Robots and Jobs:
Some Insights from Recent Research

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Information technology has been the main source of innovation in the US economy for at least three decades.

- As the **new economy** has developed, intangible assets and high-technology investments are playing an increasingly important role.

- Because firms invest heavily in **R&D**, **software**, **brands**, and other intangible assets—at a rate close to that of tangible assets—changes in measured GDP, which does not include all intangible investments, understate the actual changes in total output.

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Intangible Capital and Measured Productivity*

Ellen R. McGrattan
University of Minnesota
and Federal Reserve Bank of Minneapolis

ABSTRACT

Because firms invest heavily in R&D, software, brands, and other intangible assets—at a rate close to that of tangible assets—changes in measured GDP, which does not include all intangible investments, understate the actual changes in total output. If changes in the labor input are more precisely measured, then it is possible to observe little change in measured total factor productivity (TFP) coincidentally with large changes in hours and investment. This mismeasurement leaves business cycle modelers with large and unexplained labor wedges accounting for most of the fluctuations in aggregate data. To address this issue, I incorporate intangible investments into a multi-sector general equilibrium model and parameterize income and cost shares using data from an updated U.S. input and output table, with intangible investments reassigned from intermediate to final uses. I employ maximum likelihood methods and quarterly observations on sectoral gross outputs for the United States over the period 1985–2014 to estimate processes for latent sectoral TFPs—that have common and sector-specific components. Aggregate hours are not used to estimate TFPs, but the model predicts changes in hours that compare well with the actual hours series and account for roughly two-thirds of its standard deviation. I find that sector-specific shocks and industry linkages play an important role in accounting for fluctuations and comovements in aggregate and industry-level U.S. data, and I find that the model's common component of TFP is not correlated at business cycle frequencies with the standard measures of aggregate TFP used in the macroeconomic literature.

Technology is widely considered the main source of economic progress, but it has also generated cultural anxiety throughout history.

The Luddite Rebellion

“Between 1811 and 1877, a group of English textile workers whose jobs threatened by the automated looms of the first Industrial Revolution rallied around a perhaps mythical, Robin Hood-like figure named Ned Ludd and attacked mills and machinery before being suppressed by the British government.”

(Brynjolfsson and McAfee, 2014, p. 173)

THE LUDDITE MOVEMENT IN FRANCE

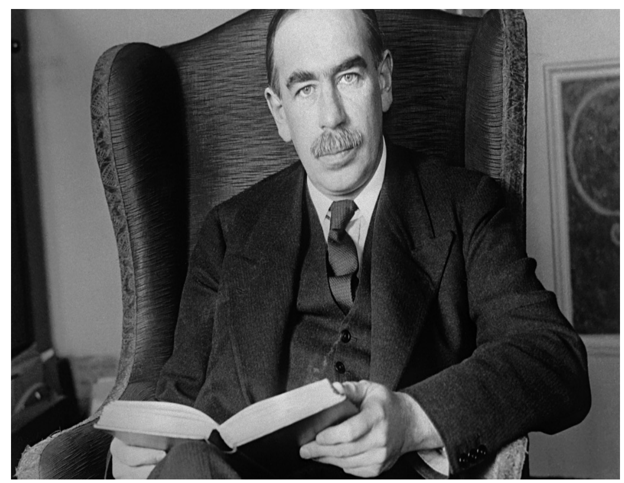
FRANK E. MANUEL

DURING the reign of Louis XIV, Colbert sent spies abroad to bring back new industrial techniques, sponsored the experiments of inventors in special laboratories, enticed foreign entrepreneurs with concessions, and attracted skilled foreign workers with special privileges.[1] In the eighteenth century, although the government manifested much less enthusiam in the pursuit of this policy, it was not completely abandoned. As England was undergoing its industrial revolution, a few models of the new machines found their way across the Channel in spite of prohibitions and embargoes. And in the last years of the *ancien régime* an ambitious group of manufacturers in Rouen, the Abbé Baudeau's Free Society for the Encouragement of Inventions Which Tend to Perfect Arts and Trades, in Imitation of the London Society (1776), and government agencies working under Calonne made a concerted effort to further the introduction of machines.[2]

Many writers conceded possibly negative effects of machinery on employment in the short run, they typically distinguished short-run dislocations from possible long-run effects.

"We are being afflicted with a new disease of which some readers may not have heard the name, but of which they will hear a great deal in the years to come—namely, **technological unemployment**."

(Keynes, 1930, *Economic Possibilities for Our Grandchildren)*



The Triple Revolution Report (1964)

"A new era of production has begun. Its principles of organization are as different from those of the industrial era as those of the industrial era were different from the agricultural. The cybernation revolution has been brought about by the combination of the computer and the automated self-regulating machine. This results in a system of almost unlimited productive capacity which requires progressively less human labor."

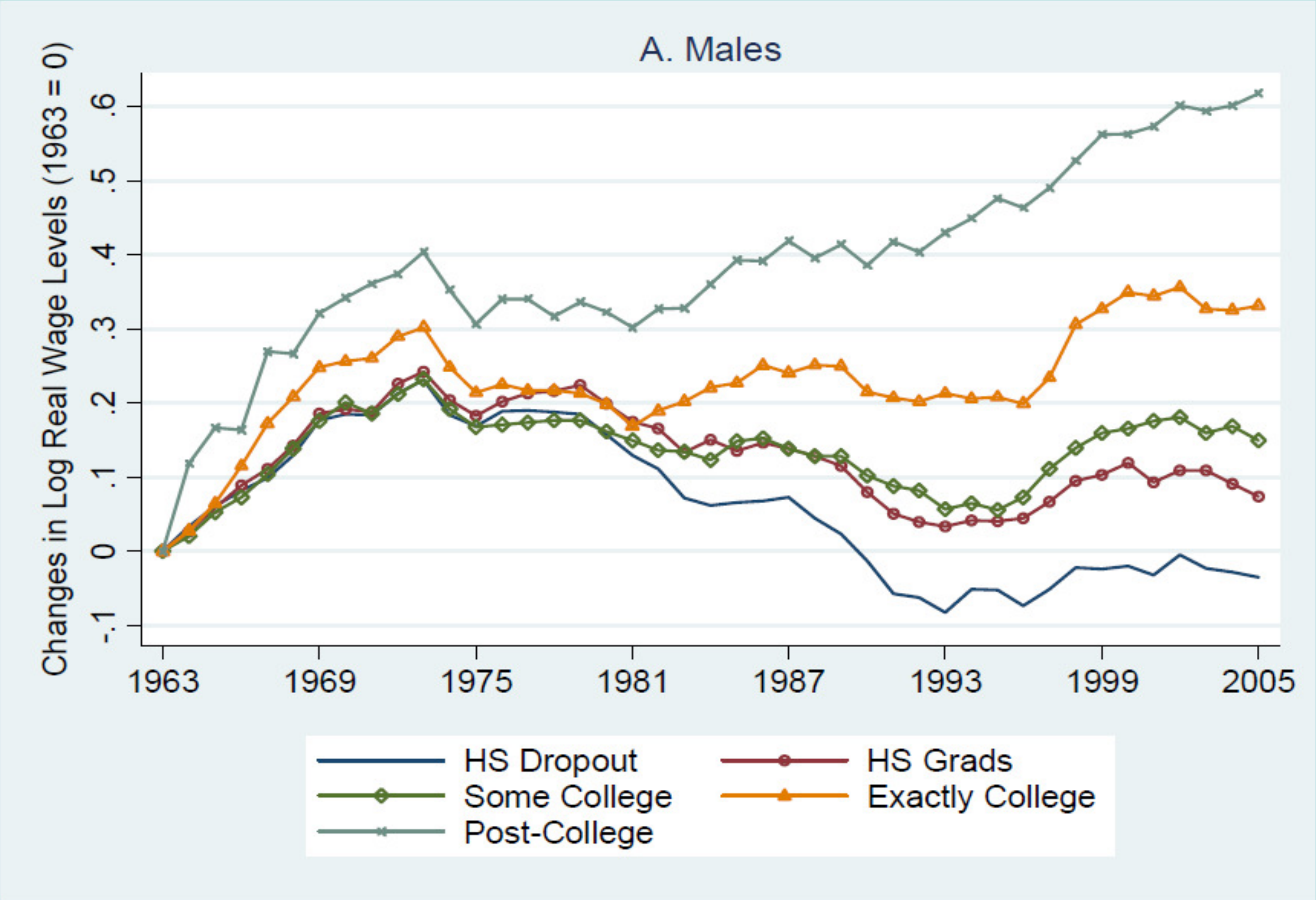
(Brynjolfsson and McAfee, 2014, p. 174-175)

In recent years, there has been a revival of public concerns about technological change destroying jobs.

Skill-biased technical change has increased the relative demand for highly educated workers while reducing demand for less workers whose jobs frequently involve *routine cognitive* and *manual tasks*.

The US middle class was built on routine work (both physical, like staffing an assembly line in a factory, and cognitive, like handling payroll for the factory) and this work has been rapidly automated in recent decades.

Changes in Composition-Adjusted Male Full Time Log Weekly Wages 1963 - 2005



Autor 2008

TABLE I

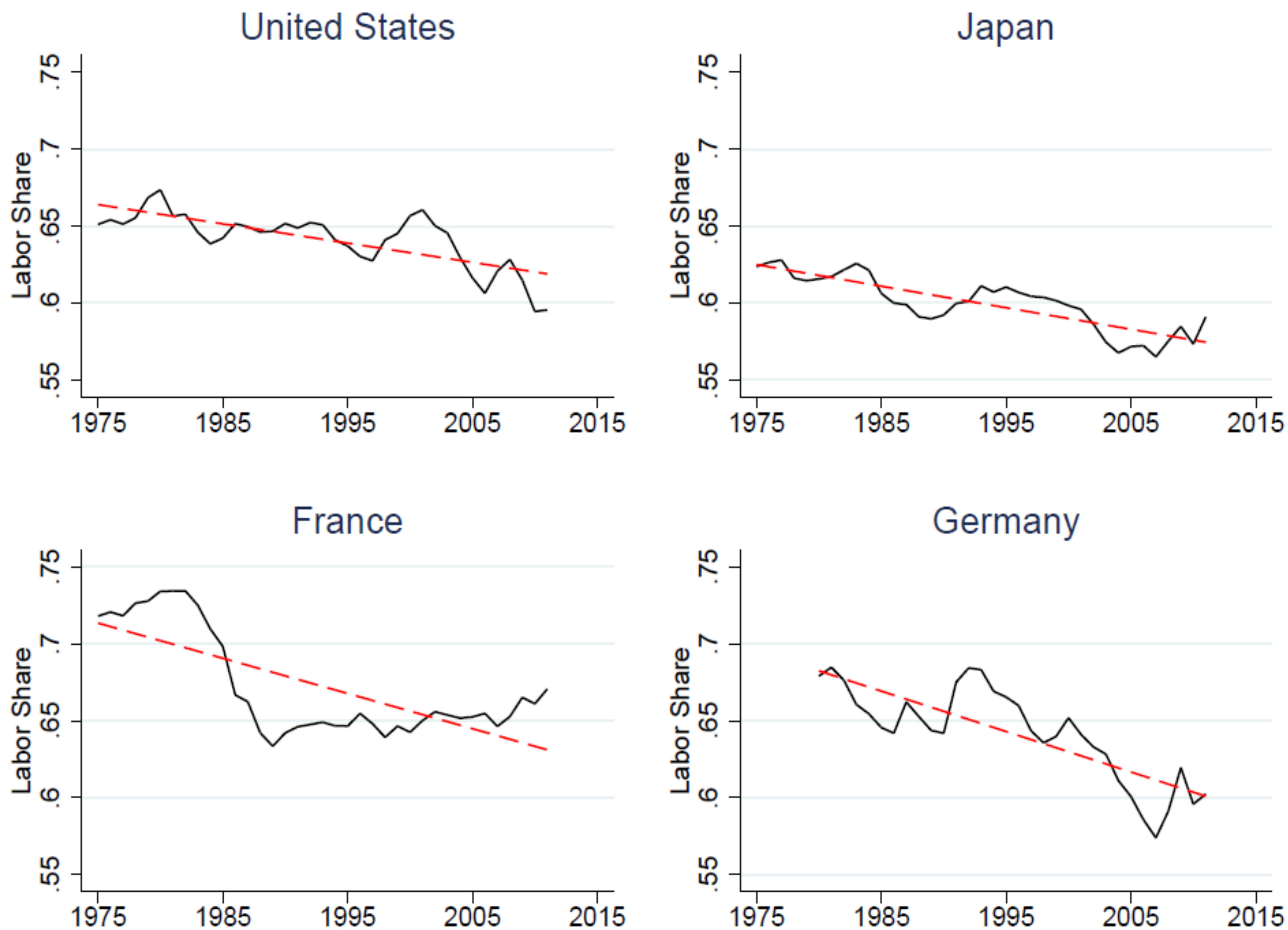
PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

