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

Ester Faia, Sebastien Laffitte, Maximilian Mayer and Gianmarco Ottaviano

Goethe U Frankfurt and CEPR, Goethe U Frankfurt, ENS Paris-Saclay, Bocconi U and CEPR

November 7, 2019

Motivation

- Concerns about the effects of new technologies on labour demand:
  - ⇒ Robots ('automation'): Routine-Biased vs. Skill-Biased TC: Brynjolfsson and McAfee (2014), Goos et al (2014), Caselli and Manning (2018)
  - ⇒ Offshoring, this works like a 'new technology': Grossman and Rossi-Hansberg (2008), Costinot and Vogel (2010), Ottaviano et al (2014)
- We have seen this before but *this time is (perhaps) different*: Bowen (1966), Autor (2015)
- Growing work on labour market effects of:
  - ⇒ *Empirical* work for automation and off-shoring: Autor and Dorn (2013),Ottaviano et al (2014),Acemoglu and Restrepo (2017)
  - ⇒ *Theoretical* work on automation: Acemoglu and Autor (2011), Aghion et al. (2017), Acemoglu and Restrepo (2016, 2018)

Motivation (Continued)

- Overview of how 'new technology' can be expected to affect labor demand (Caselli and Manning, 2018):
  - CRS: The production function has constant returns to scale in every sector
  - RK: Financial assets paying an interest rate unaffected by changes in technology
  - PC: Output and input markets are perfectly competitive
  - HOM: Consumers' preferences are homothetic

$\Rightarrow$ "It is harder than one might think to write down economic models in which workers as a group are harmed by new technology"

Motivation (Continued)

- **Neoclassical reasonings**:
  - Labor only fixed factor, relative price of investment goods declines ⇒ workers gain from new technology
  - Labor supply to different occupations perfectly elastic ⇒ then all workers gain
  - Also with skill-bias or routine-bias technological change (*vertical specialization*): higher skill workers gain more
- **Core-task-biased technological change** ⇒ *horizontal specialization*:

  ⇒ Skill-task heterogeneity: gains materialize only under perfect match

  ⇒ Search frictions hinder perfect match: workers-firms hold acceptance regions

  ⇒ Trade-off between matching today with wrong partner (mis-match) as opposed to waiting longer

  ⇒ New technology (automation and off-shoring) increases cost of mis-match by increasing th relative gains of perfect matches:

  ⇒ workers-firms wait longer, employment falls

Theory and Empirics

- **Growth model with positive assortative matching and search frictions**
  (Shimer and Smith 2000, Gauthier and Teulings 2004, Hagedorn, Law and Manovski 2017, Eeckhout and Kircher 2011/2018)

$\Rightarrow$ Technological change has two effects:

1. Raises match-productivity $\rightarrow$ raises labour demand
2. Increases the gains from perfect match and reduces acceptance region $\rightarrow$ pairs wait longer
3. First effect prevails for low level of technology, second prevails under high levels of technology

- **Empirical analysis**:
  Original dataset: tasks heterogeneity at sectoral level and skill heterogeneity at occupation level, Costinot and Vogel 2017 (EU-LFS)
  - $\Rightarrow$ 16 sectors (of 28 NACE Rev.2), 92 occupations (ISCO-88), 13 EU countries, years $1995 - 2010$
  - $\Rightarrow$ Construct automation and off-shoring

$\Rightarrow$ Automation (interacted with off-shoring) reduces employment $\rightarrow$ cost of mis-match prevails

Automation and Off-shorability Complementarity

- Data show that:
  1. Low off-shorability positive change in employment (tough smaller for high automatability)
  2. High off-shorability employment fall the more so for high automatable occupations
- **Extend the model: endogenous choice of off-shoring**
  1. Each match is a bundle of tasks and some can be off-shored at some costs (Grossmann and Rossi-Hansberg 2008, Ottaviano et. al. 2013)
  2. Choose optimal threshold to be off-shored by maximize value of filled vacancy
  3. Results confirm empirical ones

