Gender Wage Gaps Reconsidered: A Structural Approach Using Matched Employer-Employee Data

Online Appendix - Not for Publication

(http://sites.google.com/site/cristianbartolucci/DetectingWageDiscirmination OA.pdf)

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A Proofs

A.1 Wage Equation

In this subsection, we analytically derive the closed form solution of the equilibrium wage equation. The first step is to find the partial derivative with respect to the wage of the value of a job in a firm with productivity p for a worker with ability ε .

Applying the Leibniz integral rule in (1).

$$\frac{\partial \left[E(w(p,\varepsilon),\varepsilon) \right]}{\partial w(p,\varepsilon)} = \frac{1}{(r+\delta+\lambda_1 \bar{F}(w(p,\varepsilon)|\varepsilon))}.$$
(17)

Integrating (17) between $w(p_{\min}, \varepsilon)$ and $w(p, \varepsilon)$.

$$\int_{w(p_{\min},\varepsilon)}^{w(p,\varepsilon)} \frac{1}{(r+\delta+\lambda\bar{F}(\tilde{w}(p,\varepsilon)|\varepsilon))} d(\tilde{w}(p,\varepsilon)) = \int_{w(p_{\min},\varepsilon)}^{w(p,\varepsilon)} \frac{\partial \left[E(\tilde{w}(p,\varepsilon),\varepsilon)\right]}{\partial \tilde{w}(p,\varepsilon)} d(\tilde{w}(p,\varepsilon))$$

$$E(w(p,\varepsilon),\varepsilon) - E(w(p_{\min},\varepsilon),\varepsilon) = E(w(p,\varepsilon),\varepsilon) - U(\varepsilon).$$

Using the surplus-splitting rule (3), the value of the job for the worker (1), the value of the job for the firm (2) and rearranging:

$$w(p,\varepsilon) = p\varepsilon - (18)$$

$$(\rho + \delta + \lambda_1 \bar{F}(w(p,\varepsilon)|\varepsilon)) \frac{(1-\beta)}{\beta}$$

$$* \int_{w(p_{\min},\varepsilon)}^{w(p,\varepsilon)} \frac{1}{(\rho + \delta + \lambda \bar{F}(\tilde{w}(p,\varepsilon)|\varepsilon))} d(\tilde{w}(p,\varepsilon)).$$

Noting that

$$\int_{w(p_{\min},\varepsilon)}^{w(p,\varepsilon)} \frac{1}{(\rho + \delta + \lambda \bar{F}(\tilde{w}(p,\varepsilon)|\varepsilon))} d(\tilde{w}(p,\varepsilon))$$

$$= \int_{p_{\min}}^{p} \frac{1}{(\rho + \delta + \lambda \bar{H}(p'))} \frac{d(w(p,\varepsilon))}{dp'} dp',$$

and taking derivatives with respect to p

$$\frac{d(w(p,\varepsilon))}{dp'} = \varepsilon - \frac{(1-\beta)}{\beta} \frac{d(w(p,\varepsilon))}{dp'} + \lambda_1 h(p) \frac{(1-\beta)}{\beta} \int_{p_{\min}}^p \frac{1}{(\rho+\delta+\lambda \bar{H}(p'))} \frac{d(w(p,\varepsilon))}{dp'} dp'.$$

Then, plugging in equation (18):

$$\frac{d(w(p,\varepsilon))}{dp'} = \varepsilon + \lambda_1 h(p) \frac{w(p,\varepsilon) - p\varepsilon}{(\rho + \delta + \lambda \bar{H}(p'))} - \frac{(1-\beta)}{\beta} \frac{d(w(p,\varepsilon))}{dp'}.$$

Rearranging, we have a first order differential equation,

$$\frac{d(w(p,\varepsilon))}{dp'} + \frac{\beta \lambda_1 h(p)}{\rho + \delta + \lambda_1 \bar{H}(p)} w(p,\varepsilon) = \varepsilon \beta \left[\frac{\rho + \delta + \lambda_1 \bar{H}(p) + \lambda_1 h(p)p}{\rho + \delta + \lambda_1 \bar{H}(p)} \right]$$
(19)

