New Tasks, Good Automation and Bad Automation: Implications for the Future of Work

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Recap from Yesterday

- A new framework based on the allocation of tasks to factors.
- Automation — the expansion of the set of tasks that can be performed by machinery and algorithms — is crucial for labor demand.
- A large fraction of the decline in the labor share, the slowdown in labor demand, stagnant wages and surging inequality in the US are related to automation.

But Why So Much Automation?

▶ In this lecture, I will discuss why there appears to be an acceleration in automation.

▶ But, acceleration or no acceleration, automation has always been with us. If automation reduces the labor share, how come the labor share has been broadly constant in many modern economies for much of the 20th century?

▶ Could it be because of composition effects? Baumol's cost disease? Factor-augmenting technological changes?

▶ The answer to all of these questions is no. Both theoretically and empirically, these factors could not have—and have not—counterbalanced the effects of automation.

▶ Something else is necessary: the introduction of new (labor-intensive) tasks.

▶ We will see that the introduction of new tasks has played an important role in the decades that followed World War II (and before) but has slowed down significantly over the last 30 years.

▶ We will then discuss good and bad reasons for an acceleration in automation — bad automation may be increasing inequality and failing to help productivity, while good automation may be having a transformative effect on many economies.

Recap: Task-Based Framework

$$Y = \left(\int_{N-1}^{N} \mathcal{Y}(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}$$

Elast of substitution

Output

Task services

$$\mathcal{Y}(z) = \begin{cases} A^L \gamma^L(z)\ell(z) + A^K \gamma^K(z)k(z) & \text{if } z \in [N-1, I] \\ A^L \gamma^L(z)\ell(z) & \text{if } z \in (I, N]. \end{cases}$$
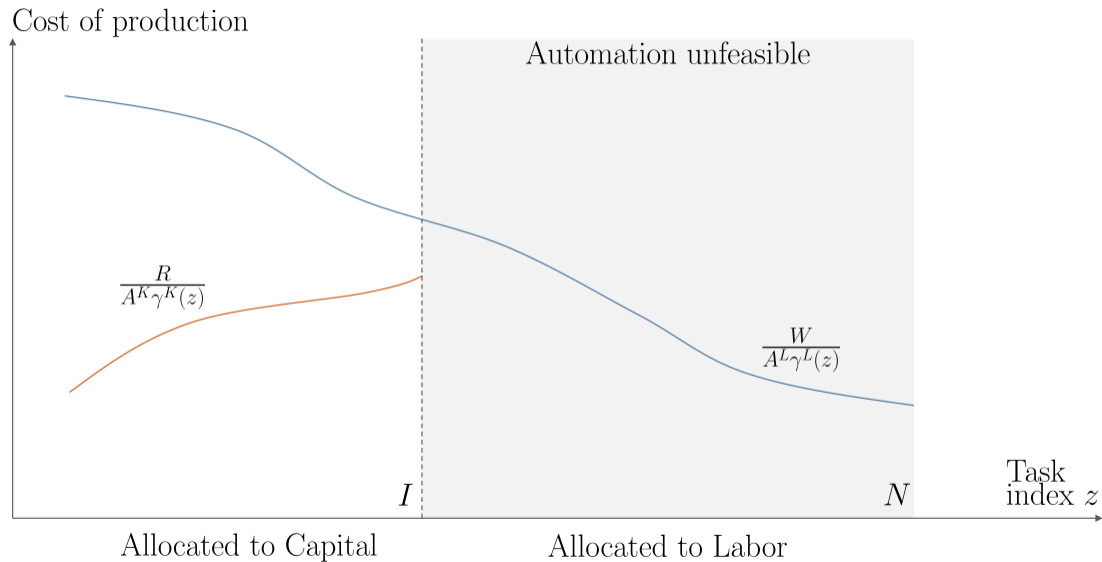
Feasible to automate

New tasks

▶ The labor share is given by

$$s^L = \frac{\Gamma(N, I)(W/A^L)^{1-\sigma}}{(1 - \Gamma(N, I))(R/A^K)^{1-\sigma} + \Gamma(N, I)(W/A^L)^{1-\sigma}}$$

Task content $\Gamma = \frac{\int_I^N \gamma^L(z)^{\sigma-1} dz}{\int_{N-1}^I \gamma^K(z)^{\sigma-1} dz + \int_I^N \gamma^L(z)^{\sigma-1} dz}$
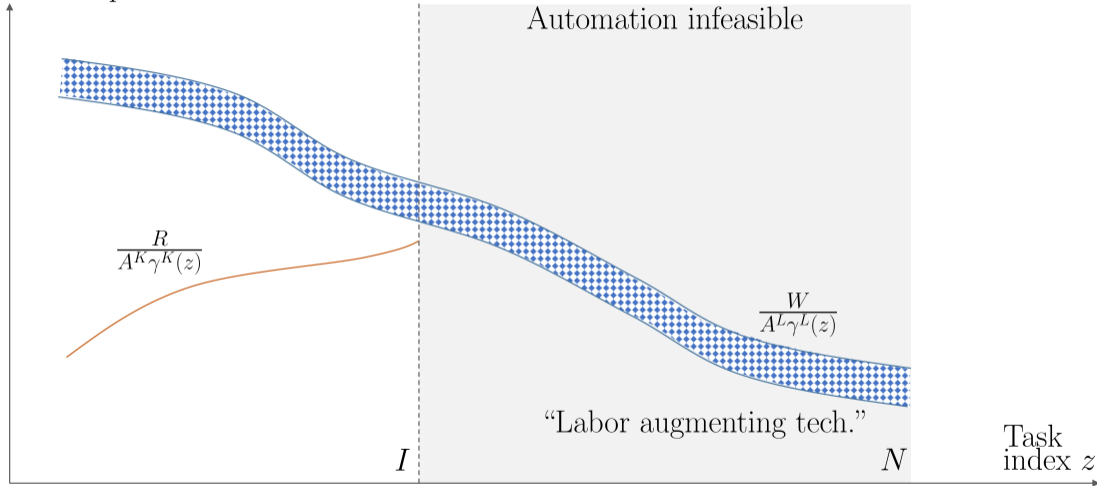
Task-price subs.
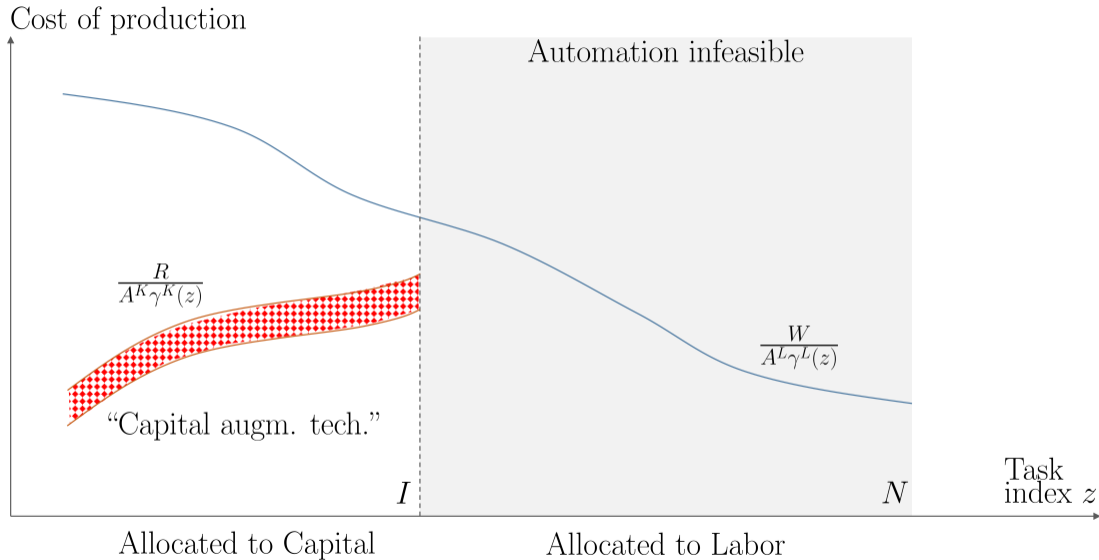
Allocation of Tasks to Factors

