The earnings effects of occupational segregation in Europe: The role of gender and migration status

Amaia Palencia-Esteban       Coral del Río

7th EU-User Conference

March 26
Migration and the labor market

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**But...how are immigrants absorbed by the labor market?**

- Large and persistent employment and wage gaps, especially among non-OECD immigrants and females (De la Rica et al., 2015).
- Trade-off between unemployment risk and job quality (Reyneri and Fullin, 2011).
- They tend to occupy positions at the bottom of the occupational ladder (Ballarino and Panichella, 2017).
Occupational segregation

- Research tackling the intersection between gender and migration status is scarce in Europe.
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Palencia-Esteban (2019) quantified the levels of segregation that male and female immigrants experienced in 20 European countries.
Occupational segregation

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- Palencia-Esteban (2019) quantified the levels of segregation that male and female immigrants experienced in 20 European countries.

- However, segregation does not tell whether a situation is beneficial or detrimental. It depends on the quality of the occupations where the group is overrepresented.
What is this paper about?

- We measure the economic and well-being consequences associated with segregation in 12 European countries.
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- We measure the economic and well-being consequences associated with segregation in 12 European countries.

- We measure social welfare losses.

- Counterfactual analysis: do cross-country disparities persist after controlling for immigrant’s characteristics?
The distribution of a target group across occupations is compared with the distribution of the whole population.

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<thead>
<tr>
<th>Occup.</th>
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**Table:** With Segregation
Local segregation indices (Alonso-Villar and Del Río, 2010)

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<td>10 = 50 * 0.2</td>
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<tr>
<td>6 = 30 * 0.2</td>
</tr>
<tr>
<td>8 = 40 * 0.2</td>
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**Table: No Segregation**
\[ D^g = \frac{1}{2} \sum_j \left| \frac{c^g_j}{C^g} - \frac{t_j}{T} \right| \in [0, 1] \] (1)

where

- \( c^g_j \): the number of individuals of group \( g \) in occupation \( j \).
- \( t_j \): the number of jobs in occupation \( j \).
- \( C^g = \sum_j c^g_j \): the size of the group \( g \) in the economy.
- \( T = \sum_j t_j \): the total number of jobs in the economy.
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The index expresses the % of the group that would have to change occupations so as not to be segregated while keeping the occupational structure of the economy unchanged.
Including information on WAGES, we proxy for occupational quality.
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\[
\Psi_{\varepsilon}(c^g; t; w) = \begin{cases} 
\sum_j \left( \frac{c^g_j}{C^g} - \frac{t_j}{T} \right) \left( \frac{w_j}{\bar{w}} \right)^{\varepsilon-1} & \text{if } \varepsilon \neq 1 \\
\sum_j \left( \frac{c^g_j}{C^g} - \frac{t_j}{T} \right) \ln \frac{w_j}{\bar{w}} & \text{if } \varepsilon = 1
\end{cases}
\]  

(2)

Where \(\varepsilon > 0\) is the inequality aversion parameter.
Well-being loss/gain of each group (Alonso-Villar and Del Río, 2017)

Including information on WAGES, we proxy for occupational quality.

$$
\Psi_{\varepsilon}(c^g; t; w) = \begin{cases} 
\sum_j \left( \frac{c_j^g}{C_g} - \frac{t_j}{T} \right) \frac{\left( \frac{w_j}{\bar{w}} \right)^{\varepsilon} - 1}{1 - \varepsilon} & \text{if } \varepsilon \neq 1 \\
\sum_j \left( \frac{c_j^g}{C_g} - \frac{t_j}{T} \right) \ln \frac{w_j}{\bar{w}} & \text{if } \varepsilon = 1
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Where $\varepsilon > 0$ is the inequality aversion parameter

Occupational segregation translates into:

- Well-being gains when the group is overrepresented in high-wage occupations.
- Well-being loss with overconcentration in low-wage jobs.
Social welfare loss (Del Río and Alonso-Villar, 2018)

1. *Social welfare loss curve associated with segregation.*
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![Diagram](https://via.placeholder.com/150)

- **Incidence**: share of workers that experience welfare losses.
- **Intensity**: per capita cumulative welfare loss.
- **Inequality**: in the loss experienced by disadvantaged groups.