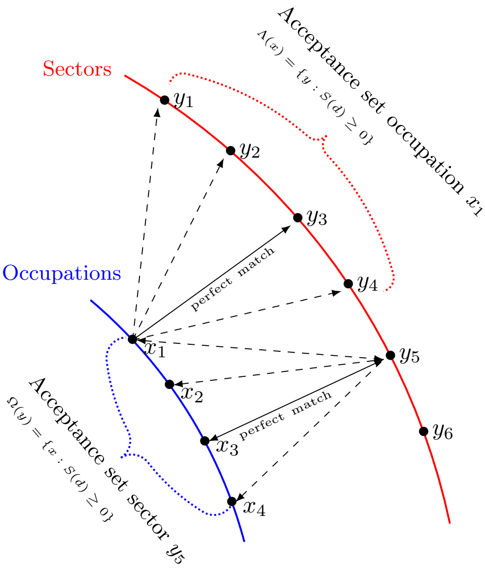
Model: Two-Sided Heterogeneity

- Search model, worker heterogeneity by occupation and firm heterogeneity by sector: *horizontal differentiation*, workers/firms with different 'address' along unit circle ($r = 1/2\pi$):
  a. Workers with heterogeneous occupation-specific 'core skills' indexed $x \in [0,1]$ uniformly distributed $g_w(x)$
  b. Firms with heterogeneous sector-specific 'core tasks' indexed $y \in [0,1]$ uniformly distributed $g_f(y)$

- 'Mismatch' between occupation and sector addresses measured by distance

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

- CRS production at the match level (one-worker-one-job) and firm/sector output being sum of outputs of matches


Sectors
Occupations
Acceptance set occupation x_1
$\Lambda(x) = \{y : S(d) \geq 0\}$
Acceptance set sector y_5
$\Omega(y) = \{x : S(d) \geq 0\}$
perfect match
perfect match
y_1
y_2
y_3
y_4
y_5
y_6
x_1
x_2
x_3
x_4

Production

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

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

with 'state of technology' and labour:

$$A = B\left(b_K\right)^{\beta}\left(b_L\right)^{1-\beta}; L(d) = \left(F - \frac{\gamma A^{\eta}}{2} d\right)$$

- With endogenous capital in elastic supply:

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

where:

  - $\varphi = (\beta/r)^{\frac{\beta}{1-\beta}}$ with return to capital r
  - $\varphi A^{\frac{1}{1-\beta}} F$ is the value of the ideal match $d = 0$
  - $d \in (0, 1/2)$ measures 'mismatch' as $f'(d) = -\gamma A^{\eta}/2 < 0$
  - $\eta = -1$ no 'mismatch effect' (Marimon and Zilibotti, 1999; Gautier and Teulings, 2004)

Production

- $\gamma A^{\eta} \geq 0 \rightarrow$ '**mis-match cost**': how much output is lost when mismatch increases $\longrightarrow$ substitutability of skills (tasks) with core ones in performing (employing) any given task (occupation)
  - $\gamma \longrightarrow 0$ no mismatch cost (all matches are equally productive $\longrightarrow$ perfect substitutability)
  - $\gamma \longrightarrow \infty$ prohibitive mismatch cost (only the ideal match is productive $\longrightarrow$ no substitutability)
  - $\eta = 0$ mismatch cost does not depend on the state of technology
- New technology $A \nearrow$ (**automation/offshoring**) has two effects
  - Increases 'match productivity' through $A^{\frac{1}{1-\beta}}$ ('productivity effect')
  - Increases 'mismatch cost' through A^{η} by making skills/tasks less substitutable
  - Production is log-submodular in d and A : closer matches exploit technology better $\longrightarrow$ *Core-Biased Technological Change*

Search and Match

- Workers and firms: infinitely lived, risk neutral, maximize future discounted income (discount rate ρ)
  - $\Rightarrow$ No information frictions: workers and firms know own type
- Firms are either producing (P) or vacant (V): c is cost of posting vacancy, zero outside option
- Workers are either employed (E) or unemployed (U): $E + U = L$
- Search is random with matching function

$$M(U, V) = \vartheta U^{\xi} V^{1-\xi}$$

  - firms' meeting rate $q_v(\theta) = M(U, V)/V = \vartheta\theta^{-\xi}$;
  - workers' meeting rate $q_u(\theta) = M(U, V)/U = \vartheta\theta^{1-\xi}$
- Match surplus shared trough Nash bargaining solution (worker bargaining $\alpha \in (0, 1)$)

