta\varepsilon_{it} = \Delta\big(\chi + \upsilon_1\, int_{it} + ... + \upsilon_3\, int^3_{it} + \upsilon_4\, k_{it} + ... + \upsilon_5\, k^3_{it} + \upsilon_6\, int^2_{it}{*}k_{it} + \upsilon_7\, int_{it}{*}k^2_{it} + ...\big) + \Delta\sigma_{it} \tag{21}$$

As the FD operator applies to a *linear* expression, the above notation is thus equivalent to

$$\Delta\varepsilon_{it} = \upsilon_1\, \Delta int_{it} + ... + \upsilon_3\, \Delta(int^3_{it}) + \upsilon_4\, \Delta k_{it} + ... + \upsilon_5\, \Delta(k^3_{it}) + \upsilon_6 \Delta(int^2_{it}{*}k_{it}) + \upsilon_7\, \Delta(int_{it}{*}k^2_{it}) + ... + \Delta\sigma_{it} \tag{22}$$

In Section 4 below, we present the results of the estimation of productivity, labour cost and productivity-labour cost gap equations under five alternative econometric strategies. The first strategy is the standard OLS using total variation [1]. Then first differences (FD) where parameters are estimated using only within-firm variation [2]. Then the LP estimation [3] where the unobserved time-varying productivity term ω_{it} is proxied by intermediate goods consumption. The next strategy [4] consists of using first-differenced variables and instrumenting the female share first differences with its second differences and lagged second differences. The last model [5] is combines first differences and the LP intermediate proxy idea.

Although they come at the cost of reduced sample sizes, specifications [5] [6] are *a priori* the best insofar as the coefficients of interest are identified from within-firm variation to control for firm unobserved heterogeneity, and that they controls for short-term endogeneity biases via the use of LP's intermediate input proxy, or internal instruments (second differences, lagged second differences). In the latter case, note that we estimate the relevant parameters of our model using the General Method of Moments (GMM), known for being more robust to the presence of heteroskedasticity. In fact, it consists of a two-step GMM estimator. In the first step a potentially inefficient estimator is recovered by 2SLS and used to estimate the optimal moment weighting matrix. This estimator is more efficient than 2SLS is presence of heteroskedasticity (see appendix in Arellano, 2003).

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, sector and region) in F_{it} can account for part of this heterogeneity bias, first-differencing as done in [2], [4] or [5] is still the most powerful way out. But first differences [2] alone are not sufficient. The endogeneity in input choices – particularly when it come to the share of female workers[20] - is well documented problem in the production function estimation literature (*e.g*. Griliches & Mairesse, 1995) and also deserved to be properly and simultaneously treated. And this is precisely what we have attempted to do in [4] and [5].

3 Data and descriptive statistics

The firm-level data we use in this paper involves input and output variables of close to 9,000 firms of the Belgian private economy observed along the period 1998-2006. The data set matches financial and operational information retrieved from Belfirst with data on individual characteristics of all employees working in the firms, obtained from the Belgium's Social Security register (the so-called Carrefour database). The data set covers all sectors in the Belgian non-farming private economy, identified by NACE2 code. [6] Monetary values are expressed in nominal terms.

The productivity outcome corresponds to the firms' net value added per worker. The measure of labour cost, which was measured independently of net value added, includes the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. The summary statistics of the variables in the data set are presented in Table 1.

As we have mentioned in the previous section, we control for price variation in firms output by using a set of dummies for sector (NACE1), year and their interaction. In our empirical analysis capital input is measured by fixed tangible assets, while labour input corresponds to total number of employees, including both full- and part-time and under permanent and temporary contract.

The end of Table 1 describes intermediate inputs. The latter variable plays a key role in our analysis, as it is an important element of our strategy to overcome the simultaneity bias. It is calculated here as the differences between the firm's turnover (in nominal terms) and its net value added. It reflects the value of goods and services consumed or used up as inputs in production by firms, including raw materials, services and various other operating expenses.

The fact that we cannot distinguish part- from full-time workers and workers under permanent and

[20] There is evidence from the Belgian labour market that women are overrepresented among temporary employment which is known for being particularly sensitive to short-term productivity developments, represented here by ω_{it}.

temporary contract is an important limitation, since women are known to be overrepresented in part-time and temporary contracts. However, note at the end of Table 1 the presence of *hours worked annually per employee*. The latter is obtained by dividing the total number of hours worked in the firms (on an annual basis) by the number of employees (full-time or part-time ones indistinctively). As explained in Section 2, we systematically include this ratio among our set of control variables F_{it} to account for the relationship between hours worked and the share of women inside firms.

