Estimating gender wage gap in the presence of efficiency wages

Joanna Tyrowicz
(joint work with Katarzyna Bech)

FAME | GRAPE, IAAEU, IZA and University of Warsaw

IAFFE @ ASSA, 2018

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We are not the first: Bulow (1986!) proposes **efficiency wages** as an explanation for GWG

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How efficiency wages and GWG interact?

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  Selectivity: efficiency wages used more often in occupations and/or industries dominated by men.

What we do

Contribution

We propose a new estimator of the adjusted gender wage gaps

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We apply our estimator to the EU countries (linked employer-employee data)

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Preview of the results

- women experience barriers accessing the privileged market

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Preview of the results

- women experience barriers accessing the privileged market
- adjusted GWGs differ between the privileged and standard markets
- accounting for the efficiency wages, adjusted GWGs different than in the pooled estimation

How to model unknown and endogenous split

The model

$$Y_i = \left\{ \begin{array}{l} Y_{1,i} \text{ iff } Y^*_{s,i} > 0 \\ Y_{0,i} \text{ iff } Y^*_{s,i} \leq 0 \end{array} \right\} \text{with}$$

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$$\begin{aligned} Y_{1,i} &= X_i\beta_1 + u_{1,i} & \leftarrow \text{"privileged market"} \\ Y_{0,i} &= X_i\beta_0 + u_{0,i} & \leftarrow \text{"standard market"} \\ Y^*_{s,i} &= W_i\alpha - v_i & \leftarrow \text{ the "split" mechanism} \end{aligned}$$

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Disturbances are jointly normally distributed with mean 0 and covariance matrix

$$\begin{pmatrix} \sigma_1^2 & 0 & \sigma_{1v} \\ 0 & \sigma_0^2 & \sigma_{0v} \\ \sigma_{1v} & \sigma_{0v} & \sigma_v^2 \end{pmatrix}.$$

How to model unknown and endogenous split

The difficulty

- OLS + probit if disturbances were pairwise uncorrelated and if the sample separation was known, i.e.

$$I_i = \left\{ \begin{array}{c} 1 \text{ iff } Y_i = Y_{1,i} \\ 0 \text{ iff } Y_i = Y_{0,i} \end{array} \right\}$$

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Obtaining the sample split

or squeezing blood out of the stone

Endogenous Switching Regression with an unknown sample separation

- Neumark and Wascher (1994, ILR) and Hovakimian and Titman (2006, JMC&B)

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$$\ln L = \sum_{i=1}^{n} \left\{ (1 - I_i) \left[\ln \phi\left(\frac{u_{0,i}}{\sigma_0}\right) - \ln \sigma_0 + \ln \left\{ 1 - \Phi\left(\frac{W_i\alpha - \rho_0 \frac{u_{0,i}}{\sigma_0}}{\sqrt{1-\rho_0^2}} \right) \right\} \right] \right.$$
$$\left. + I_i \left[\ln \phi\left(\frac{u_{1,i}}{\sigma_1}\right) - \ln \sigma_1 + \ln \Phi\left(\frac{W_i\alpha - \rho_1 \frac{u_{1,i}}{\sigma_1}}{\sqrt{1-\rho_1^2}} \right) \right] \right\}$$

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Table: Variables determining split and determining wages

Variable	Switching regression W	Wage regression X
Age	Y	Y
Gender	Y	Y
Education	Y	Y
Occupation	Y	Y
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$+$ interactions between *gender* and all other variables.

Gender wage gap decomposition

After obtaining the estimates of the sample split

- We decompose GWG into six components:
  - explained and unexplained components from the switching equation
  - explained and unexplained components from the privileged market equation
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- using Oaxaca-Blinder decomposition (any decomposition could be used!)

$$\ln \overline{W}_m - \ln \overline{W}_f = \beta^*(\overline{X}_m - \overline{X}_f) + \overline{X}_m(\beta_m - \beta^*) + \overline{X}_f(\beta^* - \beta_f).$$

- The choice of β^* following Słoczyński (2015).

Data

Structure of Earnings, Eurostat

- Linked employer-employee data
- *The largest* individual level data available (100k - 2m observations)
- Waves every two years
- Comparable methodology
- Sample design
  - All workers in small firms
  - Random selection of workers in medium and large firms
  - Only definition of small/medium/large varies across countries
- We use 2006 wave, all available countries (few dropped because of missing data)

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Table: Sample results - Poland

	OLS		Privileged market		Standard market		Switching	
Split	Raw	Adj.	Raw	Adj.	Raw	Adjusted	Raw	Adj.
85th	5.0%	23.6%	-51.8%	28.3%	13.8%	8.3%	3.9%	6.9%

