Have women really a better access to best-paid jobs in the public sector? Counterfactuals based on a job assignment model

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Motivations

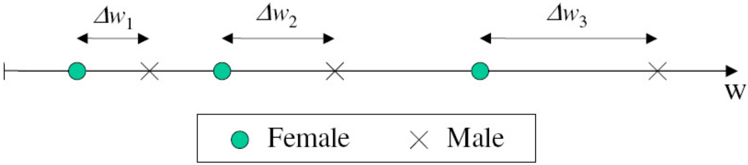
Mean (std) daily wage for full-time workers in the Public and Private sectors in 2011:

	Females	Males	Gender diff	Diff (%)
Public	65.2	76.2	-11.0	-14.4%
	(27.4)	(36.0)	-8.6	-23.8%
Private	68.7	84.9	-16.2	-19.1%
	(51.0)	(77.6)	-27.5	-34.3%
Sector	-3.5	-8.7		
diff	-23.6	-41.6		

Questions:

- Differences in female access to best-paid jobs across sectors?
- Job access differences measured well with wage differences?
- Differences related to worker characteristics or their returns?

About the approach using gender quantile differences



Increase in gender wage quantile difference with rank but...

Similar access to every job for males and females

$\Longrightarrow$ need for an economic model to assess gender differences in access to jobs

What we do

Job assignment model involving individual observed heterogeneity

Derivation of a measure of gender differences in access to jobs along the wage distribution for given observable characteristics

Quantification of these differences in public and private sectors using DADS-EDP panel data

Decomposition of gender differences in access to jobs in each sector into the contributions of observable characteristics and their returns

Gender wage counterfactuals for the public sector when gender access is the same as in the private sector

Our results

Gender differences in access to jobs increasing with rank along the job hierarchy both in the public and private sectors

The access profiles are rather similar in the two sectors

The contribution of observables characteristics (age, education, family, experience,...) to explaining these differences are small

Long part-time experience is the only factor with explanatory power

The gender gap increases by only 0.7 pts in the public sector when workers are reassigned following rules in the private sector but...

the gender quantile gap at the 9th decile increases by 4.6 pts

Related literature

Decomposition and counterfactual descriptive approaches

(Oaxaca, 1973; Blinder, 1973; Machado and Mata, 2005; Firpo, Fortin and Lemieux, 2009; Chernozhukov, Fernandez-Val and Melly, 2013, etc.)

Gender differences in access to high-paid jobs

(Bertrand and Hallock, 2001; Albrecht, Bjorklund and Vroman, 2003; Gobillon, Meurs and Roux, 2015, etc.)

Gender differences in specific sectors

(public: Gregory and Borland, 1999; Melly, 2005; Lucifora and Meurs, 2006; Postel-Vinay and Turon, 2007; Bradley, Postel-Vinay and Turon, 2013; academic: Blackaby, Booth and Franck, 2005; army: Killingsworth and Reimers, 1983; grocery: Ransom and Oaxaca, 2005; etc.)

Roadmap

1. Job assignment model
2. Estimation method
3. Counterfactuals of gender difference in access to jobs and wages
4. Dataset and descriptive statistics
5. Estimation results and counterfactuals

Mechanisms

Job positions are heterogeneous in wage

Fixed wage for each job position through a contract

Wage is not allowed to depend on the gender of applicant or any other individual characteristic

Worker primarily interested in the job yielding the highest wage

They are all in competition whatever their characteristics

Manager chooses an applicant taking into account obs. charac.

Applicants not hired turn to second highest paid job, and so on

All positions are filled, no unemployment

Assignment mechanism

Consider a job of rank u in the wage distribution of job positions

The propensity of an individual i to get the job depends on an exogenous parameter $\mu\left(u \,|X_i, j\left(i\right)\right)$

The manager chooses the applicant with the highest value of:

$$V_i\left(u\right) = \ln \mu\left(u \,|X_i, j\left(i\right)\right) + \varepsilon_i\left(u\right)$$

where $\varepsilon_i\left(u\right)$ follow iid extreme value laws.

