

# 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 alongside instrumental variable-general method of moments (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.

## 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 per cent (European Commission, 2007), whereas in the USA this figure amounted to 23.5 per cent (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 per cent for white-collar workers to 21 per cent for blue-collar workers.<sup>1</sup>

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 USA. 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.

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Strictly speaking, however, from an economic point of view, gender wage *discrimination* requires more than wage differences between men and women. It implies that equal labour services provided by equally productive workers have a sustained price/wage difference.<sup>2</sup>

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.

### 1.1 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.<sup>3</sup> Wage discrimination is measured as the average mark-up on some measure of individual compensation (hourly, monthly wages, etc.), 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, etc.). Second, he or she needs to find or create appropriate measures of those characteristics. Although 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, in so far as discrimination affects individual choices regarding human capital decisions or occupational choices, the measure of discrimination obtained from wage equations will likely understate discrimination (Altonji and 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 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. In 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 and Neumark (1999) (HN henceforth).<sup>4</sup> 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 with 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,<sup>5</sup> with data from Belgian’s Social Security register containing detailed information 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)<sup>6</sup> and a measure of women’s productivity relative to men’s (the gender productivity differential).

Hellerstein and Neumark’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, 2011; Vandenberghe and Waltenberg, 2010). But applications of the HN methodology also comprises the analysis of race, education, and marital status (e.g. Crépon *et al.*, 2002; Hellerstein *et al.*, 1999). In this paper, we focus exclusively on gender and the interaction between gender and the worker’s blue- versus white-collar labour market status.<sup>7</sup>

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 Akerberg *et al.*, 2006 for a recent review). One set of techniques follows the dynamic panel literature (Arellano and Bond, 1991; Aubert and Crépon, 2003; Blundell and Bond, 2000; van Ours and 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 and Pakes (1996) (OP hereafter) or more recently by Levinsohn and Petrin (2003) (LP henceforth), are somewhat more structural in nature. They consist of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity, etc.) to ‘control’ for (or proxy) unobserved productivity shocks.

In this paper, we follow these most recent applications of HN’s methodology. We combine and 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.<sup>8</sup>

Our preferred estimates indicate that the cost of employing women<sup>9</sup> is 3–7 per cent 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 16–17 per cent points lower than that of the group of male workers. The key result of the paper is thus that female workers they get paid 10–14 per cent 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 (Meulders and Sissoko, 2002; Rycx and Tojerow, 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 show indeed that firm employing more women also generate significantly less value added *ceteris paribus*.

The rest of the paper is organized 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’ productivity, we consider a Cobb–Douglas production function (Aubert and Crépon, 2003, 2007; Dostie, 2006; Hellerstein *et al.*, 1999; van Ours and Stoeldraijer, 2011):

$$\ln(Y_{it}/L_{it}) = \ln A + \alpha \ln QL_{it} + \beta \ln K_{it} - \ln L_{it} \quad [1]$$

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:

$$QL_{it} = \mu_{M}M_{it} + \mu_{F}F_{it} = \mu_{M}L_{it} + (\mu_{F} - \mu_{M})F_{it} \quad [2]$$

where:  $L_{it} \equiv F_{it} + M_{it}$  is the total number of workers in the firm,  $\mu_M$  the marginal productivity of men (i.e. reference) and  $\mu_F$  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:

$$\ln QL_{it} = \ln \mu_M + \ln L_{it} + \ln[1 + (\lambda_F - 1)SF_{it}] \quad [3]$$

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 firm's total workforce.

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

$$\ln QL_{it} = \ln \mu_M + \ln L_{it} + (\lambda_F - 1)SF_{it}. \quad [4]$$

And the production function becomes:

$$\ln(Y_{it}/L_{it}) = \ln A + \alpha[\ln \mu_M + \ln L_{it} + (\lambda_F - 1)SF_{it}] + \beta \ln K_{it} - \ln L_{it} \quad [5]$$

or, equivalently,

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

where:

$$B = \ln A + \alpha \ln \mu_M$$

$$\eta = \alpha(\lambda_F - 1)$$

$$\lambda_F = \mu_F/\mu_M$$

....