To solve this differential equation, note that:

$$\frac{d(\rho + \delta + \lambda_1 \bar{H}(p))^{-\beta}}{dp} = (\rho + \delta + \lambda_1 \bar{H}(p))^{-\beta} \frac{\beta \lambda_1 h(p)}{\rho + \delta + \lambda_1 \bar{H}(p)}.$$

Then, multiplying both sides of equation (19) by $(\rho + \delta + \lambda_1 \bar{H}(p))^{-\beta}$ and rearranging

$$\frac{d\left[w(p,\varepsilon)(\rho+\delta+\lambda_1\bar{H}(p))^{-\beta}\right]}{dp} = \varepsilon\beta \left[\frac{\rho+\delta+\lambda_1\bar{H}(p)+\lambda_1h(p)p}{\left(\rho+\delta+\lambda_1\bar{H}(p)\right)^{1+\beta}}\right].$$
 (20)

Integrating (20) between p_{\min} and p, and noting that the lowest productivity firm will produce no surplus $\Leftrightarrow w(p_{\min}, \varepsilon) = p_{\min}\varepsilon$, straightforward algebra shows that:

$$w(p,\varepsilon)(\rho+\delta+\lambda_1\bar{H}(p))^{-\beta}$$

$$= (\rho+\delta+\lambda_1)^{-\beta}p_{\min}\varepsilon+\varepsilon\beta\int_{p_{\min}}^{p}\left[\frac{\rho+\delta+\lambda_1\bar{H}(p')+\lambda_1h(p')p'}{\left(\rho+\delta+\lambda_1\bar{H}(p')\right)^{1+\beta}}\right]dp'.$$

Separating the integral in a convenient way and noting that:

$$\frac{\partial \left(\left(\rho + \delta + \lambda_1 \bar{H}(p') \right)^{-\beta} p' \right)}{\partial p'} = \left(\rho + \delta + \lambda_1 \bar{H}(p') \right)^{-\beta} + \frac{\beta \lambda_1 h(p') p'}{\left(\rho + \delta + \lambda_1 \bar{H}(p') \right)^{1+\beta}} dp',$$

it solves as:

$$w(p,\varepsilon) = \frac{(\rho + \delta + \lambda_1 \bar{H}(p))^{\beta}}{(\rho + \delta + \lambda_1)^{\beta}} p_{\min} \varepsilon - \varepsilon (1 - \beta) (\rho + \delta + \lambda_1 \bar{H}(p))^{\beta} \int_{p \min}^{p} (\rho + \delta + \lambda_1 \bar{H}(p'))^{-\beta} dp' + \varepsilon (\rho + \delta + \lambda_1 \bar{H}(p))^{\beta} \int_{p \min}^{p} \frac{\partial ((\rho + \delta + \lambda_1 \bar{H}(p'))^{-\beta} p')}{\partial p'} dp'.$$

Rearranging, we get the wage equation as a function of individual ability (ε) , friction patterns $(\delta$ and $\lambda_1)$ and firm's productivity (p).

$$w(p,\varepsilon) = \varepsilon p - \varepsilon (1-\beta)(\rho + \delta + \lambda_1 \bar{H}(p))^{\beta} \int_{p \min}^{p} (\rho + \delta + \lambda_1 \bar{H}(p'))^{-\beta} dp' \blacksquare$$

A.2 Minimum Productivity

Now we show that p_{min} is independent of ε . p_{min} is the minimum observed productivity level. Firms with productivity p_{min} make zero profit, and therefore the whole productivity goes to the worker, who receives εp_{min} . This wage exactly compensate the worker to leave the unemployment, Therefore:

$$E(p_{\min}\varepsilon,\varepsilon) = U(\varepsilon)$$

$$p_{\min}\varepsilon + \lambda_1 \int_{w(p_{\min},\varepsilon)}^{w(p_{\max},\varepsilon)} \left[E(w(p',\varepsilon),\varepsilon) - U(\varepsilon) \right] dF(W(p',\varepsilon))$$

$$= b\varepsilon + \lambda_0 \int_{w(p_{\min},\varepsilon)}^{w(p_{\max},\varepsilon)} \left[E(w(p',\varepsilon),\varepsilon) - U(\varepsilon) \right] dF(W(p',\varepsilon))$$

$$p_{\min}\varepsilon = b\varepsilon + (\lambda_0 - \lambda_1) \int_{w(p_{\min},\varepsilon)}^{w(p_{\max},\varepsilon)} \left[E(w(p',\varepsilon),\varepsilon) - U(\varepsilon) \right] dF(W(p',\varepsilon)).$$