Measure $n\left(u|\; X, j\right)$ of gender-j workers with characteristics X available for the job of rank u.

Determination of workers available for each job

$\phi(u|\ X, j)$: probability of an available gender-j worker with characteristics X getting a job in interval $[u - du, u]$.

$$\phi(u|X,j) = \frac{\mu(u|X,j)}{\int n(u|X,f)\,\mu(u|X,f)\,dX + \int n(u|X,m)\,\mu(u|X,m)\,dX}$$

Evolution of available workers with rank:

$$n(u - du|X,j) = n(u|X,j) - n(u|X,j)\,\phi(u|X,j)\,du$$

Having $du \to 0$, we get:

$$n'(u|X,j) = \phi(u|X,j)\,n(u|X,j)$$

This describes the allocation of workers along the job hierarchy
Initial conditions: $n(1|\ X, j) = n(X, j)$

We show the existence and uniqueness of the solution

Outcomes of interest

The gender-j probability of getting the job:

$$\phi(u|j) = \int \frac{n(u|X,j)}{n(u|j)} \phi(u|X,j)\, dX$$

where $n(u|j) = \int n(u|X,j)\, dX$.

The gender probability ratios:

$$\frac{\phi(u|f)}{\phi(u|m)} \text{ and } \frac{\phi(u|X,f)}{\phi(u|X,m)} = \frac{\mu(u|X,f)}{\mu(u|X,m)}$$

The gender-j wage cumulative and density:

$$F_j(w) = \int \frac{n(F(w)|X,j)}{n(1|j)} dX,\ f_j(w) = f(w) \int \frac{n'(F(w)|X,j)}{n(1|j)} dX$$

Interpretations

Females have lower access to high-paid jobs when gender probability ratio lower at higher ranks

Gender probability ratio captures in reduced form:

- Taste discrimination
- Statistical discrimination
- Labor supply effect

The intensity of these three effects allowed to vary along the job hierarchy

Specification

Specification of worker value:

$$\mu(u|X,j) = \exp[X\beta_j(u)]$$

Approximation of $\beta_j(u)$ with series of polynomials:

$$\beta_j^k(u) = \sum_{p=0}^{P} \beta_{jp}^k u^p$$

Parameters β_{jp}^k to be estimated (we fix $P = 5$ in practice).

Reference category: $\beta^1(u) = 0$.

Estimation of parameters by maximum likelihood.

Additional notations

Model estimated by maximum likelihood

Notations:

- u_i: rank of individual i
- $u^k = (k-1)/(N-1)$ the k^{th} rank and i_k the individual occupying this rank such that $\{i_1, ..., i_k\}$ is the set of applicants
- $\vec{j}_k = \{j(i_1), ..., j(i_k)\}$ and $\vec{X}_k = \{X(i_1), ..., X(i_k)\}$, the gender and characteristics of workers occupying the k less-paid jobs

Likelihood maximization

$P\left(u_{i_k} = u^k \middle| \{i_1, ..., i_k\}, \overrightarrow{X}_k, \overrightarrow{j}_k\right)$ empirical counterpart of $\phi\left(u_{i_k} | X_{i_k}, j\left(i_k\right)\right)$

It verifies:

$$P\left(u_{i_k} = u^k \middle| \{i_1, ..., i_k\}), \overrightarrow{X}_k, \overrightarrow{j}_k\right) = \frac{\mu\left(u_{i_k} | X_{i_k}, j\left(i_k\right)\right)}{\sum_{\ell \leqslant k} \mu\left(u_{i_k} | X_{i_\ell}, j\left(i_\ell\right)\right)} = \frac{\exp\left[X_{i_k}\beta_{j(i_k)}\left(u_{i_k}\right)\right]}{\sum_{\ell \leqslant k} \exp\left[X_{i_\ell}\beta_{j(i_\ell)}\left(u_{i_k}\right)\right]}$$

