

# Automation and Job Polarization: On the Decline of Middling Occupations in Europe

Vahagn Jerbashian

*Universitat de Barcelona*

June 4, 2017

# Motivation

- ▶ In labor markets, a prominent and relatively recent phenomenon is
  - ▶ Increasing shares of employment (as well as wages) in low and high wage occupations
  - ▶ Falling share of employment in medium wage occupations
- ▶ Goos and Manning (2007) call this “Job Polarization”

# Motivation

- ▶ Information technologies (IT) are thought to be one of the major causes of these trends
  - ▶ IT substitute for routine tasks, which are readily automatable and are usually performed by middle wage occupations, such as office clerks
  - ▶ IT complement nonroutine cognitive tasks, which require abstract reasoning and are usually performed by high wage occupations, such as managers
- ▶ The raise of employment in highly paid occupations increases the demand for nonroutine manual tasks, which are usually performed by low wage occupations, such as personal services

# Research

- ▶ I investigate the effect of the fall in IT prices on industries' demand for high, middle and low wage occupations
  - ▶ I use a DiD framework in the spirit of Rajan and Zingales (1998)

# Research

- ▶ I ask whether the fall in IT prices has affected the demand for high, middle and low wage occupations more in industries which depend more on IT compared to industries which depend less
  - ▶ I use industry- and country-level data from 10 Western European countries and 1993-2007 period

# Results

- ▶ The share of employment in middling occupations has declined and the share of employment in high wage occupations has increased with the fall in IT prices
- ▶ I find no systematic evidence that the fall in IT prices affects the share of employment in the lowest paid occupations
- ▶ Similar results hold within age, gender, and education groups
  - ▶ These findings provide a support for the hypothesis put forward for explaining job polarization
  - ▶ They are broadly in line with and complement the results of Autor et al. (2003); Autor and Dorn (2013); Goos et al. (2014), and Michaels et al. (2014), amongst others

# Results

- ▶ The fall in IT prices has increased (reduced) the share of employment in high (medium) wage occupations among females more than among males
- ▶ It has increased (reduced) the share of employment in high (medium) wage occupations among old workers less than among young and medium-age workers
- ▶ It has increased (reduced) the share of employment in high (medium) wage occupations among medium-educated workers more than among highly and low-educated workers
  - ▶ These results are robust to a wide range of specification checks and alternative identifying assumptions

# Potential Rationales

An explanation is that comparative advantage in performing tasks varies with gender, age and education-level

- ▶ Women have a comparative advantage in communication and social skills (high wage occupations). Men have comparative advantage in hard-motor skills (medium wage occupations)
- ▶ Older employees have a higher comparative advantage in medium wage occupations since workers accumulate routine skills as they age
- ▶ Workers with medium-level of education can have a comparative advantage in high wage occupations if their abilities are more dispersed than the abilities of workers with low- and high-level of education



## Related Literature

- ▶ Autor et al. (2006); Goos and Manning (2007); Autor et al. (2008); Goos et al. (2009); Acemoglu and Autor (2011); Autor and Dorn (2013); Goos et al. (2014): Polarization in the US and EU
- ▶ Autor and Dorn (2013); Michaels et al. (2014): The effects of IT in commuting zones in the US and on high, medium and low educated workers
- ▶ Cortes et al. (2016); Cerina et al. (2016): Differences in the trends of polarization across genders in the US

# Theoretical Background

The producers use abstract and routine task inputs,  $T_A$  and  $T_R$ , and  $IT$ , to produce homogenous goods,  $Y$

$$Y = \left[ \alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1} \alpha} T_A^{1-\alpha},$$

where  $\alpha_{IT} > 0$ ,  $\alpha_{T_R} > 0$ ,  $\alpha \in (0, 1)$ , and  $\varepsilon > 1$ .