Acceptance Ranges

- *Acceptance ranges* for y and x:
$$\begin{aligned} \Lambda(x) &= \{y : S(x,y) \geq 0\} \\ \Omega(y) &= \{x : S(x,y) \geq 0\}\,, \end{aligned}$$
- Matches are destroyed with exogenous probability δ or when 'Technology shock' shrinks the acceptance ranges, by increasing cost of mis-match
- *Symmetry and PAM in acceptance ranges* are $[y - d^*, y + d^*]$ and $[x - d^*, x + d^*]$:
  - Values of unemployment U and vacancies V are identical for all worker and firm types
  - Values of employment $v_e(d)$ and production $v_p(d)$ depend on d only
  - Nash wage bargain $w(d)$ depends on d only

Steady State Equilibrium

Given $r = \rho$, the equilibrium is characterized by the values of 13 unknowns $(E, U, V, M, q_v, q_u, w, v_e, v_p, v_u, v_v, d^*, f)$ that solve 13 equations:

- Technological constraints and firms' and workers' FOCs:

$$\rho v_e(d) = w(d) - \delta\left(v_e(d) - v_u\right)$$

$$\rho v_p(d) = \left(f(d) - w(d) - c\right) - \delta\left(v_p(d) - v_v\right)$$

$$\rho v_u = 2q_u(\theta)\int_0^{d^*}\left(v_e(z) - v_u\right)dz$$

$$\rho v_v = -c + 2q_v(\theta)\int_0^{d^*}\left(v_p(z) - v_v\right)dz$$

- Nash Bargaining:

$$(1-\alpha)\left(v_e(d) - v_u\right) = \alpha\left(v_p(d) - v_v\right)$$

- Flow condition: $M(U, V) = \delta E$. Firms' free entry: $v_v = 0$. Zero value of producing for marginal matches: $v_p(d^*) = 0$.

Final Equilibrium

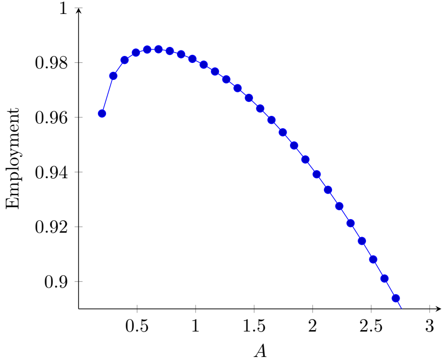
System of equations can be reduced to:

$$(1-\alpha)\,\frac{2\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}} A\left(F-\frac{\gamma}{4}A^{\eta}d^*\right)d^*}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}+2\alpha\left(q_u\right)}=c$$

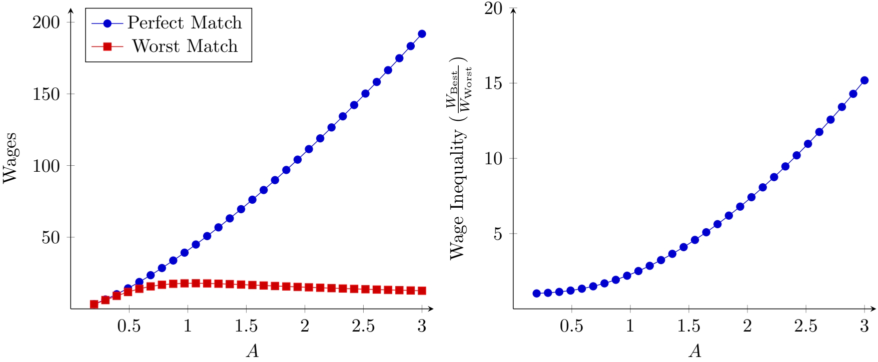
$$(1-\alpha)\,\frac{\delta+\rho+2\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}} A\left(F-\frac{\gamma}{2}A^{\eta}d^*\right)}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}+2\alpha\left(q_u\right)}=c$$

with: $q_u=\frac{\delta E}{L-E}$. This can be solved numerically for employment E and acceptance range d^*.$\Rightarrow$ Note employment and mis-match (specialization, $\frac{1}{d^*}$) are endogenous