Parameters in $\beta_j\left(u\right)$ estimated by maximizing:

$$L = \frac{1}{N}\sum_k \ln P\left(u_{i_k} = u^k \middle| \Omega(u^k), \overrightarrow{X}_k, \overrightarrow{j}_k\right)$$

Same as partial likelihood for Cox duration model

$\Longrightarrow$ asymptotic distribution of estimated parameters established

Decomposition of gender differences in access to job

Decomposition of the log gender probability ratio of getting a job of rank u:

$$\begin{aligned}
\log\left[\phi\left(u\,|f\right)/\phi\left(u\,|m\right)\right] &= \left[E\left(X\,|f,u\right)-E\left(X\,|m,u\right)\right]\beta^{r}\left(u\right)\\
&+ E\left(X\,|f,u\right)\left[\beta_{f}\left(u\right)-\beta^{r}\left(u\right)\right]\\
&- E\left(X\,|m,u\right)\left[\beta_{m}\left(u\right)-\beta^{r}\left(u\right)\right]\\
&+ r\left(u\right)
\end{aligned}$$

$E\left(X\,|j,u\right)$ average charac. of gender-j workers available for job of rank u

$\beta^{r}\left(u\right)$ gender-neutral benchmark value of parameters

$r\left(u\right)$ residual accounting for non-linearities

Counterfactual assignments

Counterfactuals using alternative assignment mechanisms $\beta_j^*(u)$:

- Gender-specific assignment $\beta_j(u)$ of the sector

  $\Rightarrow$ Assessment: fit of the model

- Equal gender assignment $\beta^r(u)$ of the sector

  $\Rightarrow$ Assessment: importance of observable characteristics

- Gender-specific assignment $\beta_j(u)$ of the other sector

  $\Rightarrow$ Assessment: importance of assignment rule

Need to compute counterfactual $n^*(u|X,j)$ to recover counterfactual outcomes of interest

$\Rightarrow$ Simulations

Simulation of available workers

There are N jobs, a simulation is indexed by $s = 1, ..., S$

$\Omega_j^s(u, X)$: set of gender-j workers with X available at rank u

Sets at empirical rank u^k deduced from sets at next rank
by removing the worker getting the job at rank u^{k+1}

The unit probability of getting a job u is given by a logit model
Alternatives are all available workers competing for the job

Hence, it is possible to simulate which worker gets the job
by drawing values in an extreme value law

We deduce the number of available workers $n^s\left(u^k | X, j\right)$
They are averaged across the S simulations

Consistency

Assigning workers to jobs is similar to sampling without replacement with sampling probabilities varying with the rank

Extending Rosen (1972)'s result on sampling without replacement, we show that when $N \to +\infty$:

$$E\left[N^*\left(u^{\lfloor vN \rfloor+1} \,|X,j\right)\right]/N \underset{a.s.}{\to} n^*\left(v\,|X,j\right) \text{ for all } v \in \left]0,1\right[$$

It is possible to show that when $S \to +\infty$:

$$\frac{1}{S}\sum\nolimits_{s=1}^{S} N^s\left(u^{\lfloor vN \rfloor+1} \,|X,j\right) \underset{a.s.}{\to} E\left[N^*\left(u^{\lfloor vN \rfloor+1} \,|X,j\right)\right] \text{ for all } v \in \left]0,1\right[$$

Dataset

DADS *Grand Format*-EDP, 1976-2011

- All individuals born the first four days of October of an even year
- Records of all jobs in the Public and Private sectors
- *Déclarations Annuelles des Données Sociales* (DADS): collected for tax purposes

  includes wages, days worked, age, sector, job location
- *Echantillon Démographique Permanent* (EDP): constructed from censuses and civil registries

  includes education and family variables (number of children)

Sample construction

Panel used to construct past part-time experience and interruptions but we keep only year 2011 for our cross-section estimations

