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

Amaia Palencia-Esteban Coral del Río

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Outline

Migration and the labor market

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- 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).

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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.

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- We measure social welfare losses.
- Counterfactual analysis: do cross-country disparities persist after controlling for immigrant's characteristics?

Outline

Local segregation indices (Alonso-Villar and Del Río, 2010)

The distribution of a target group across occupations is compared with the distribution of the whole population.

Occup.	Economy	FI (20%)
1	60 (30%)	10 (25%)
2	20 (10%)	5 (12.5%)
3	50 (25%)	3 (7.5%)
4	30 (15%)	20 (50%)
5	40 (20%)	2 (5%)
Total	200	40

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FI (20%)
12=60*0.2
4=20*0.2
10=50*0.2
6=30*0.2
8=40*0.2
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Table: No Segregation

$$D^g = \frac{1}{2}\sum_j \left| \frac{c_j^g}{C^g} - \frac{t_j}{T} \right| \in [0, 1] \qquad (1)$$

where

- c_j^g : the number of individuals of group g in occupation j.
- t_j: : the number of jobs in occupation j.
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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.

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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.

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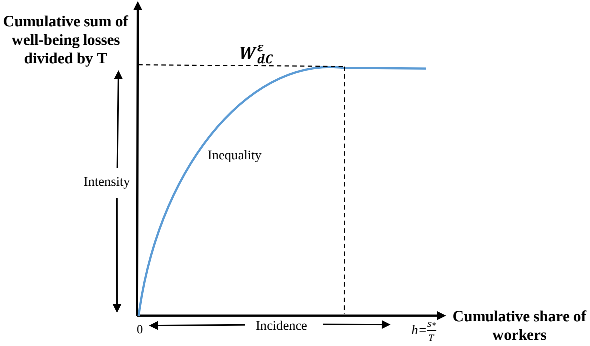

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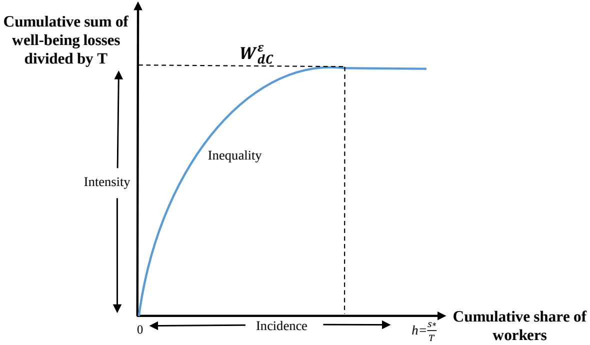

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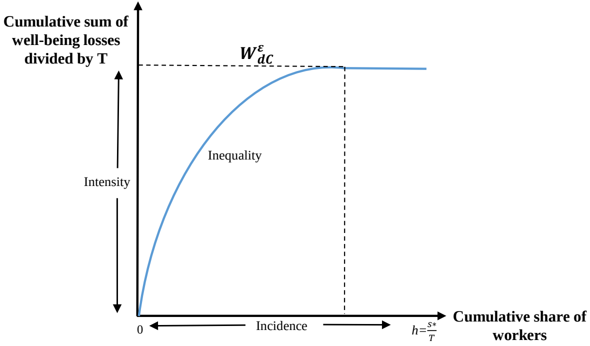

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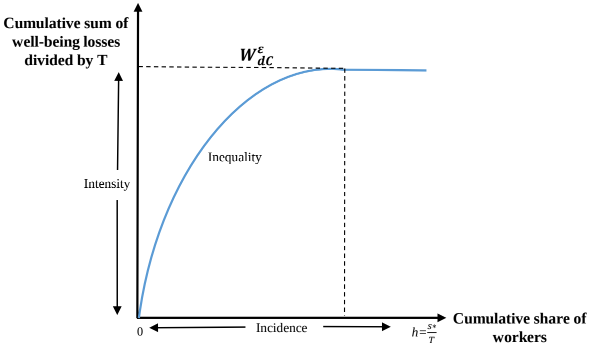