	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, Levy, Murnane 2003

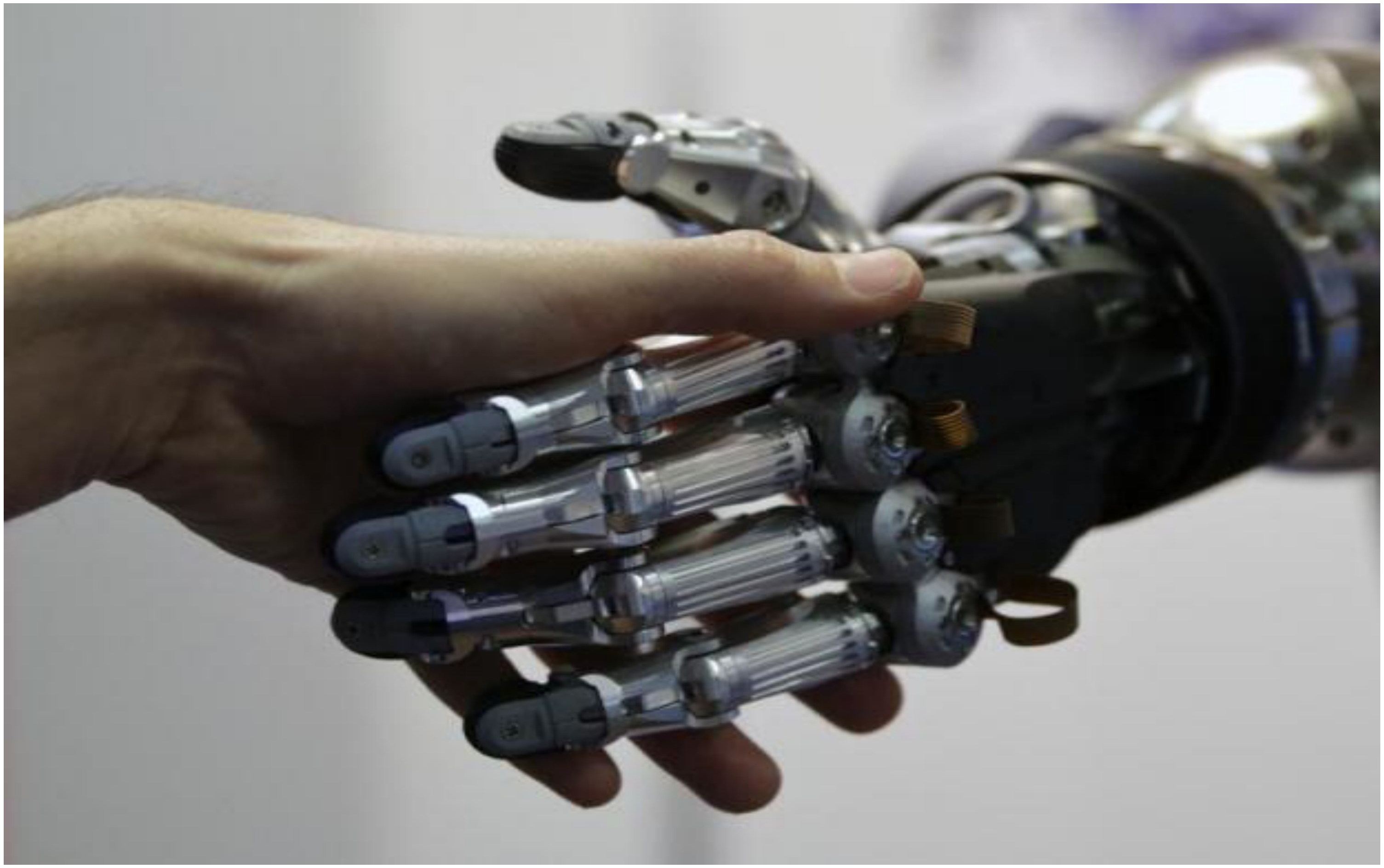
Capital-biased technological changes that encourage substitution of capital for labour have increased the profits earned by capital owners and reduced the share of income going to labour.

Labor Shares in Advanced Economies



Karabarbounis, L., Neiman, B. 2014. "The Global Decline of the Labor Share" Quarterly Journal of Economics, 129(1): 61-103.

Robots are taking human jobs



Note: A man shakes hands with a humanoid robot during the International Conference on Humanoid Robots in Madrid November 19, 2014. REUTERS/Andrea Comas

Androids, such as this one directing shoppers in Tokyo, will replace humans in many service occupations in the next 10–20 years.

Source: https://www.nature.com/news/track-how-technology-is-transforming-work-1.21837

A robot delivers takeaway food to customers in a trial in London

Source: https://www.nature.com/news/track-how-technology-is-transforming-work-1.21837

Large-scale automation entering the workplace and affecting people's wage and employment prospects.

What will happen to jobs as more tasks are done by robots?

Will mass unemployment ensue, or will humanity adjust as it has to new technologies in the past?

Symposium: Automation and Labor Markets

- *Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." Journal of Economic Perspectives, 29(3): 3-30.*

- *Mokyr, Joel, Chris Vickers, and Nicolas L. Ziebarth. 2015. "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?" Journal of Economic Perspectives, 29(3): 31-50.*

- *Pratt, Gill A. 2015. "Is a Cambrian Explosion Coming for Robotics?" Journal of Economic Perspectives, 29(3): 51-60.*

Robots: Curse or Blessing? A Basic Framework

Jeffrey D. Sachs[1], Seth G. Benzell[2], and Guillermo LaGarda[2]

[1]The Earth Institute, Columbia University*
[2]Department of Economics, Boston University†

October 26, 2016

Abstract

Do robots raise or lower economic well-being? On the one hand, they raise output and bring more goods and services into reach. On the other hand, they eliminate jobs, shift investments away from machines that complement labor, lower wages, and immiserize workers who cannot compete. The net effect of these offsetting forces is unclear. This paper seeks to clarify how economic outcomes, positive and negative, depend on parameters of the economy and public policy. We find that a rise in robotic productivity is more likely to lower the welfare of young workers and future generations when the saving rate is low, automatable and non-automatable goods are more substitutable in consumption, and when traditional capital is a more important complement to labor. In some parameterizations the relationship of utility to robotic productivity follows a 'noisy U' as large innovations are long-run welfare improving even though small innovations are immiserizing. Policies that redistribute income across generations can ensure that a rise in robotic productivity benefits all generations.

Robots Are Us: Some Economics of Human Replacement*

Seth G. Benzell[1], Laurence J. Kotlikoff[1], Guillermo LaGarda[1], and Jeffrey D. Sachs[2]

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October 26, 2016

Abstract

Will smart machines replace humans like the internal combustion engine replaced horses? If so, can putting people out of work, or at least out of good work, also put the economy out of business? Our model says yes. Under the right conditions, more supply produces, over time, less demand as the smart machines undermine their customer base. Highly tailored skill- and generation-specific redistribution policies can keep smart machines from immiserating our posterity. But blunt policies, such as mandating open-source technology, can make matters worse.

The Lost Race Against the Machine: Automation, Education, and Inequality in an R&D-based Growth Model*

Klaus Prettner†
Holger Strulik‡

March 2017

Abstract. We analyze the effect of automation on economic growth and inequality in an R&D-based growth model with two types of labor: high-skilled labor that is complementary to machines and low-skilled labor that is a substitute for machines. The model predicts that innovation-driven growth leads to increasing automation, an increasing skill premium, an increasing population share of graduates, increasing income and wealth inequality, a declining labor share, and (in an extension of the basic model) increasing unemployment. In contrast to Piketty's famous claim that faster economic growth reduces inequality, our theory predicts that faster economic growth promotes inequality.

Automation and demographic change

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Abstract

We analyze the effects of declining population growth on the adoption of automation technology. A standard theoretical framework of the accumulation of traditional physical capital and of automation capital predicts that countries with a lower population growth rate are the ones that innovate and/or adopt new automation technologies faster. We test the theoretical prediction by means of panel data for 60 countries over the time span from 1993 to 2013. Regression estimates provide empirical support for the theoretical prediction and suggest that a 1% increase in population growth is associated with approximately a 2% reduction in the growth rate of robot density. Our results are robust to the inclusion of standard control variables, the use of different estimation methods, the consideration of a dynamic framework with the lagged dependent variable as regressor, and changing the measurement of the stock of robots.

Racing With or Against the Machine? Evidence from Europe*

Terry Gregory† ZEW Mannheim

Anna Salomons‡ Utrecht University

Ulrich Zierahn§ ZEW Mannheim

July 2016

Abstract

A fast-growing literature shows that technological change is replacing labor in routine tasks, raising concerns that labor is racing against the machine. This paper is the first to estimate the labor demand effects of routine-replacing technological change (RRTC) for Europe as a whole and at the level of 238 European regions. We develop and estimate a task framework of regional labor demand in tradable and non-tradable industries, building on Autor and Dorn (2013) and Goos et al. (2014), and distinguish the main channels through which technological change affects labor demand. These channels include the direct substitution of capital for labor in task production, but also the compensating effects operating through product demand and local demand spillovers. Our results show that RRTC has on net led to positive labor demand effects across 27 European countries over 1999-2010, indicating that labor is racing with the machine. This is not due to limited scope for human-machine substitution, but rather because sizable substitution effects have been overcompensated by product demand and its associated spillovers. However, the size of the product demand spillover – and therefore also RRTC's total labor demand effect– depends critically on where the gains from the increased productivity of technological capital accrue.

OECD*publishing*

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http://dx.doi.org/10.1787/5jlz9h56dvq7-en

OECD Social, Employment and Migration Working Papers No. 189

The Risk of Automation for Jobs in OECD Countries

A COMPARATIVE ANALYSIS

Melanie Arntz, Terry Gregory,
Ulrich Zierahn

What types of labour will be replaced by machines, and what types of labour will be in greater demand?