$$l_{it} = \ln L_{it}$$

$$k_{it} = \ln K_{it}.$$

Note first that [6] being loglinear in  $SF$  the coefficient  $\eta$  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  $\pi_F$  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,

$$W_{it}/L_{it} = \pi_M + (\pi_F - \pi_M)F_{it}/L_{it} = \pi_M[1 + (\pi_F/\pi_M - 1)]F_{it}/L_{it}. \quad [7]$$

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

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

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:

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

where:

$$B^w = \ln \pi_M$$

$$\eta^w = \Phi_F - 1$$

$$\Phi_F \equiv \pi_F/\pi_M.$$

Like in the productivity equation [6] coefficient  $\eta^w$  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<sup>10</sup> 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].

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

$$\ln(W_{it}/L_{it}) = B^w + (\alpha^w - l)l_{it} + \eta^w SF_{it} + \beta^w k_{it} + \gamma^w F_{it} + \varepsilon_{it}^w. \quad [11]$$

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

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

where:  $B^G = B - B^w$ ;  $\alpha^G = \alpha - \alpha^w$ ;  $\eta^G = \eta - \eta^w$ ;  $\beta^G = \beta - \beta^w$ ;  $\gamma^G = \gamma - \gamma^w$ ; and  $\varepsilon_{it}^G = \varepsilon_{it} - \varepsilon_{it}^w$ . It is immediate to see that the coefficient  $\eta^G$  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  $F_{it}$ . In all the estimations presented hereafter  $F_{it}$  contains region,<sup>13</sup> year and sector<sup>14</sup> 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, as 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 systematically 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. 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  $\varepsilon_{it}$  of productivity equation [12]. We assume that the latter has a structure that comprises three elements:

$$\varepsilon_{it} = \theta_i + \omega_{it} + \sigma_{it} \quad [13]$$

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

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

Parameter  $\theta_i$  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,<sup>15</sup> firm-specific managerial skills, location-driven comparative advantages.<sup>16</sup> And these might be correlated with the gender structure of the firm's workforce, and resulting in *heterogeneity bias* with ordinary least squares (OLS) results. Women for instance might be underrepresented among plants built a long time ago using older technology.<sup>17</sup> However, the panel structure of our data allows us to estimate models with firm fixed effects. The results from the FE estimation [using first differences (FD) 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, an increase of that group's share in the overall workforce translates into productivity gains (loss). Algebraically, the estimated FE model corresponds to:

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

$$\Delta \ln(W_{it}/L_{it}) = \Delta B^w + (\alpha^w - l)\Delta l_{it} + \eta^w \Delta SF_{it} + \beta^w \Delta k_{it} + \gamma^w \Delta F_{it} + \Delta \varepsilon_{it}^w \quad [15]$$

$$\Delta \text{Ratio}_{it} = \Delta B^G + \alpha^G \Delta l_{it} + \eta^G \Delta SF_{it} + \beta^G \Delta k_{it} + \gamma^G \Delta F_{it} + \Delta \varepsilon_{it}^G. \quad [16]$$

And the error terms becomes:

$$\Delta \varepsilon_{it} = \Delta \omega_{it} + \Delta \sigma_{it} \quad [17]$$

where  $\text{cov}(\Delta \omega_{it}, \Delta SF_{it}) \neq 0$  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  $\omega_{it}$  (Griliches and Mairesse, 1995). The economics underlying that concern is intuitive. In the short run firms could be confronted to productivity deviations  $\omega_{it}$  (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  $\omega_{it}$  (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 and Crépon, 2003, 2007; van Ours and Stoeldraijer, 2011). Our choice is to instrument the potentially endogenous FD of female share ( $\Delta SF_{it}$ ) with the second differences ( $\Delta SF_{it} - \Delta SF_{it-1}$ ) and lagged second differences ( $\Delta SF_{it-1} - \Delta SF_{it-2}$ ), 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  $\Delta SF_{it}$ .

