Employment Prospects in the Era of Automation

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Questions

- What are labor market effects of the recent wave of automation?
  - Automation is the adoption and use of computerized/automated industrial machines
- Is capital a complement or a substitute for labor?
  - In the commonly used Cobb-Douglas production function we have unit elasticity

Outline

- Historical perspective on capital-labor complementarity (substitutability)
- Current research on capital-labor complementarity (substitutability)
  - Skill levels, occupations, and tasks
- My own research (Jerbashian, 2016)
  - Automation and Job Polarization: On the Decline of Middling Occupations in Europe

Historical Perspective - Capital and Labor

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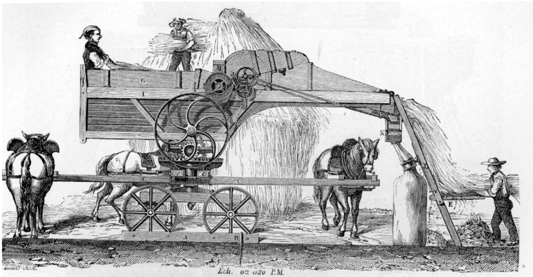

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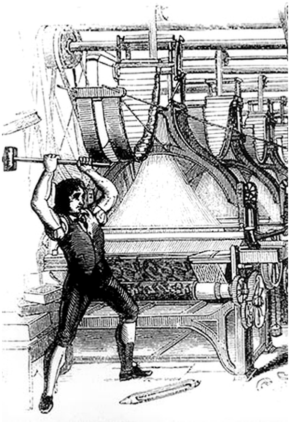
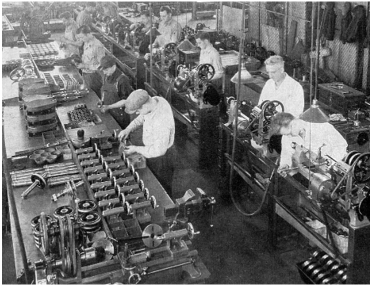
Fig. 349. — Batteuse Damey à manège direct placé sous la batteuse.

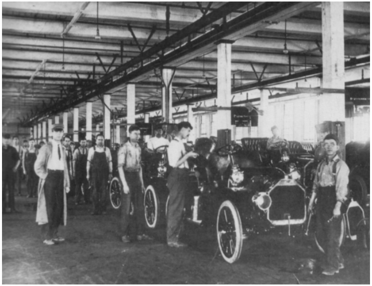
Historical Perspective - Luddites



Luddites were the members of bands of English workers who destroyed machinery, especially in cotton/wool mills, which they believed was threatening their jobs (1811–1816)

Historical Perspective - Telephony and Accounting





Historical Perspective - Economic Thought and Arguments

- Elizabeth I (Queen of England and Ireland; 1533–1603) refused to patent a knitting machine invented by William Lee
  - Consider thou what the invention could do to my poor subjects. It would assuredly bring them to ruin by depriving them of employment, thus making them beggars
- Thomas Robert Malthus and David Ricardo, among others, argued that innovation and technologies can cause long-term unemployment
  - Karl Marx took these arguments to the extreme
- Wassily Leontief (1952)
  - Labor will become less and less important... More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job

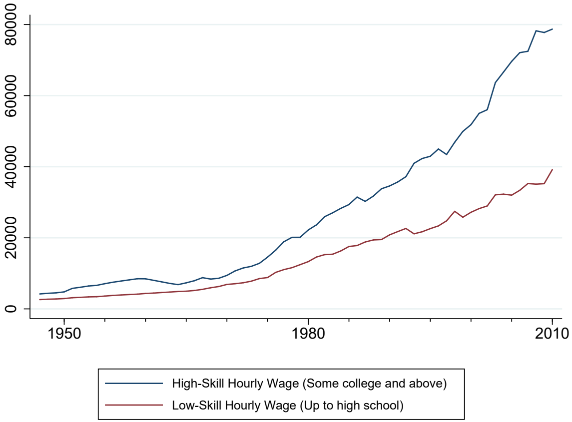
Historical Perspective - Economic Thought and Arguments