Cost of production

Automation unfeasible

$\frac{R}{A^K \gamma^K(z)}$

$\frac{W}{A^L \gamma^L(z)}$

I

N

Task index z

Allocated to Capital

Allocated to Labor

Labor-Augmenting Technological Change

Cost of production

Automation infeasible

$\frac{R}{A^K \gamma^K(z)}$

$\frac{W}{A^L \gamma^L(z)}$

"Labor augmenting tech."

I

N

Task index z

Capital-Augmenting Technological Change

Cost of production

$\frac{R}{A^K \gamma^K(z)}$

"Capital augm. tech."

Automation infeasible

$\frac{W}{A^L \gamma^L(z)}$

I

N

Task index z

Allocated to Capital

Allocated to Labor

Automation

Cost of production

"Automation tech."

Automation unfeasible

$\frac{R}{A^K \gamma^K(z)}$

$\frac{W}{A^L \gamma^L(z)}$

I' N

Task index z

Allocated to Capital   Allocated to Labor
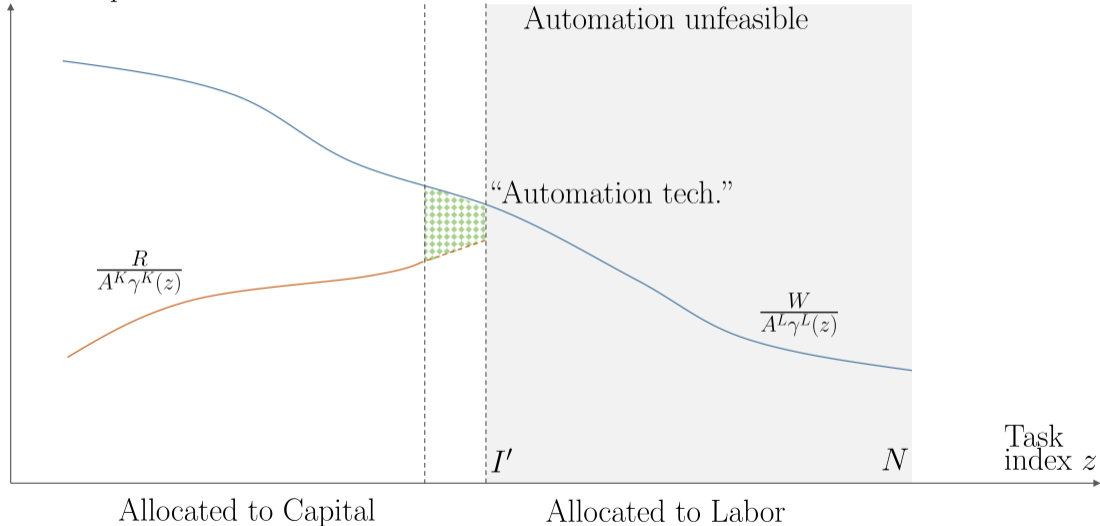
New Tasks: N shifts to N'

Cost of production

Automation unfeasible

$\frac{R}{A^K \gamma^K(z)}$

$\frac{W}{A^L \gamma^L(z)}$

"New tasks."

I'

N'

Task index z

Allocated to Capital

Allocated to Labor
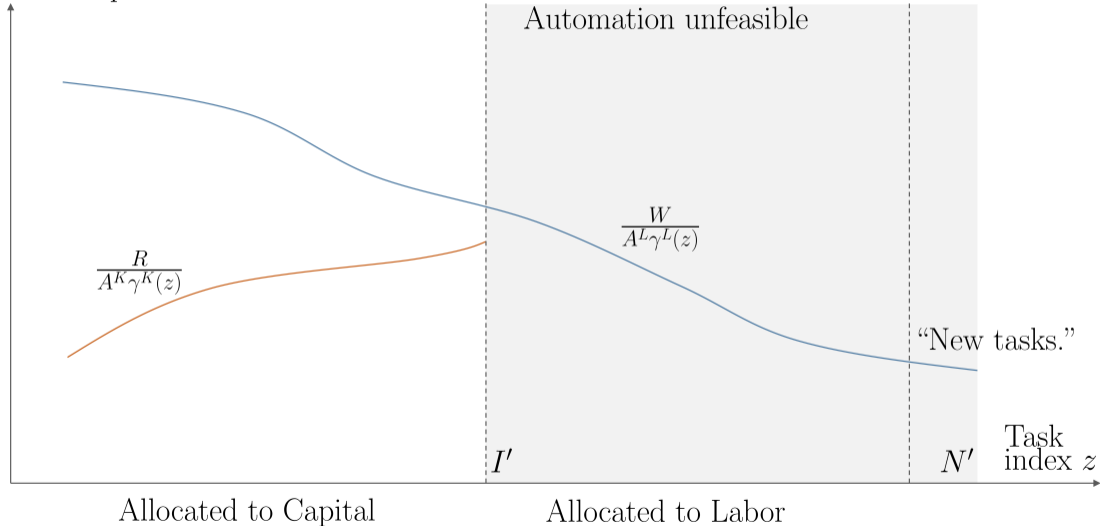
New Tasks and Labor Demand