Finally, Table 2 contains information about the breakdown of our sample by broadly-defined sector[21] and by firm size. We make use of these breakdowns to carry out some robustness checks on our main results.

Table 1: Belfirst-Carrefour panel. Basic descriptive statistics. Mean and Standard deviation

Variable	**Mean**	**Std. Dev.**
------------	--------------	----------
Log of net value added per employee (th.€)[in logs [a]	4.08	0.56
Log of labour costs per employee (th.€) [b]	3.71	0.38
Value added /labour cost ratio: [a]-[b][£]	0.37	0.40
Number of employees	122.87	585.85
Capital (th.€)	11,982	159,787
------------	--------------	----------
Share of female in total workforce	0.27	0.24
Share of blue-collar female	0.08	0.16
Share of blue-collar male	0.47	0.34
Share of white-collar female	0.19	0.21
Shar of white-collar male	0.26	0.23
------------	--------------	----------
Intermediate goods cons. (in th. €)	38,697	307,503
Hours worked annually per worker	1547.95	715.73

[£]Measured in %. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e., percentage) differences

Source: Carrefour, Belfirst

[21] See the appendix on this

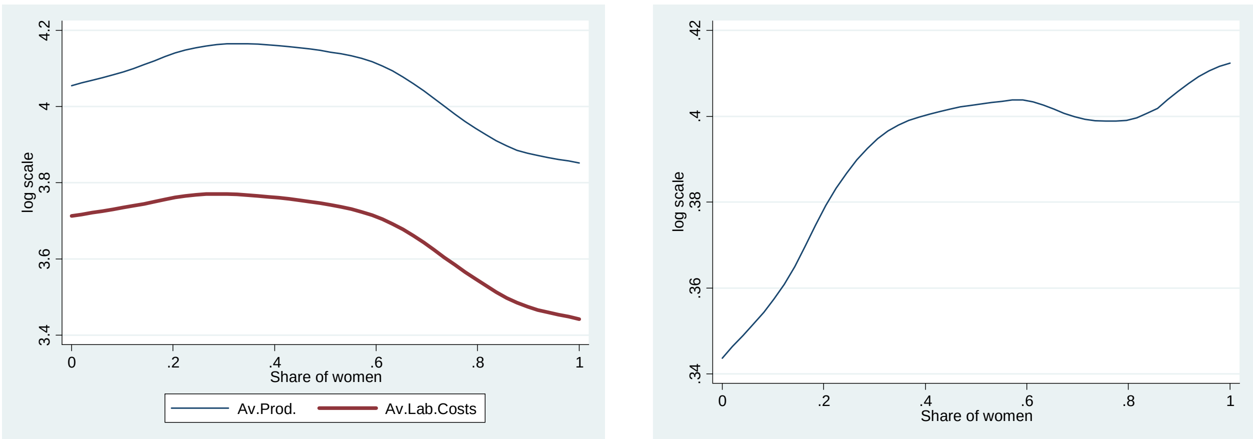
Table 2: Belfirst-Carrefour panel. Basic descriptive statistics, pooled data

Firm size (number of workers)	Freq.
<50	47,336
50-99	16,068
100-+	15,816
Sector	Freq.
Commerce	20,199
Industry	36,248
Services	22,773

Source: Carrefour, Belfirst

Figure 1 (left panel) depicts the OLS-predicted relationship between the share of women and the two key dependent variables in this analysis: per employee productivity and labour cost. Both curves first rise slightly, then, beyond the .35 threshold, decline with the share of women employed. The most interesting feature it that the productivity-labour cost ratio (right-hand panel of Figure 1) is a rising function of the share of women employed by private firms; something that suggests the presence of market-wide gender wage discrimination.

Figure 1: (Left panel) Productivity per employee [a] and labour cost per employee [b]in logs. (Right panel) Productivity/Labour cost ratio [a]-[b]£ according to share of women.



Local polynomial smooth plots using values predicted by OLS-estimated equations 10 & 11.
£Measured in %. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e., percentage) differences
Source: Carrefour, Belfirst

4 Econometric Analysis

This section presents the main results of our estimations (subsection 4.1). Some robustness extensions follow (subsection 4.2). In Table 3 we present results of the estimation of productivity, labour cost and productivity-labour cost ratio equations under the above-presented five alternative econometric strategies.