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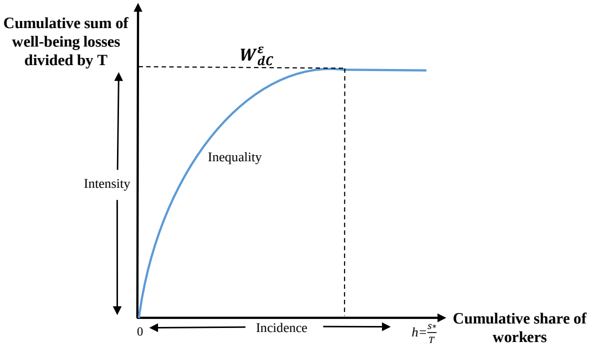

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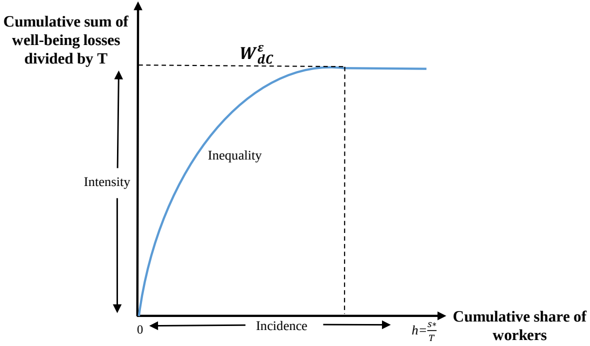

2. *Family of measures for social welfare loss.*

Outline

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FINAL SAMPLE: 12 European countries.

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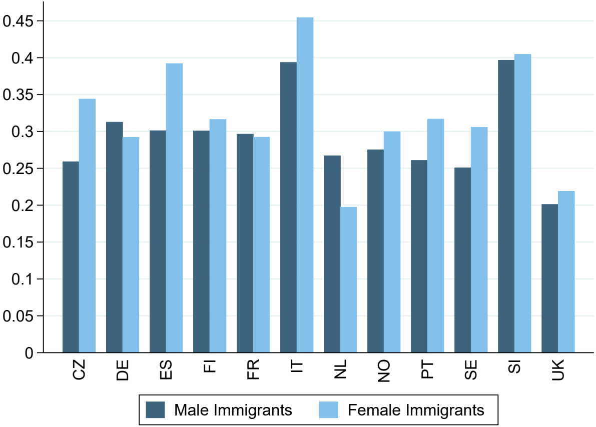
Occupational segregation by gender and immigration status



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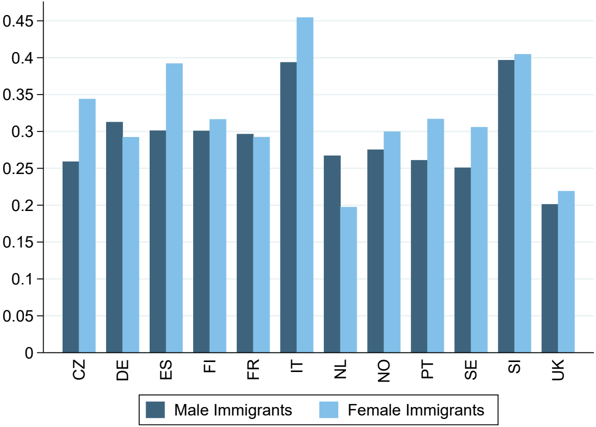

Females:

- IT: 0.45
- NL: 0.19

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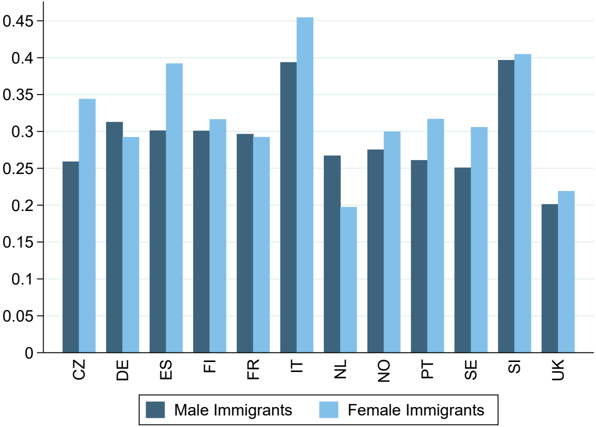

