#### Automation, Globalization and Vanishing Jobs: A Labor Market Sorting View

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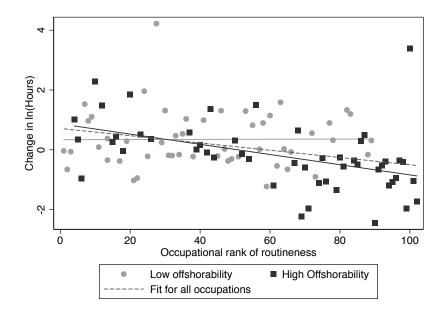
15th ECB/CEPR Labour Market Workshop

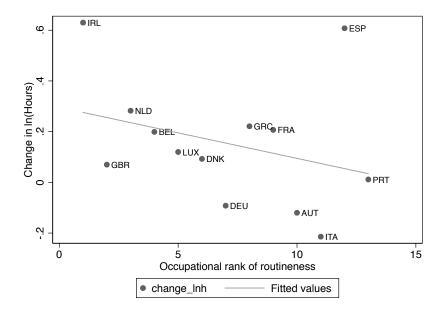
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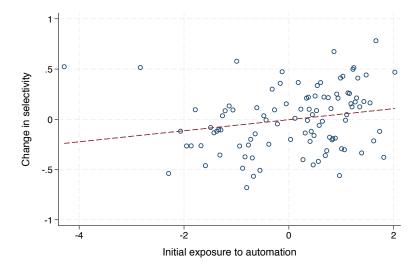
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#### Motivation

- Concerns about the effects of new technologies on labour demand:
  - Routine-Biased Technological Change / Automation
  - Offshoring (works just like a "new technology")
- BUT "it is harder than one might think to write down economic models in which workers as a group are harmed by new technology" (Caselli, Manning, 2018)
  - Threats to employment from new technology may come more from impacts on the competitiveness of markets in the presence of *frictions* than from changes in the production function in the presence of *frictionless* markets.





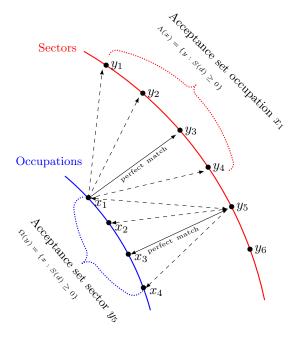


- Challenges to the "rosy" neoclassical view come from ....
  - ... "Structural Story"
    - Structural demand shift for certain skills (RBTC vs. SBTC).
    - Vertical skill-task mismatch.
    - Growing empirical and theoretical evidence.
  - ... "Frictional Story"
    - Search frictions hinder the efficient matching between heterogeneous firms and workers.
    - *Horizontal* skill-task mismatch.
    - TC increases productivity of ideal match relative to less-than-ideal ones, above and beyond any considerations of skill or routine bias.
    - ⇒ Core-Biased Technological Change
    - Additional effects of automation and offshoring that are at work independently from any vertical heterogeneity.

#### The Model: Two-Sided Heterogeneity

- Firms that need heterogeneous tasks to be performed and workers who are endowed with heterogeneous skills to perform those tasks.
- Heterogeneity as *horizontal differentiation* with workers/firms having a different "address" along the unit circle.
  - Circular Sorting Model
  - Symmetry!
- Continuum of workers with heterogeneous occupation-specific "core-skills" indexed  $x \in [0, 1]$  clockwise from noon, uniform pdf  $g_w[x]$  and measure L.
- Continuum of firms with heterogeneous sector-specifc "core-tasks" indexed y ∈ [0, 1] clockwise from noon (free entry).
- Complementarity induces sorting
  - "Mismatch" between occupation and sector adresses:

$$d(x,y) = min(x-y+1,y-x)$$



#### The Model: Search

- Workers/Firms are infinetly lived, risk-neutral, discount rate ho
- Search is random with matching function:

$$M(U,V) = \theta U^{\varphi} V^{1-\varphi}$$

 Productive matches fall in the acceptance ranges for y and x ⇒ Symmetry implies one d\*

$$V_{E}(d) = w(d) - \delta (V_{E}(d) - V_{U})$$

$$V_{U} = 2 * q_{u}(\theta) \int_{0}^{d^{*}} (V_{E}(z) - V_{U}) dz$$

$$V_{P}(d) = f(d) - w(d) - c) - \delta * (V_{P}(d) - V_{V}) > V_{P}(d^{*}) = 0$$

$$V_{V} = -c + 2 * q_{v}(\theta) \int_{0}^{d^{*}} (V_{P}(z) - V_{V}) \stackrel{!}{=} 0$$

 Nash Bargaining, free-entry and steady-state flow condition close the model.