▶ The effects of creation of new tasks in which labor has a competitive advantage—an expansion in N—can be determined similarly to our analysis of automation:

$$\frac{\partial \ln WL^d(L, K; \theta)}{\partial N} = \frac{\partial \ln Y(L, K; \theta)}{\partial N} \qquad \text{(Productivity effect)}$$

$$+ \frac{1}{\sigma} \frac{1 - s^L}{1 - \Gamma(N, I)} \frac{\partial \ln \Gamma(N, I)}{\partial N} \qquad \text{(Reinstatement effect)}$$

▶ The productivity effect is now given by

$$\frac{\partial \ln Y(L, K; \theta)}{\partial N} = \frac{1}{\sigma - 1} \left[\left(\frac{W}{A^L \gamma^L(N)} \right)^{1-\sigma} - \left(\frac{R}{A^K \gamma^K(N-1)} \right)^{1-\sigma} \right] > 0.$$

▶ The reinstatement effect is always positive, increasing the labor share.

Multi-Sector Economy: Decomposition

▶ Has the reinstatement effect been important in the US economy? To answer this question, we need to turn to a multi-sector economy.

▶ We index sectors by subscript i and let $\mathcal{I}$ represent the set of industries.

▶ Factor prices are denoted by W_i and R_i. χ_i denotes share of sector i in value added and s_i^L its labor share.

▶ Then, we have the following exact decomposition of changes in labor demand:

$$
\begin{aligned}
d\ln(WL) =\; & d\ln Y && \text{(Productivity effect)} \\
& + \sum_{i\in\mathcal{I}} \left(\frac{s_i^L}{s^L} - 1 \right) d\chi_i && \text{(Composition effect)} \\
& + \sum_{i\in\mathcal{I}} \ell_i (1-\sigma)(1-s_i^L) d\ln\left(\frac{W_i/A_i^L}{R_i/A_i^K} \right) && \text{(Subs across tasks)} \\
& + \sum_{i\in\mathcal{I}} \ell_i \frac{1-s_i^L}{1-\Gamma_i} d\ln\Gamma_i && \text{(Change task content)}
\end{aligned}
$$

Multi-Sector Economy: Summary

Overall change in labor demand   =   Productivity effect
+ Composition effect
+ Substitution effects
+ Change in task content

▶ We directly observe all the terms here except the change in task content and substitution effects—where the latter are due to substitution between tasks because of changes in factor prices (which are observed) and factor-augmenting technologies (which are not observed).

▶ Strategy: under plausible lower and upper bound assumptions on the extent of factor-augmenting technological change, we can obtain lower and upper bounds on changes in task content.

▶ In practice, very similar results regardless of the range of assumptions — because the plausible range of the elasticity of substitution between tasks is quite close to 1, approximately 0.7-0.8.
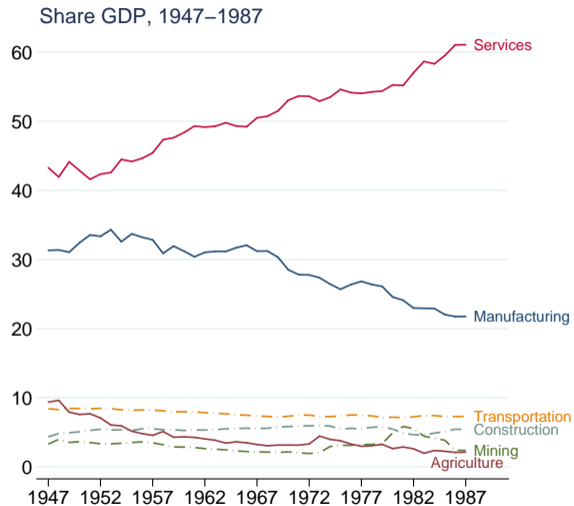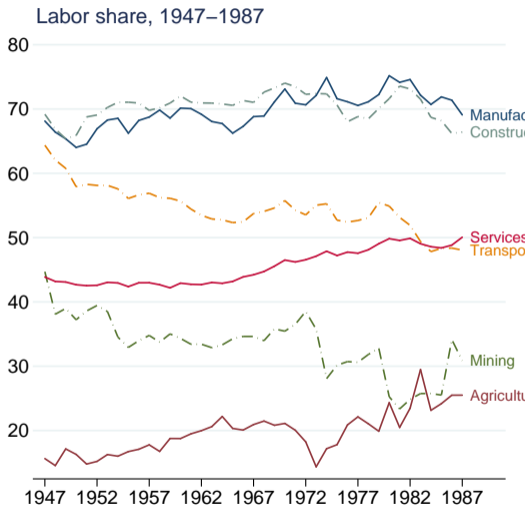
Broad Patterns, 1947-1987

Figure: The labor share and sectoral evolutions, 1947-1987.

Decomposing Labor Demand, 1947-1987

Wage bill, 1947–1987

Observed wage bill
Productivity effect
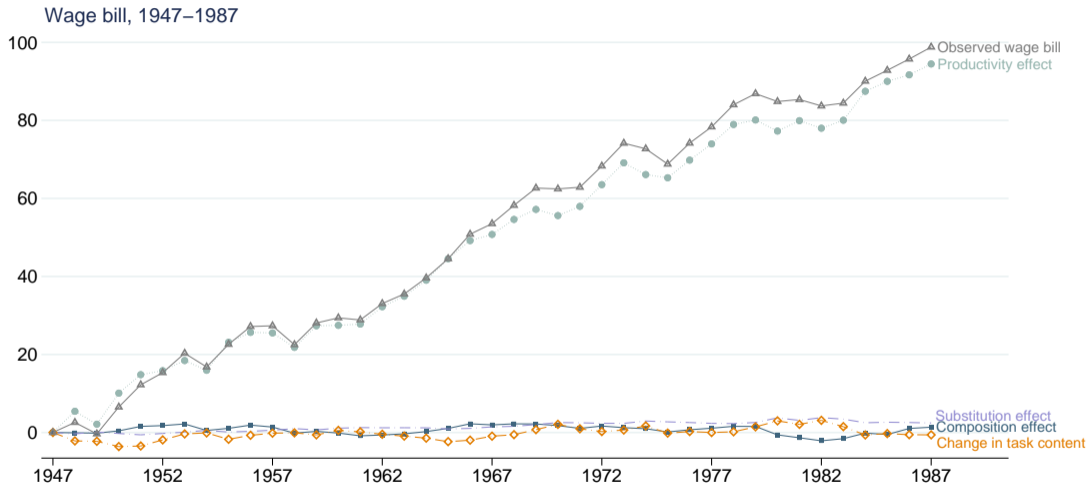Substitution effect
Composition effect
Change in task content

Figure: Sources of changes in labor demand, 1947-1987.