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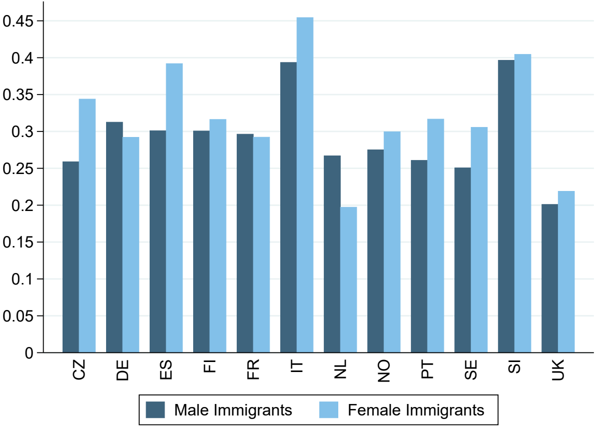

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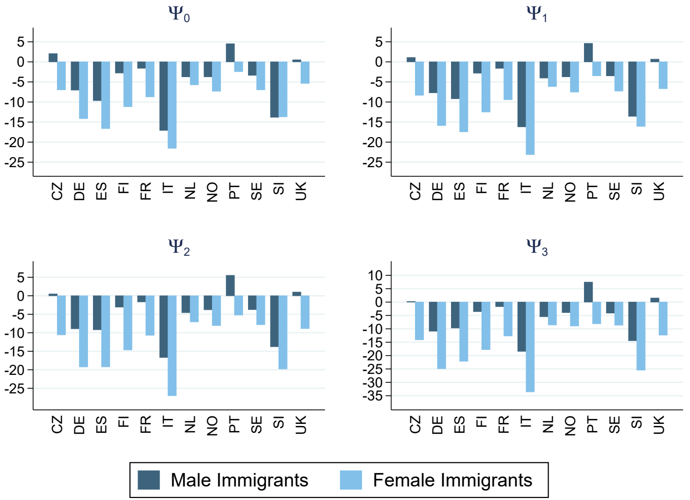
Absolute terms:

650,000 FI in Italy.

Well-being loss/gain of male and female immigrants

Portugal is the exception.



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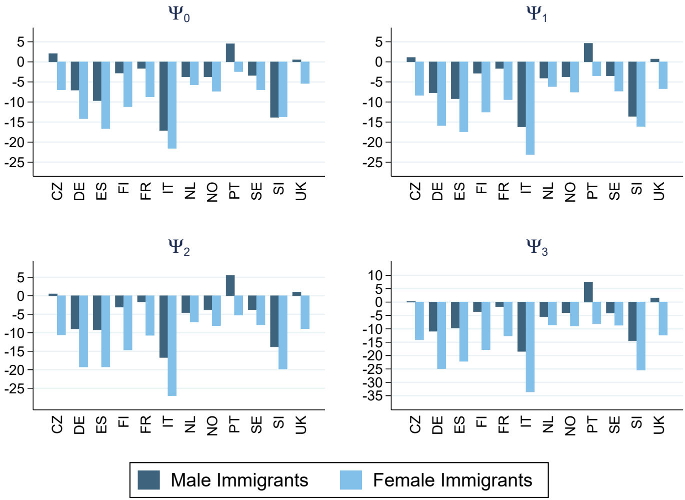
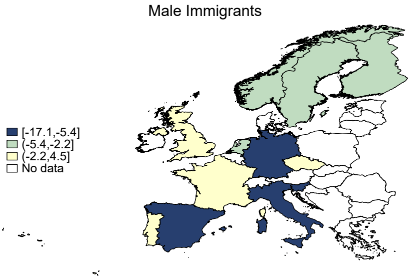
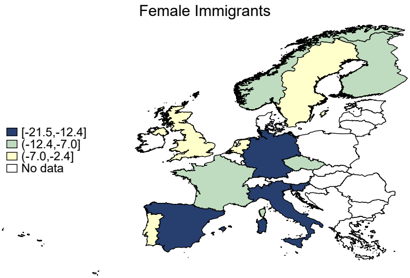


Geographical pattern of immigrants' welfare loss/gain Ψ_0

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





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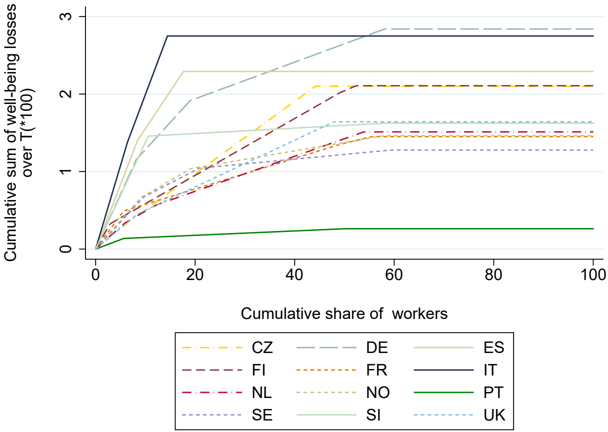