#### **Production Function**

• Cobb-Douglas production function at match level with distance d

$$f(d) = AK(d)^{\beta} L(d)^{1-\beta}$$
(1)

with state of technology:

A (2)

With endogenous capital in elastic supply production becomes

$$f(d) = \phi A^{\frac{1}{1-\beta}} \left( F - \frac{\gamma A^{\eta}}{2} d \right)$$
(3)

with effective labor

$$L(d) = \left(F - \frac{\gamma A^{\eta}}{2}d\right) \tag{4}$$

where

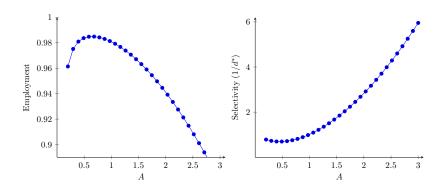
• 
$$\xi = \left(\frac{\beta}{r}\right)^{\frac{\beta}{1-\beta}}$$
 with return to capital r.

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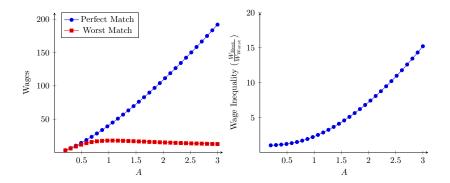
$$f(d) = \phi A^{\frac{1}{1-\beta}} \left( F - \frac{\gamma A^{\eta}}{2} d \right)$$
(5)

- log-submodular in d and A
- $\gamma A^{\eta}$  is a "mismatch cost" parameter capturing how much output is lost when mismatch increases:
  - ⇒ Substitutability of skills (tasks) with core ones in performing (employing) any given task (occupation).
  - $\Rightarrow \gamma \longrightarrow 0$  no mismatch cost (perfect substitutability).
  - $\Rightarrow \gamma \longrightarrow \infty$  prohibitive mismatch cost (no substitutability).
  - $\Rightarrow$   $\eta = 0$  mismatch cost does not depend on the state of technology.
- $A \nearrow$  (automation/offshoring) has two opposing effects:
  - $\Rightarrow$  Neoclassical Effect through  $A^{\frac{1}{1-\beta}}$
  - $\Rightarrow$  *Mismatch Effect* through  $\gamma A^{\eta}$
  - $\Rightarrow$  Core-biased Technological Change
- Key intuition: If change in productivity is large, the value of the ideal match increases such that both parties prefer to sit on the fence waiting for a better match and employment decreases!

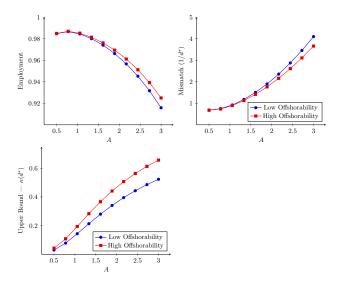
#### The Model: Simulation I



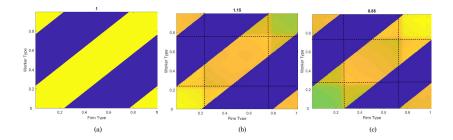
#### The Model: Simulation II



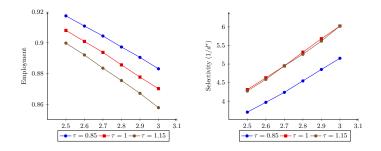
#### Model Robustness I: Offshoring



## Model Robustness II: Vertical Heterogeneity I



## Model Robustness II: Vertical Heterogeneity II



#### Data

- We capture skill heterogeneity at the occupational level and task heterogeneity at the sectoral level.
- Data on employment and mismatch from EULFS for country  $\times$  industry  $\times$  occupation  $\times$  year
  - 16 sectors (out of 21 sectors in the NACE Rev.2 classification; dropped public and agricultural sectors).
  - 92 occupations (out of 28 occupations in the ISCO-88 classification; dropped occupations closely associated to public and agricultural sectors).
  - Years: 1995-2010.
  - 13 Countries with full coverage (Austria, Belgium, Germany, Denmark, Spain, France, Great Britain, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal).