Displacement and Reinstatement, 1947-1987

- Change in task content=displacement + reinstatement.
- Requires two additional assumptions:
    1. no technological regress
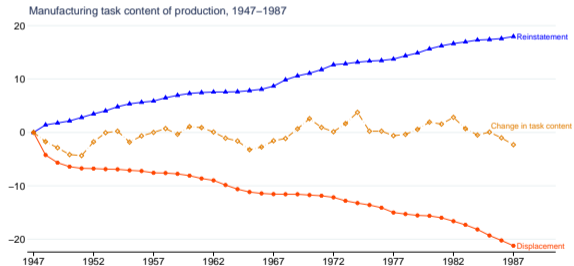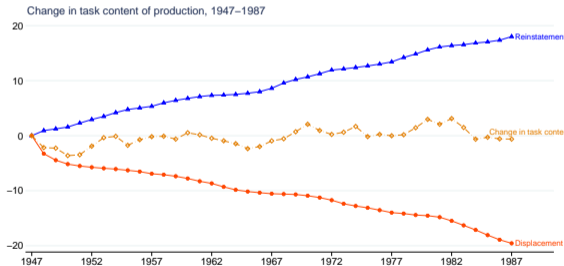   2. at a point in time, an industry either automates or creates new tasks

Figure: Estimates of the displacement and reinstatement effects, 1947-1987.
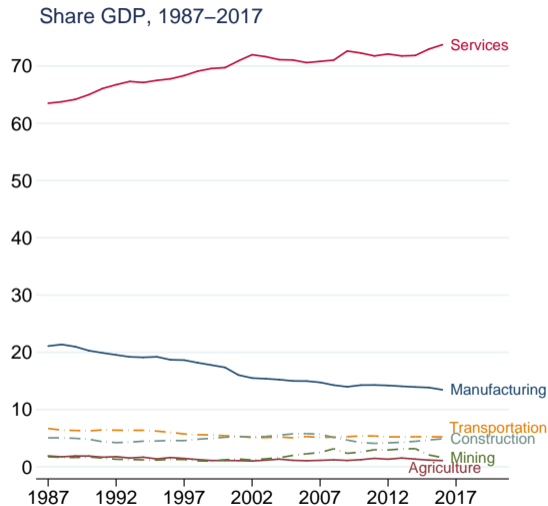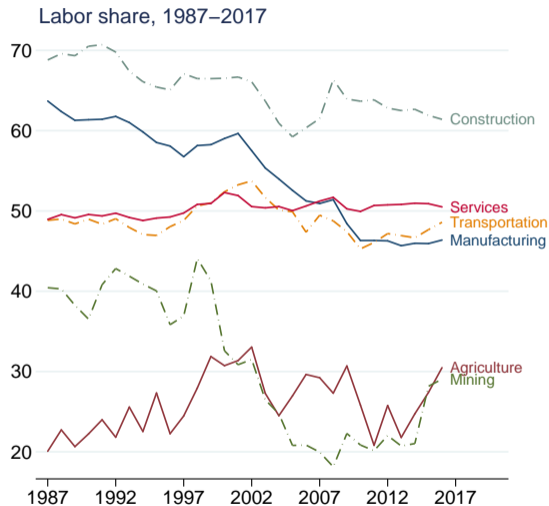
Broad Patterns, 1987-2017

Figure: The labor share and sectoral evolutions, 1987-2017.
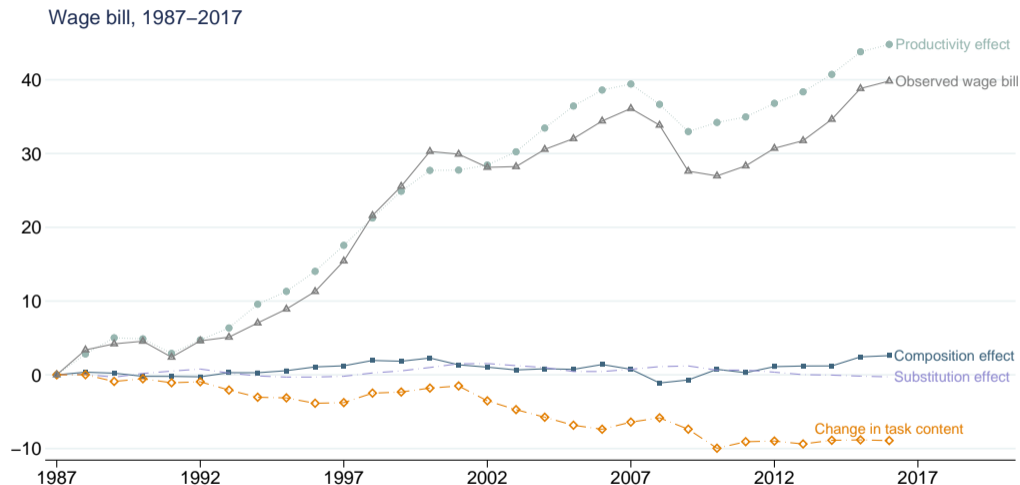
Decomposing Labor Demand, 1987-2017

Figure: Sources of changes in labor demand, 1987-2017.
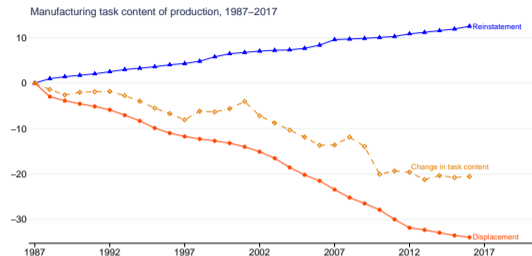
Displacement and Reinstatement, 1987-2017
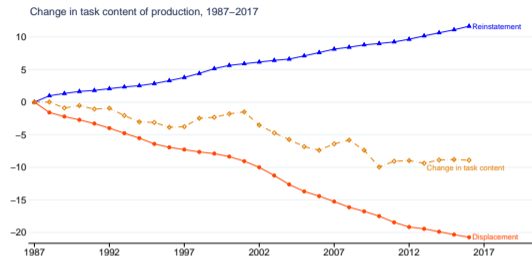
Figure: Estimates of the displacement and reinstatement effects, 1987-2017.

▶ Very different than during 1947-1987.

▶ Much faster displacement and much slower reinstatement.

▶ Changes in tasks content correlated with measures of automation and new tasks — consistent with theory.