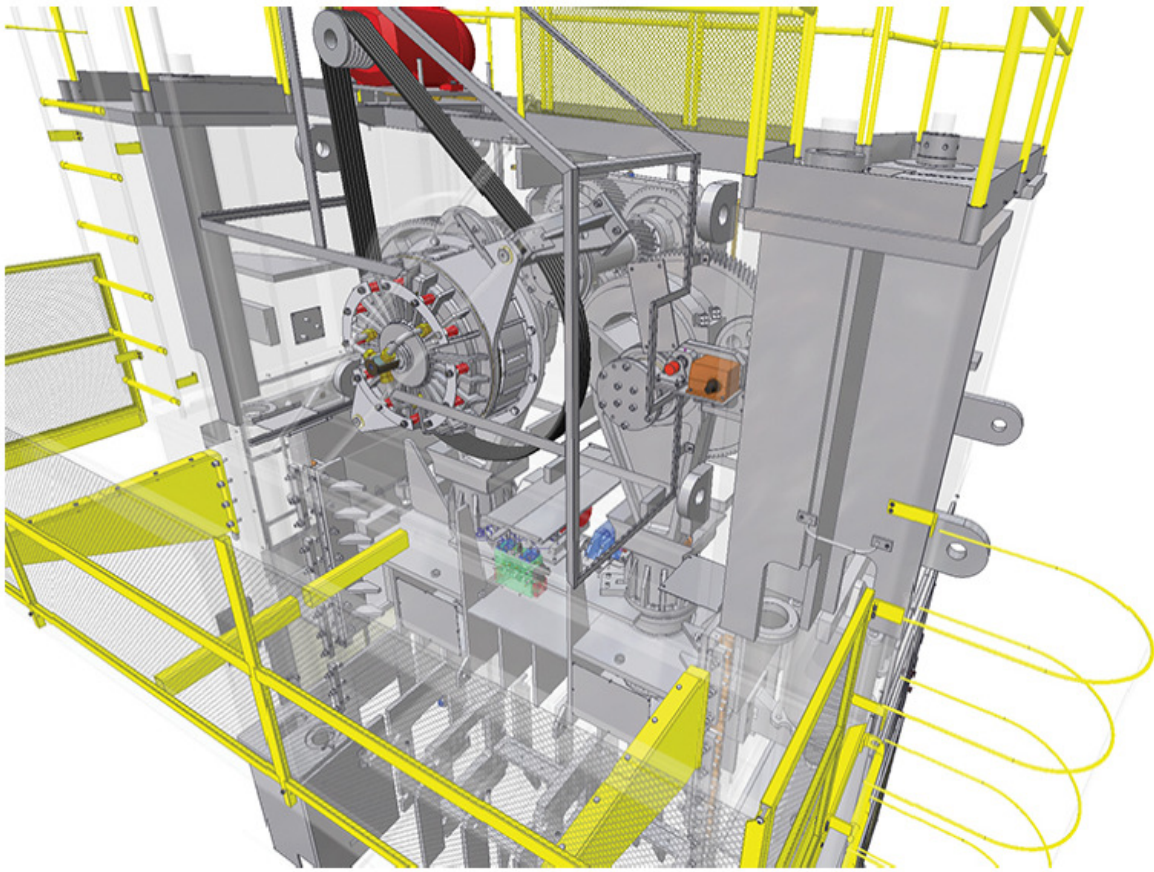
Two potential – very different- labour market implications:

1. **Enabling**: they complement and increase the productivity of certain types of skills (e.g., CAD for design workers, laptops for managers and workers specialising in problem-solving, scanners for cashiers).

2. **Replacing**: they take over tasks previously performed by labour (e.g., assembly tasks, switchboard operation, mail sorting, packing, stock trading, dispensing cash, operating machines, etc.).

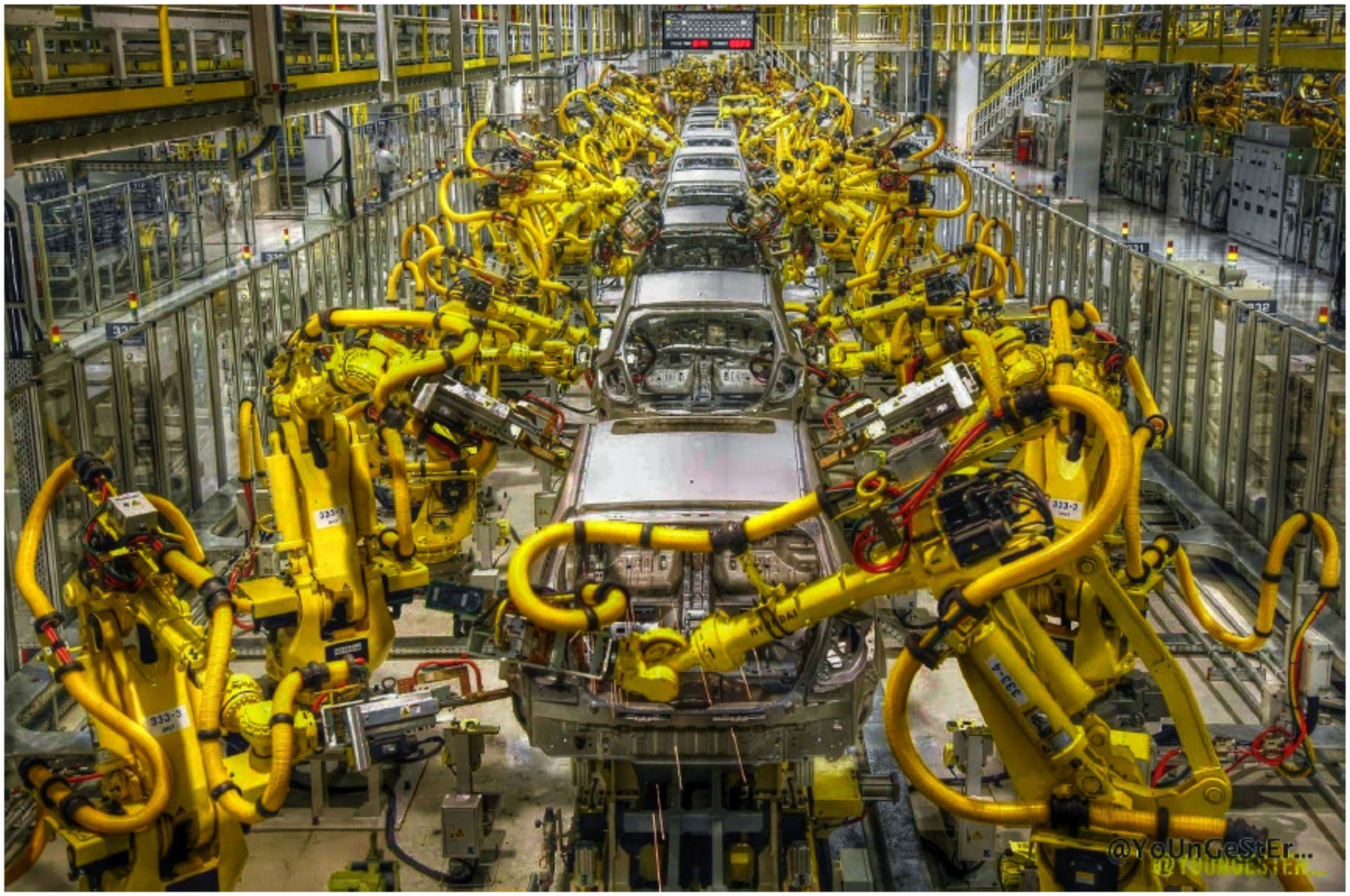
Modern Examples of Enabling Technologies

- Computer-assisted design

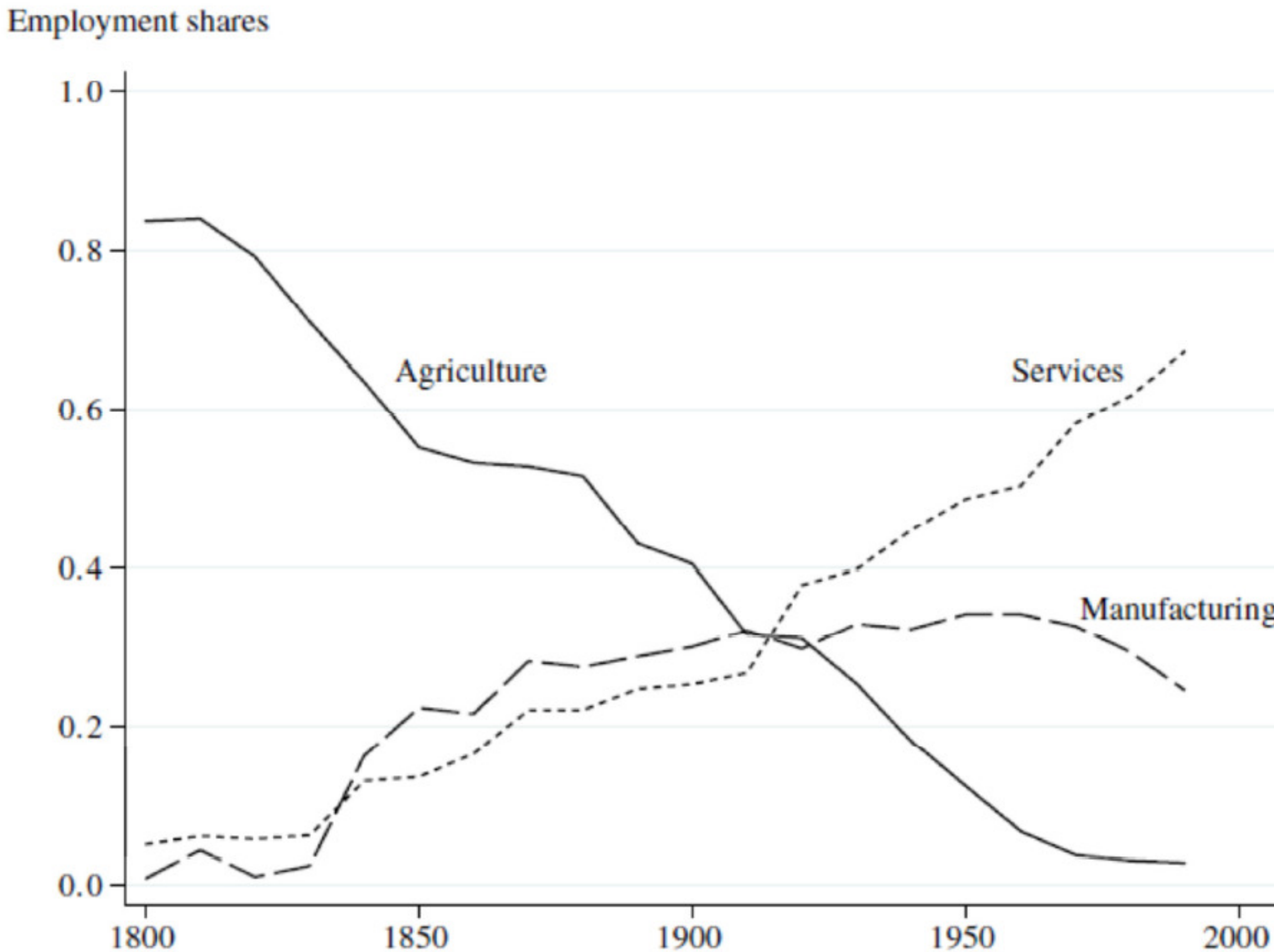


Modern Examples of Replacing Technologies

- Industrial robots



The share of U.S. employment by sector, 1800-2000



Why have so many manufacturing jobs been lost in the richest countries in recent decades?

The Rise of China

Acemoglu et al. (2016) estimate that **2.0-2.4 million people** in the US lost their jobs as a result of increasing Chinese import competition during 1999-2011.

Source: Acemoglu, D., Autor, D. H., Dorn, D., Hanson, G. H., and Price, B. (2016), "Import competition and the great US employment sag of the 2000s", Journal of Labor Economics, 34(S1), S141-S198.

The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment
Daron Acemoglu and Pascual Restrepo
NBER Working Paper No. 22252
May 2016, Revised June 2017
JEL No. J23,J24,O14,O31,O33

ABSTRACT

We examine the concerns that new technologies will render labor redundant in a framework in which tasks previously performed by labor can be automated and new versions of existing tasks, in which labor has a comparative advantage, can be created. In a static version where capital is fixed and technology is exogenous, automation reduces employment and the labor share, and may even reduce wages, while the creation of new tasks has the opposite effects. Our full model endogenizes capital accumulation and the direction of research towards automation and the creation of new tasks. If the long-run rental rate of capital relative to the wage is sufficiently low, the long-run equilibrium involves automation of all tasks. Otherwise, there exists a stable balanced growth path in which the two types of innovations go hand-in-hand. Stability is a consequence of the fact that automation reduces the cost of producing using labor, and thus discourages further automation and encourages the creation of new tasks. In an extension with heterogeneous skills, we show that inequality increases during transitions driven both by faster automation and introduction of new tasks, and characterize the conditions under which inequality is increasing or stable in the long run.