Distinction between Private and Public sectors
(Teaching and Health excluded)

Restriction to full-time workers aged 30-65

We keep only jobs lasting at least 30 days during the year that are occupied on July, 1^{st}

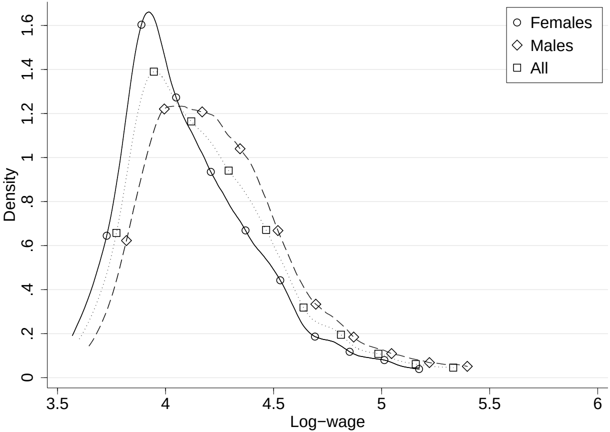
We delete jobs when wage below minimum wage (1000 €/month)

55,881 observations (females: 37.8%, Private sector: 82.6%)
Females in the Private sector: 35.1%, in the Public sector: 50.9%

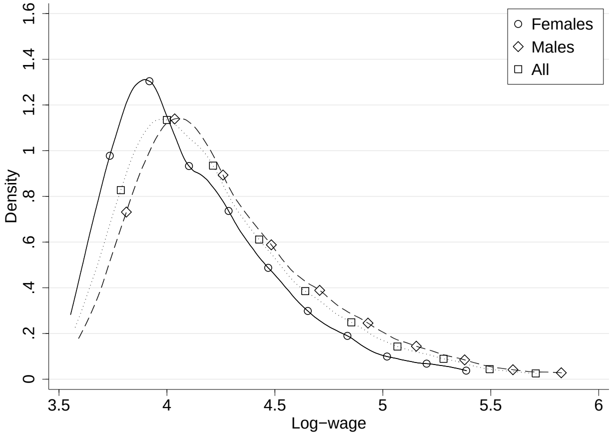
Descriptive statistics on log-wages

	Public Sector			Private Sector		
	Male	Female	Diff	Male	Female	Diff
Mean	4.26	4.12	0.14	4.30	4.13	0.17
St. Dev	0.36	0.33	0.03	0.47	0.40	0.07
P10	3.87	3.77	0.10	3.81	3.70	0.10
P25	4.00	3.89	0.12	3.97	3.84	0.13
Median	4.21	4.05	0.16	4.19	4.04	0.15
P75	4.44	4.30	0.14	4.52	4.34	0.19
P90	4.72	4.54	0.18	4.93	4.66	0.27

Log-wage densities in the Public sector



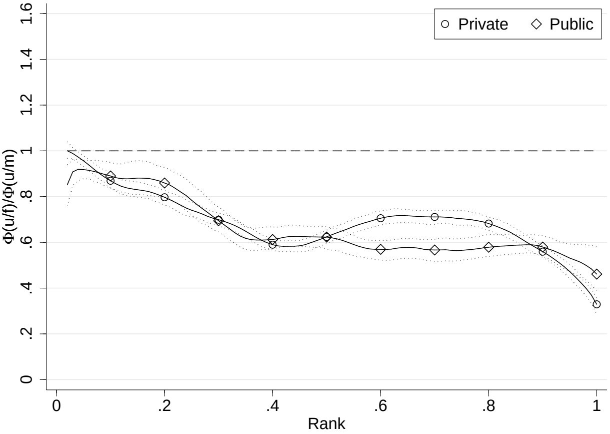
Log-wage densities in the Private sector