4.1 Empirical Results

In Table 3 we present results of the estimation of productivity, labour cost and productivity-labour cost ratio equations under the above-presented five alternative econometric strategies. Note that the same data transformations implied by the retained strategies have been applied to each of the three equations. Reported coefficients in the upper parts of Table 3 correspond to the productivity coefficient η and labour cost coefficient η^w. The crucial issue in this paper, however, is the gap between these two $\eta^G = \eta - \eta^w$ that captures the intensity of gender wage discrimination as usually defined by economists. We report different estimates of this gap on the lower part of Table 3. OLS estimates (column [1]) suggest that women in the Belgian labour market are 4.9 %-points less productive than men. But they are paid 14.9%-points less than their male counterparts, implying that they get paid 10 %-points less than what their (relative) productivity would imply. At first sight, this is supportive of the gender wage discrimination regularly denounced in Belgium (Institut pour l'égalité des Femmes et des Hommes, 2006).

But turning to FD estimates (column [2]), where parameters are solely estimated by the within firm variation, delivers a completely different picture. Whereas the productivity disadvantage of women vis-à-vis men is estimated to be slightly higher at -7.4% points, their wage disadvantage now appears much smaller at -5.1%-points; with the implication that women get paid 2.8 %-points above their productivity. The latter coefficient is not statistically significant however.

Column [3] contains the results of the LP estimation (without first-differencing). These suggest larger productivity (-12.5% points) and wage (-17.1%-points) disadvantages for women than OLS, and moderate (and statistically significant) wage discrimination of about 4.7%-points.

Of greater interest however are the results of the next two models that simultaneously control for *i)* cross-firm time-invariant heterogeneity via FD and *ii)* short-term endogeneity of labour input choices. First the FD+ IV-GMM estimation (column [4]) which points a larger productivity (-16.6% points) disadvantages for women that are barely compensated in terms of lower wage (-2.6%). Logically, this means that female workers they get paid 14.3 %-points *more* than what their (relative) productivity would imply.

To assess the credibility of this IV-GMM approach we performed a range of diagnostic tests. First, a Anderson correlation relevance test. If the correlation between the instrumental variables and the endogenous variable is poor (*i.e.* if we have "weak" instruments) our parameter estimate may be biased. The null hypothesis is that the instruments are weak (correlation in nil). Rejection of the null hypothesis (low p-values) implies that the instruments pass the weak instruments test, i.e. they are highly correlated with the endogenous variables. In all our GMM estimates reported in Table 3 our instruments pass the Anderson correlation relevance test. Second, to further assess the validity of our instrument we use the Hansen-Sargan test. – also called Hansen's J test – of overidentifying restrictions. The null hypothesis is that the instruments are valid instruments (i.e., uncorrelated with the error term), and that the instruments are correctly "excluded" from the estimated equation. The null hypothesis of the test is that the overidentifying restrictions are valid. Under the null, the test statistic is distributed as chi-squared in the number of overidentifying restrictions. A failure to reject the null hypothesis (high p-values) implies that the instruments are exogenous. In all our IV-GMM estimates we cannot reject the null hypothesis that these restrictions are valid.

Our second favoured model (column [5]) is the one that combines FD and the LP's proxy strategy. Its results are similar to those delivered by FD+ IV-GMM. Women's productivity handicap is estimated to be of -17.6%-points, whereas their wage disadvantage is only of -6.8%-points. The two elements combine to suggest that female workers they get paid 11%-points *more* than what their (relative) productivity would command. Although results [4] and [5] require further qualifications (more on this below), they suggest that all the evidence in support of gender wage discrimination vanishes once cross-firm unobserved heterogeneity and endogeneity bias have been controlled for. What is more, they even hint at that female workers being *positively* discriminated, in the sense that they get paid 11 to 14 %-points in excess of than what their (relative) productivity would command.

The dramatic reduction of the gender gap when moving from total- to within-firm variation constitutes important evidence in support of controlling for cross-firm heterogeneity and rejecting OLS [1], or LP-only [3] estimates. This is particularly true for the labour cost equation. The FD [2] labour cost estimate (η^{w}) is much smaller than its OLS equivalent. The various estimates of productivity (η) are also affected by the within/FD transformation, although to a lesser extent than labour cost estimates.

This said combining FD with IV-GMM or LP to account for the simultaneity bias leads to even bigger changes, particularly in terms of productivity. The female productivity handicap of -4.9%- with OLS [1] becomes -16 to -17%-points with our preferred estimates [4] [5] (upper part of Table 3). The latter results accord with our initial prediction. Based on evidence for the Belgian labour market summarized in Meulders & Sissoko (2002), we were convinced that, if anything, the presence of endogeneity/simultaneity bias would lead to an underestimation of the female productivity handicap in OLS estimations. Our reasoning was the following: since in Belgium temporary contract employment is asymmetrically concentrated in female employment,[22] we should expect that, if temporary employment is one, or the main, labour adjustment variable to unobserved changes in firms economic environments (ω_{it}), the share of female employment should increase in periods of positive productivity changes and decrease in periods of negative productivity changes. This would generate positive correlation between the share of female labour force and the productivity of firms, thereby leading to underestimated OLS estimates of the gender productivity differential.[23] As we have just argued our results do confirm this prediction.