An alternative to IV-GMM that seems promising and relevant, given the content of our data, is to adopt the more structural approach initiated by Olley and Pakes (1996) and further developed by Levinsohn and 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  $\omega_{it}$ . 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, etc.) instead of investment in the estimation of unobserved productivity. Firms can swiftly (and also at a relatively low cost) respond to productivity developments  $\omega_{it}$  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  $\omega_{it}$  as well as the current level of capital:

$$int_{it} = f(\omega_{it}, k_{it}). \quad [18]$$

Levinsohn and Petrin further assume that this function is monotonic in  $\omega_{it}$  and  $k_{it}$ , meaning that it can be inverted to deliver an expression of  $\omega_{it}$  as a function of  $int_{it}$  and  $k_{it}$ . In the LP framework, equation [13] thus becomes:

$$\varepsilon_{it} = \theta_i + f^{-1}(int_{it}, k_{it}) + \sigma_{it}. \quad [19]$$



And LP argue that  $\omega_{it} = f^{-1}(int_{it}, k_{it})$  that can be approximated by a third-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 FD to account for firm fixed effects  $\theta_i$ .

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 to be able to invert out  $\omega_{it}$ , and completely remove the endogeneity problem. In the standard LP framework, the firm fixed effects are *de facto* part of  $\omega_{it}$ .<sup>18</sup> The evidence with firm panel data is that these can be large and explain a significant proportion (>50 per cent) of the total productivity variation. This means that, in the LP intermediate good function  $int_{it} = f(\omega_{it}, k_{it})$ , the term  $\omega_{it}$  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  $int_{it}$  (and  $k_{it}$ ) are characterized by very different values of  $\omega_{it}$ . 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<sup>19</sup>) that have been first differenced. Justification is straightforward. First differencing means that one deals with an expression for residuals equals to:

$$\Delta \varepsilon_{it} = \Delta (f^{-1}(int_{it}, k_{it})) + \Delta \sigma_{it}. \quad [20]$$

If one assumes, like LP, that the inverse demand function  $f^{-1}(\cdot)$  can be proxied by a third-order polynomial expansion in  $int_{it}$  and  $k_{it}$ , that expression becomes:

$$\Delta \varepsilon_{it} = \Delta (\chi + v_1 int_{it} + \dots + v_3 int_{it}^3 + v_4 k_{it} + \dots + v_5 k_{it}^3 + v_6 int_{it}^2 * k_{it} + v_7 int_{it} * k_{it}^2 + \dots) + \Delta \sigma_{it}. \quad [21]$$

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

$$\begin{aligned} \Delta \varepsilon_{it} = & v_1 \Delta int_{it} + \dots + v_3 \Delta (int_{it}^3) + v_4 \Delta k_{it} + \dots + v_5 \Delta (k_{it}^3) + v_6 \Delta (int_{it}^2 * k_{it}) \\ & + v_7 \Delta (int_{it} * k_{it}^2) + \dots + \Delta \sigma_{it}. \end{aligned} \quad [22]$$

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

Although they come at the cost of reduced sample sizes, specifications [5] [6] are *a priori* the best in so far 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 two-stage least squares (2SLS) and used to estimate the optimal moment weighting matrix. This estimator is more efficient than 2SLS in presence of heteroskedasticity (see appendix in Arellano, 2003).

Heterogeneity bias might be present as 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 FD [2] alone is not sufficient. The endogeneity in input choices — particularly when it come to the share of female workers<sup>20</sup> — is well-documented problem in the production function estimation literature (e.g. Griliches and 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 involve 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.<sup>21</sup> 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 (NACE2), year, and region. In our empirical analysis

**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] <sup>a</sup>	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
Share of white-collar male	0.26	0.23
Intermediate goods consumption (in th.€)	38,697	307,503
Hours worked annually per worker	1,547.95	715.73

<sup>a</sup> Measured in per cent. This is because logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e. percentage) differences.

**Table 2.** Belfirst–Carrefour panel. Basic descriptive statistics, pooled data

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

Source: Carrefour, Belfirst.

capital input is measured by fixed tangible assets, whereas 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 temporary contract is an important limitation, as women are known to be over-represented in part-time and temporary contracts. However, note at the end of Table 1 the presence of *hours worked annually per employee*. 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.