Explanatory variables

Category	Public			Private		
	All	Males	Females	All	Males	Females
High school and more	27.2	25.6	28.8	29.9	27.1	34.9
40-49 years old	35.3	35.4	35.1	36.9	36.9	36.9
50 years old and more	40.2	37.1	43.2	30.0	29.6	30.9
$7-18\%$ Part-time exp.	40.0	34.9	44.9	41.9	38.0	49.0
$>18\%$ Part-time exp.	14.1	5.1	22.9	8.1	3.8	16.1
Seniority >10 years	57.9	58.7	57.2	31.2	31.6	30.8
No child	33.4	33.2	33.7	32.9	33.0	32.7
3 children or more	12.4	13.0	11.8	12.2	13.6	9.5
Interruption $1-3$ years	18.4	20.7	16.2	27.4	28.9	24.6
Interruption $3-6$ years	23.9	25.6	22.3	27.1	27.7	25.9
Interruption >6 years	34.4	30.0	38.5	25.2	22.7	29.9
Paris region	23.4	21.1	25.5	23.5	22.4	25.5
Observations	9,732	4,781	4,951	46,149	29,964	16,185

Gender probability ratio in the Public and Private sectors

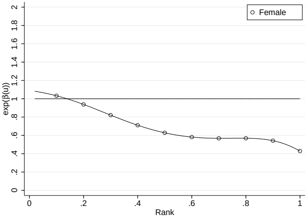


Gender effect on access to jobs, $\exp(\beta^{r,fem}(u))$

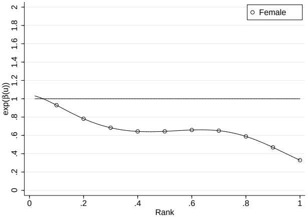
Constrained model: $\beta_f(u) = \beta_m(u) = \beta^r(u)$, female dummy included

Controls: education, age, seniority, children, Paris, career interruption, part-time experience

Public Sector



Private Sector

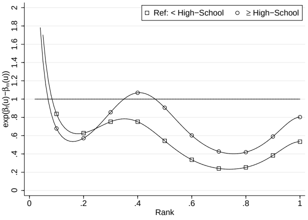


Patterns rather similar for the Public and Private sectors

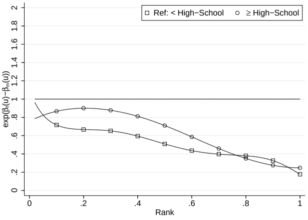
No strong changes when controlling for observables

Effect of education on gender difference in access to jobs, $\exp\left(\beta^{f,ed}(u) - \beta^{m,ed}(u)\right)$

Public Sector



Private Sector

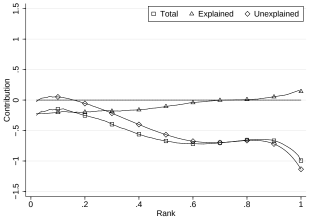


Smaller gender difference in access to jobs for the more educated

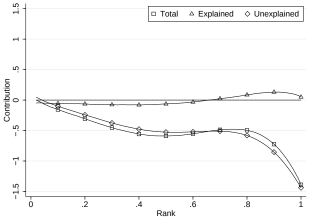
There is even a better access at some ranks for educated females in the Public sector

Oaxaca decomposition of the log-gender probability ratio

Public Sector



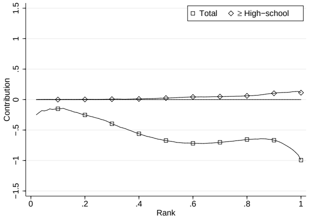
Private Sector



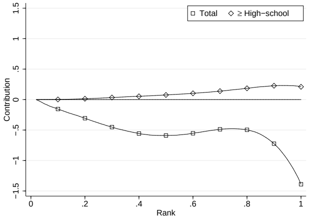
Small contribution of explained variables at high ranks