#### Automatability and Offshorability

- Conceptually different:
  - Offshorability (Blinder, Krueger; 2013): "the ability to perform one's work duties in a foreign country, but supply good/service at home."
  - Automatability: linked to the routineness of a task, possibility to be solved algorithmically.
- Automability:
  - Autor and Dorn (2013): Routine Task Intensity (RTI)
    - ⇒ Log of Routine tasks minus Sum Log of Abstract and Log of Manual tasks.
- Off-shoring:
  - Blinder (2009) and Blinder and Krueger (2013): questionnaires and qualitative observations:
    - $\Rightarrow$  Professional coders based on a worker's occupational classification (PDII: Princeton Data Improvement Initiative).

#### Specialization

- Sectors to proxy "tasks" and occupations to proxy "skills".
- Define selectivity as the concentration of an occupation's employment across sectors ⇒ "Sectoral Specialization of the Occupation" (SSO).
- Herfindahl Index of occupation's employment share across industries.
- ⇒ High SSO: few sectors account for a large share of the occupation's employment.
- ⇒ Low SSO: implies that employees in an occupation are similarly spread across many sectors.
- $\Rightarrow$  Inversely related to size of the theoretical matching set.

#### **Empirical Strategy**

• Step 1: From Technology to Selectivity

$$\Delta In(SSO_{oi}) = \alpha + \beta_1 RTI_o^H + \beta_2 RTI_o^L + \beta_3 Offshor_o^{95} + Z'_{oi} \mathbf{C} + \mu_i + \epsilon_{oi}$$
(6)

• Step 2: From Selectivity to Employment

$$\Delta ln(Hours_{oi}) = \gamma + \underbrace{\delta_1 \Delta ln(SSO_{oi})}_{\text{Enodgeneity/Rev. Causality}} + \mathcal{K}' \mathbf{C_2} + \eta_i + \upsilon_{oi}$$
(7)  
= Double-Bartik Instrument

The model has two main implications:

**1**  $\beta_1 > 0$ 

• Automation and offshoring fosters selectivity from 1995 to 2010.

**2**  $\delta_1 < 0$ 

Increased selectivity decreases employment.

## From Technology to Selectivity I

#### $\Delta ln(SSO)$

		(	,	
RTI <sub>95</sub>	0.207**	0.168*		0.301**
	(0.100)	(0.0994)		(0.150)
$RTI_{95}^{L}$	-0.0151	0.00885		0.00952
	(0.0792)	(0.0781)		(0.0972)
Offshor.95	-0.0923**	-0.123**	-0.0691	-0.0943**
	(0.0432)	(0.0525)	(0.0427)	(0.0440)
$RTI \times Offshor.$		0.0667		
		(0.0470)		
RTI <sub>95</sub>			0.0312	
			(0.0552)	
Share <sub>95</sub>			0.0727	
			(2.117)	
$\mathit{Share}_{95}  imes \mathit{RTI}_{95}$			4.874***	
			(1.596)	
Observations	1,063	1,063	1,063	1,063
R-squared	0.143	0.149	0.146	0.115
Fixed effects	Country	Country	Country	Country
Spillover Controls				Yes

### From Technology to Selectivity II ---

#### Spillovers Concerns

- Reallocation following a potential shock may bias the selectivity measure in other occupations of the same country (assuming that spillover effects are restricted within country)
  - In column (5) we control for potential spillover effects following Berg and Streitz (2019).
  - Effectively a linear-in-means estimate where spillovers are assumed to vary linearly with group-average treatment effect
  - Convert continuous RTI into indicator variable at the median  $1_{RTI_{a}^{95} > q_{50}(RTI_{a}^{95})}$
  - Mean-linearity implies the omission of any fixed effects at the group-level.

$$\begin{aligned} \Delta \ln(SSO_{oi}) &= \beta_1(RTI_o^{95} \times \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}) + \beta_2 \left(RTI_o^{95} \times \left(1 - \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}\right)\right) \\ &+ \beta_3 \left(\overline{RTI}_i \times \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}\right) + \beta_4 \left(\overline{RTI}_i \times \left(1 - \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}\right)\right) \\ &+ Z'\mathbf{C} + \epsilon_{oi}\end{aligned}$$

