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

Laurent Gobillon (*Paris School of Economics-CNRS and INED*)

Dominique Meurs (*EconomiX and INED*)

Sébastien Roux (*Banque de France, INED and CREST*)

AMSE-BdF conference 2015
Mean (std) daily wage for full-time workers in the Public and Private sectors in 2011:

<table>
<thead>
<tr>
<th></th>
<th>Females</th>
<th>Males</th>
<th>Gender diff</th>
<th>Diff (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public</td>
<td>65.2</td>
<td>76.2</td>
<td>-11.0</td>
<td>-14.4%</td>
</tr>
<tr>
<td></td>
<td>(27.4)</td>
<td>(36.0)</td>
<td>-8.6</td>
<td>-23.8%</td>
</tr>
<tr>
<td>Private</td>
<td>68.7</td>
<td>84.9</td>
<td>-16.2</td>
<td>-19.1%</td>
</tr>
<tr>
<td></td>
<td>(51.0)</td>
<td>(77.6)</td>
<td>-27.5</td>
<td>-34.3%</td>
</tr>
<tr>
<td>Sector</td>
<td>-3.5</td>
<td>-8.7</td>
<td>-23.6</td>
<td>-41.6</td>
</tr>
<tr>
<td>diff</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

⇒ 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.
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.)
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 $\mu(u|X_i, j(i))$.

The manager chooses the applicant with the highest value of:

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

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

Measure $n(u|X, j)$ 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:

\[
\phi(u \mid j) = \int \frac{n(u \mid X, j)}{n(u \mid j)} \phi(u \mid X, j) \, dX
\]

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

The gender probability ratios:

\[
\frac{\phi(u \mid f)}{\phi(u \mid m)} \quad \text{and} \quad \frac{\phi(u \mid X, f)}{\phi(u \mid X, m)} = \frac{\mu(u \mid X, f)}{\mu(u \mid X, m)}
\]

The gender-\(j\) wage cumulative and density:

\[
F_j(w) = \int \frac{n(F(w) \mid X, j)}{n(1 \mid j)} \, dX, \quad f_j(w) = f(w) \int \frac{n'(F(w) \mid X, j)}{n(1 \mid j)} \, dX
\]
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 \( \beta_{jp}^k \) to be estimated (we fix \( P = 5 \) in practice).

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

Estimation of parameters by maximum likelihood.
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

\[ P \left( u_{i_k} = u^k \mid \{i_1, \ldots, i_k\}, \vec{X}_k, \vec{j}_k \right) \] empirical counterpart of \( \phi (u_{i_k} \mid X_{i_k}, j (i_k)) \)

It verifies:

\[ P \left( u_{i_k} = u^k \mid \{i_1, \ldots, i_k\}, \vec{X}_k, \vec{j}_k \right) = \frac{\mu (u_{i_k} \mid X_{i_k}, j (i_k))}{\sum_{\ell \leq k} \mu (u_{i_k} \mid X_{i_\ell}, j (i_\ell))} = \frac{\exp \left[ X_{i_k} \beta_j (i_k) (u_{i_k}) \right]}{\sum_{\ell \leq k} \exp \left[ X_{i_\ell} \beta_j (i_\ell) (u_{i_k}) \right]} \]

Parameters in \( \beta_j (u) \) estimated by maximizing:

\[ L = \frac{1}{N} \sum_k \ln P \left( u_{i_k} = u^k \mid \Omega (u^k), \vec{X}_k, \vec{j}_k \right) \]

Same as partial likelihood for Cox duration model

\( \Longrightarrow \) asymptotic distribution of estimated parameters established
Decomposition of the log gender probability ratio of getting a job of rank $u$:

$$\log \left[ \frac{\phi(u|f)}{\phi(u|m)} \right] = \left[ E(X|f,u) - E(X|m,u) \right] \beta^r(u) + E(X|f,u) \left[ \beta_f(u) - \beta^r(u) \right] - E(X|m,u) \left[ \beta_m(u) - \beta^r(u) \right] + r(u)$$

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

$\beta^r(u)$ gender-neutral benchmark value of parameters

$r(u)$ 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 $\beta^r(u)$ 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 $s = 1, ..., S$

$\Omega^s_j (u, X)$: 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 $n^s (u^k | X, j)$
They are averaged across the $S$ simulations
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 $N \to +\infty$:

$$E\left[N^*(u^{\lceil vN \rceil+1} | X, j)\right]/N \to n^*(v | X, j) \text{ for all } v \in ]0, 1[$$

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

$$\frac{1}{S} \sum_{s=1}^{S} N_s^{s}\left(u^{\lceil vN \rceil+1} | X, j\right) \to E\left[N^*(u^{\lceil vN \rceil+1} | X, j)\right] \text{ for all } v \in ]0, 1[$$
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, 1st