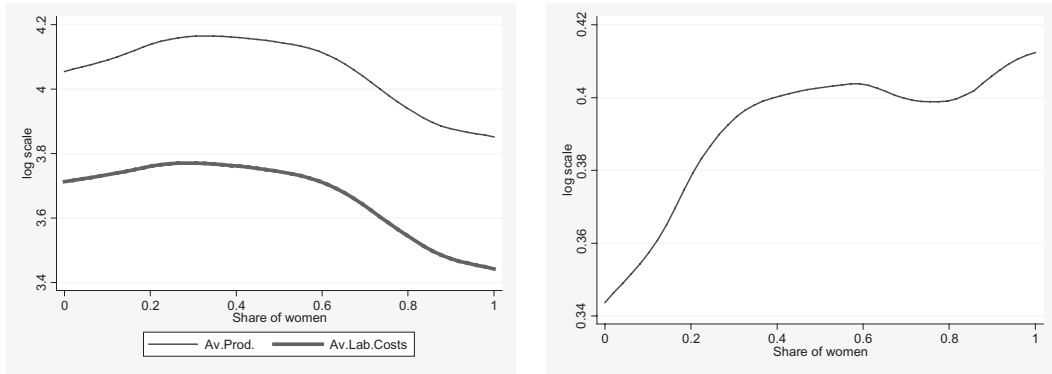
Finally, Table 2 contains information about the breakdown of our sample by broadly defined sector<sup>22</sup> and by firm size. We make use of these breakdowns to carry out some robustness checks on our main results.

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 0.35 threshold, decline with the share of women employed. The most interesting feature is 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.

#### 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.

**Figure 1.** (Left panel) Productivity per employee [ $a$ ] and labour cost per employee [ $b$ ] in logs. (Right panel) Productivity/labour cost ratio [ $a$ ] – [ $b$ ]<sup>a</sup> according to share of women



Notes: Local polynomial smooth plots using values predicted by OLS-estimated equations [10] and [11].

<sup>a</sup> Measured in per cent. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e. percentage) differences.

Source: Carrefour, Belfirst.

#### 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  $\eta$  and labour cost coefficient  $\eta^w$ . 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 per cent points less productive than men. But they are paid 14.9 per cent points less than their male counterparts, implying that they get paid 10 per cent 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  $-7.4$  per cent points, their wage disadvantage now appears much smaller at  $-5.1$  per cent points; with the implication that women get paid 2.8 per cent 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 ( $-12.5$  per cent points) and wage ( $-17.1$  per cent points) disadvantages for women than OLS, and moderate (and statistically significant) wage discrimination of about 4.7 per cent 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

**Table 3.** Estimation of productivity, labour cost, and productivity–labour cost ratio equations

<b>Ref = men</b>	<b>(1)</b> <b>OLS</b>	<b>(2)</b> <b>FD</b>	<b>(3)</b> <b>Intermediate inputs (Levinsohn–Pettrin)</b>	<b>(4)</b> <b>FD IV-GMM</b>	<b>(5)</b> <b>FD + intermediate inputs (Levinsohn–Pettrin)</b>
Productivity equation ( $\eta$ )					
Share of women (std-dev)	-0.049*** (0.009) 60,417	-0.074* (0.028) 49,793	-0.125* (0.009) 49,582	-0.166** (0.039) 38,116	-0.176*** (0.038) 30,661
N obs.					
Labour cost equation ( $\eta^w$ )					
Share of women (std-dev)	-0.149*** (0.005) 60,674	-0.051*** (0.014) 50,082	-0.171*** (0.006) 49,581	-0.026 (0.033) 38,307	-0.068*** (0.017) 30,661
N obs.					
Productivity–labour cost ratio ( $\eta - \eta^w$ )					
Share of women (std-dev)	0.100*** (0.007) 60,414	-0.028 (0.987) 49,792	0.047*** (0.008) 49,581	-0.143*** (0.050) 38,115	-0.109*** (0.037) 30,661
N obs.					
Controls	Capital, number of employees, hours worked per employee + fixed effects: firm, 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.