#### Alternative Measures of Selectivity

	$\Delta$ Mismatch	$\Delta$ Under-educ.	$\Delta$ Over-educ.	$\Delta$ Unemp. Dur.	
RTI <sub>95</sub>	-0.0347	-0.00340***	0.00305***	0.0409*	
	(0.0984)	(0.000742)	(0.000778)	(0.0243)	
Offshor.95	0.0532	0.00220**	-0.00167**	-0.0183	
	(0.114)	(0.000858)	(0.000795)	(0.0319)	
$\textit{RTI}_{95}  imes \textit{Offshor}_{.95}$	-0.290***	-0.00177**	-0.00113	0.0454	
	(0.111)	(0.000814)	(0.000805)	(0.0328)	
Observations	1,915	1,915	1,915	905	
R-squared	0.236	0.143	0.235	0.183	
Fixed effects	Country-Industry				

- For educational mismatch, over-education and under-education,
  - Compare each worker's education in terms of years to the educational level of his peers (as defined by occupation, sector or country) at the date of the observation.
  - A worker is over-educated (under- educated) if her educational level is above (below) the average in her occupation, industry, country and 10-year cohort by more than 2 standard deviations.
- To compute the unemployment duration in a cell, we assign an unemployed worker to the cell of his last job and aggregate the observations at the 2-digit ISCO level.

#### From Selectivity to Employment I

$$\Delta ln(Hours_{oi}) = \gamma + \underbrace{\delta_1 \Delta ln(SSO_{oi})}_{K'} + K' \mathbf{C}_2 + \eta_i + \upsilon_{oi}$$
(9)

 $\begin{array}{l} {\sf Enodgeneity}/{\sf Rev.} \ {\sf Causlity} \\ \Rightarrow {\sf Double-Bartik \ Instrument} \end{array}$ 

- Construction of **Double-Bartik Instrument** (similar to Chodorow-Reich, Wieland 2019):
  - Compute the Bartik-predicted change (cell-level employment growth exactly the same as in that occupation and industry in all other countries in our sample).

$$\widehat{L_{oik,2010}^{b}} = g_{o,-i,k,2010}^{b} \times s_{o,i,k,1995}$$
(10)

2 Compute the Bartik-predicted selectivity using the shares computed in the first step to derive the Herfindahl index

$$\widehat{SSO_{oi,2010}^{b}} = \sum_{k \in \mathcal{K}} (\hat{s}_{oik,2010}^{b})^{2}$$

$$\widehat{\Delta SSO_{oi}^{b}} = ln \left( \frac{\widehat{SSO_{oi,2010}^{b}}}{\overline{SSO_{oi,1995}}} \right)$$
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#### From Selectivity to Employment II

$\Delta$ In(Hours)				
-0.160***	-0.161*	-0.169***	-0.267***	-0.446***
(0.0417)	(0.0852)	(0.0349)	(0.0658)	(0.0809)
0.266***	0.266***	0.297***	0.302***	0.0697
(0.0640)	(0.0647)	(0.0629)	(0.0650)	(0.0883)
		-0.226***	-0.225***	
		(0.0425)	(0.0427)	
		0.0719	0.0668	
		(0.0562)	(0.0578)	
		-0.178***	-0.181***	
		(0.0447)	(0.0453)	
Country	Country	Country	Country	Country $\times$ Occup.
No	Bartik	No	Bartik	Bartik
1,073	1,073	1,062	1,062	1,073
-	(0.0417) 0.266*** (0.0640) Country No	(0.0417) (0.0852) 0.266*** 0.266*** (0.0640) (0.0647) Country Country No Bartik	-0.160***         -0.161*         -0.169***           (0.0417)         (0.0852)         (0.0349)           0.266***         0.266***         0.297***           (0.0640)         (0.0647)         (0.0629)           -0.226***         (0.0425)           0.0719         (0.0562)           -0.178***         (0.0447)           Country         Country         Country           No         Bartik         No	-0.160***         -0.161*         -0.169***         -0.267***           (0.0417)         (0.0852)         (0.0349)         (0.0658)           0.266***         0.266***         0.297***         0.302***           (0.0640)         (0.0647)         (0.0629)         (0.0650)           -0.226***         -0.226***         -0.225***           (0.0427)         0.0719         0.0668           (0.0562)         (0.0578)         -0.181***           (0.0447)         (0.0453)         (0.0453)           Country         Country         Country         Country           No         Bartik         No         Bartik