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

<table>
<thead>
<tr>
<th></th>
<th>Public Sector</th>
<th>Private Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
</tr>
<tr>
<td>Mean</td>
<td>4.26</td>
<td>4.12</td>
</tr>
<tr>
<td>St. Dev</td>
<td>0.36</td>
<td>0.33</td>
</tr>
<tr>
<td>P10</td>
<td>3.87</td>
<td>3.77</td>
</tr>
<tr>
<td>P25</td>
<td>4.00</td>
<td>3.89</td>
</tr>
<tr>
<td>Median</td>
<td>4.21</td>
<td>4.05</td>
</tr>
<tr>
<td>P75</td>
<td>4.44</td>
<td>4.30</td>
</tr>
<tr>
<td>P90</td>
<td>4.72</td>
<td>4.54</td>
</tr>
</tbody>
</table>
Log-wage densities in the Public sector
Log-wage densities in the Private sector
## Explanatory variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Public</th>
<th>Females</th>
<th>Public</th>
<th>Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>High school and more</td>
<td>27.2</td>
<td>25.6</td>
<td>28.8</td>
<td>29.9</td>
</tr>
<tr>
<td>40-49 years old</td>
<td>35.3</td>
<td>35.4</td>
<td>35.1</td>
<td>36.9</td>
</tr>
<tr>
<td>50 years old and more</td>
<td>40.2</td>
<td>37.1</td>
<td>43.2</td>
<td>30.0</td>
</tr>
<tr>
<td>7 – 18% Part-time exp.</td>
<td>40.0</td>
<td>34.9</td>
<td>44.9</td>
<td>41.9</td>
</tr>
<tr>
<td>&gt; 18% Part-time exp.</td>
<td>14.1</td>
<td>5.1</td>
<td>22.9</td>
<td>8.1</td>
</tr>
<tr>
<td>Seniority &gt; 10 years</td>
<td>57.9</td>
<td>58.7</td>
<td>57.2</td>
<td>31.2</td>
</tr>
<tr>
<td>No child</td>
<td>33.4</td>
<td>33.2</td>
<td>33.7</td>
<td>32.9</td>
</tr>
<tr>
<td>3 children or more</td>
<td>12.4</td>
<td>13.0</td>
<td>11.8</td>
<td>12.2</td>
</tr>
<tr>
<td>Interruption 1 – 3 years</td>
<td>18.4</td>
<td>20.7</td>
<td>16.2</td>
<td>27.4</td>
</tr>
<tr>
<td>Interruption 3 – 6 years</td>
<td>23.9</td>
<td>25.6</td>
<td>22.3</td>
<td>27.1</td>
</tr>
<tr>
<td>Interruption &gt; 6 years</td>
<td>34.4</td>
<td>30.0</td>
<td>38.5</td>
<td>25.2</td>
</tr>
<tr>
<td>Paris region</td>
<td>23.4</td>
<td>21.1</td>
<td>25.5</td>
<td>23.5</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>9,732</td>
<td>4,781</td>
<td>4,951</td>
<td>46,149</td>
</tr>
</tbody>
</table>
Gender probability ratio in the Public and Private sectors

The diagram shows the probability ratio of gender (u/f) over gender (u/m) for different ranks. The Private sector is represented by circles, and the Public sector by diamonds. The ratio decreases as the rank increases, with the Private sector consistently lower than the Public sector.
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

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,
\[ \exp \left( \beta^f_{ed}(u) - \beta^m_{ed}(u) \right) \]

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 $\hat{\beta}_j(u)$
  $\implies$ We test the fit of the model.

- From estimated parameters $\hat{\beta}_r(u)$: same assignment mechanisms for males and females
  $\implies$ Only observed characteristics matter.

- From estimated parameters $\hat{\beta}_j(u)$ of the other sector: counterfactual assignment.
  $\implies$ We assess the importance of the assignment rule.
Fit of the model

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

<table>
<thead>
<tr>
<th></th>
<th>Public sector</th>
<th>Private sector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Males</td>
<td>Females</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.0008</td>
<td>0.0008</td>
</tr>
<tr>
<td>St. Dev</td>
<td>-0.0016</td>
<td>0.0019</td>
</tr>
<tr>
<td>P10</td>
<td>0.0017</td>
<td>0.0002</td>
</tr>
<tr>
<td>P25</td>
<td>-0.0006</td>
<td>-0.0008</td>
</tr>
<tr>
<td>Median</td>
<td>-0.0013</td>
<td>-0.0013</td>
</tr>
<tr>
<td>P75</td>
<td>0.0022</td>
<td>0.0003</td>
</tr>
<tr>
<td>P90</td>
<td>0.0002</td>
<td>0.0048</td>
</tr>
</tbody>
</table>

Note: Statistics based on 100 simulations.
Fit of the gender probability ratio

Curves nearly confounded $\implies$ very good fit.
Gender probability ratio in case of equal assignment

Small gender differences in access to jobs related to gender differences in observable characteristics.
Profile of counterfactual 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