Comparative Statics (Employment and Mis-match)



Comparative Statics (Wages and Inequality)



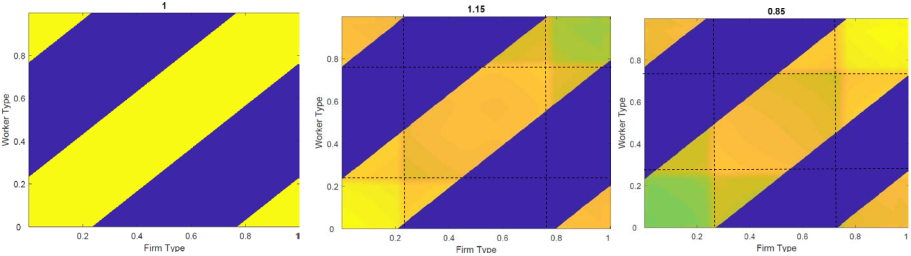
Model Predictions

1. E is a *concave* function of the state of technology A
2. $1/d^*$ is an increasing function of the state of technology A
3. Top wage is an increasing function of the state of technology A
4. Bottom wage is a *concave* function of the state of technology A
5. Inequality is an increasing function of the state of technology A

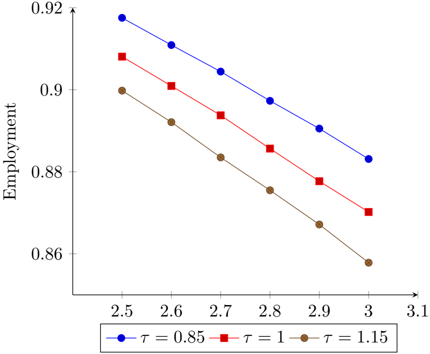
- Hence, if the initial A is high (low) enough, larger A ('new technology'):
  - $\Rightarrow$ Decreases (increases) employment E
  - $\Rightarrow$ Especially so for high (low) initial specialization i.e. small (large) initial d^*

Model Robustness — Asymmetric Matching Sets

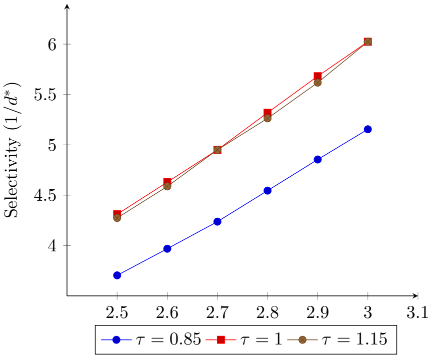
- In reality, however, such symmetry does not necessarily hold as skills and tasks are not only horizontally but also vertically differentiated.
    - Mechanism is still at work and is even reinforced in the presence of vertical differentiation.



(a) (b) (c)



(a)



(b)

Figure: Effects on employment (left panel) and selectivity (right)

Data

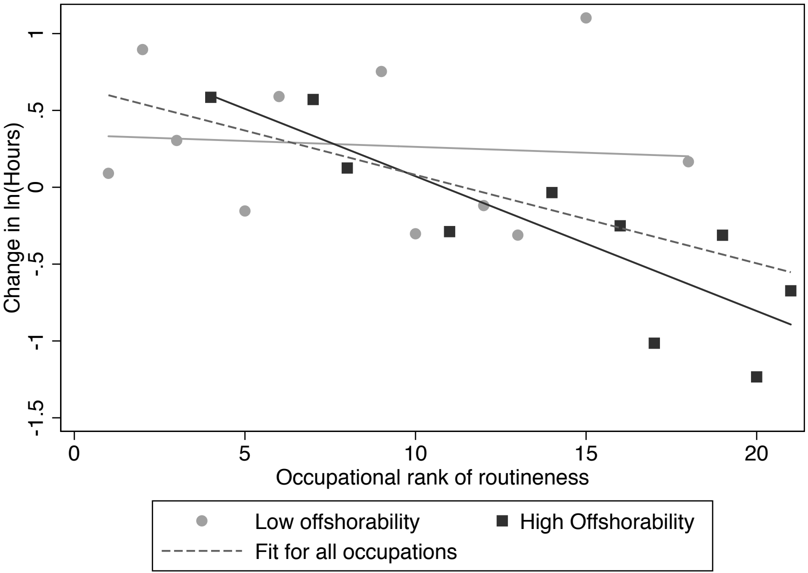
- Employment and mis-match from EULFS for *country* $\times$ *industry* $\times$ *occupation* $\times$ *year*
- Sectors: 16 sectors (out of 21 sectors in the NACE Rev.2 classification; no public and agricultural)
- Occupations: 21 occupations (out of 28 occupations in the ISCO-88 classification; no public and agricultural)
- Years: 1995-2010 (in 2010 occupation classification changes from ISCO-88 to ISCO-08)
- Countries: 13 (Austria, Belgium, Germany, Denmark, Spain, France, Great Britain, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal; full coverage available)