- ▶  $\alpha_{IT}$  measures the relative importance of  $IT$  and higher  $\alpha_{IT}$  implies higher share of compensation for  $IT$
- ▶ Since  $\varepsilon > 1$ , information technologies are more complementary to abstract tasks than to routine tasks.

# Theoretical Background

Let  $p_z$  be the price of input  $z$ . It can be shown that  $\partial \ln IT / \partial p_{IT} < 0$ ,

$$\frac{\partial T_A/T_R}{\partial p_{IT}} = \frac{\varepsilon - 1}{\varepsilon} \frac{\partial \ln IT}{\partial p_{IT}} \frac{1 - \alpha}{\alpha} \frac{p_{T_R}}{p_{T_A}} \frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{T_R} T_R^{\frac{\varepsilon-1}{\varepsilon}}} < 0$$

and

$$\frac{\partial}{\partial \alpha_{IT}} \left| \frac{\partial T_A/T_R}{\partial p_{IT}} \right| = \frac{1}{\alpha_{IT}} \left| \frac{\partial T_A/T_R}{\partial p_{IT}} \right| > 0$$

This implies that the decline of  $p_{IT}$  increases  $T_A$  more than the demand for  $T_R$  and this effect is stronger in industries with a larger  $\alpha_{IT}$

# Theoretical Background

I incorporate the demand side into a Ricardian comparative advantage model for within gender, education-level, and age groups inference

- ▶ Workers are endowed with labor hours  $L$  which need to be converted into abstract and routine tasks
- ▶ The conversion function of task  $k = T_A, T_R$  is  $\alpha_{L,k} f(L_k)$ , where  $\alpha_{L,k} > 0$ ,  $f' > 0$ , and  $f'' < 0$

# Theoretical Background

This setup implies that the supply of abstract tasks relative to the supply of routine tasks is given by

$$\frac{p_{T_A}}{p_{T_R}} = \frac{\alpha_{L, T_R}}{\alpha_{L, T_A}} \frac{f'(L_{T_R})}{f'(L_{T_A})},$$

and

$$\frac{\partial}{\partial \frac{\alpha_{L, T_A}}{\alpha_{L, T_R}}} \frac{\partial}{\partial \frac{p_{T_A}}{p_{T_R}}} \frac{f'(L_{T_R})}{f'(L_{T_A})} > 0,$$

where  $\frac{p_{T_A}}{p_{T_R}}$  increases with the fall in  $p_{IT}$

The fall in  $p_{IT}$  implies bigger changes in  $T_A$  and  $T_R$  in industries with a larger  $\alpha_{IT}$  and these differential changes are more pronounced within groups which have a higher comparative advantage in abstract tasks

- ▶ I look exactly for such differential changes across industries in the empirical specification

# Empirical Specification

For each occupation group, I estimate

$$\text{Employment Share}_{c,i,t} = \beta \left[ \text{Industry } i\text{'s Dependence on IT}_i \times (1/\text{IT Price})_{c,t} \right] \\ + \sum_c \sum_i \zeta_{c,i} + \sum_c \sum_t \xi_{c,t} + \eta_{c,i,t},$$

where

- ▶ Employment Share $_{c,i,t}$  is the share of employment in one of the occupation groups, country  $c$ , industry  $i$ , and year  $t$
- ▶  $\zeta$  and  $\xi$  are country-industry and country-year fixed effects, and  $\eta$  is an error term