4.2. Robustness analysis

We undertake three further steps (Table 4) in our analysis to assess the robustness of these results. First, we consider the role of the (broadly-defined) sector of activity.[24] Second, we examine whether our results change much when we partition the sample in terms of firm size. Third, we go beyond the simple distinction between men and women and consider the interaction of status (blue-collar/white collar) and gende*r*. Referring to equations 10 or 11, this means estimating these models with k=0,1,2,3 categories of workers, where the reference category (k=0) in our case are the blue-collar men. Note in particular that the white vs. blue-collar workers comparison is a way to somehow

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22 The same could be said of part-time employment, but remember that we explicitly control for the latter by including average hsours worked per employee (part-time or full-time employees confounded) in all our estimations.

23 In absolute value.

compensate for the lack of information on the level of education (which is one shortcoming of our data). For each of these extensions, the focus will be on the results of the model combining FD and intermediate inputs control *à-la*-LP.

The main results (Table 4) from these extensions do not differ in qualitative terms from those obtained so fat, but interesting nuances emerge. Regarding the breakdown by sector, there seems to be a significant difference between industry and commerce on the one hand, and the service industry on the other hand. While in the two first sectors we get that women are paid above their (relative) productivity, in services their wage seem to be strictly aligned on their productivity performance. Another interesting nuance arises when considering the size of firms. It is indeed in small firms (with less than 50 employees) that *i)* productivity and wage of women diverge from those of men, and *ii)* are misaligned in the sense that women get paid above their productivity. By contrast, in large firms (100+ employees) there is no divergence vis-à-vis men in terms of productivity or wage and, consequently, no (positive or negative) wage discrimination. Finally, and in contrast with the two previous developments, the breakdown according to white- vs. blue-collar status does not suggest any difference between these two categories of female workers. Small sample size for female blue-collars translate into less precise estimates. Nonetheless, their suggest, as those for white-collar females, that women are paid above their productivity in the range of 11 to 14% -points.

[24] See Appendix for a detailed presentation of what these categories encompass.

Table 3: Estimation of Productivity, Labour Cost and Productivity-Labour Cost Ratio Equations

ref= men	**1-OLS**	**2-First-Differences**	**3-Intermediate inputs (Levinsohn-Petrin)**	**4-First-Differences IV-GMM**	**5-First-Differences + Intermediate inputs (Levinsohn-Petrin)**
Productivity equation (η)					
Share of women	-0.049***	-0.074*	-0.125*	-0.166**	-0.176***
(std-dev)	(0.009)	(0.028)	(0.009)	(0.039)	(0.038)
Nobs.	60,417	49,793	49,582	38,116	30,661
Labour cost equation (η^w)					
Share of women	-0.149***	-0.051***	-0.171***	-0.026	-0.068***
(std-dev)	(0.005)	(0.014)	(0.006)	(0.033)	(0.017)
Nobs.	60,674	50,082	49,581	38,307	30,661
Productivity-Labour cost ratio (η-η^w)					
Share of women	0.100***	-0.028	0.047***	-0.143***	-0.109***
(std-dev)	(0.007)	(0.987)	(0.008)	(0.050)	(0.037)
Nobs.	60,414	49,792	49,581	38,115	30,661
Controls	capital, number of employees, hours worked per employee + fixed effects: year* nace1, region	capita, number of employees, hours worked per employee + fixed effects: firm, year*nace1	capital, number of employees, hours worked per employee + fixed effects: year* nace1, region	capital, number of employees, hours worked per employee + fixed effects: firm, year*nace1	capital, number of employees, hours worked per employee + fixed effects: firm, year*nace1

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

Table 4: Estimation of Productivity, Labour Cost and Productivity-Labour Cost Ratio Equations. Breakdown by Sector and Firm size. Interaction of Gender and Labour Status