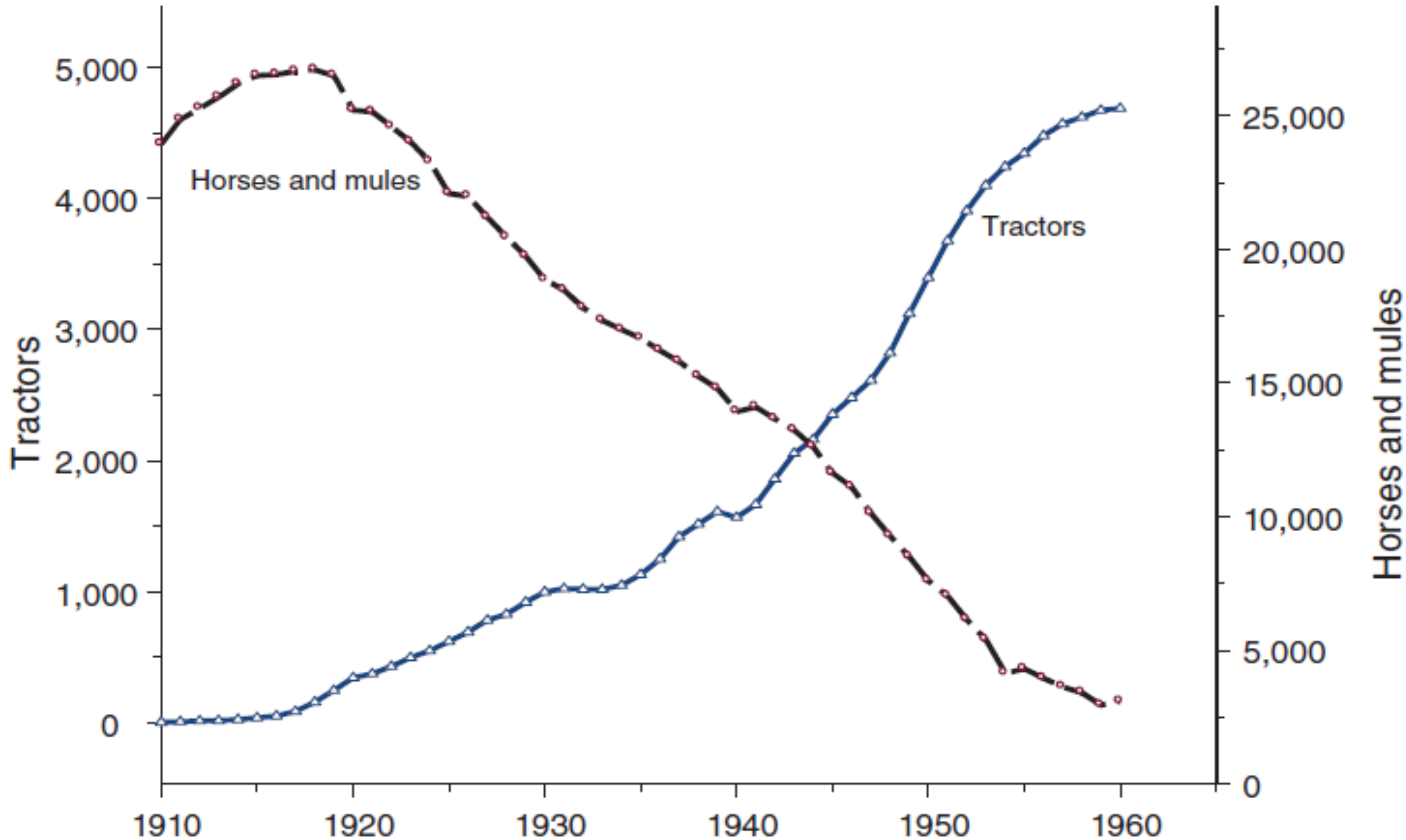
Robots and Jobs: Evidence from US Labor Markets
Daron Acemoglu and Pascual Restrepo
NBER Working Paper No. 23285
March 2017
JEL No. J23,J24

ABSTRACT

As robots and other computer-assisted technologies take over tasks previously performed by labor, there is increasing concern about the future of jobs and wages. We analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets. Using a model in which robots compete against human labor in the production of different tasks, we show that robots may reduce employment and wages, and that the local labor market effects of robots can be estimated by regressing the change in employment and wages on the exposure to robots in each local labor market—defined from the national penetration of robots into each industry and the local distribution of employment across industries. Using this approach, we estimate large and robust negative effects of robots on employment and wages across commuting zones. We bolster this evidence by showing that the commuting zones most exposed to robots in the post-1990 era do not exhibit any differential trends before 1990. The impact of robots is distinct from the impact of imports from China and Mexico, the decline of routine jobs, offshoring, other types of IT capital, and the total capital stock (in fact, exposure to robots is only weakly correlated with these other variables). According to our estimates, one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent.

The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment

Horse, Mules, and Tractors in Farms: 1910-1960



Source: Manuelli, R. E., and Seshadri, A. (2014), “Frictionless Technology Diffusion: The Case of Tractors”, American Economic Review, 104(4), 1368-1391.

Machines replaced horses, why not labour?

Horses don’t have comparative advantage in tasks, but human labour does.

Two key ideas

- During most times, there is a continuous process of tasks previously performed by labour being mechanised and automated, while at the same time, new employment opportunities for labour are created.

- New employment opportunities come mostly from the introduction of new and more complex tasks in which labour has a comparative advantage relative to capital.

These two key building blocks imply that one should consider the dynamics of modern labour markets in advanced economies as being characterised by a race between **two technological forces:**

- automation on the side of machines
- the creation of new complex tasks on the side of man

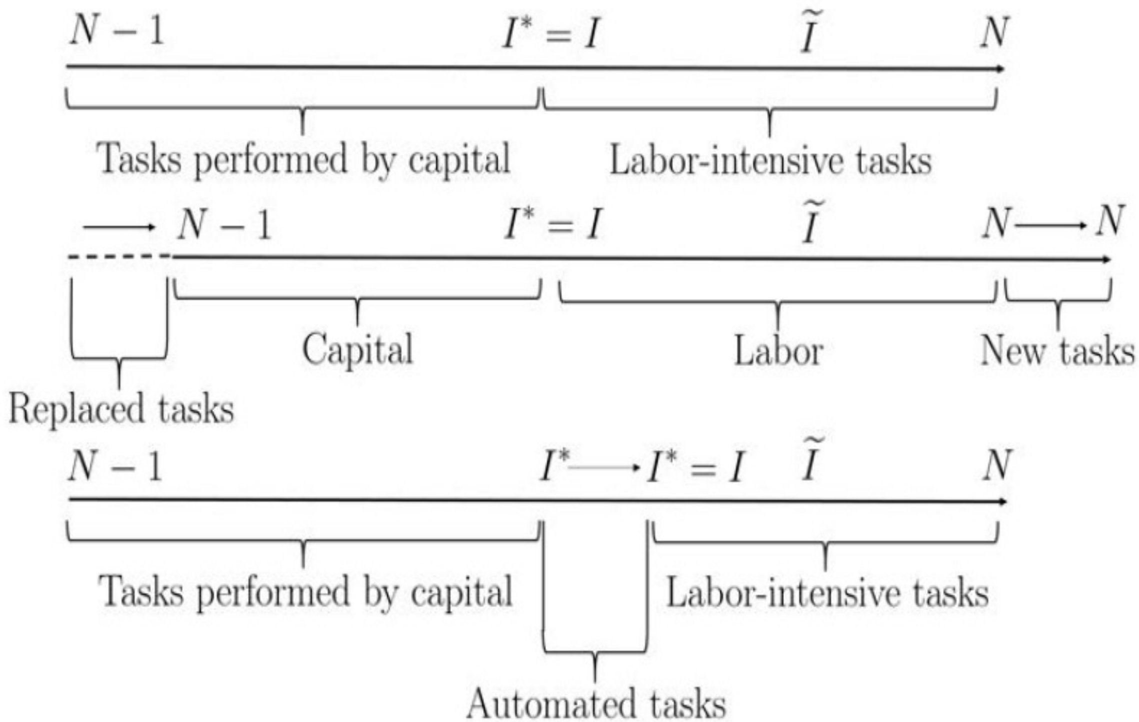


Figure 2: The task space and a representation of the effect of introducing new tasks (middle panel) and automating existing tasks (bottom panel).

The measure of tasks used in production remains at 1.

A new (more complex) task replaces or upgrades the lowest-index task.

As *N* increases the set of feasible tasks shifts to the right, and only tasks above *N-1* remain compatible with and combined with those currently in use.

- **If the first force outpaces the second**, there will be a declining share of labour in national income and technological non-employment.

- **If the first force outpaces the second**, there will be a declining share of labour in national income and technological non-employment.

- **If the second force outpaces the first**, the reverse will happen – there will be a greater share of labour in national income and rising employment.

On the implications of automation for inequality

- When different workers have different amounts of skills, both automation and the creation of new tasks may lead to greater inequality:

1. **because machines compete more strongly against less skilled labour**

2. **because the more skilled workers have greater competitive advantage than the less skilled in new complex tasks**.

The final sentence of the paper

"Finally, and perhaps most importantly, our model **highlights the need for additional empirical evidence on how automation impacts employment and wages** (which we investigate in Acemoglu and Restrepo, 2017) and how the incentives for automation and the creation of new tasks respond to policies, factor prices and supplies."

Robots and Jobs:

Evidence from US labor markets.

- There is no guarantee that firms would choose to automate; that would depend on the costs of substituting machines for labor and how much wages change in response to this threat.

- There is no guarantee that firms would choose to automate; that would depend on the costs of substituting machines for labor and how much wages change in response to this threat.

- The labour market impacts of new technologies depend not only on where they hit but also on the adjustment in other parts of the economy.

Acemoglu and Restrepo analyse the effect of the increase in **industrial robot** usage between 1990 and 2007 on US local labour markets.

Industrial robot as defined by ISO 8373:2012:

An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.

- **Reprogrammable:** designed so that the programmed motions or auxiliary functions can be changed without physical alteration;

- **Multipurpose:** capable of being adapted to a different application with physical alteration;

- **Physical alteration:** alteration of the mechanical system (the mechanical system does not include storage media, ROMs, etc.)

- **Axis**: direction used to specify the robot motion in a linear or rotary mode

- Textile looms,
- elevators,
- cranes,
- transportation bands,
- coffee makers

are not industrial robots

as they have a unique purpose, cannot be reprogrammed to perform other tasks, and/or require a human operator.