Contribution of education to Oaxaca decomposition

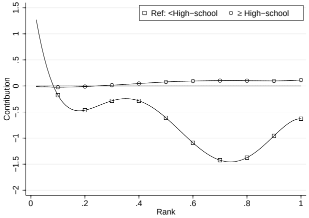
Public Sector, explained



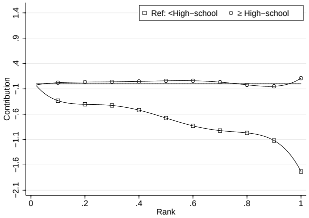
Private Sector, explained



Public Sector, unexplained

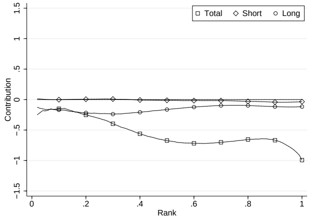


Private Sector, unexplained

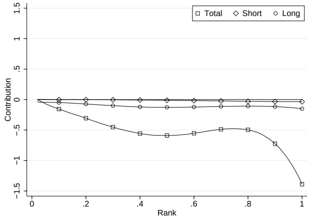


Contribution of part-time exp. to Oaxaca decomposition

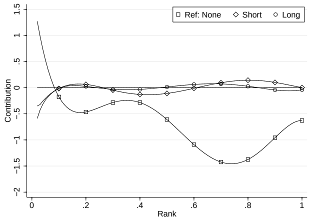
Public Sector, explained



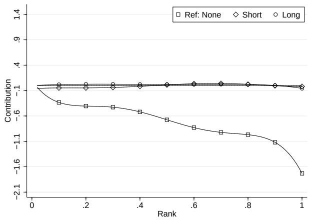
Private Sector, explained



Public Sector, unexplained



Private Sector, unexplained



Counterfactual exercises

For each sector, three counterfactuals are constructed with simulations:

- From estimated parameters $\widehat{\beta}_j(u)$

  $\Longrightarrow$ We test the fit of the model.
- From estimated parameters $\widehat{\beta}^r(u)$: same assignment mechanisms for males and females

  $\Longrightarrow$ Only observed characteristics matter.
- From estimated parameters $\widehat{\beta}_j(u)$ of the other sector: counterfactual assignment.

  $\Longrightarrow$ We assess the importance of the assignment rule.

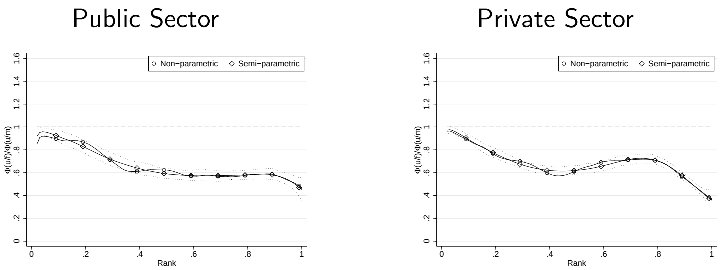
Fit of the model

Differences between observed and counterfactal wages when using estimated parameters for the construction of the counterfactual.

	Public sector		Private sector	
	Males	Females	Males	Females
Mean	-0.0008	0.0008	-0.0006	0.0011
St. Dev	-0.0016	0.0019	-0.0026	0.0060
P10	0.0017	0.0002	0.0004	0.0002
P25	-0.0006	-0.0008	0.0005	0.0004
Median	-0.0013	-0.0013	0.0017	0.0017
P75	0.0022	0.0003	0.0006	0.0043
P90	0.0002	0.0048	-0.0011	0.0037

Note: Statistics based on 100 simulations.

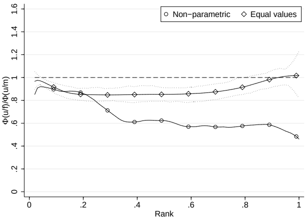
Fit of the gender probability ratio



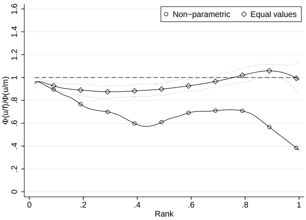
Curves nearly confounded $\Longrightarrow$ very good fit.