of labour input choices. First the FD + IV-GMM estimation [column (4)], which shows a larger productivity (−16.6 per cent points) disadvantage for women that is barely compensated in terms of lower wage (−2.6 per cent). Logically, this means that female workers get paid 14.3 per cent 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, an 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 per cent points, whereas their wage disadvantage is only of −6.8 per cent points. The two elements combine to suggest that female workers get paid 11 per cent 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 support that female workers are *positively* discriminated, in the sense that they get paid 11–14 per cent 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 ( $\eta^w$ ) is much smaller than its OLS equivalent. The various estimates of productivity ( $\eta$ ) 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 per cent with OLS [1] becomes −16 to −17 per cent 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 and 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: as in Belgium temporary contract employment is concentrated in female employment,<sup>23</sup> we should expect that, if temporary employment is one, or the main, labour adjustment variable to unobserved changes in firms economic environments ( $\omega_i$ ), 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.<sup>24</sup> 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.<sup>25</sup> 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 gender. 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-versus blue-collar workers comparison is a way to somehow 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 far, 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. Although in the two first sectors we get that women are paid above their (relative) productivity, in services their wage seems 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 productivity and wage of women (i) diverge from those of men, and (ii) are misaligned in the sense that women get paid

**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 ( $\eta$ )	Labour cost ( $\eta^m$ )	Productivity–labour cost ratio ( $\eta - \eta^m$ )
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)

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

above their productivity. In 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- versus blue-collar status does not suggest any difference between these two categories of female workers. Small sample size for female blue-collar translates into less precise estimates. Nonetheless, they suggest, as those for white-collar women, that women are paid above their productivity in the range of 11–14 per cent points.

## 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 ratios 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 distinguishes 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 with estimates of relative wage and address the gender wage discrimination that has 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.

Ordinary least squares estimates suggest that women in the Belgian labour market are 5 per cent points less productive than men but that they are paid 15 per cent 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).

First difference estimates, once combined with IV-GMM or LP estimation, point indeed at larger productivity (–16 to –17 per cent points) disadvantages for women. What is more, these are barely compensated in terms of lower labour costs (–3 to –7 per cent points). Logically, this suggests that female workers get paid 10–14 per cent 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.

### Appendix: Sectors (Industry; Commerce versus Services) and NACE2 codes/definitions

NACE2 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 products
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 equipment
35	Electricity, gas, steam, and air-conditioning supply
36 to 39	Water supply, sewerage, waste management, and remediation
41 to 43	Construction
	<b>Commerce</b>
45 to 47	Wholesale and retail trade, repair of motor vehicles and motorcycles
	<b>Services</b>
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 extraterritorial organizations and bodies

### Notes

<sup>1</sup> These are figures for the private sector. The gap in the public sector is only 5 per cent.

<sup>2</sup> In this paper, we will refer to labour costs differences and assume that they are good proxies for wages.

<sup>3</sup> For a recent application of this decomposition method to individual, worker-level, panel data see Pfeifer and Sohr (2009). For an application to Belgian data see Rycx and Tojerow (2002).

<sup>4</sup> 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.

<sup>5</sup> <http://www.bvdep.com/en/bel-first.html>

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

<sup>7</sup> 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, etc.).

<sup>8</sup> 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.

<sup>9</sup> And presumably their wage.

<sup>10</sup> Note that these include a residual term and a set of controls  $F$ . More of the justification of these in the data section below.

<sup>11</sup> 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.

<sup>12</sup> Measured in per cent. This is because logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e. percentage) differences: i.e.  $(Y - W)/W$ .

<sup>13</sup> NUTS1 Belgian regions: Wallonia, Flanders, and Brussels.

<sup>14</sup> NACE2 level.

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

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

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

<sup>18</sup> LP assume that the error term has only two components:  $\omega_{it}$  and a random term  $\sigma_{it}$ .

<sup>19</sup>  $int_{it}, int_{it}^2, int_{it}^3, k_{it}, k_{it}^2, k_{it}^3, int_{it}^2 * k_{it}, int_{it} * k_{it}^2, \dots$

<sup>20</sup> There is evidence from the Belgian labour market that women are over-represented among temporary employment, which is known for being particularly sensitive to short-term productivity developments, represented here by  $\omega_{it}$ .

<sup>21</sup> See the Appendix.

<sup>22</sup> See the Appendix on this.

<sup>23</sup> The same could be said of part-time employment, but remember that we explicitly control for the latter by including average hours worked per employee (part-time or full-time employees confounded) in all our estimations.

<sup>24</sup> In absolute value.

<sup>25</sup> See the Appendix for a detailed presentation of what these categories encompass.

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