Recap: Automation and Changes in Task Content
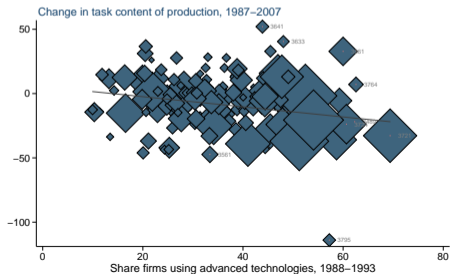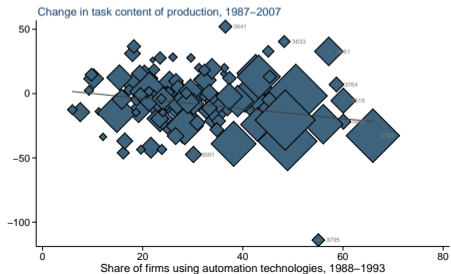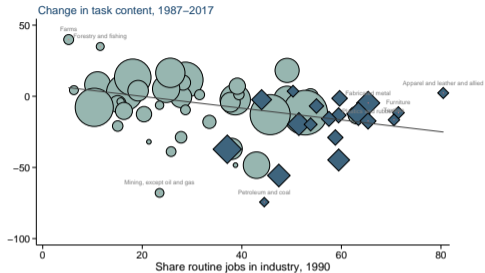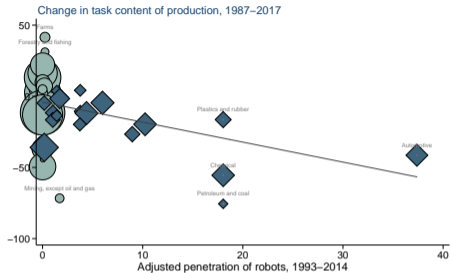
New Tasks and Changes in Task Content
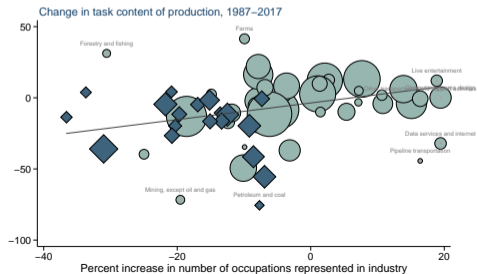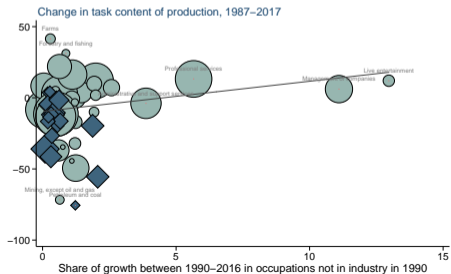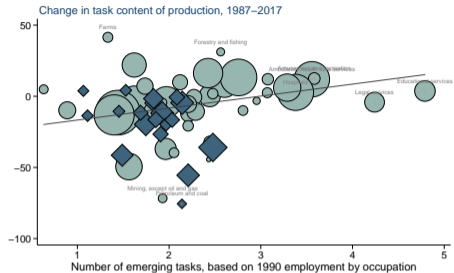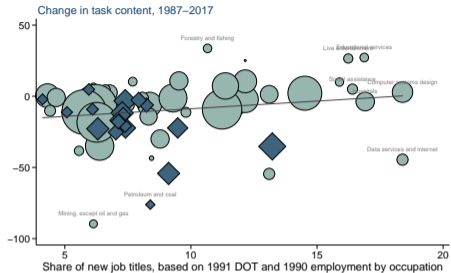
Labor Demand In the Age of Agricultural Mechanization, 1850-1910

▶ Composition effects have been important during other episodes:
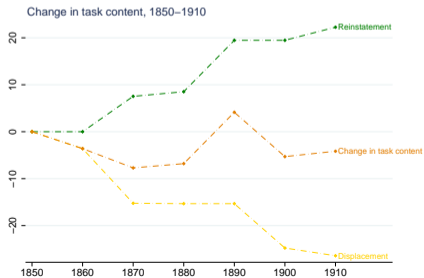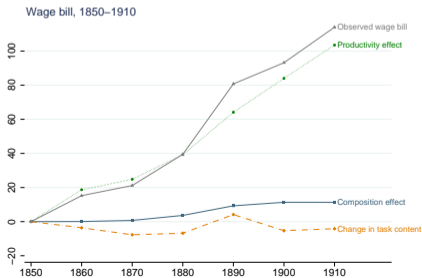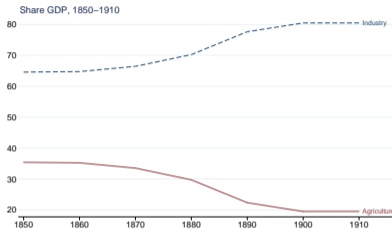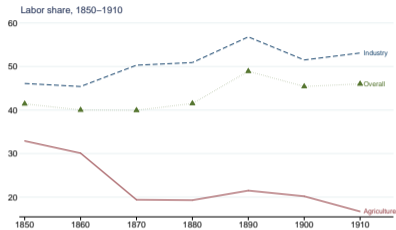
Endogenous Automation

- Why the slowdown in reinstatement and the acceleration in automation?
- This is, in essence, a question about endogenous automation — and what other technologies we can develop with our know-how.
- General framework developed in Acemoglu and Restrepo (AER, 2018).
- I will return to some of the implications of the theory later.
- But for now we can recap the main factors affecting the direction of technological change.

Direction of Technological Change between Automation and New Tasks

▶ Let us summarize the main outlines of a theory of equilibrium direction of technological change.

▶ Suppose that changes in the automation margin, I, and new tasks, N, are given by:

$$\dot{I} = \eta_I S_I$$
$$\dot{N} = \eta_N S_N$$

▶ Here, S_I and S_N denote the number of scientists working on automation and new tasks.

▶ Let the expectations of researchers/firms regarding the productivity of the two innovation technologies be denoted by $\mathbb{E}\eta_I$ and $\mathbb{E}\eta_N$.

▶ Let government taxes/subsidies on technologies be denoted by τ_I and τ_N.

Equilibrium Directed Technological Change

▶ Finally, denote the net present discounted value of (pre-tax) profits from the two technologies by π_I and π_N, and suppose that these are known.

▶ Then, the equilibrium condition is:

$$\mathbb{E}\eta_I \cdot (1 + \tau_I) \cdot \pi_I = \mathbb{E}\eta_N \cdot (1 + \tau_N) \cdot \pi_N$$

▶ So research can be directed towards different technologies because of differences in profitabilities, differences in policies (taxes/subsidies) and differences in expectations/visions.