Using the surplus splitting rule (3):

$$p_{\min}\varepsilon = b\varepsilon + (\lambda_0 - \lambda_1) \frac{\beta}{1 - \beta} \int_{w(p_{\min}, \varepsilon)}^{w(p_{\max}, \varepsilon)} \frac{p'\varepsilon - w(p', \varepsilon)}{(\rho + \delta + \lambda \bar{F}(w(p', \varepsilon)|\varepsilon))} dF(W(p', \varepsilon)).$$

This is the value function for a worker of a given ε , so we can rearrange everything in terms of p.

$$p_{\min}\varepsilon = b\varepsilon + (\lambda_0 - \lambda_1) \frac{\beta}{1 - \beta} \int_{p_{\min}}^{p_{\max}} \frac{p'\varepsilon - w(p', \varepsilon)}{(\rho + \delta + \lambda \bar{H}(p'))} dH(p'),$$

using equation (4) and rearranging:

$$p_{\min}\varepsilon = b\varepsilon + \varepsilon(\lambda_0 - \lambda_1) \frac{\beta}{1 - \beta} \times \int_{p_{\min}}^{p_{\max}} \frac{(1 - \beta) \int_{p_{\min}}^{p'} (\rho + \delta + \lambda_1 \bar{H}(\widetilde{p}))^{-\beta} d\widetilde{p}}{(\rho + \delta + \lambda \bar{H}(p'))^{(1-\beta)}} dH(p'))$$

 ε becomes irrelevant:

$$p_{\min} = b + (\lambda_0 - \lambda_1)\beta \int_{p_{\min}}^{p_{\max}} \frac{\int_{p_{\min}}^{p'} (\rho + \delta + \lambda_1 \bar{H}(\widetilde{p}))^{-\beta} d\widetilde{p}}{(\rho + \delta + \lambda \bar{H}(p'))^{(1-\beta)}} dH(p'))$$

Note that p_{\min} is a function of the distribution of p and the parameters of the model. The intuition, in discrete time, is clear because the value of being employed and the value of being unemployed are infinite additions of flows which are linear on ε ($w(\varepsilon, p)$ and $b\varepsilon$). Each flow is multiplied by the discount rate and the probability of being in each state, that do not depend on ε . Hence the value of being employed and the value of being unemployed are both linear in ε . This condition must hold in order to avoid sorting between p and ε .

A.3 Duration model - Maximum Likelihood Specification

The unconditional likelihood of job-spell durations is:

$$\mathcal{L}(t) = \int \mathcal{L}(t|p)g(p)dp.$$

$$\mathcal{L}(t) = \int_{p_{\min}}^{p_{\max}} \frac{(1 + \frac{\lambda_1}{\delta})h(p)}{1 + \frac{\lambda_1}{\delta}\bar{H}(p)} \left[\delta + \lambda_1 H(p)\right] e^{-[\delta + \lambda_1 H(p)]t} dp.$$

Rearranging,

$$\mathcal{L}(t) = \frac{\left(1 + \frac{\lambda_1}{\delta}\right)\delta}{\frac{\lambda_1}{\delta}} \int_{p_{\min}}^{p_{\max}} \frac{1}{\delta + \lambda_1 \bar{H}(p)} e^{-[\delta + \lambda_1 H(p)]t} \lambda_1 h(p) dp$$

Changing the variable within the integral, $x = [\delta + \lambda_1 \bar{H}(p)] t$. After straightforward algebra we get:

$$\mathcal{L}(t) = \frac{(1 + \frac{\lambda_1}{\delta})\delta}{\frac{\lambda_1}{\delta}} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right].$$

where $E_1(t) = \int_t^\infty \frac{e^{-x}}{x} dx$ is the exponential integral function \blacksquare .