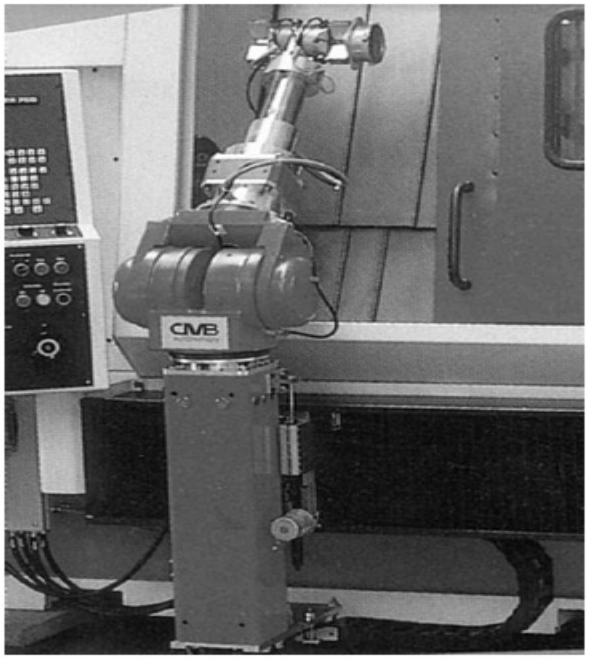
Their measure also excludes "dedicated industrial robots"

- Equipment dedicated for loading/unloading of machine tools
- Dedicated assembly equipment, e.g. for assembly on printed circuit boards
- Automated storage and retrieval systems
- Integrated Circuit Handlers (pick and place)
- Automated guided vehicles (AGVs)

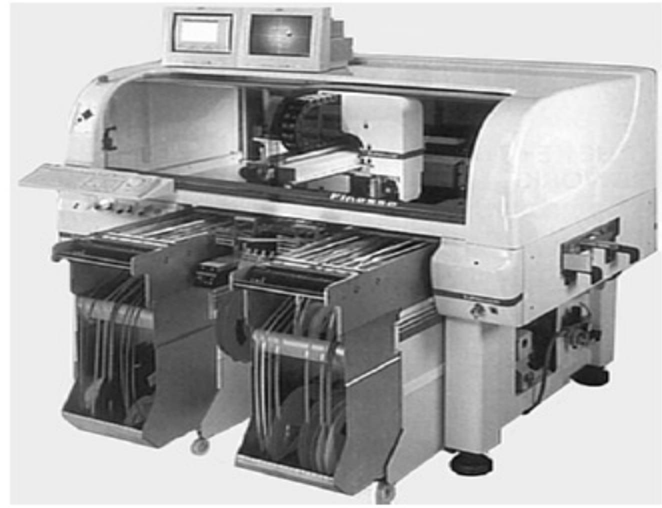
Although dedicated industrial robots might have a similar impact as industrial robots, the IFR does not collect data on their numbers.

Examples of dedicated industrial robots not to be included in the statistics

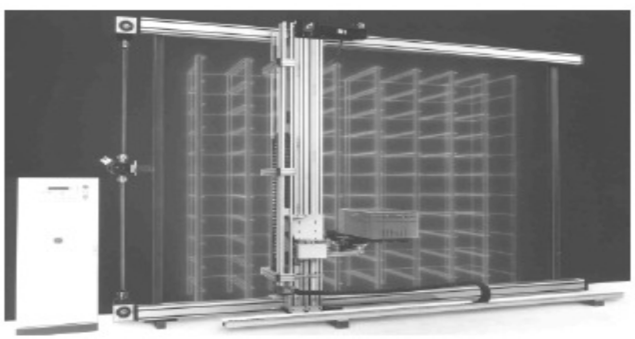
Dedicated machine-tool loader



Printed circuit board assembler



Automated storage and retrieval system



by mechanical structure:

- **Cartesian robot**: robot whose arm has three prismatic joints and whose axes are coincident with a Cartesian coordinate system
- **SCARA robot**: a robot, which has two parallel rotary joints to provide compliance in a plane
- **Articulated robot**: a robot whose arm has at least three rotary joints
- **Parallel robot**: a robot whose arms have concurrent prismatic or rotary joints
- **Cylindrical robot**: a robot whose axes form a cylindrical coordinate system

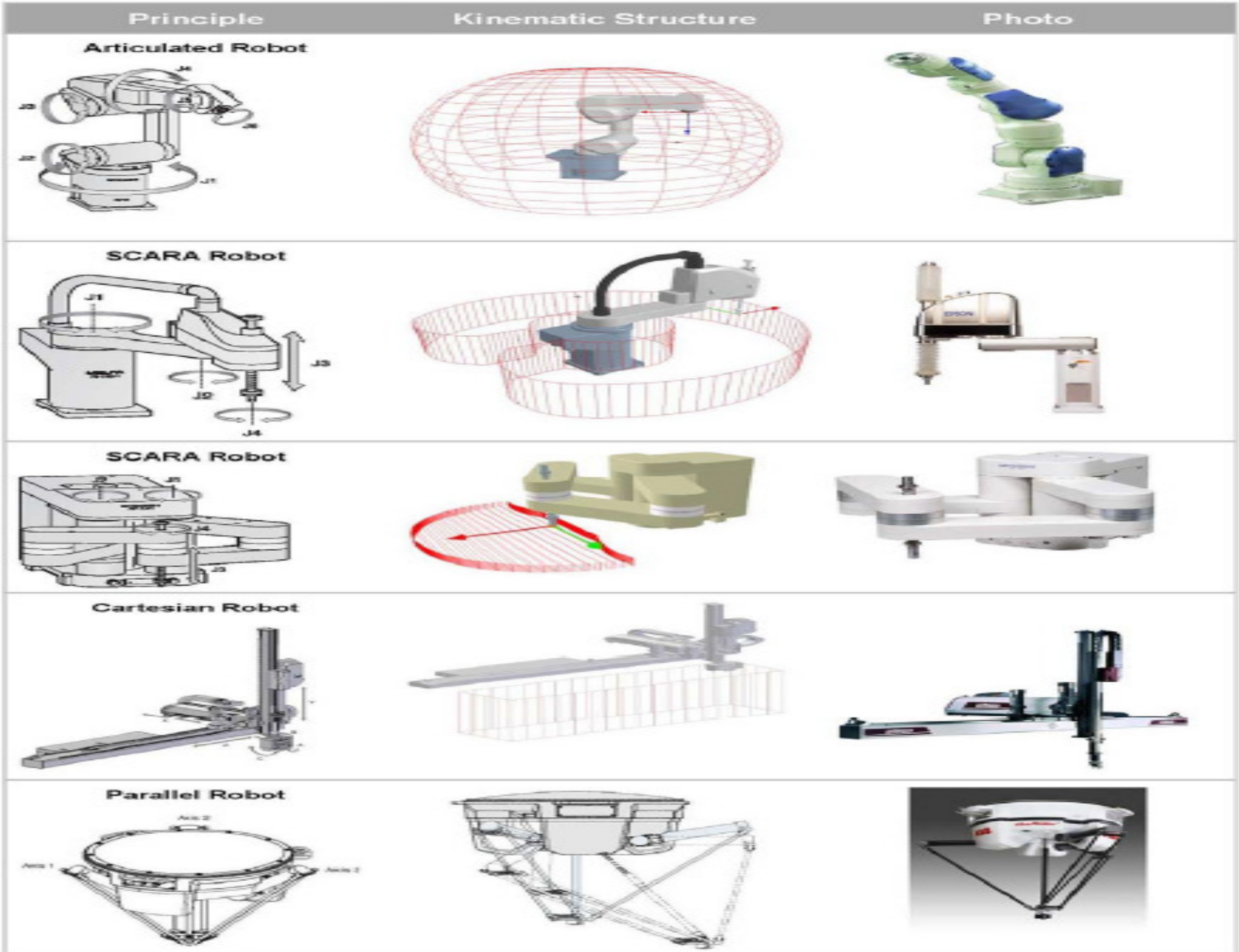


Figure 1.1: Classification of industrial robots by mechanical structure

Examples articulated robots

1,200 kg payload capacity - Handling of largest parts and structures

Flexible mounting possibilities – optimized working range

Welding robot

Examples of applications of articulated robots

Welding

Painting

Packaging

Handling for forging

Handling for metal casting

Palletizing

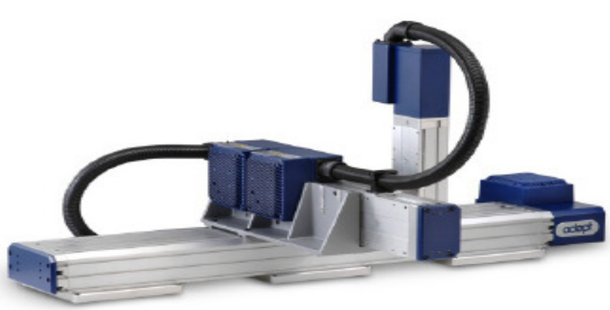
Examples of SCARA Robots

Examples of applications of SCARA Robots

Assembly

Packaging

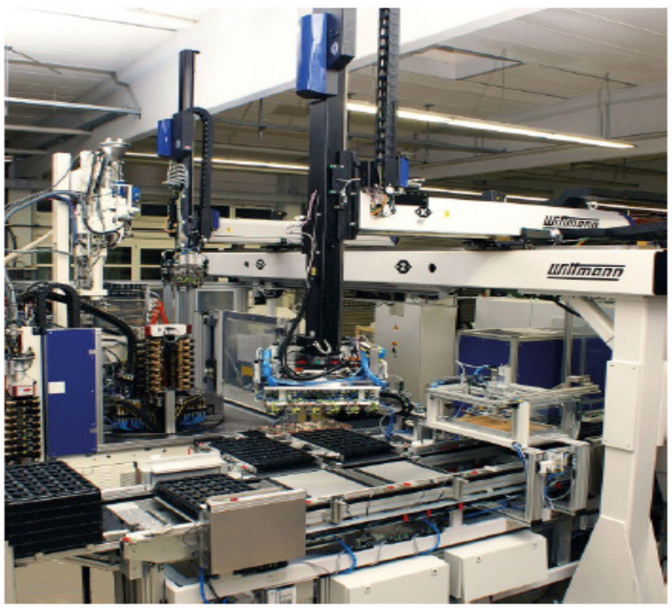
Examples of linear/cartesian/gantry robots



Linear Robot

Gantry Robot

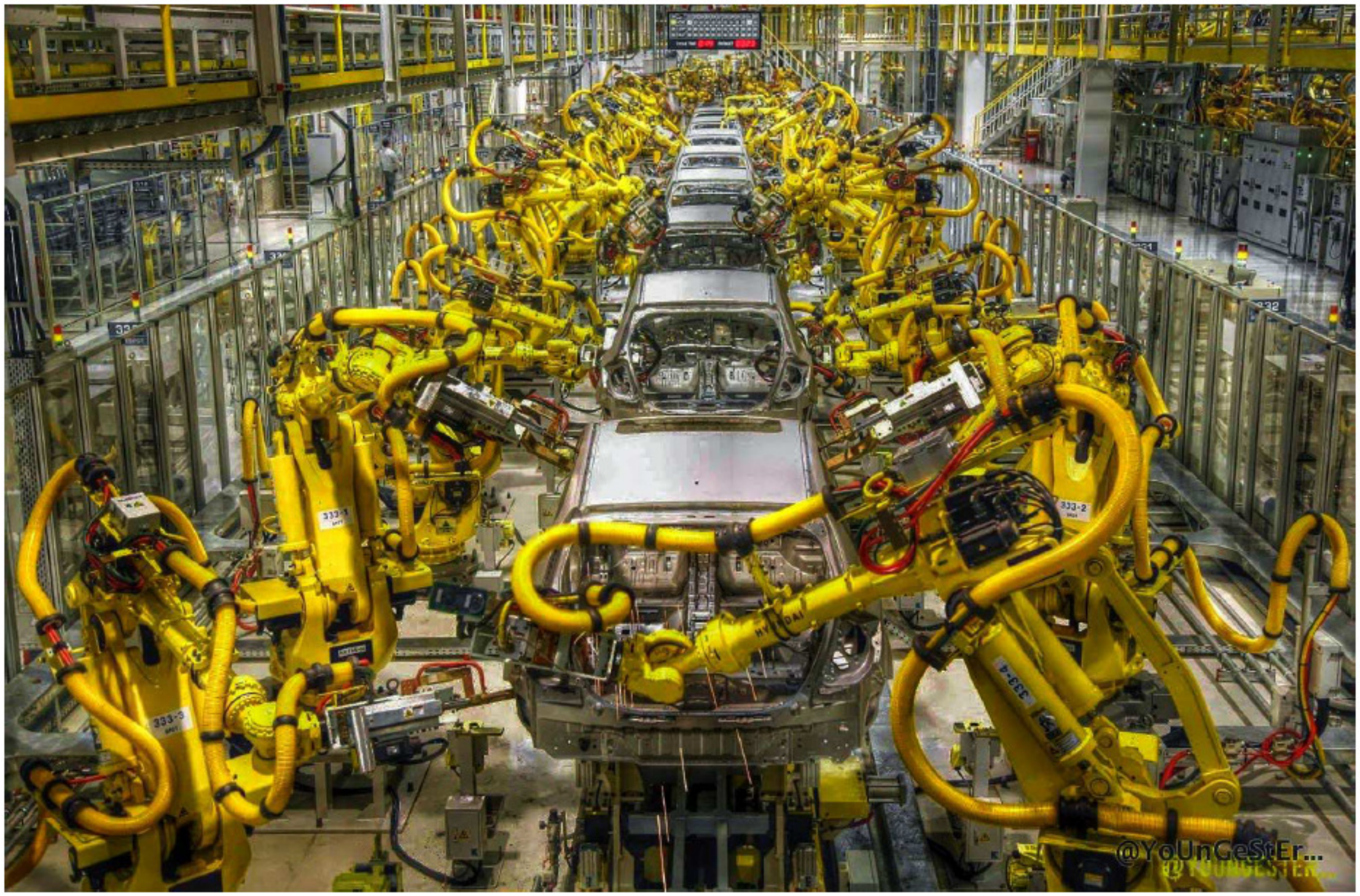
Examples of applications of linear/cartesian/gantry robots



Handling for plastic moulding

Sealing

Industrial robots in car manufacturing



Industrial robots in the pharmaceutical industry

Industrial robots in food processing

Why focus on industrial robots?