#### From Selectivity to Employment III

	$\Delta$ In(Hours)					
$\Delta ln(SSO)$	-0.339***	-0.694***				
$\Delta ln(SSO) \times RTI_{Q5}^H$	(0.101)	(0.151)	-0.343***	-0.507***	-0.357***	-0.714*
∆m(330) × K11 <sub>95</sub>			(0.119)	(0.159)	(0.126)	(0.288
$\Delta ln(SSO) \times RTI_{95}^{L}$			0.105	0.0594	0.244**	0.241*
∆m(350) × m <sub>95</sub>			(0.107)	(0.112)	(0.0973)	(0.109)
$\Delta ln(L^b)$	0.223***	-0.145	0.326***	0.248***	0.113	-0.0954
· /	(0.0845)	(0.109)	(0.0700)	(0.0764)	(0.0846)	(0.116)
RTI <sub>95</sub>	-0.194***			,	,	
55	(0.0511)					
Offshor.95	0.0445		0.00564	0.0340		
	(0.0644)		(0.0521)	(0.0606)		
$RTI \times Offshor.$	-0.182***		-0.205***	-0.147***		
	(0.0507)		(0.0394)	(0.0485)		
FE		ISCO3			ISCO3	ISCO3
Instrument	Bartik	Bartik	Bartik	Bartik	Bartik	Bartik
$\Delta ln(SSO) > 0$	Yes	Yes		Yes		Yes
Observations	558	563	1,062	558	1,073	563
K-P F-Test 1st	90.11	63.88	24.31	17.93	9.593	11

#### Aggregate Effects

- Less structural approach than e.g. Salomons et al. (2019)
- Instead estimate econometric model and create counterfactual predictions without effect of initial automatability:

$$\Delta In(Hours_{oik}) = \beta_1 RT I_{oik}^{95} + \beta_2 Off_{oik}^{95} + \beta_3 RT I_{oik}^{95} \times Off_{oik}^{95}$$
  
+  $\mu_{ik} + \mu_{oi} + \epsilon_{okc},$  (11)

• with  $\ln\left(\widehat{H_{10}^k/H_{95}^k}\right) = \ln\left(\widehat{H_{10}^k}/H_{95}^k\right)$  we obtain predictions

$$\widehat{H_{10}^{k}} = H_{10}^{k} \exp\left(\ln\left(\frac{\widehat{H_{10}^{k}}}{H_{95}^{k}}\right) - \ln\left(\frac{H_{10}^{k}}{H_{95}^{k}}\right)\right)$$

and counterfactual predictions  $\widetilde{H}^k_{10}$  with  $\beta_1=\beta_3=0$ 

# Predicted impact of automation on aggregate employment

	Number of hours				
Country	Observed - Counterfactual				
	$\Delta_1 = H^k_{10} - \widetilde{H}^k_{10}$	$\Delta_2 = \widehat{H_{10}^k} - \widetilde{H}_{10}^k$			
AUT	5588166	-3400177			
BEL	4682215	2741240			
DEU	-7083773	-15680964			
DNK	3544136	51327			
ESP	-33149281	-39131725			
FRA	13787699	-10408017			
GBR	65426662	6381045			
GRC	-3572807	-5935122			
IRL	12653495	1409682			
ITA	39957419	-20904866			
LUX	436904	-69497			
NLD	12442593	4042058			
PRT	10267282	-10856301			

#### Conclusion

- Our aim is to understand the impact of "new technology" (automation/offshoring) on employment in frictional labor markets with sorting.
- Key hypothesis is that better-matched workers and firms enjoy a comparative advantage in exploiting new technologies.
- Productivity Effect vs. Mismatch Effect
- Capture task heterogeneity at the sectoral level and skill heterogeneity at the occupational level:
  - New technologies increase *Selectivity*
  - Higher Selectivity reduces Employment