Our sample covers a fixed number of periods, so that some job durations are right censored, and other job spells started before the panel's beginning. This means that the exact likelihood function that takes into account these events is:

$$l(t_i) = (1 - c_i) \log \left(\frac{\mathcal{L}(t_i)}{\int_{H_i}^{\infty} \mathcal{L}(t) dt} \right) + c_i \log \left(\frac{\int_{t_i}^{\infty} \mathcal{L}(t) dt}{\int_{H_i}^{\infty} \mathcal{L}(t) dt} \right),$$

where c_i is a truncated spell indicator and H_i is the time period elapsed before the sample.

$$l(t_i) = (1 - c_i) \log \left(\frac{\left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right]}{\int_{H_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt} \right) + c_i \log \left(\frac{\int_{t_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt}{\int_{H_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt} \right).$$

Using the fact that $\int E_1(at)dt = -\int E_1(-at)dt = -\left(tE_1(-at) + \frac{e^{-at}}{a}\right)$ (see Abramowitz and Stegun, 1972), and noting that $E_1(-\infty) = 0$,

$$\int_{t_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt = \int_{t_i}^{\infty} E_1(\delta t) dt - \int_{t_i}^{\infty} E_1(\delta (1 + \frac{\lambda_1}{\delta})t) dt$$

$$= -t E_1(-\delta t) + \frac{e^{-\delta t}}{\delta} \Big|_{t_i}^{\infty} +$$

$$t E_1(-(1 + \frac{\lambda_1}{\delta})\delta t) + \frac{e^{-\delta t}}{(1 + \frac{\lambda_1}{\delta})\delta} \Big|_{t_i}^{\infty}$$

$$\int_{t_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt$$

$$= t_i E_1(-\delta t_i) + \frac{e^{-\delta t_i}}{\delta} - t_i E_1(-(1 + \frac{\lambda_1}{\delta})\delta t) - \frac{e^{-\delta t_i}}{(1 + \frac{\lambda_1}{\delta})\delta}.$$

Since $E_i(-at) = -E_1(at) = -\int_{at_i}^{\infty} \frac{e^{-x}}{x} dx$.

$$\int_{t_i}^{\infty} \left[E_1(\delta t) - E_1(\delta (1 + \frac{\lambda_1}{\delta})t) \right] dt$$

$$= \frac{e^{-\delta t_i}}{\delta} - t_i \int_{\delta t_i}^{\delta (1 + \frac{\lambda_1}{\delta})t} \frac{e^{-x}}{x} dx - \frac{e^{-\delta t_i}}{(1 + \frac{\lambda_1}{\delta})\delta}$$

The same is true for $\int_{H_i}^{\infty} \mathcal{L}(t)dt$. Then the likelihood takes the following form:

$$l(t_i) = (1 - c_i) \log \left(\frac{\int_{\delta t}^{(1 + \frac{\lambda_1}{\delta})\delta t} \frac{e^{-x}}{x} dx}{\frac{e^{-\delta H_i}}{\delta} - \frac{e^{-\delta(1 + \frac{\lambda_1}{\delta})H_i}}{\delta(1 + \frac{\lambda_1}{\delta})} - H_i \int_{\delta H_i}^{(1 + \frac{\lambda_1}{\delta})\delta H_i} \frac{e^{-x}}{x} dx} \right) +$$

$$c_i \log \left(\frac{\frac{e^{-\delta t_i}}{\delta} - \frac{e^{-\delta(1 + \frac{\lambda_1}{\delta})t_i}}{\delta(1 + \frac{\lambda_1}{\delta})} - t_i \int_{\delta t_i}^{(1 + \frac{\lambda_1}{\delta})\delta t_i} \frac{e^{-x}}{x} dx}{\frac{e^{-\delta H_i}}{\delta} - \frac{e^{-\delta(1 + \frac{\lambda_1}{\delta})H_i}}{\delta(1 + \frac{\lambda_1}{\delta})} - H_i \int_{\delta H_i}^{(1 + \frac{\lambda_1}{\delta})\delta H_i} \frac{e^{-x}}{x} dx} \right)$$

B Robustness Checks

B.1 Allowing for Between-Firms Bertrand Competition

In the model presented in Section 2, workers do not have the option of recalling old employers. In this subsection we estimate the model allowing recalling and Bertrand competition between firms as in Cahuc, Postel-Vinay and Robin (2006). β has a different interpretation in this model, it is still a surplus-splitting parameter where the surplus has been defined in terms of a time varying outside option given by a poaching firm.⁶⁴

The estimated bargaining power are smaller than in the model without Bertrand competition: now the weighted average is 21.8 percent. We find similar patterns in terms of gender, than in the model without renegotiation. Women are found to have smaller bargaining power than men

⁶⁴For the exact formulation of the bargaining scenario and a discussion on its implication see Cahuc, Postel-Vinay and Robin (2006).