# Data

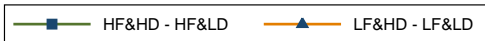
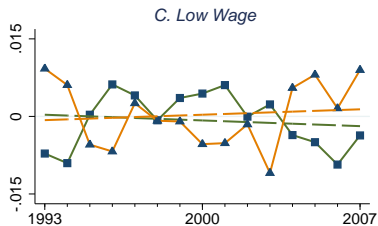
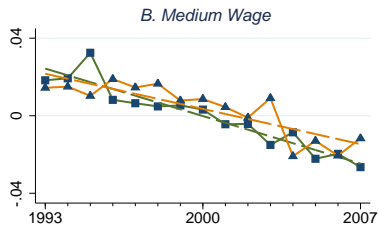
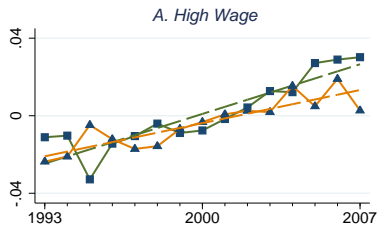
- ▶ The sample consists of 10 Western European countries
- ▶ On average, for each country I have 14 years of observations from the period of 1993-2007
- ▶ For each country and year, I obtain from the EU LFS database the number of employed individuals in each
  - ▶ occupation (2 digit ISCO-88) - I group occupations into high, medium and low wage (Goos et al., 2014)
  - ▶ industry (1 digit NACE Rev. 1)
  - ▶ gender
  - ▶ education-level (ISCED-97 0-2: low-skilled; ISCED-97 3-4: medium-skilled; ISCED-97 5-6: highly skilled)
  - ▶ age group (in-between 17-32: young; in-between 32 and 47: medium-age; in-between 47-62: old)
  - ▶ and their usual weekly employment hours

# IT Measures

- ▶ IT Price: The price of investments in information technologies relative to the price of value added in sample countries
  - ▶ I use the inverse of this measure in the estimations
  - ▶  $\beta$  is expected to be positive for high wage occupations and negative for medium wage occupations
- ▶ IT Dependence: The share of IT capital compensation in industrial value added in the US industries, averaged over the sample period



# The Interpretation of $\beta$



# Results

**Table :** Results for Employment Shares in High, Medium and Low Wage Occupations

	(1) High	(2) Medium	(3) Low
IT Dep. × 1/IT Price	0.217*** (0.026)	-0.212*** (0.022)	-0.005 (0.019)
Obs	1,360	1,360	1,360
R2 (Partial)	0.083	0.122	0.000

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Results (within Genders)

**Table :** Results for Employment Shares in High, Medium and Low Wage Occupations within Genders

	<i>Among Males</i>			<i>Among Females</i>		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep. × 1/IT Price	0.156*** (0.027)	-0.152*** (0.030)	-0.004 (0.021)	0.235*** (0.035)	-0.237*** (0.030)	0.001 (0.018)
Obs	1,352	1,352	1,352	1,347	1,347	1,347
R2 (Partial)	0.040	0.054	0.000	0.050	0.062	0.000

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Results (within Age-Groups)

**Table :** Results for Employment Shares in High, Medium and Low Wage Occupations within Age-Groups

	<i>Among Young</i>			<i>Among Medium-Age</i>			<i>Among Old</i>		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep. × 1/IT Price	0.219*** (0.043)	-0.220*** (0.038)	0.000 (0.019)	0.235*** (0.035)	-0.232*** (0.031)	-0.004 (0.019)	0.160*** (0.037)	-0.133*** (0.025)	-0.028 (0.026)
Obs	1,319	1,319	1,319	1,343	1,343	1,343	1,356	1,356	1,356
R2 (Partial)	0.051	0.059	0.000	0.061	0.088	0.000	0.030	0.037	0.001

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Results (within Education-Levels)

**Table :** Results for Employment Shares in High, Medium and Low Wage Occupations within Education-Levels

	<i>Among Highly Educated</i>			<i>Among Medium Educated</i>			<i>Among Low Educated</i>		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep. × 1/IT Price	0.147*** (0.040)	-0.108*** (0.030)	-0.038 (0.027)	0.294*** (0.033)	-0.222*** (0.033)	-0.071*** (0.024)	0.152*** (0.058)	-0.134** (0.054)	-0.018 (0.027)
Obs	1,172	1,172	1,172	1,297	1,297	1,297	1,293	1,293	1,293
R2 (Partial)	0.019	0.018	0.002	0.089	0.083	0.007	0.028	0.022	0.000