Compensation effects and optimistic views

- New machines
  - Higher demand for labor to build the new machines
- Changes in wages
  - Wages adjust in response to increase unemployment
  - Labor productivity and wages increase at least for some workers
- Lower prices
  - Higher demand and higher employment
  - Lower prices offset lower wages
- New products
  - New jobs

Current Research - Skill-Biased Technological Change

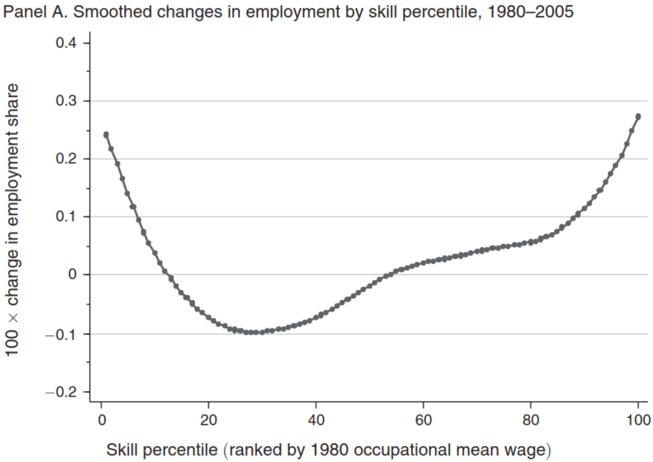
- e.g., Katz and Autor (1999), Acemoglu (1998), Krusell, Ohanian, Ríos-Rull, and Violante (2000)



Current Research - Skill-Biased Technological Change

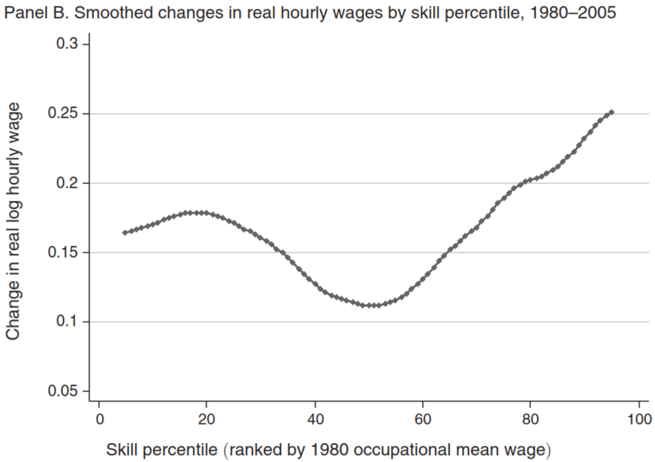
- It is hard to understand why we should have skill biased technological change
- Why did high-skill compensation start sharply increasing after 1975?
  - Computers and automation? Why is this linked to high-skill?
- Skill-biased technological change misses an important point
  - Middle wage occupations have hollowed out and the demand for high and low wage occupation has increased
  - e.g., Autor, Levy, and Murnane (2003), Autor and Dorn (2013), Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014)

Current Research - Trends in Labor Markets



Source: Autor and Dorn (2013)

Current Research - Trends in Labor Markets



Source: Autor and Dorn (2013)

Current Research - Tasks

Types of tasks (Autor et al., 2003)

- Abstract tasks (non-routine cognitive): problem-solving, analytical, and complex communication activities
- Routine tasks: well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules
- Manual tasks: manual activities which cannot be accomplished by following explicit rules

Current Research - Tasks

TABLE I
PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

	Routine tasks	Nonroutine tasks
	Analytic and interactive tasks	
Examples	• Record-keeping • Calculation • Repetitive customer service (e.g., bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	• Substantial substitution	• Strong complementarities
	Manual tasks	
Examples	• Picking or sorting • Repetitive assembly	• Janitorial services • Truck driving
Computer impact	• Substantial substitution	• Limited opportunities for substitution or complementarity