Table 14: Robustness Check: Allowing for Renegotiation

| | | Women | Men |
|---------------|--------|---------------|---------------|
| | | β_{CPR} | β_{CPR} |
| MANUFACTURING | Low-Q | 0.212 | 0.182 |
| | High-Q | 0.163 | 0.172 |
| Construction | Low-Q | 0.223 | 0.289 |
| | High-Q | 0.182 | 0.206 |
| TRADE | Low-Q | 0.238 | 0.254 |
| | High-Q | 0.203 | 0.215 |
| SERVICES | Low-Q | 0.325 | 0.341 |
| | High-Q | 0.241 | 0.231 |

Note: β_{CPR} is the Nash bargaining power of the worker in the model with renegotiation proposed in Cahuc, Postel-Vinay and Robin (2006). β_{CPR} are recovered by simulated method of moments.

in most of the groups. As in the model proposed in this paper, female workers are only found to have larger β in services and in manufacturing and then only in low-qualification occupations.

Workers in low-qualification occupation are found to have higher bargaining power than workers in high-qualification occupation. This results have been found also estimating the model without renegotiation but it is different from what has been found by Cahuc, Postel-Vinay and Robin (2006), who estimate a similar model with French data.

The counterfactual decomposition works in the same way as the decomposition described in Section 5. We first calculate the mean wages of female workers, as a function of female wage determinants, and we sequentially change each parameter until reaching the male mean wages.

Table 15: Gender Wage-Gap decomposition - Allowing for Renegotiation

| | Counterfactual | Sectors | | | |
|---------------|---|---------|-------|-------|-------|
| | MEAN-DAILY WAGES | M | С | Т | S |
| | $w(\lambda_1^M, \delta^M, \gamma^M, \beta^M)$ | 190.3 | 150.0 | 119.2 | 155.9 |
| ${ m HIGH}$ | $w(\lambda_1^M, \delta^M, \gamma^M, \beta^F)$ | 182.9 | 125.2 | 115.1 | 162.7 |
| QUALIFICATION | $w(\lambda_1^M, \delta^M, \gamma^F, \beta^F)$ | 116.3 | 91.3 | 79.9 | 95.7 |
| OCCUPATIONS | $w(\lambda_1^M, \delta^F, \gamma^F, \beta^F)$ | 100.3 | 80.5 | 70.1 | 79.8 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, \beta^F)$ | 106.5 | 82.8 | 67.7 | 88.6 |
| | $w(\lambda_1^M, \delta^M, \gamma^M, \beta^M)$ | 109.1 | 96.3 | 84.1 | 88.8 |
| Low | $w(\lambda_1^M, \delta^M, \gamma^M, \beta^F)$ | 126.6 | 67.9 | 80.5 | 81.6 |
| QUALIFICATION | $w(\lambda_1^M, \delta^M, \gamma^F, \beta^F)$ | 83.4 | 47.0 | 51.8 | 48.2 |
| OCCUPATIONS | $w(\lambda_1^M, \delta^F, \gamma^F, \beta^F)$ | 69.6 | 48.4 | 45.1 | 45.7 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, \beta^F)$ | 74.3 | 53.0 | 47.5 | 49.1 |

The decomposition is similar to the one that comes out from the model without Bertrand Competition. Now 6.2 percent of the wage gap is explained by differences in the bargaining power, slightly less than before. Female workers in high qualification occupations are suffering more wage discrimination. Differences in productivity are responsible for most of the wage gap. Allowing for Bertrand competition also increases the effect of differences in destruction rates, decreases the effect of differences in job-offers arrival rates, and the net effect of friction is now more important.