Measurement and conceptual advantages:

- Unlike other forms of capital or technologies, industrial robots mostly replace—not complement—labor in the production of certain tasks.
- Comparable measure of robots across industries and countries.
- But it misses dedicated machines (ATMs, bending machines) and AGVs (Amazon warehouses)...

"The next big leap in manufacturing" (BCG 2016):

- Fourfold increase from 400,000 robots in 1993 to 1.75 million industrial robots in 2014.
- Already widespread in some manufacturing industries: automotive (39 percent); electronics (19 percent); metal products (9 percent); and plastic and chemicals (9 percent).
- Industrial robots expected to increase to 4.5-6 million by 2025.

The US trends are closely mirrored by the 30th percentile of robot usage among the European countries in their data.

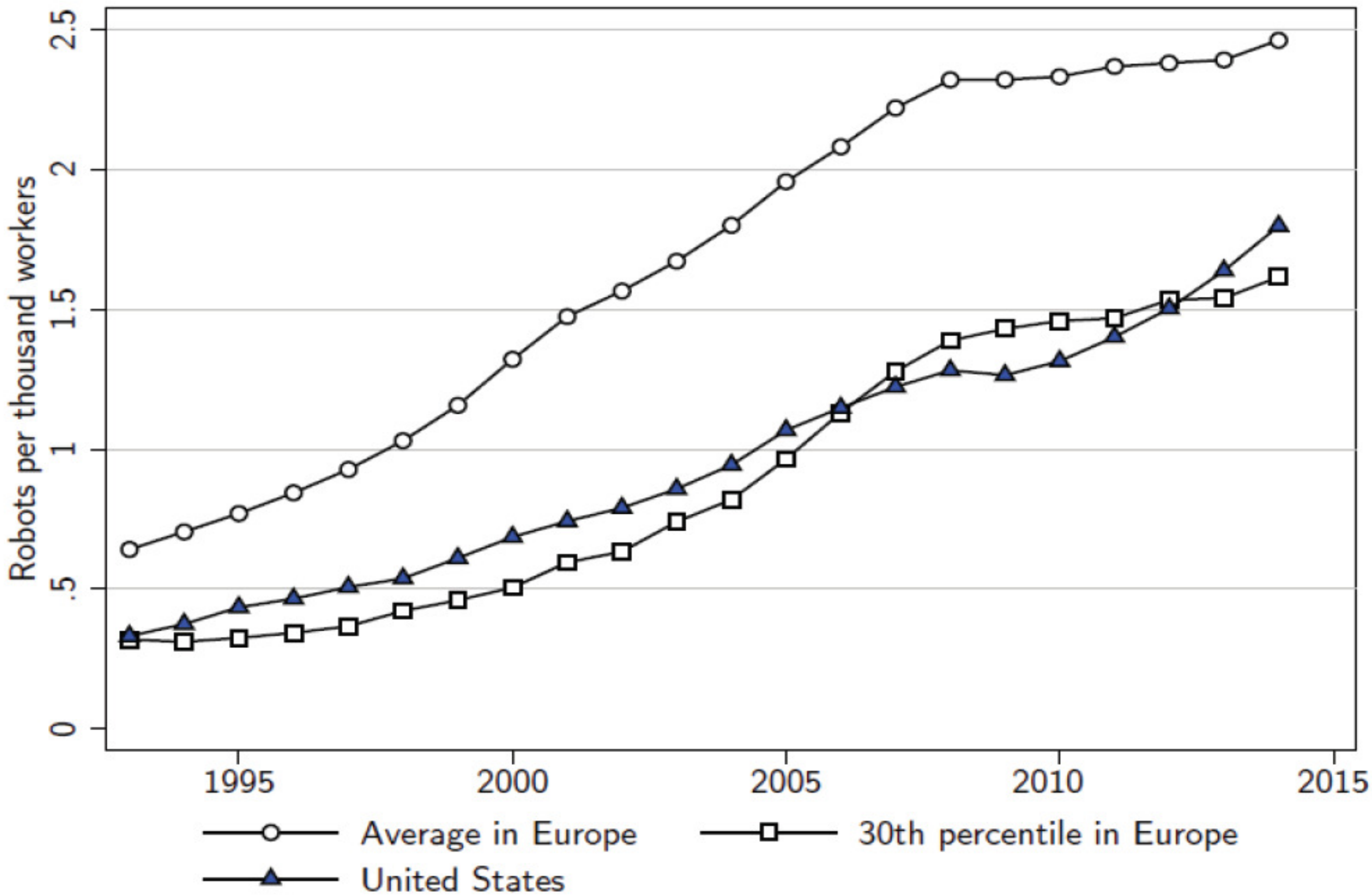


Figure 1: Industrial robots in the United States and Europe.

Note: Industrial robots per thousand workers in the United States and Europe. Data from the International Federation of Robotics (IFR).

Acemoglu and Restrepo analyse the effect of the increase in **industrial robot** usage between 1990 and 2007 on **US local labour markets**.

CZs are particularly suitable for analysis of local labour markets because they cover the entire US continental territory except for Alaska and Hawaii, CZs are particularly suitable for analysis of local labour markets because they cover the entire US continental territory except for Alaska and Hawaii, are based primarily on economic geography rather than incidental factors such as minimum population, and can be consistently constructed using Census Public Use Micro Areas (PUMAs).

Commuting Zones

CZs were first developed in the 1980s as ways to better delineate local economies.

County boundaries are not always adequate confines for a local economy and often reflect political boundaries rather than an area’s local economy.

A local economy and its labor market are bounded not by the nearest county line, but by interrelationships between buyers and sellers of labour.

CZs are clusters of U.S. counties: geographic units of analysis intended to more closely reflect the local economy where people live and work.

Commuting Zones for the United States, 2000

Source: U.S. Department of Agriculture, Economic Research Service.

Commuting zones vary in their distribution of industrial employment, making some commuting zones more exposed to the use of robots than others.

- Robots compete task-by-task against labour.

- Increase in the share of tasks performed by robots **displaces labour** from some tasks, but also **raises productivity**.

- The impact of robots on employment and wages in a labour market can be estimated by regressing the change in these variables on the ***exposure to robots***.

$$\begin{array}{c}\text{Change in exposure}\\ \text{to robots in a}\\ \text{local labor market}\end{array} = \sum_i \begin{array}{c}\text{Base employment}\\ \text{in industry i}\\ \text{in this market}\end{array} \times \begin{array}{c}\text{National increase}\\ \text{in robots per}\\ \text{base workers in}\\ \text{in industry i.}\end{array}$$

- Constructing measure of exposure to robots using data from the IFR on the increase in robot usage in 19 industries (roughly at the two-digit level outside manufacturing and at the three-digit level within manufacturing) and their baseline employment shares from the Census before the onset of recent robotic advances.

4.1 Data Sources

Our main data consist of counts of the stock of robots by industry, country and year from the IFR, which is based on yearly surveys of robot suppliers. The IFR data cover 50 countries from 1993 to 2014, corresponding to about 90 percent of the industrial robots market. However, the stock of industrial robots by industry going back to the 90s is only available for a subset of countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. These countries account for 41 percent of the world industrial robot market. Although the IFR reports data on the total stock of industrial robots in the United States from 1993 onwards, it does not provide industry breakdowns until 2004.[10] Outside of manufacturing, we have consistent data for the use of robots in six broad industries (roughly at the two-digit level): agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and other non-manufacturing industries (e.g., services and entertainment). In manufacturing, we have consistent data on the use of robots for a more detailed set of 13 industries (roughly at the three-digit level): food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; and other manufacturing industries (e.g. recycling). Table A1 in the Appendix shows the evolution of robots usage in these industries in the nine European countries in our sample and in the United States.

The IFR data also have some shortcomings. First, not all robots are classified into one of the 19 industries. About 30 percent of robots are unclassified, and this fraction has declined

[10]Though the IFR also reports data by industry for Japan, these data underwent a major reclassification. We follow the recommendations of the IFR and exclude Japan from our analysis.

Table A1: Robot adoption by industry in Europe and the United States

	Use of industrial robots in Europe								Use of industrial robots in the United States		
	30th percentile				Mean						
	1993	2004	2007	2014	1993	2004	2007	2014	2004	2007	2014
Extractive:											
1. Agriculture, forestry and fishing	0.000	0.004	0.010	0.029	0.000	0.073	0.102	0.161	0.002	0.005	0.037
2. Mining and quarrying	0.000	0.000	0.000	0.028	0.175	1.889	1.788	1.238	0.002	0.006	0.061
Manufacturing:											
3. Food and Beveradges	0.163	1.778	2.668	6.776	0.434	2.714	4.643	8.730	2.906	3.919	6.169
4. Textiles	0.032	0.071	0.148	0.154	0.333	0.779	0.797	0.946	0.002	0.007	0.048
5. Wood and furniture	0.250	2.217	2.348	2.155	2.682	6.956	8.028	6.731	0.012	0.025	0.241
6. Paper	0.007	0.197	0.246	0.273	0.186	0.530	0.717	0.907	0.001	0.003	0.110
7. Plastic and chemicals	0.957	8.515	13.523	13.497	2.917	14.314	18.872	17.828	5.122	6.950	9.906
8. Glass and ceramics	0.182	1.096	2.451	1.409	0.743	2.724	3.731	4.404	0.115	0.234	0.673
9. Basic metals	0.146	1.723	2.505	4.406	2.237	4.132	5.258	7.613	0.000	0.000	7.170
10. Metal machinery	1.340	3.020	5.031	3.994	2.824	4.369	5.684	8.230	0.000	0.002	2.373
11. Metal products	4.516	5.520	9.421	10.599	7.090	12.182	16.149	17.432	7.487	9.495	8.289
12. Electronics	1.050	1.893	2.622	2.701	2.411	6.160	6.980	5.580	5.713	8.657	13.109
13. Automotive	9.238	19.478	30.816	47.101	17.557	62.897	73.936	80.865	69.007	85.722	117.721
14. Other vehicles	0.044	0.503	0.719	1.580	2.540	4.520	3.344	2.735	0.052	0.120	0.542
15. Other manufacturing	0.603	2.038	1.102	1.703	3.508	4.025	3.379	4.018	0.838	1.176	8.288
Remaining industries:											
16. Electricity, gas, water supply	0.000	0.000	0.024	0.085	0.000	0.067	0.103	0.219	0.000	0.000	0.027
17. Construction	0.000	0.007	0.023	0.053	0.000	0.044	0.061	0.097	0.003	0.007	0.020
18. Education, research and development	0.000	0.117	0.159	0.214	0.024	0.404	0.465	0.448	0.011	0.014	0.064
19. Other non-manufacturing industries	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.006	0.000	0.000	0.004

Note: Robots per thousand workers. The number of robots is from the IFR and the number of workers in each industry is from EUKLEMS.