Source: Autor et al. (2003)

Current Research - Tasks

TABLE 2—TASK INTENSITY OF MAJOR OCCUPATION GROUPS

	RTI index	Abstract tasks	Routine tasks	Manual tasks
Managers/prof/tech/finance/public safety	−	+	−	−
Production/craft	+	+	+	−
Transport/construct/mech/mining/farm	−	−	+	+
Machine operators/assemblers	+	−	+	+
Clerical/retail sales	+	−	+	−
Service occupations	−	−	−	+

Notes: The table indicates whether the average task value in occupation group is larger (+) or smaller (−) than the task average across all occupations. Shaded fields indicate the largest task value for each occupation group.

Source: Autor and Dorn (2013)

Current Research - Tasks

Table: Abstract Tasks - High Wage Occupations (Goos et al., 2014)

Corporate Managers
Physical, Mathematical, and Engineering Science Professionals
Life Science and Health Professionals
Other Professionals
General Managers
Physical and Engineering Science Associate Professionals
Other Associate Professionals
Life Science and Health Associate Professionals

Current Research - Tasks

Table: Routine Tasks - Medium Wage Occupations (Goos et al., 2014)

Stationary-plant and Related Operators
Metal, Machinery, and Related Trades Workers
Drivers and Mobile-plant Operators
Office Clerks
Precision, Handicraft, Printing, and Related Trades Workers
Extraction and Building Trades Workers
Customer Services Clerks
Machine Operators and Assemblers
Other Craft and Related Trades Workers

Current Research - Tasks

Table: Manual Tasks - Low Wage Occupations (Goos et al., 2014)

Labourers in Mining, Construction, Manufacturing, and Transport
Personal and Protective Services Workers
Models, Salespersons, and Demonstrators
Sales and Services Elementary Occupations

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

Motivation

- Increasing shares of employment (as well as wages) in low and high wage occupations
- Falling share of employment in medium wage occupations
- 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 gender and age 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, Natraj, and van Reenen (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
  - These results are robust to a wide range of specification checks and alternative identifying assumptions

Potential Rationales

An explanation is that efficiency (advantage) in performing tasks varies with age and gender

- Men are more endowed with hard motor skills (brawn) than women, which are important in many medium wage occupations
- Older employees can be more efficient in routine occupations since workers accumulate routine skills as they age (Autor and Dorn, 2009)

Related Literature

- Autor, Katz, and Kearney (2006), Goos and Manning (2007), Autor, Katz, and Kearney (2008), Goos, Manning, and Salomons (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, Jaimovich, and Siu (2018), Cerina, Moro, and Rendall (2017): 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 $\varepsilon > 1$.

- α_{IT} measures the relative importance of IT and higher α_{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 α_{IT}

Theoretical Background

I incorporate the demand side into a simple Ricardian model for within age and gender 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 $\alpha_{L,k}\left(u_k L\right)^{\gamma}$, where
  - $\alpha_{L,k} > 0$ and $\gamma \in (0,1)$
  - u_k is the share of labor hours converted to task k

Theoretical Background

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

$$\frac{p_{T_A}}{p_{T_R}} = \frac{\alpha_{L,T_R}}{\alpha_{L,T_A}} \frac{\left(u_{T_R} L\right)^{\gamma-1}}{\left(u_{T_A} L\right)^{\gamma-1}},$$

and the share of employment in abstract tasks is given by

$$\frac{u_{T_A}}{1-u_{T_A}} = \frac{1-\alpha}{\alpha} \left(\frac{\alpha_{IT} IT^{\frac{\varepsilon-1}{\varepsilon}}}{\alpha_{T_R} \left\{\alpha_{L,T_R} \left[\left(1-u_{T_A}\right) L\right]^{\gamma}\right\}^{\frac{\varepsilon-1}{\varepsilon}}} + 1 \right)$$