Details of the simulations:

The model used for simulations is a simplified version of the Cahuc, Postel-Vinay and Robin (2006) model, where the worker heterogeneity has been omitted.⁶⁵

- β_{CPR} are recovered by the simulated method of moments.
- Simulations use the punctual estimates of λ_1 , δ , γ_w , γ_u and α_l for every sector and worker group, reported in Section 3.
- We assume that the primitive distribution of firm's productivity is log-normal.
- 32 moments have been matched
 - The mean-wages of female and male workers in each occupation group and in each sector.
 - The mean-productivity of the endogenously truncated distribution of firms faced by female and male workers in each occupation group and in each sector.
- Using condition (5), the unemployment rate of each group as reported in EUROSTAT⁶⁶ and the estimates of δ for each group, we recover an estimate of λ_0 for female and male workers in each occupation group and in each sector.

⁶⁵Given that we match sample means, and the wage equation is linear in worker ability, worker heterogeneity does not play any role in these simulations.

MATA codes for simulating the model previously described are available from the author upon request.

⁶⁶The mean unemployment rate between 1996 and 2005 was 9.64 percent for females and 9.11 percent for males (see EUROSTAT).

B.2 Wage Gap Decomposition - Inverse Order

The decomposition results depend upon the sequence of decompositions implemented. This is because each sequence stands for a different series of counterfactual wage distributions. We suggest an order of decomposition for which we think the sequence of counterfactuals is of interest. Our sequential decomposition involves five components for each group. It would be beyond the scope of this paper to report all the conceivable $8 \times 5! = 960$ permutations of the sequence of decompositions. In any case, we also estimate an alternative sequence of our decomposition, in reversed order, as a robustness check. Results are presented in Table 16.

Table 16: Counterfactual wages - Inverse Decomposition

| | Counterfactual | | SECT | ΓORS | |
|--------------------------|---|-------|-------|--------------|-------|
| | Mean-Daily Wages | M | С | Τ | S |
| | $w(\lambda_1^M, \delta^M, \gamma^M, H(p)^M, \beta^M)$ | 190.3 | 150.9 | 119.2 | 156.3 |
| $\mathbf{H}\mathbf{IGH}$ | $w(\lambda_1^F, \delta^M, \gamma^M, H(p)^M, \beta^M)$ | 208.9 | 187.1 | 127.1 | 137.9 |
| QUALIFICATION | $w(\lambda_1^F, \delta^F, \gamma^M, H(p)^M, \beta^M)$ | 194.8 | 174.5 | 118.7 | 119.7 |
| OCCUPATIONS | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^M, \beta^M)$ | 158.1 | 132.4 | 90.1 | 75.3 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^F, \beta^M)$ | 131.0 | 122.3 | 95.2 | 70.3 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^F, \beta^F)$ | 105.7 | 82.8 | 67.8 | 87.4 |
| | $w(\lambda_1^M, \delta^M, \gamma^M, H(p)^M, \beta^M)$ | 109.2 | 96.6 | 84.9 | 88.5 |
| Low | $w(\lambda_1^F, \delta^M, \gamma^M, H(p)^M, \beta^M)$ | 119.9 | 108.4 | 82.1 | 78.6 |
| QUALIFICATION | $w(\lambda_1^F, \delta^F, \gamma^M, H(p)^M, \beta^M)$ | 109.6 | 110.7 | 76.0 | 75.8 |
| OCCUPATIONS | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^M, \beta^M)$ | 77.8 | 88.7 | 75.8 | 61.7 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^F, \beta^M)$ | 73.7 | 81.6 | 63.6 | 44.5 |
| | $w(\lambda_1^F, \delta^F, \gamma^F, H(p)^F, \beta^F)$ | 76.9 | 53.3 | 47.6 | 49.1 |

This alternative decomposition is qualitatively similar to the one that comes out from the original order. Now 18.1 percent of the wage gap is explained by differences in the bargaining power, slightly more than before. As before, female workers in high qualification occupations are suffering more wage discrimination. Differences in productivity are still responsible for most of the wage gap, 47 percent in the case of low-qualification occupations and 52 percent in the case of high-qualification occupations.