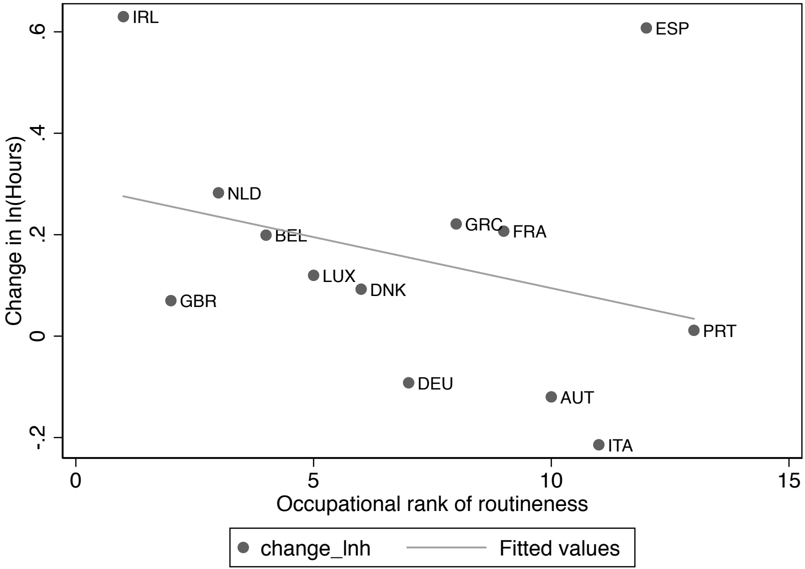
Automatability of Occupations

- Automability:
  1. Autor and Dorn (2013): Routine Task Intensity (RTI):
     - ⇒ Log of Routine tasks minus Sum Log of Abstract and Log of Manual tasks
  2. Frey and Osborne (2017): probability of computerization with Gaussian process classifier:
     - ⇒ Problems engineers need to solve for specific occupations to be automated
- Off-shoring:
  1. Blinder (2009) and Blinder and Krueger (2013): questionnaires and qualitative observations:
     - ⇒ Professional coders based on a worker's occupational classification (PDII: Princeton Data Improvement Initiative)
  2. Acemoglu and Autor (2011), on ONET indicators:
     - ⇒ Face to face discussions

Automatability and Off-shorability

- Conceptually different:
  - Off-shorability (BK): “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
- Global positive correlation, but occupations are:
  - Both automatable and off-shorable: Precision, handicraft, printing and related trades workers; Stationary-plant and related operators
  - Automatable but not off-shorable: Models, salespersons and demonstrators; Drivers and mobile-plant operators
  - Offshorable but not automatable: Physical, mathematical and engineering science professional
  - Neither automatable nor off-shorable: Life science and health associate professionals; Life science and health professionals; General managers


Change in ln(Hours)
1
.5
0
-.5
-1
-1.5
0
5
10
15
20
Occupational rank of routineness
Low offshorability
High Offshorability
Fit for all occupations


IRL
ESP
NLD
GRC
FRA
BEL
LUX
DNK
GBR
PRT
DEU
AUT
ITA
-.2
0
.2
.4
.6
Change in ln(Hours)
0
5
10
15
Occupational rank of routineness
change_lnh
Fitted values

Specialization

- How to bring 'acceptance ranges' to data?
- Proxy skills and occupations to proxy tasks
  - ⇒ Selectivity as the concentration (HHI) of an occupations employment across sectors (computed at the occupation $\times$ country level).
  - ⇒ Sectoral Specialization of the Occupation — **SSO**
  - ⇒ **High SSO**: few sectors account for a large share of the occupations employment.
  - ⇒ **low SSO**: implies that employees in an occupation are similarly spread across many sectors.