Theoretical Background

It is straightforward to show that

- A fall in p_{IT} increases the share of employment in abstract tasks u_{T_A} and it has a stronger effect in industries which have a higher α_{IT}
- This differential effect of the fall in p_{IT} on u_{T_A} (and u_{T_R}) is weaker in groups which have a higher α_{T_R}:

$$\frac{\partial}{\partial \alpha_{T_R}} \frac{\partial}{\partial \alpha_{IT}} \left| \frac{\partial u_{T_A}}{\partial p_{IT}} \right| < 0$$

Empirical Specification

For each occupation group, I estimate

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

where

- $\text{Employment Share}_{c,i,t}$ is the share of employment in one of the occupation groups, country c, industry i, and year t
- ζ and ξ are country-industry and country-year fixed effects, and η is an error term

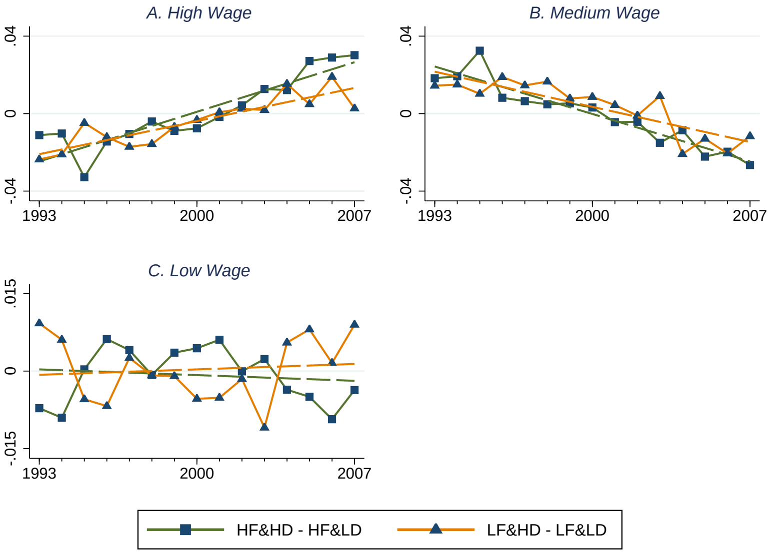
Data

- 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
  - 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
  - β 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 β



Results

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

	(1) High	(2) Medium	(3) Low
IT Dep.	0.217***	-0.212***	-0.005
$\times$ 1/IT Price	(0.026)	(0.022)	(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

	Among Males			*Among Females*		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep. $\times$ 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

	Among Young			*Among Medium-Age*			*Among Old*		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep.	0.219***	-0.220***	0.000	0.235***	-0.232***	-0.004	0.160***	-0.133***	-0.028
$\times$ 1/IT Price	(0.043)	(0.038)	(0.019)	(0.035)	(0.031)	(0.019)	(0.037)	(0.025)	(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.

Additional Results

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

	W/o High IT Compensation Industries			*Instrumental Variables*			*Capital Dependence*		
	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low	(1) High	(2) Medium	(3) Low
IT Dep	0.395***	-0.416***	0.021	0.220***	-0.202***	-0.018	0.215***	-0.210***	-0.005
× 1/IT Price	(0.057)	(0.060)	(0.044)	(0.029)	(0.028)	(0.016)	(0.026)	(0.024)	(0.018)
K Dep							0.190*	-0.178*	-0.012
× 1/K Price							(0.108)	(0.100)	(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

	Medium-Skill Dependence			*Industry Group × Year Dummies*			*Medium- and Low-Skill Wage Rates*		
	(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
  - Technological heterogeneity across industries creates important differences in terms of response of employment shares to changes in IT prices
- The effects of IT on employment shares are stronger
  - for women than for men
  - for young and medium-age than for old

Relevance for Armenia

- Mixed results for developing countries, in general
  - Labor usually is not very expensive
  - Business regulations and property rights
- Perhaps very relevant for our future and future generations

Thank you!

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