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Additional Results

**Table :** Additional Results for Employment Shares in High, Medium and Low Wage Occupations

	<i>W/o High IT Compensation Industries</i>			<i>Instrumental Variables</i>			<i>Capital Dependence</i>		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep × 1/IT Price	0.395*** (0.057)	-0.416*** (0.060)	0.021 (0.044)	0.220*** (0.029)	-0.202*** (0.028)	-0.018 (0.016)	0.215*** (0.026)	-0.210*** (0.024)	-0.005 (0.018)
K Dep × 1/K Price							0.190* (0.108)	-0.178* (0.100)	-0.012 (0.070)
Obs	963	963	963	1,360	1,360	1,360	1,360	1,360	1,360
R2 (Partial)	0.083	0.151	0.000	0.083	0.122	-0.000	0.086	0.126	0.000

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Additional Results

**Table :** Additional Results for Employment Shares in High, Medium and Low Wage Occupations

	<i>Medium-Skill Dependence</i>			<i>Industry Group × Year Dummies</i>			<i>Medium- and Low-Skill Wage Rates</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
IT Dep	0.171***	-0.161***	-0.010	0.187***	-0.196***	0.010	0.305***	-0.275***	-0.030
× 1/IT Price	(0.030)	(0.026)	(0.018)	(0.033)	(0.027)	(0.024)	(0.043)	(0.035)	(0.032)
MS Dep	-0.012***	0.013***	-0.001						
× 1/IT Price	(0.003)	(0.003)	(0.002)						
MS Wage Rate							-0.028	0.138***	-0.109
							(0.088)	(0.046)	(0.069)
LS Wage Rate							-0.085	0.196**	-0.111
							(0.143)	(0.088)	(0.106)
Obs	1,360	1,360	1,360	1,360	1,360	1,360	980	980	980
R2 (Partial)	0.102	0.158	0.000	0.037	0.065	0.000	0.107	0.176	0.006

Note: SE are bootstrapped and 2-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. \*\* indicates significance at the 1% level, \* at the 5% level, and at the 10% level.

# Conclusions

I offer international evidence corroborating one of the main hypotheses for “Job Polarization”

- ▶ The share of employment in high (medium) wage occupations has increased with the fall of IT prices
- ▶ The effects of IT on employment shares are stronger
  - ▶ for women than for men
  - ▶ for young and medium-age than for old
  - ▶ for medium-educated than for low- and highly educated



Thank you!

- Acemoglu, D. and D. H. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. C. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 4b, pp. 1043–1171. North-Holland: Elsevier B.V.
- Autor, D. H. and D. Dorn (2013). The growth of low skill service jobs and the polarization of the U.S. labor market. *American Economic Review* 103(5), 1553–1597.
- Autor, D. H., L. F. Katz, and M. S. Kearney (2006). The polarization of the US labor market. *American Economic Review* 96(2), 189–194.
- Autor, D. H., L. F. Katz, and M. S. Kearney (2008). Trends in US wage inequality: Revising the revisionists. *Review of Economics and Statistics* 90(2), 300–323.
- Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118(4), 1279–1333.
- Cerina, F., A. Moro, and M. Rendall (2016). Employment polarization, structural change and women. Mimeo.
- Cortes, G. M., N. Jaimovich, and H. E. Siu (2016). The end of men? Gender differences in the high-skill labor market since 1980. Mimeo.

- Goos, M. and A. Manning (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *Review of Economics and Statistics* 89(1), 118–133.
- Goos, M., A. Manning, and A. Salomons (2009). Job polarization in Europe. *American Economic Review: Papers & Proceedings* 99(2), 58–63.
- Goos, M., A. Manning, and A. Salomons (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104(8), 2509–2526.
- Michaels, G., A. Natraj, and J. van Reenen (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics* 96(1), 60–77.
- Rajan, R. G. and L. Zingales (1998). Financial dependence and growth. *American Economic Review* 88(3), 559–586.