The IFR only reports the overall stock of robots for North America. Though this aggregation introduces noise in our measures of US exposure to robots, this is not a major concern, since the US accounts for more than 90% of the North American market, and their IV procedure should purge the US exposure to robots from this type of measurement error.

- A major concern with their empirical strategy is that the adoption of robots in a given US industry could be related to **other trends affecting that industry**

- A major concern with their empirical strategy is that the adoption of robots in a given US industry could be related to **other trends affecting that industry** or **to economic conditions in the commuting zones that specialise in that industry**.

Both possibilities would confound the impact of robots.

To address this concern, they use the industry-level spread of robots in other advanced economies—meant to proxy improvements in the world technology frontier of robots—as an instrument for the adoption of robots in US industries.

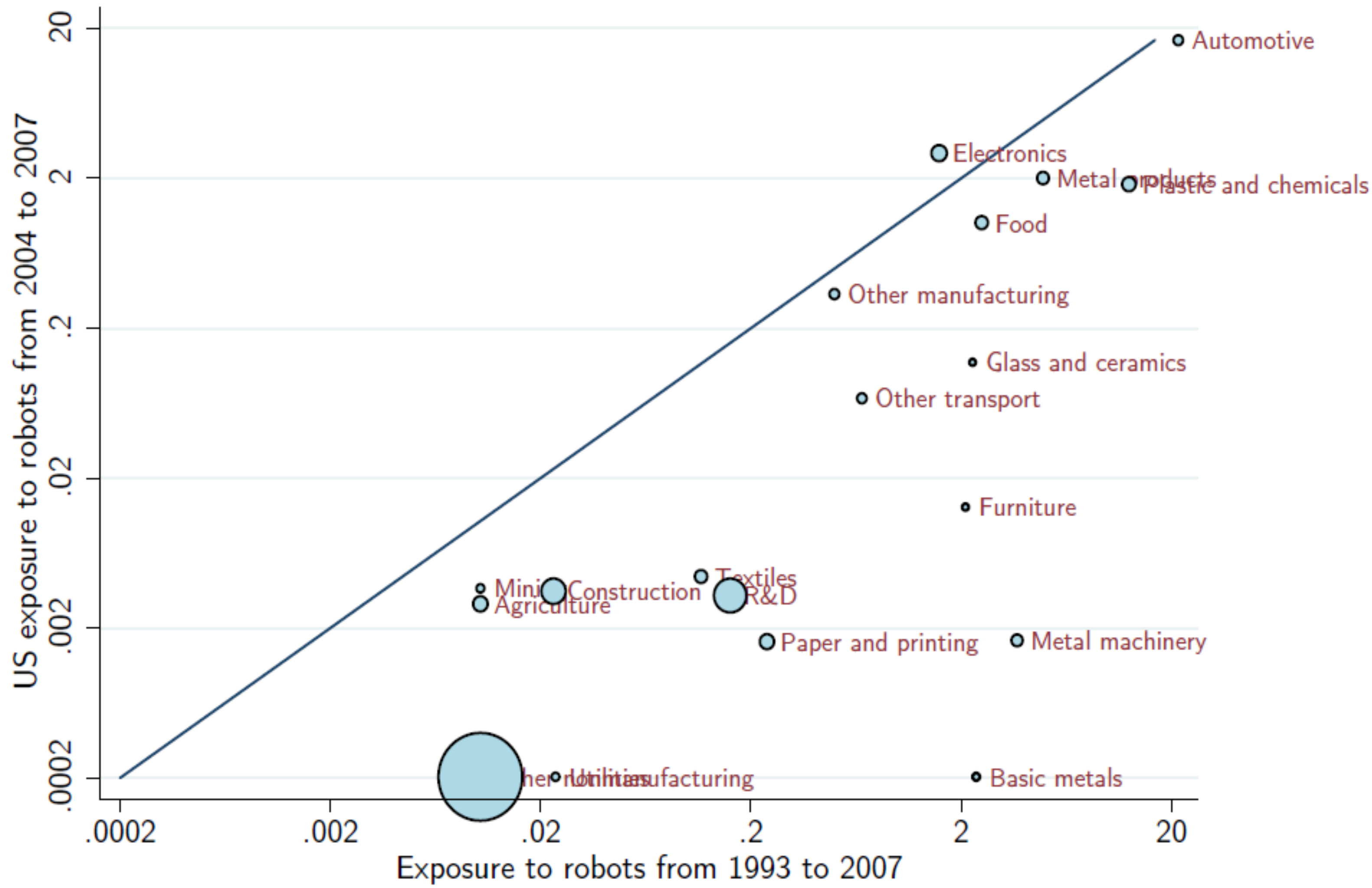
This strategy allows them to focus on the variation that results solely from industries in which the robots has been concurrent in most advanced economies.

$$\text{Exposure to robots from 1993 to 2007}_c = \sum_{i \in \mathcal{I}} \ell_{ci}^{1970} \left(p30 \left(\frac{R_{i,2007}}{L_{i,1990}} \right) - p30 \left(\frac{R_{i,1993}}{L_{i,1990}} \right) \right),$$

where the sum runs over all the industries in the IFR data, ℓ_{ci}^{1970} stands for the 1970 share of commuting zone c employment in industry i, which we compute from the 1970 Census, and $p30\left(\frac{R_{i,t}}{L_{i,1990}}\right)$ denotes the 30th percentile of robot usage among European countries in industry i and year t. Our main measure of (exogenous) exposure to robots is based on the 1970 values for the distribution of employment across industries, which enables us to focus on historical and persistent differences in the specialization of commuting zones in different industries, and to avoid any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes.[15]

- **The industries that adopted more robots in Europe between 1993 and 2007 also adopted more robots in the United States between 2004 and 2007.**

- With a few exceptions (basic metals, metal machinery and other manufacturing), **the industries that adopted more robots in Europe between 1993 and 2007 also adopted more robots in the United States between 2004 and 2007.**



The scatter plot of the change in the number of robots per thousand workers in Europe between 1993 and 2007 and in the US between 2004 and 2007.

The solid line corresponds to the 45^{o} line. Marker size indicates the share of US employment in the corresponding industry.

- They first ignore any interaction between local labour markets (commuting zones), and then enrich this framework by introducing trade between CZs.

Their estimates remain negative and significant when they control for

- broad industry composition (including shares of manufacturing, durables, and construction)

- detailed demographics

- competing factors impacting workers in CZs:

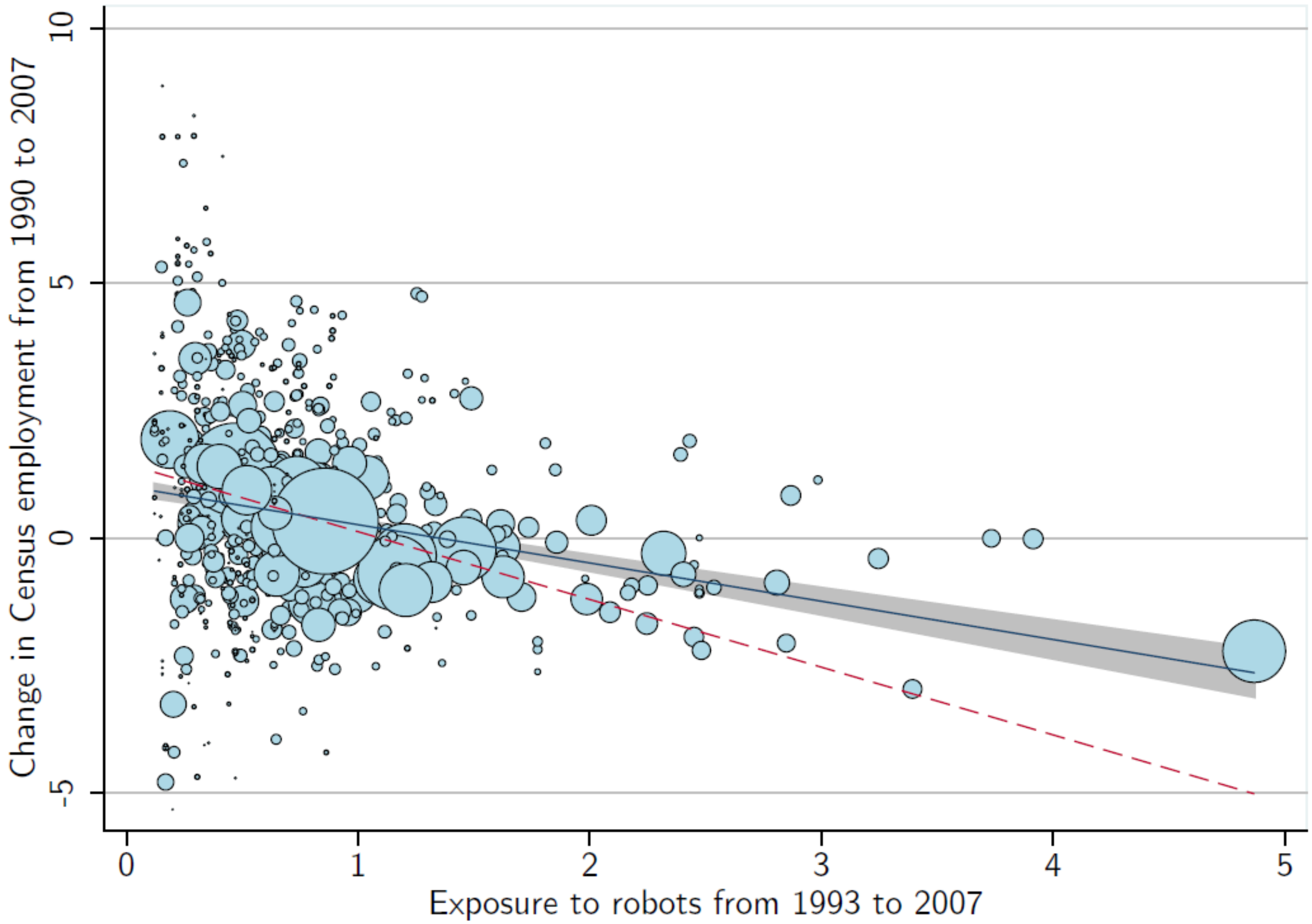
  i. exposure to imports from China
  ii. exposure to imports from Mexico
  iii. the decline in routine jobs following the use of software to perform information processing tasks
  iv. offshoring of intermediate inputs

→ The automobile industry, which uses the largest number of robots per worker, is not driving the results.