▶ Acemoglu and Restrepo (2018) show that differences in profitabilities is an equilibriating force: the more automation there is, the lower is the labor share, and investing in new tasks is more profitable than automation.

▶ This will generally (but not always) lead to an interior BGP (not just automation in the long run).

▶ But not necessarily efficient.

Reasons for Inefficiencies: Excessive Automation

▶ Even if the market generates economic forces that push towards an interior BGP, there is no reason to expect that the composition of innovations will be efficient in the decentralized equilibrium.

▶ There are various reasons for this:

1. Different types of innovations may create different amounts of spillovers to other technologies — creation of new tasks may involve more "blue sky" thinking, generating more external effects but by the same token, weaker private incentives.
2. Labor market imperfections may fuel excessive automation.
3. Policies favoring automation/capital instead of labor.
4. The vision or beliefs of leading companies/researchers may favor automation instead of new tasks.

Labor Market Imperfections

▶ Labor market imperfections typically create a red wedge between the equilibrium wage and the (social) opportunity cost of labor (e.g., bargaining, efficiency wages or nonpecuniary mobility costs).

▶ The social planner would like to decide employment based on labor's opportunity cost, while the market will use labor according to the wage.

▶ The same decoupling between the efficient allocation and the market's choices are transmitted to innovation decisions.

▶ Put differently, in the presence of labor market imperfections, there will typically be excessive automation.

▶ An additional consideration: if employed individuals or individuals in "good jobs" are better citizens and contribute more to their communities/families/polities, then this will be ignored by the market as well. Hence another reason for excessive automation.

Policies

▶ Policies can correct for biases towards automation resulting from innovation dynamics or market distortions — e.g., via targeted research subsidies or taxes on automation.

▶ But the opposite has been the case in most advanced economies, especially the US and especially lately: low capital taxes encourage excessive automation.

Effective taxes in the US 1981–2018 (in %)
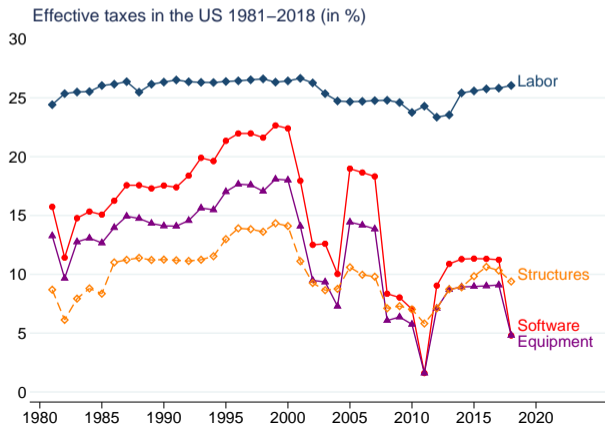
Visions

▶ Views and values of leading companies and researchers are important for the direction of technology (even if typically ignored in economics).

▶ In this simple framework, these can be captured by means of $\mathbb{E}\eta_I$ and $\mathbb{E}\eta_N$ (potentially incorrect views about the prospects for different technologies).

▶ Suppose, for example, that researchers overestimate $\mathbb{E}\eta_I$, which could be because they are overoptimistic about automation or because they view automation as more "cool".

▶ Alternatively, if companies that are at the forefront of new technologies, such as AI, have a business model that is based on automation, then their research will also reflect this focus.

▶ Worse, all of these incentives will be transmitted to universities and students wishing to get jobs as researchers, engineers or managers in these companies.

▶ Though we do not, at the moment, know how to quantify these mechanisms, in principle they can be powerful forces towards excessive automation.

Double Whammy: So-so Automation

▶ Recall that — via productivity effect — automation may generate benefits for labor.

▶ However, when policies or distorted visions encourage excessive automation, we end up with so-so automation technologies — hence plenty of labor displacement, but not much productivity gains (impact on TFP may even be negative).
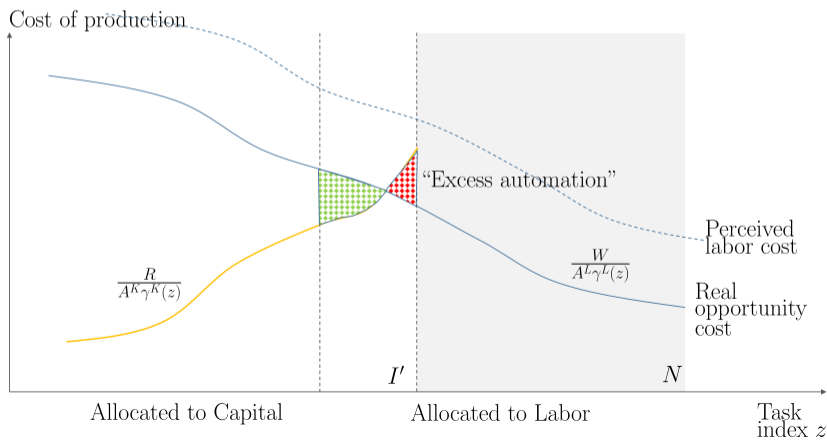
The Demographic Challenge: Rapid Aging of the World Population
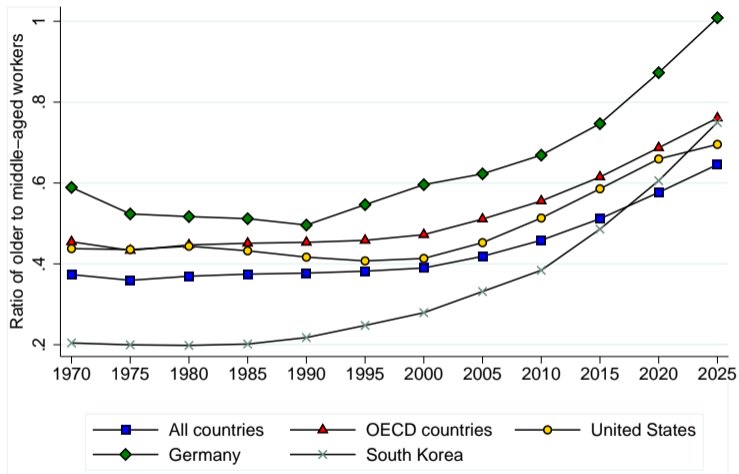
Figure: Aging from 1950 to 2015 and expected behavior until 2025. Aging is measured by the ratio of older (56 years and above) to middle-aged workers (between 21 and 55 years). Source: UN.