	Productivity (η)	Labour cost (η^w)	Productivity-Labour cost ratio (η-η^w)
Sector			
Industry	-0.290***	-0.098***	-0.192***
(std- dev)	(0.071)	(0.029)	(0.069)
Commerce	-0.221***	0.012	-0.233***
(std- dev)	(0.070)	(0.030)	(0.070)
Service	-0.102*	-0.118***	0.016
(std- dev)	(0.059)	(0.030)	(0.055)
Firm size			
1-49	-0.240***	-0.104***	-0.136***
(std- dev)	(0.054)	(0.023)	(0.052)
50-99	-0.153	-0.004	-0.149
(std- dev)	(0.112)	(0.044)	(0.107)
>=100	-0.018	-0.011	-0.007
(std- dev)	(0.117)	(0.049)	(0.115)
Gender/Status (ref= blue-collar men)			
blue-collar women	-0.092	0.022	-0.114*
(std- dev)	(0.061)	(0.027)	(0.059)
white-collar women	-0.153***	-0.013	-0.140***
(std- dev)	(0.046)	(0.020)	(0.044)

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

5 Conclusion

In this paper - in contrast with many existing studies based on the Oaxaca-Blinder decomposition methods using individual earnings - we use firm-level data from a matched employer-employee data set to test for the presence of gender wage discrimination in the Belgian labour market. The great advantage of firm-level data is that they contain information on productivity (value added) and labour costs. Consequently, they allow for a direct measures of *i)* gender productivity differential, *ii)* gender wage differentials and – by combination of the two dimensions - *iii)* gender productivity-wage gaps that can be directly interpreted in terms of gender discrimination. Although production function and labour cost estimation is a complicated task, and even more so in our case where, we are adding a labour quality term that distinguish among male and female workers, we obtain relatively robust (and seemingly reasonable) estimates of these relative marginal products. We then compare these estimates of relative marginal products to estimates of relative wage and address the gender wage discrimination that have previously been addressed without the advantage of an independent productivity measure.

Our benchmark definition of gender wage discrimination is that of market-wide and statistically significant gaps between gender productivity differences and gender wage differences. This methodology based on HN does not provide a direct test of any particular theory of gender wage discrimination. Rather, it supplies an empirical measure of the above benchmark concept of gender wage discrimination.

Another particularity of this paper is that gender wage discrimination is identified from within-firm variation and via the use of IV-GMM methods, but also a structural production function estimator to control for the short-term endogeneity in labour input choices.

OLS estimates suggest that women in the Belgian labour market are 5 %-points less productive than men but that they are paid 15%-points less than their male counterparts. At first sight, this is supportive of the presence of gender wage discrimination in Belgium. We argue, however, that these OLS estimates are not trustworthy, and that the proper identification of the *causal* effect of women on productivity and labour cost requires controlling for *i)* cross-firm time-invariant heterogeneity and *ii)* short-term endogeneity of the share of female workers. This implies estimating the coefficients of interest from within-firm variation (*e.g.* resorting to FD) *and* simultaneously to controls for the potential endogeneity of the share of women using LP's intermediate input proxy, or internal, lagged instruments (IV-GMM).

FD estimates, once combined with IV-GMM or LP estimation, point indeed at larger productivity (-16 to 17% points) disadvantages for women. What is more, these are barely compensated in terms of lower labour costs (-3 to -8%-points). Logically, this suggests that female workers they get paid 11 to 14 %-points in excess of what their (relative) productivity would imply. In short, our findings indicate that, on average, women earn less than men but also that they are collectively less productive than men. The tentative conclusion is that there seems to be no gender wage discrimination inside private firms located in Belgium, on the contrary.

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Annex: Sectors (Industry; Commerce vs Services) and NACE2 codes/definitions

Nac2 code	Industry
10 to 12	Manufacture of food products, beverages and tobacco products
13 to 15	Manufacture of textiles, apparel, leather and related products
16 to 18	Manufacture of wood and paper products, and printing
19	Manufacture of coke, and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of pharmaceuticals, medicinal chemical and botanical pro
22 + 23	Manufacture of rubber and plastics products, and other non-metallic
24 + 25	Manufacture of basic metals and fabricated metal products
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29 + 30	Manufacture of transport equipment
31 to 33	Other manufacturing, and repair and installation of machinery and e
35	Electricity, gas, steam and air-conditioning supply
36 to 39	Water supply, sewerage, waste management and remediation
41 to 43	Construction
	Commerce
45 to 47	Wholesale and retail trade, repair of motor vehicles and motorcycles
	Services
49 to 53	Transportation and storage
55 + 56	Accommodation and food service activities
58 to 60	Publishing, audiovisual and broadcasting activities
61	Telecommunications
62 +63	IT and other information services
64 to 66	Financial and insurance activities
68	Real estate activities
69 to 71	Legal, accounting, management, architecture, engineering, technical
72	Scientific research and development
73 to 75	Other professional, scientific and technical activities
77 to 82	Administrative and support service activities
90 to 93	Arts, entertainment and recreation
94 to 96	Other services
97 to 98	Activities of households as employers; undifferentiated goods
99	Activities of extra-territorial organisations and bodies

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