TABLE 2: The impact of the exposure to robots on employment and wages (long differences)

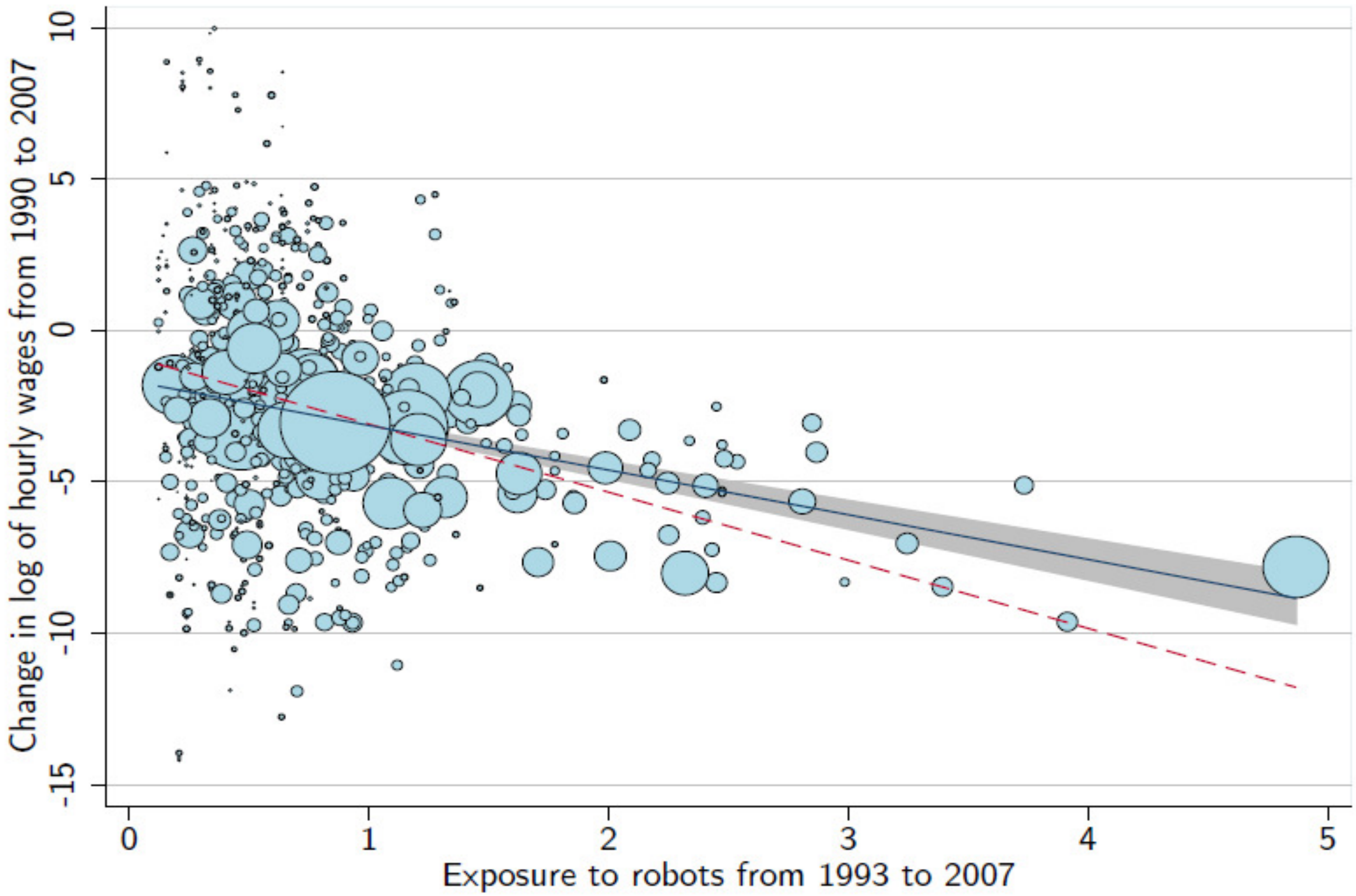
	Estimates for employment and wages from 1990 to 2007						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Census private employment to population ratio.						
Exposure to robots from 1993 to 2007	-0.916***	-0.782***	-0.769***	-0.751***	-1.125***	-1.096***	-1.330***
	(0.304)	(0.262)	(0.185)	(0.166)	(0.264)	(0.234)	(0.368)
Observations	722	722	722	722	722	721	714
	Panel B. CBP employment to population ratio.						
Exposure to robots from 1993 to 2007	-1.435***	-1.175***	-1.231***	-1.310***	-1.118***	-1.018***	-1.899**
	(0.503)	(0.377)	(0.372)	(0.347)	(0.410)	(0.327)	(0.883)
Observations	722	722	722	722	722	719	714
	Panel C. Log hourly wage.						
Exposure to robots from 1993 to 2007	-2.273***	-1.941***	-1.409***	-1.476***	-1.950***	-2.107***	-2.253***
	(0.391)	(0.249)	(0.272)	(0.322)	(0.399)	(0.382)	(0.566)
Observations	163114	163114	163114	163114	163114	160027	160534
	Panel D. Log weekly wage.						
Exposure to robots from 1993 to 2007	-2.982***	-2.562***	-2.068***	-2.126***	-2.527***	-2.593***	-2.791***
	(0.389)	(0.270)	(0.267)	(0.301)	(0.498)	(0.414)	(0.563)
Observations	163114	163114	163114	163114	163114	159657	160534
Covariates & sample restrictions:							
Census division dummies	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Trade, Routinization and Offshoring				✓	✓	✓	✓
Unweighted					✓		
Down-weights outliers						✓	
Removes highly exposed areas							✓

Relationship between the exposure to robots and employment



Marker size indicates the share of the 1990 US working age population in the corresponding commuting zone.

Relationship between the exposure to robots and wages



Marker size indicates the share of the 1990 US working age population in the corresponding commuting zone.

- The employment effects of robots are most pronounced in manufacturing, and in particular, in industries most exposed to robots; in routine manual, blue collar, assembly and related occupations; and for workers with less than college education.

- The effects of robots on men and women are similar, though the impact on male employment is more negative.

- **No trade between CZs:**

(i.e., each CZ can consume only its own production of each good)

each additional robot per thousand workers reduces aggregate employment to population ratio by 0.37 percentage points and aggregate wages by about 0.73%.

(one new robot reducing employment by 6.2 workers)

- **No trade between CZs:**

  each additional robot per thousand workers reduces aggregate employment to population ratio by 0.37 percentage points and aggregate wages by about 0.73%.

  (one new robot reducing employment by 6.2 workers)

- **Trade between CZs:**

  one additional robot per thousand workers now reduces aggregate employment to population ratio by 0.34 percentage points and aggregate wages by 0.5%.

  (one new robot reducing employment by 5.6 workers)

- If they focus only on declines in employment in heavily-robotized manufacturing, and presume that employment losses in other sectors are due to local demand and will not directly translate into national effects, these effects can be as low as 0.18 percentage points for employment and 0.25% for wages.

Because there are relatively few robots in the US economy, the number of jobs lost due to robots has been limited so far

Because there are relatively few robots in the US economy, the number of jobs lost due to robots has been limited so far (ranging between 360,000 and 670,000 jobs, equivalent to a 0.18-0.34 percentage point decline in the employment to population ratio).

CONCLUDING REMARKS

Work in progress…

- Acemoglu, Daron, and Pascual Restrepo. 2017. “Demographics and Robots: Theory and Evidence.” Unpublished.

- Countries experiencing more rapid aging are the ones that have been at the forefront of the adoption of one important type of automation technology: industrial robots.

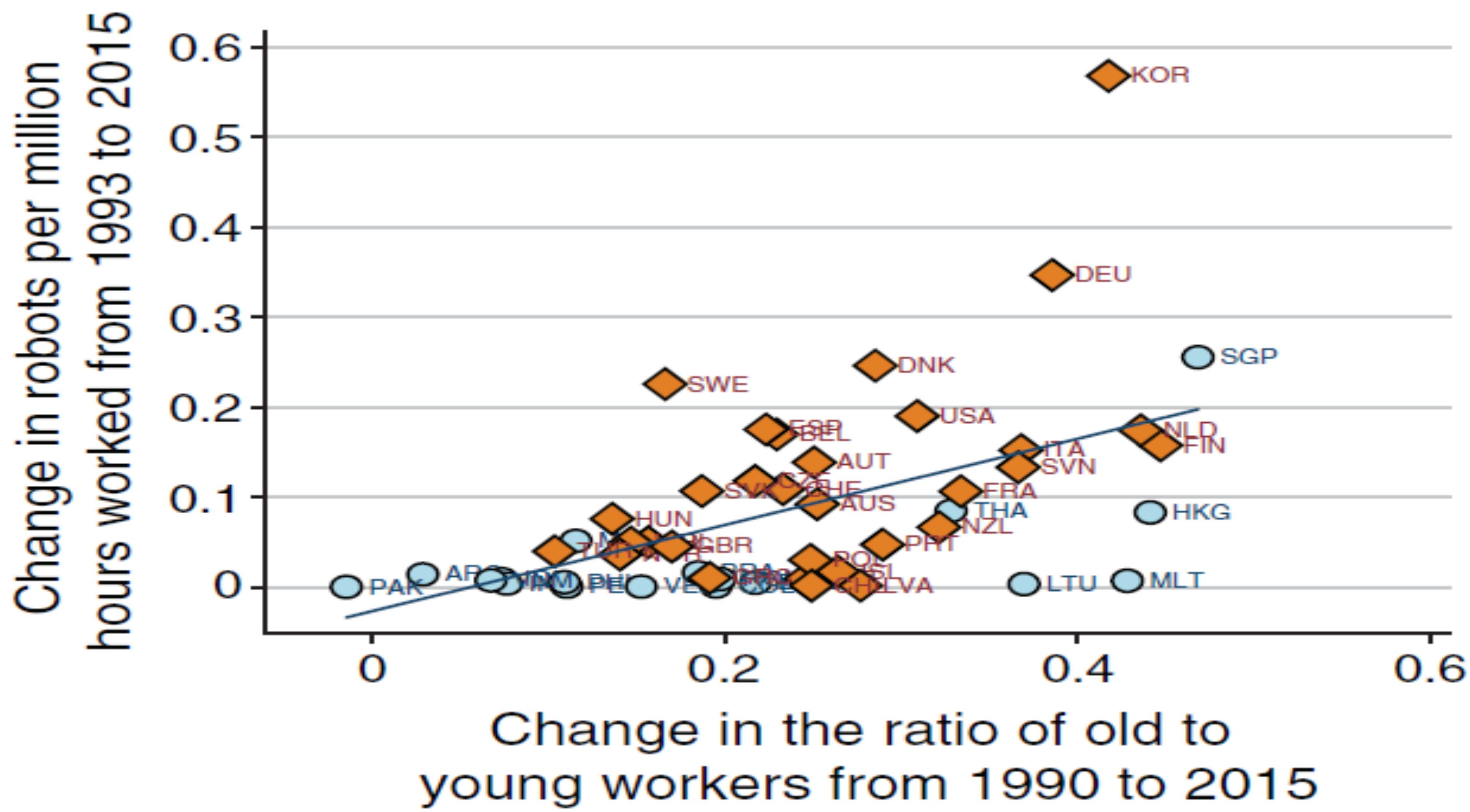


FIGURE 3. CORRELATION BETWEEN CHANGE IN THE RATIO OF OLD TO YOUNG WORKERS BETWEEN 1990 AND 2015 AND CHANGE IN ROBOTS PER MILLION HOURS WORKED BETWEEN 1993 AND 2014 (*From IFR*)

Acemoglu, Daron, and Pascual Restrepo. 2017. "Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation." American Economic Review, 107(5): 174-79.

POLICY IMPLICATIONS

- What is the scope and rate of change of the key technologies, especially AI?

- Which technologies are already eliminating, augmenting or transforming which types of jobs?

- What new work opportunities are emerging, and which policy options might create jobs in this context?

As massive technological innovation radically reshapes our world, we need to develop **new business models**, new technologies, and new policies that amplify our human capabilities, so every person can stay economically viable in an age of increasing automation.

RECENT NEWS FROM MIT:

Students can now declare a joint major in computer science and economics.

The major is the first joint computer science and economics major in the country, “as far as we know,” Constantinos Daskalakis, associate professor of electrical engineering and computer science, said in an interview with *The Tech*.

“The first in the history of the universe, as far as we know,” David Autor, professor of economics, added, laughing.

(https://thetech.com/2017/06/08/6-14-major-announced)