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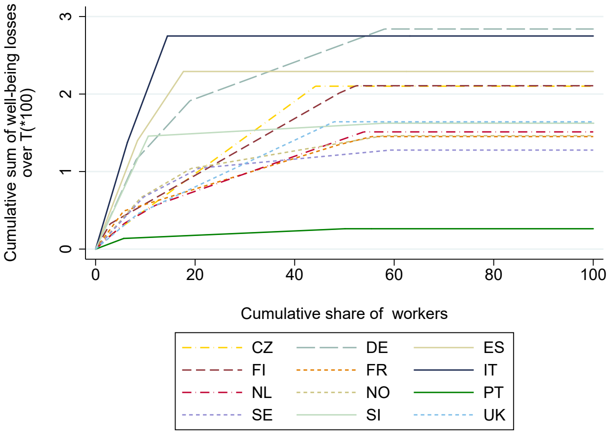

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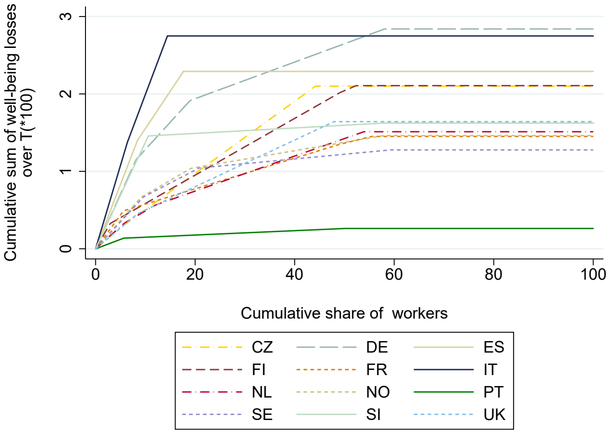

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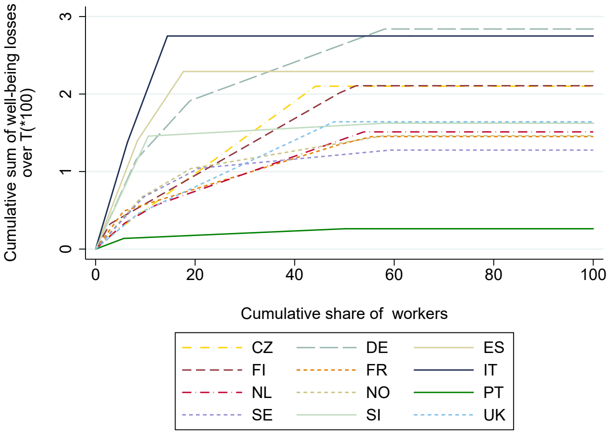

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We create counterfactual distributions, removing the cross-country heterogeneity in immigrants' characteristics (DiNardo, Fortin and Lemieux, 1996; Gradín, 2013).

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In our case:

- Covariates: education, origin and years of residence.
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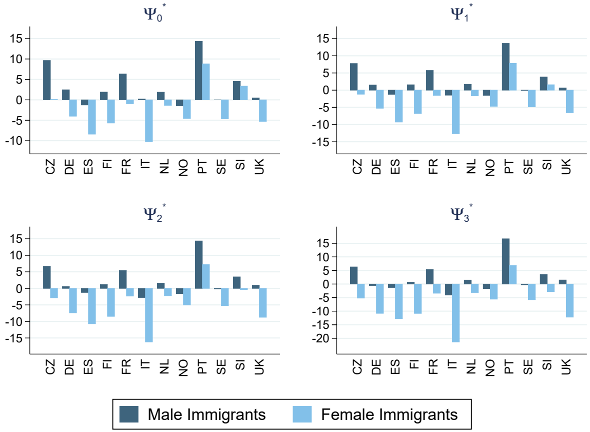
Counterfactual

Male-female immigrants' conditional welfare loss/gain.