Aging Could Restrict Economic Activity:

1. **Demand side/ output gap (Alvin Hansen):**
   Excess of savings over desired investment could lead to shortfall in aggregate demand.
2. **Supply side/ potential GDP (Robert Gordon):**
   People drop out of the labor force or their productivity peaks.
   Aging creates a shortage of the manual labor provided by middle-age workers employed in industry jobs.

Aging and Change in GDP per Capita
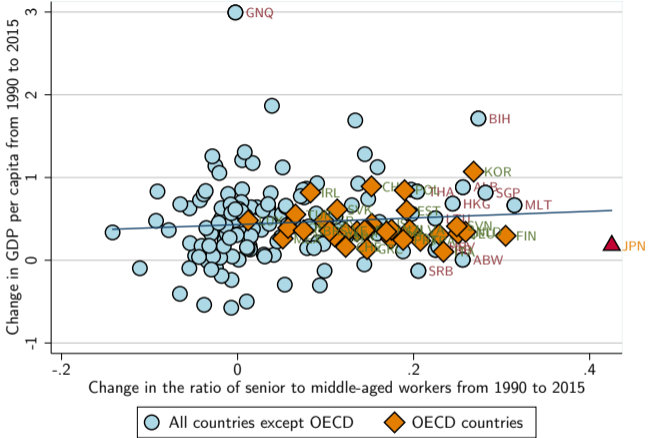
Figure: Correlation between aging and growth in the log of GDP per capita between 1990 and 2015. Aging measured by the ratio of older (56 years and above) to middle-aged (between 21 and 55 years).

Why?

▶ Because of "good automation": automation responding to the shortages of certain skills created by demographic change.
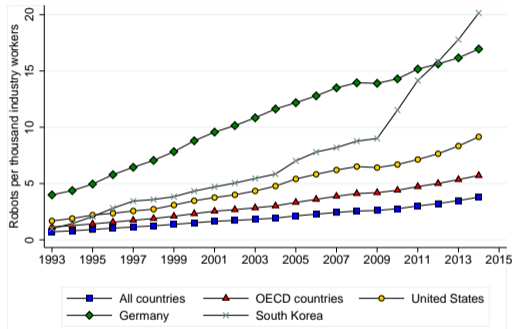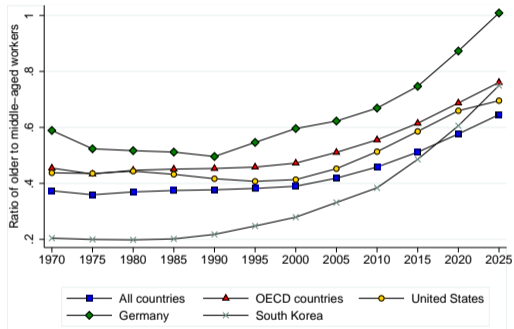
Figure: Worldwide trends in robot adoption from the IFR and trends in aging using UN data on population by age groups and forecasts of demographic change. Aging is measured by the ratio of older (56 years and above) to middle-aged workers (between 21 and 55 years). Robot adoption measured by the number of robots per thousand workers in industry.

Cross-Country Differences

Big differences in the speed in which new automation technologies are being adopted and developed:

- Number of industrial robots per thousand workers in US industries was 9.1 in 2014,
- Number is 14.2 in Japan, 16.9 in Germany and 20.1 in South Korea.
- The United States lags behind in the production of robots relative to Germany and Japan, which have each six of the major producers of industrial robots, while the United States has only one.
- What is the relationship between demographic change in the direction of technological change?
- Can there be good automation in this context?

A Model of Automation

▶ Let us present some more modeling details to clarify what we mean by good automation.

▶ Households consume varieties in $\mathcal{I}$:

$$Y = \left(\sum_{i \in \mathcal{I}} Y(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \text{ with } \sigma > 1.$$

▶ Firm producing i faces elastic demand $Y(i) = YP(i)^{-\sigma}$ and earns a constant markup $\sigma/(\sigma-1) > 0$.

▶ Output requires production tasks (X) and support/service tasks (S):

$$Y(i) = X(i)^{\alpha(i)} S(i)^{1-\alpha(i)}.$$

▶ $\alpha(i) =$ importance of production inputs relative to support inputs.

▶ Production tasks, $X(i)$, comprise a unit measure of tasks

$$\ln X(i) = \int_0^1 \ln X(i, z) dz.$$

performed by middle-aged workers or machines.

A Model of Automation (continued)

- **Key assumption:** Middle-aged workers specialize in production tasks; older workers in support tasks.
- Support tasks completed by older workers, $S(i)$.
- Production tasks produced either by middle-aged workers, ℓ, or machines, m:

$$X(i, z) = \begin{cases} \ell(i, z) + m(i, z) & \text{if } z \in [0, \theta(i)] \\ \ell(i, z) & \text{if } z \in (\theta(i), 1], \end{cases}$$
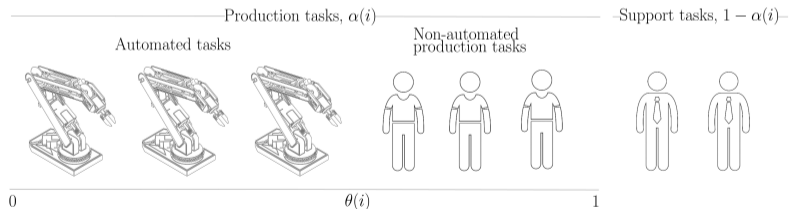
- Firms may use machines in tasks below $\theta(i)$ at a cost of P_M (adoption) or invest in increasing $\theta(i)$ (develop new automation technologies).

Demographic Changes and Factor Prices

- Machines: fixed rental price P_M. Middle-aged workers: supply L and wage W. Older workers: supply S and wage V.
- Let $\phi = \frac{S}{S+L}$ measure aging and $\Theta = \{\theta(i)\}_{i \in \mathcal{I}}$ technology.

Proposition

Given ϕ and Θ, unique equilibrium wages $W^E(\phi, \Theta)$ and $V^E(\phi, \Theta)$. Aging—move to $\phi' > \phi$—raises $W^E(\phi, \Theta)$ and lowers $V^E(\phi, \Theta)$.
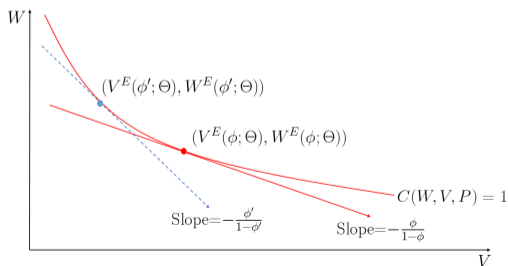
Figure: Equilibrium determination. $C(W, V, P_M) = 1$ is an iso-cost curve.