Gender probability ratio in case of equal assignment

Public Sector



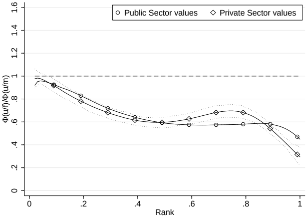
Private Sector



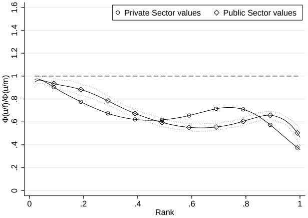
Small gender differences in access to jobs related to gender differences in observable characteristics.

Gender probability ratio in case of other-sector assignment

Public Sector



Private Sector

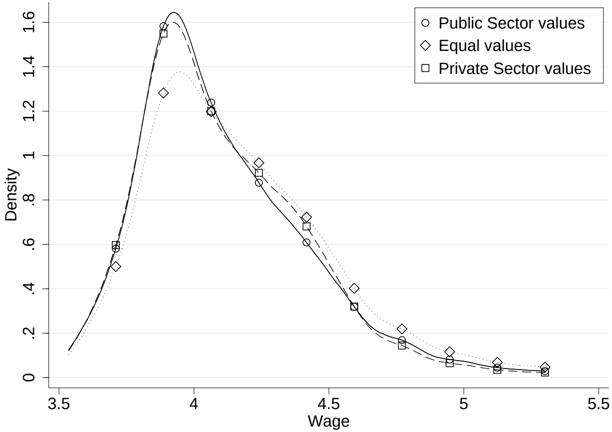


Profile of couterfactual gender probability similar to that of other sector

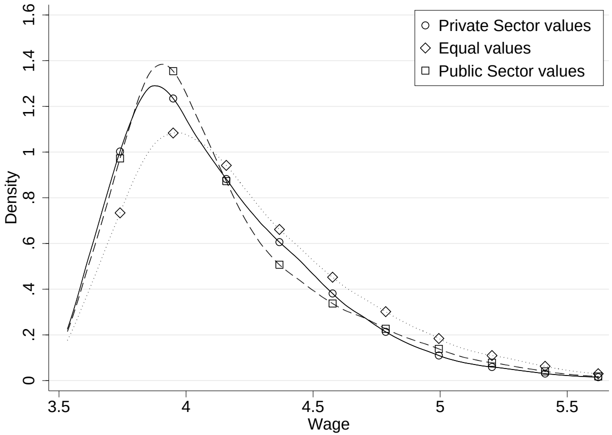
Female access to jobs is slightly better with Private sector assignment rule for ranks between 0.5 and 0.85.

It is better with Public sector assignment rule at higher ranks.

Counterfactual female wage distributions in the Public Sector



Counterfactual female wage distributions in the Private Sector



Wage distributions, alternative assignments

Gender wage differences in the Public sector

	Observed	Benchmark simulation	Equal assignment	Private sector assignment
Mean	0.14	0.14	0.02	0.15
St. Dev	0.03	0.03	-0.01	0.05
P10	0.10	0.10	0.04	0.10
P25	0.12	0.12	0.03	0.11
Median	0.16	0.16	0.03	0.15
P75	0.14	0.15	0.01	0.15
P90	0.18	0.18	0.00	0.23

Note: Statistics based on 100 simulations.

Wage distributions, alternative assignments

Gender wage differences in the Private sector

	Observed	Benchmark simulation	Equal assignment	Public sector assignment
Mean	0.17	0.17	0.01	0.16
St. Dev	0.07	0.06	-0.01	0.04
P10	0.10	0.10	0.03	0.09
P25	0.13	0.13	0.02	0.12
Median	0.15	0.15	0.01	0.17
P75	0.19	0.18	-0.01	0.18
P90	0.27	0.26	-0.01	0.18

Note: Statistics based on 100 simulations.