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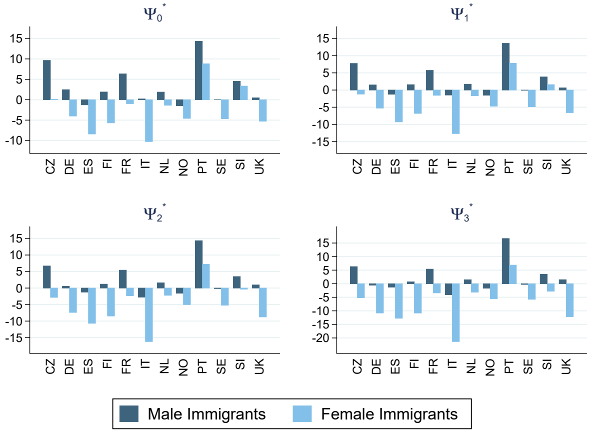

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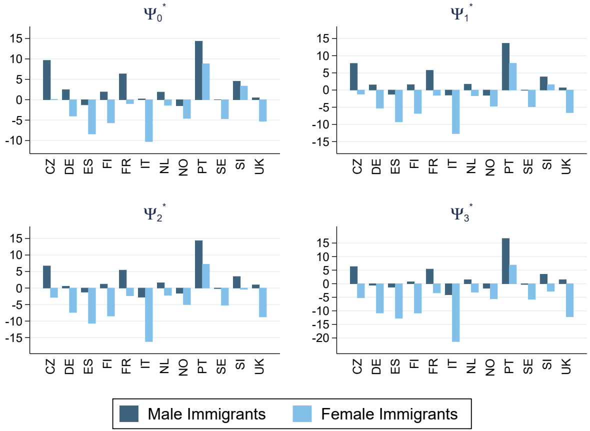

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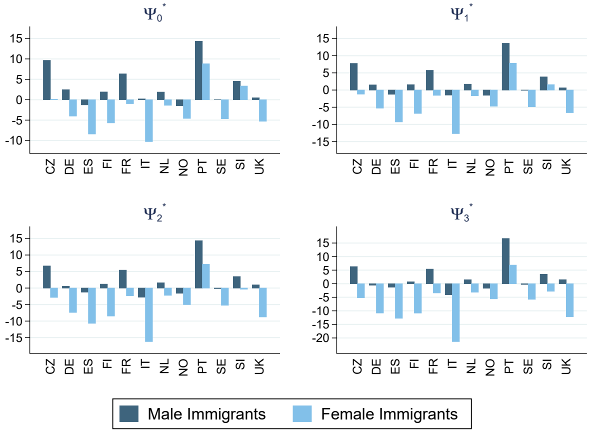

▸ Unonditional

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Take-home ideas

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- Losses are greater for females.
- Big cross-country differences: Portugal and Italy extreme cases.
- Counterfactual analysis: immigrants' characteristics explain part of those disparities.

Farewell

Thank you!

Comments, questions or miscelanea: apalencia@uvigo.es

Outline

Main References

- Alonso-Villar, Olga; Del Río, Coral. 2010. “Local versus overall segregation measures”, Mathematical Social Sciences, 60(1):30–38.
- Alonso-Villar, Olga; Del Río, Coral. 2010. “Occupational Segregation and Well-being.” Review of Income and Wealth, 63: 269-287
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- Del Río, Coral; Alonso-Villar, Olga. 2018. “Segregation and Social Welfare: A Methodological Proposal with an Application to the U.S.” Social Indicators Research, 137: 257-280.

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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.

$$\Psi_z = \frac{\frac{Pr(g=UK|z)}{Pr(g=UK)}}{\frac{Pr(g=A|z)}{Pr(g=A)}} = \frac{Pr(g=A)}{Pr(g=UK)} \frac{Pr(g=UK|z)}{Pr((g=A|z)} \tag{3}$$

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

$$Pr(g=UK|z) = \frac{exp(z\hat{\beta})}{1+exp(z\hat{\beta})} \tag{4}$$

Presentation

Decomposition

Apply different indices to this new counterfactual distribution:

$$\widetilde{\Psi}_{\varepsilon_g}^{A}$$

$$\Psi_{\varepsilon_{FI}}^{A} - \Psi_{\varepsilon_{FI}}^{UK} = \underbrace{\Psi_{\varepsilon_{FI}}^{A} - \widetilde{\Psi}_{\varepsilon_{FI}}^{A}}_{\text{Compositional effect}} + \underbrace{\widetilde{\Psi}_{\varepsilon_{FI}}^{A} - \Psi_{\varepsilon_{FI}}^{UK}}_{\text{Intrinsic effect}}$$