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75th	5.0%	23.6%	-46.7%	27.4%	21.6%	8.1%	3.9%	6.9%
95th	5.0%	23.6%	.	.	1.8%	7.7%	3.9%	6.9%

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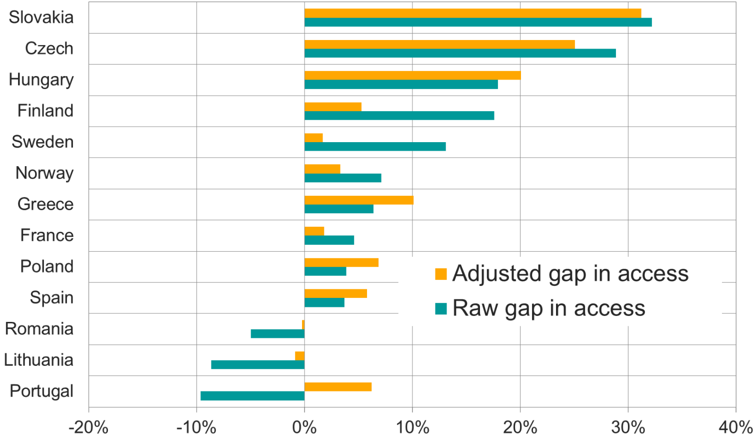
95th	5.0%	23.6%	.	.	1.8%	7.7%	3.9%	6.9%
Cramer	5.0%	23.6%	-23.7%	26.8%	11.6%	7.8%	3.9%	6.9%

* Cramer at 42%

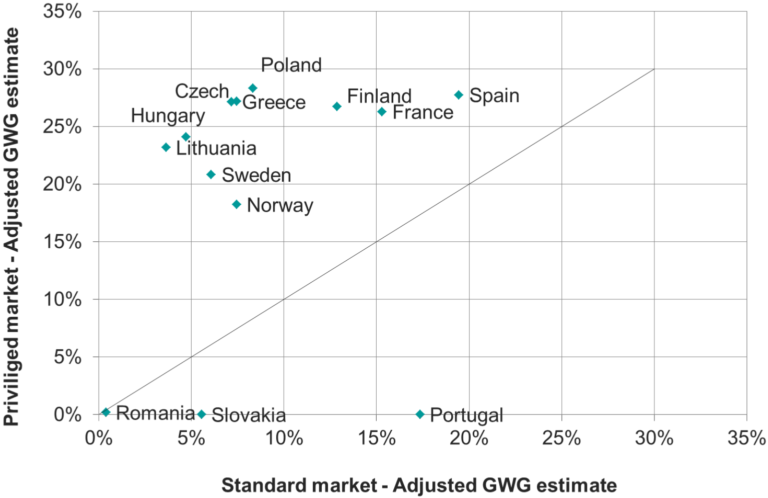
Women experience barriers accessing the privileged market

Switching regression decomposition – raw and adjusted gaps (LPM), 85% split



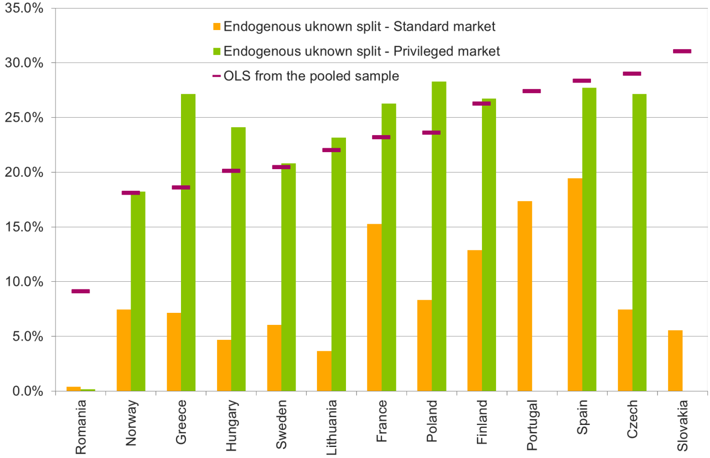
Adjusted GWGs differ between the markets

Scatter plot of the standard vs privileged market estimates, 85% split



Accounting for efficiency wages, adjusted GWGs $\neq$ pooled

Comparing estimates from pooled OLS to endogenous switching regression, 85% split



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  - two regimes (if they exist) → they always do
  - significance of gender in the selection equation (joint significance on all interactions) → they always are

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- Lower estimates adjusted GWG in standard market is a good news: most of the market "discriminates" less → policy implications for gender mainstreaming policies
- In some of the markets, virtually all of the "discrimination" is from the gendered labor market segmentation, wages are equal.

Conclusion

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Ahead of us:

- More insights on the properties of this estimator
- Alternative optimization algorithms (FIML? Bayesian?)

Questions?

Thank you for your attention!

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