Main Econometric Specification

- **Step 1:** From Technology to Selectivity

$$\Delta ln(SSO_{oi}) = \alpha + \beta_1 RTI_o^H + \beta_2 RTI_o^L + \beta_3 Offshor_o^{95} + Z_{oi}'\mathbf{C} + \mu_i + \epsilon_{oi} \quad (1)$$

- **Step2:** From Selectivity to Employment

$$\Delta ln(Hours_{oi}) = \gamma + \underbrace{\delta_1 \Delta ln(SSO_{oi})}_{\substack{\text{Enodgeneity/Rev. Causlity} \\ \Rightarrow \textbf{Double-Bartik Instrument}}} + K'\mathbf{C_2} + \eta_i + v_{oi} \quad (2)$$

The model has two main implications:

1. $\beta_1 > 0$
   - Automation and offshoring foster selectivity from 1995 to 2010.
2. $\delta_1 < 0$
   - Increased selectivity decreases employment.

From Technology to Selectivity I

	$\Delta ln(SSO)$	$\Delta ln(SSO)$	$\Delta ln(SSO)$	$\Delta ln(SSO)$
RTI^H_{95}	0.207**	0.168*		0.301**
	(0.100)	(0.0994)		(0.150)
RTI^L_{95}	-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_{95}			0.0312	
			(0.0552)	
$Share_{95}$			0.0727	
			(2.117)	
$Share_{95} \times RTI_{95}$			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)
  - $\Rightarrow$ 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 $\mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}$
  - Mean-linearity implies the omission of any fixed effects at the group-level.

$$
\begin{aligned}
\Delta ln(SSO_{oi}) \quad = \quad & \beta_1 (RTI_o^{95} \times \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}) + \beta_2 \left(RTI_o^{95} \times \left(1 - \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})} \right) \right) \\
+ \quad & \beta_3 \left(\overline{RTI}_i \times \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})} \right) + \beta_4 \left(\overline{RTI}_i \times \left(1 - \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})} \right) \right) \\
+ \quad & Z'\mathbf{C} + \epsilon_{oi}
\end{aligned}
\tag{3}
$$

From Selectivity to Employment I

	$\Delta ln(Hours)$				
First Stage		1.780***		1.789***	1.925***
		(0.127)		(0.139)	(0.204)
$\Delta ln(SSO)$	-0.160***	-0.161*	-0.169***	-0.267***	-0.446***
	(0.0417)	(0.0852)	(0.0349)	(0.0658)	(0.0809)
$\Delta ln(L^b)$	0.266***	0.266***	0.297***	0.302***	0.0697
	(0.0640)	(0.0647)	(0.0629)	(0.0650)	(0.0883)
RTI_{95}			-0.226***	-0.225***	
			(0.0425)	(0.0427)	
$Offshor._{95}$			0.0719	0.0668	
			(0.0562)	(0.0578)	
RTI × Offshor.			-0.178***	-0.181***	
			(0.0447)	(0.0453)	
FE	Country	Country	Country	Country	Country Occup.
Instrument	No	Bartik	No	Bartik	Bartik
Observations	1,073	1,073	1,062	1,062	1,073
K-P F-Test 1st		196.6		165.1	88.71

Robust standard errors clustered at the occupation level in parentheses. Data is aggregated at the country × occupation level.*** p<0.01, ** p<0.05, * p<0.1

From Selectivity to Employment II

- Construction of **Double-Bartik Instrument** (similar to Chodorow-Reich, Wieland 2019) :
  1. 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).

$$\widehat{L^{b}_{oik,2010}} = g^{b}_{o,-i,k,2010} \times s_{o,i,k,1995} \tag{4}$$