![Graph showing wage distributions in the Public Sector, Equal values, and Private Sector values.]
Counterfactual female wage distributions in the Private Sector
Wage distributions, alternative assignments

Gender wage differences in the Public sector

<table>
<thead>
<tr>
<th></th>
<th>Observed</th>
<th>Benchmark simulation</th>
<th>Equal assignment</th>
<th>Private sector assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.14</td>
<td>0.14</td>
<td>0.02</td>
<td>0.15</td>
</tr>
<tr>
<td>St. Dev</td>
<td>0.03</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>P10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>P25</td>
<td>0.12</td>
<td>0.12</td>
<td>0.03</td>
<td>0.11</td>
</tr>
<tr>
<td>Median</td>
<td>0.16</td>
<td>0.16</td>
<td>0.03</td>
<td>0.15</td>
</tr>
<tr>
<td>P75</td>
<td>0.14</td>
<td>0.15</td>
<td>0.01</td>
<td>0.15</td>
</tr>
<tr>
<td>P90</td>
<td>0.18</td>
<td>0.18</td>
<td>0.00</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Note: Statistics based on 100 simulations.
Wage distributions, alternative assignments

Gender wage differences in the Private sector

<table>
<thead>
<tr>
<th></th>
<th>Observed</th>
<th>Benchmark simulation</th>
<th>Equal assignment</th>
<th>Public sector assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.17</td>
<td>0.17</td>
<td>0.01</td>
<td>0.16</td>
</tr>
<tr>
<td>St. Dev</td>
<td>0.07</td>
<td>0.06</td>
<td>-0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>P10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.03</td>
<td>0.09</td>
</tr>
<tr>
<td>P25</td>
<td>0.13</td>
<td>0.13</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>Median</td>
<td>0.15</td>
<td>0.15</td>
<td>0.01</td>
<td>0.17</td>
</tr>
<tr>
<td>P75</td>
<td>0.19</td>
<td>0.18</td>
<td>-0.01</td>
<td>0.18</td>
</tr>
<tr>
<td>P90</td>
<td>0.27</td>
<td>0.26</td>
<td>-0.01</td>
<td>0.18</td>
</tr>
</tbody>
</table>

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
Larger share of females ends up in part-time jobs

Ignoring them $\implies$ 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 $\implies$ overestimation of the gender differences at some ranks, and underestimation at lower ranks

$\implies$ 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

<table>
<thead>
<tr>
<th></th>
<th>Observed</th>
<th>Benchmark simulation</th>
<th>Equal assignment</th>
<th>Private sector assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.14</td>
<td>0.14</td>
<td>0.04</td>
<td>0.15</td>
</tr>
<tr>
<td>St. Dev</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.00</td>
<td>0.05</td>
</tr>
<tr>
<td>P10</td>
<td>0.08</td>
<td>0.08</td>
<td>0.05</td>
<td>0.10</td>
</tr>
<tr>
<td>P25</td>
<td>0.11</td>
<td>0.10</td>
<td>0.04</td>
<td>0.11</td>
</tr>
<tr>
<td>Median</td>
<td>0.16</td>
<td>0.16</td>
<td>0.05</td>
<td>0.16</td>
</tr>
<tr>
<td>P75</td>
<td>0.15</td>
<td>0.15</td>
<td>0.03</td>
<td>0.17</td>
</tr>
<tr>
<td>P90</td>
<td>0.19</td>
<td>0.19</td>
<td>0.00</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Note: Statistics based on 100 simulations.
Hourly wage distributions, part-time jobs included, alternative assignments

Gender wage differences in the Private sector

<table>
<thead>
<tr>
<th></th>
<th>Observed Mean</th>
<th>Benchmark simulation Mean</th>
<th>Equal assignment Mean</th>
<th>Public sector assignment Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.18</td>
<td>0.17</td>
<td>0.01</td>
<td>0.16</td>
</tr>
<tr>
<td>St. Dev</td>
<td>0.08</td>
<td>0.06</td>
<td>-0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>P10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>P25</td>
<td>0.13</td>
<td>0.13</td>
<td>0.04</td>
<td>0.12</td>
</tr>
<tr>
<td>Median</td>
<td>0.17</td>
<td>0.17</td>
<td>0.03</td>
<td>0.17</td>
</tr>
<tr>
<td>P75</td>
<td>0.22</td>
<td>0.22</td>
<td>0.01</td>
<td>0.21</td>
</tr>
<tr>
<td>P90</td>
<td>0.26</td>
<td>0.23</td>
<td>-0.00</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Note: Statistics based on 100 simulations.
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:

$$V = k^2 \cdot V(X_i \bar{\beta}_j(i)) \text{ where } \bar{\beta}_j = \int_0^1 \beta_j(u) \, du$$

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

![Graph showing gender probability ratio in the Public sector](image-url)
Gender probability ratio in the Private sector, unobserved individual heterogeneity included.