Summary

Similar large gender difference in access to high-paid jobs in the Public and Private sectors

The contribution of observables characteristics to explaining these differences are small

The gender gap increases by only 0.7 pts in the public sector when workers are reassigned following rules in the private sector but...

the gender quantile gap at the 9th decile increases by 4.6 points

Extensions

Make an international comparison of gender differences

Apply the job assignment model to other contexts

Consider sector choice

Extend the job assignment model to a dynamic framework

Appendices

1. Part-time and hourly wage
2. Unobserved heterogeneity

Part-time jobs and hourly wages

Larger share of females ends up in part-time jobs

Ignoring them $\Longrightarrow$ underestimation of the gender differences in propensity to get full-time job positions

Females may work less hours in some positions than males and this may decrease their daily wage

Ignoring that $\Longrightarrow$ overestimation of the gender differences at some ranks, and underestimation at lower ranks

$\Longrightarrow$ re-estimation including part-time jobs in the sample and considering hourly wages

Hourly wage distributions, part-time jobs included, alternative assignments

Gender wage differences in the Public sector

	Observed	Benchmark simulation	Equal assignment	Private sector assignment
Mean	0.14	0.14	0.04	0.15
St. Dev	0.05	0.04	-0.00	0.05
P10	0.08	0.08	0.05	0.10
P25	0.11	0.10	0.04	0.11
Median	0.16	0.16	0.05	0.16
P75	0.15	0.15	0.03	0.17
P90	0.19	0.19	0.00	0.24

Note: Statistics based on 100 simulations.

Hourly wage distributions, part-time jobs included, alternative assignments

Gender wage differences in the Private sector

	Observed	Benchmark simulation	Equal assignment	Public sector assignment
Mean	0.18	0.17	0.01	0.16
St. Dev	0.08	0.06	-0.01	0.05
P10	0.10	0.10	0.04	0.08
P25	0.13	0.13	0.04	0.12
Median	0.17	0.17	0.03	0.17
P75	0.22	0.22	0.01	0.21
P90	0.26	0.23	-0.00	0.18

Note: Statistics based on 100 simulations.

Influence of unobserved individual heterogeneity

We assess to what extent the gender probability ratio of getting a job is influenced by unobserved individual heterogeneity

Once the model is estimated, we conduct simulations adding an individual effect to the value of each worker

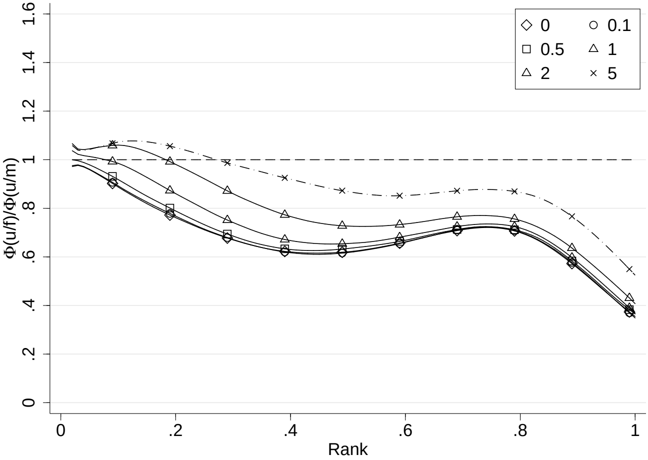
Individual effects are drawn in a centered normal law with variance:

$$V = k^2.V\left(X_i\bar{\beta}_{j(i)}\right) \text{ where } \bar{\beta}_j = \int_0^1 \beta_j\left(u\right)du$$

with $k \in \{0, 0.1, 0.5, 1, 2, 5\}$

We compute the ratio of gender probabilities averaged across simulations

Gender probability ratio in the Public sector, unobserved individual heterogeneity included



Gender probability ratio in the Private sector, unobserved individual heterogeneity included