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

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

$$\widehat{\Delta SSO^{b}_{oi}} = ln\left(\frac{\widehat{SSO^{b}_{oi,2010}}}{SSO_{oi,1995}}\right)$$

From Selectivity to Employment III

	$\Delta ln(Hours)$					
$\Delta ln(SSO)$	-0.339***	-0.694***				
	(0.101)	(0.151)				
$\Delta ln(SSO) \times RTI^H_{95}$			-0.343***	-0.507***	-0.357***	-0.714**
			(0.119)	(0.159)	(0.126)	(0.288)
$\Delta ln(SSO) \times RTI^L_{95}$			0.105	0.0594	0.244**	0.241**
			(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_{95}	-0.194***					
	(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

Robust standard errors clustered at the occupation level in parentheses. Data is aggregated at the country $\times$ occupation level; *** p<0.01, ** p<0.05, * p<0.1

Alternative Measures of Selectivity

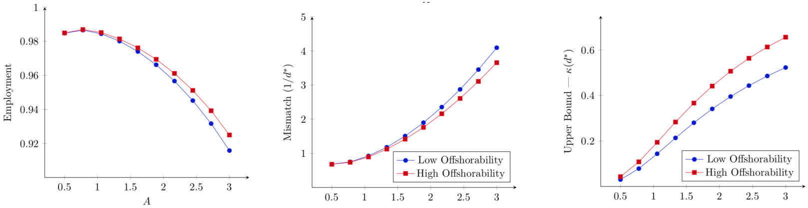
	(1) Δ Mismatch	(2) Δ Under-educ.	(3) Δ Over-educ.	(4) Δ Unemp. duration
RTI_{95}	-0.0347	-0.00340***	0.00305***	0.0409*
	(0.0984)	(0.000742)	(0.000778)	(0.0243)
$Offshor._{95}$	0.0532	0.00220**	-0.00167**	-0.0183
	(0.114)	(0.000858)	(0.000795)	(0.0319)
$RTI_{95} \times Offshor._{95}$	-0.290***	-0.00177**	-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			

Robust standard errors clustered at the occupation $\times$ country level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

- For educational mismatch, over-education and under-education,
  - Compare each workers 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.

Model-Extension with Offshoring

- We embed the Grossman, Rossi-Hansberg (2016) into the circular sorting model:



Back-of-the-Envelope Calculation of Aggregate Effects

- Less structural approach than e.g. Salomons et. al. (2019).
- Instead we build on counterfactual outcomes:
- Estimate econometric model and create counterfactual predictions by shuting down the impact of initial automatability.

$$\begin{aligned} \Delta ln(Hours_{oik}) &= \beta_1 RTI_{oik}^{95} + \beta_2 Off_{oik}^{95} + \beta_3 RTI_{oik}^{95} \times Off_{oik}^{95} \\ &+ \mu_{ik} + \mu_{oi} + \epsilon_{okc}, \end{aligned} \tag{5}$$

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

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

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

Predicted impact of automation on aggregate employment

Country	Number of hours	
	Observed - Counterfactual $\Delta_1 = H^k_{10} - \widetilde{H}^k_{10}$	Predicted - Counterfactual $\Delta_2 = \widehat{H^k_{10}} - \widetilde{H}^k_{10}$
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

- Small negative effects in some countries
- i.e. assuming 35 hours a week for 45 weeks a year, the negative effect in the first column for Germany corresponds to a loss of 4585 jobs in 2010

Conclusions

- Impact of 'new technology' (automation/offshoring) on employment in frictional labor markets with sorting
- Theoretical model: investigate the different channels
  $\longrightarrow$ *Productivity vs Mismatch*
- Novel cross-country dataset with information on:
  - Automatability, off-shorability, sectoral specialization of occupations (SSO)
- We find that:
  - Automation increases selectivity and reduces employment, the more so for highly offshorable occupations.
  - This fall is *even larger* for occupations that in year 1995 also feature *higher off-shorability*
  - At the aggregate level, however, the impact of automation on employment is either positive or slightly negative for all countries despite large negative developments for specific occupations.
  - These results are in line with the model if the dominant effect of new technology is to increase mis-match cost