B.3 Detecting Discrimination - Traditional Approach

In order to compare different strategies to detect wage discrimination, we perform the traditional approach using Mincer-type wage equations. As can be seen in Table 17, women have large wage

differentials. Controlling for observable characteristics, they receive wages, on average, 21 percent lower than men. This difference is significant and consistent with what has been found in previous research: Blau and Kahn (2000), with OECD data reports a difference of 25.5 percent between male and female mean wages, while Fitzenberger and Wunderlich (2002) with the same data as in this paper, but using quantile regression, the estimated German gender wage gap ranges between 16 percent and 25 percent depending on the job's qualification.

Oaxaca-Blinder Decomposition

Using the results presented in Table 17, we calculate a Oaxaca-Blinder decomposition, which basically decomposes the wage-gap into differences in observable and unobservable characteristics. The counterfactual female mean-wage has to be interpreted as the mean-wage that women would have if they had the male distribution of observable characteristics. Therefore, the difference between the counterfactual female mean-wage and the observed women mean-wage is the portion of the gap understood as discrimination.

Following this approach, we would conclude that women are being discriminated against. They are receiving wages which are on average almost 15 percent lower than wages of similar men in terms of observable characteristics. These results are slightly different to those obtained in this paper.

Additional References:

Abramowitz, M., and. A. Stegun (1972), "Handbook of Mathematical Functions, with Formulas, Graphs, and Mathematical Tables" National Bureau of Standards Applied Mathematics Series, Vol. 55. Washington, DC: U.S. Government Printing Office.

Fitzenberger, B. and Wunderlich, G. (2002). "Gender Wage Differences in West Germany: A Cohort Analysis", German Economic Review, 3(4) pp.379-414.

 ${\bf Table\ 17:\ Mincer\ Wage\ Equations\ -\ Censored\ -Normal\ Regression.\ Maximum\ Likelihood\ Estimates}$

| $\overline{\text{Y=Log(WAGE)}}$ | All | Men | Women |
|---------------------------------|----------|----------|----------|
| WOMEN | -0.211 | - | - |
| | (0.0004) | - | - |
| IMMIGRANT | 0.073 | 0.061 | 0.076 |
| | (0.0006) | (0.0016) | (0.0006) |
| HIGH-QUALIFICATION | 0.255 | 0.178 | 0.276 |
| | (0.0004) | (0.0010) | (0.0005) |
| AGE | 0.056 | 0.068 | 0.054 |
| | (0.0002) | (0.0004) | (0.0002) |
| AGE^{2} | -0.001 | -0.001 | -0.001 |
| | (0.0000) | (0.0000) | (0.0000) |
| PRIMARY EDUCATION | 0.236 | 0.257 | 0.234 |
| | (0.0004) | (0.0011) | (0.0005) |
| College | -0.127 | -0.082 | -0.162 |
| (INCOMPLETE) | (0.0014) | (0.0028) | (0.0015) |
| TECHNICAL COLLEGE | 0.386 | 0.436 | 0.354 |
| (COMPLETED) | (0.0010) | (0.0021) | (0.0012) |
| College | 0.609 | 0.616 | 0.566 |
| | (0.0011) | (0.0033) | (0.0011) |
| University Degree | 0.757 | 0.819 | 0.700 |
| | (0.0011) | (0.0027) | (0.0012) |
| TENURE | 0.017 | 0.025 | 0.015 |
| | (0.0001) | (0.0002) | (0.0001) |
| EXPERIENCE | 0.033 | 0.021 | 0.036 |
| | (0.0001) | (0.0003) | (0.0001) |
| Part-Time | -0.638 | -0.651 | -0.608 |
| | (0.0007) | (0.0010) | (0.0011) |
| Manufacturing | 0.178 | 0.175 | 0.103 |
| | (0.0008) | (0.0016) | (0.0010) |
| CONSTRUCTION | 0.063 | 0.026 | -0.081 |
| | (0.0013) | (0.0029) | (0.0014) |
| SERVICES | 0.037 | 0.025 | -0.023 |
| | (0.0009) | (0.0017) | (0.0011) |
| Constant | 2.500 | 2.189 | 2.599 |
| | (0.0029) | (0.0066) | (0.0031) |
| Pseudo R ² | 47.23 | 30.92 | 52.53 |
| SIGMA | 0.38 | 0.48 | 0.34 |

Note: Std. errors are given in parentheses. Time Dummies included.