### Formulas

$$h = s \ast \frac{T}{T}$$

Cumulative share of workers

$$\text{Cumulative sum of well-being losses divided by } T$$

$W_{dc}^e$

Intensity

0  Incidence  $h = \frac{s}{T}$

Cumulative share of workers

Inequality

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\[
W^{s}_{ac}
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- **Dominance criteria.**

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![Diagram of social welfare loss curve](image)

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2. *Family of measures for social welfare loss.*
1. Second quarter of the **2019 European Labour Force Survey**.
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**FINAL SAMPLE**: 12 European countries.
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<td>1</td>
<td>Introduction</td>
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<tr>
<td>2</td>
<td>Methods</td>
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<td>3</td>
<td>Data</td>
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<td>4</td>
<td>Results</td>
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<tr>
<td>5</td>
<td>Conclusions</td>
</tr>
<tr>
<td>6</td>
<td>Appendix</td>
</tr>
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</table>
Occupational segregation by gender and immigration status

Females:
- IT: 0.45
- NL: 0.19

Males:
- SI: 0.39
- UK: 0.20

Absolute terms:
- 650,000 FI in Italy.
Occupational segregation by gender and immigration status

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Well-being loss/gain of male and female immigrants

Portugal is the exception.
Well-being loss/gain of male and female immigrants

Portugal is the exception.

\[
\Psi_0, \Psi_1, \Psi_2, \Psi_3
\]

Male Immigrants
Female Immigrants
Geographical pattern of immigrants’ welfare loss/gain $\Psi_0$

Portugal and West-North VS. South-East and Germany

[Maps showing the geographical pattern of male and female immigrants with different regions shaded based on welfare loss/gain categories.]

- Male Immigrants: Categories [-17.1,-5.4], (-5.4,-2.2], (-2.2,4.5], No data
- Female Immigrants: Categories [21.5,-12.4], (-12.4,-7.0], (-7.0,-2.4], No data
**Social welfare losses (SWL)**

- **Dominance:**
  - PT: smallest SWL.
  - IT: largest SWL.

- **Incidence:**
  - Over 45% excluding IT & SP.

- **Intensity:**
  - Lowest in PT.
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- Human capital theories (Becker, 1962; Chiswick and Miller, 2008).
- Years of residence (Alonso-Villar and Del Río, 2013; Zwysen, 2018).
- Networks (Stirling, 2015).
Do geographical disparities in welfare losses and gains disappear when immigrants have the same characteristics across Europe?
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We create counterfactual distributions, removing the cross-country heterogeneity in immigrants’ characteristics (DiNardo, Fortin and Lemieux, 1996; Gradín, 2013).
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Basically, we REWEIGHT the observations such that the covariates describing the characteristics of a group follow the distribution that its corresponding group has in a reference country.
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In our case:

- Covariates: education, origin and years of residence.
- Reference country: the UK (France and Italy for robustness).
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Male-female immigrants’ conditional welfare loss/gain.
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- Overall improvement.
- PT: gains increase.
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- Education main factor.
Male-female immigrants’ conditional welfare loss/gain.

- Overall improvement.
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![Graphs showing conditional welfare loss/gain for male and female immigrants across different countries.](image-url)
Take-home ideas

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Big cross-country differences: Portugal and Italy extreme cases.
Take-home ideas

- The monetary and well-being consequences arising from segregation are negative for most foreign workers.

- Losses are greater for females.

- Big cross-country differences: Portugal and Italy extreme cases.

- Counterfactual analysis: immigrants’ characteristics explain part of those disparities.
Thank you!
Comments, questions or miscelanea: apalencia@uvigo.es
Main References

Counterfactual

Select covariates and reference county.
Combine covariates to classify group g into mutually exclusive subgroups.
Make group g's subgroups in country A have the same relative size as in the reference country.

\[ \Psi_z = \frac{\Pr(g = \text{UK} | z)}{\Pr(g = \text{UK})} \frac{\Pr(g = \text{A} | z)}{\Pr(g = \text{A})} \]

Pool group g's from both counties and estimate the logit model:

\[ \Pr(g = \text{UK} | z) = \frac{\exp(z \hat{\beta})}{1 + \exp(z \hat{\beta})} \]

Presentation
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\[ \Psi_z = \frac{Pr(g=UK|z)}{Pr(g=UK)} = \frac{Pr(g = A)}{Pr(g = UK)} \frac{Pr(g = UK|z)}{Pr(g = A|z)} \]  

(3)

Pool group g’s from both counties and estimate the logit model:
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$$\Psi_z = \frac{Pr(g=UK|z)}{Pr(g=UK)} = \frac{Pr(g = A) \cdot Pr(g = UK|z)}{Pr(g = A) \cdot Pr((g = A|z)}$$

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Pool group g’s from both counties and estimate the logit model:

\[
Pr(g = UK|z) = \frac{\exp(z\hat{\beta})}{1 + \exp(z\hat{\beta})}
\] (4)
Apply different indices to this new counterfactual distribution:

\[
\Psi^A_{\varepsilon g} = \Psi^A_{\varepsilon_{\text{FI}}} - \Psi^A_{\varepsilon_{\text{FI}}} + \Psi^A_{\varepsilon_{\text{FI}}} - \Psi^A_{\varepsilon_{\text{FI}}}
\]

Compositional effect

Intrinsic effect