Adoption of Automation Technologies

Proposition

Adoption decisions are summarized by an automation threshold, $\theta^A(i)$, which satisfies:

$$\theta^A(i) = \begin{cases} \theta(i) & \text{if } W^E(\phi, \Theta) > P_M \\ 0 & \text{if } W^E(\phi, \Theta) \leq P_M, \end{cases}$$

For $\phi \leq \widetilde{\phi}$ (or $W^E(\phi, \Theta) \leq P_M$) we have $\theta^A(i) = 0$ and firms wont adopt existing automation technologies.

For $\phi > \widetilde{\phi}$ (or $W^E(\phi, \Theta) > P_M$) we have $\theta^A(i) = \theta$ and firms will adopt existing automation technologies.

- Aging increases the middle-aged wage, W, and encourages the adoption of automation technologies.
- Aging is one of the many factors that affect wages, W.

Equilibrium with Endogenous Technology

- We now endogenize the development of automation technologies using an approach similar to that in Acemoglu (2007, 2010).

- Developing an automation technology $\theta(i)$ costs the firm $\frac{1-\eta}{2-\eta} P_Y(i) Y(i) \cdot C_i(\theta(i))$ units of the final good, where

$$C_i(\theta(i)) = 1 - (1 - H(\theta(i)))^{\frac{1}{\rho(i)}}.$$

- Here: $\rho(i)$ is a measure of "opportunities for automation" in industry i — the elasticity of the cost function.

- H is an increasing and convex function that satisfies $H'(0) = 0$, $\lim_{x \to 1} H(x) = 1$, and $h(x) \geq 1/(1-x)$, where $h(x) = H'(x)/(1 - H(x))$.

Endogenous Technology

▶ The objective of the technology monopolist to industry i is to maximize

$$\max_{\theta(i)\in[0,1]} \pi^M(i) = (1-\sigma)\ln P(i) + \frac{1}{\rho(i)}\ln\left(1 - H(\theta(i))\right)$$

where the (log) price/cost of industry i's good is

$$\ln P(i) = \alpha(i)\theta^A(i)\ln P_M + \alpha(i)(1 - \theta^A(i))\ln W + (1 - \alpha(i))\ln V$$

Lemma:
For all $i \in \mathcal{I}$, the profit function $\pi^M(i)$ is supermodular in $\theta(i)$ and W. Moreover, firms invest in automation only if $\pi(i) > 0$. Thus, $\theta^A(i) = \theta(i)$.

▶ Let $\theta_i^R(W)$ denote the technology choice of the monopolist when the middle-aged wage is W.

▶ Supermodularity ensures that $\theta_i^R(W)$ is increasing in W.

Equilibrium with Endogenous Technology

- Let $\Theta^R(W) = \{\theta_i^R(W)\}_{i \in \mathcal{I}}$. An equilibrium with endogenous technology is a fixed point of the mapping:

$$W = W^E(\phi, \Theta^R(W)).$$

Proposition

For any $\phi > 0$ there exists an equilibrium with endogenous technology. For each fixed point W^* there is a uniquely defined set of technology choices given by $\Theta^* = \Theta^R(W^*)$.

Unique Equilibrium with Endogenous Technology

▶ Suppose that automation reduces the middle-age wage, W.
▶ That is: $W^E(\phi; \Theta^R(W))$ is nonincreasing and automation decisions are strategic substitutes, which ensures that the equilibrium is unique.
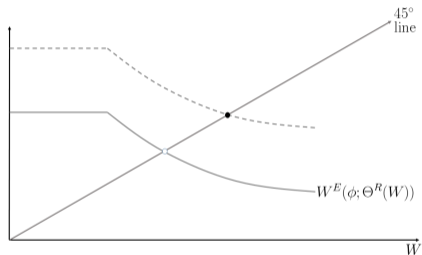
Figure: Impact of aging on the wage of middle-aged workers when the equilibrium with endogenous technology is unique. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the unique equilibrium.

▶ This is good automation because additional automation is always associated with higher

Multiple Equilibrium with Endogenous Technology

▶ But in general, the productivity effect could make the mapping $W^E(\phi; \Theta^R(W))$ upward slopping, introducing multiplicities.

▶ Similar comparative statics in the least and greatest equilibria.
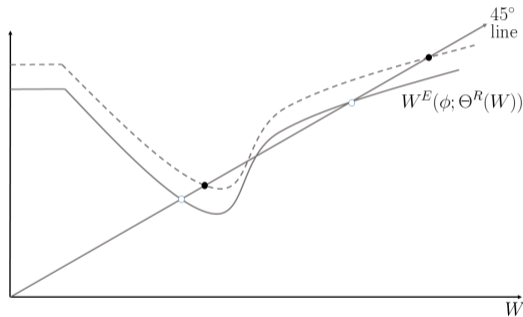
Figure: Determination of the wage of middle-aged workers in the equilibrium with endogenous technology. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.

Comparative Statics of Automation Technology

Proposition

1. In the least and in the greatest equilibrium, aging ()an increase in ϕ):
   - increases the equilibrium wage W^*;
   - increases automation technologies $\{\theta(i)^*\}_{i \in \mathcal{I}^+(\phi, \Theta^*)}$;
   - expands the set of industries that adopt automation technologies $\mathcal{I}^+(\phi, \Theta^*)$.
2. The impact of aging on $\theta(i)^*$ is more pronounced in:
   - industries that rely more heavily on middle-aged workers (i.e., those with high $\alpha(i)$);
   - industries that present greater opportunities for automation (i.e., those with high $\rho(i)$).
3. In the least and the greatest equilibrium, equilibrium output in industry i, $Y^*(i)$, exhibits increasing differences between ϕ and $\rho(i)$.

- Cross-industry, cross-country predictions — both on the direction of innovation and productivity effects — that can be tested.

Data on Robotics Development and Adoption

- International Federation of Robotics (IFR) data:
  - Compiled by surveying global robot suppliers.
  - 52 countries from 1993 to 2014.
  - Available separately for 19 industries.
- Comtrade data on imports and exports of automation technologies:
  - Dollar value from 1990 to 2015 for different types of machinery, including industrial robots.
- Data from the USPTO on robotics-related patents assigned to each country.
  - Patents referenced by USPTO class 901 ("Robots").
  - Additional measures based on keywords in abstracts.
- Data on the number of robot integrators in each US commuting zone from Leigh and Kraft (2017)

Age and Industry Employment

▶ Middle-aged workers specialize in industries with the greatest opportunities for the use of robots (car manufacturing, electronics, metals, and plastic and chemicals).
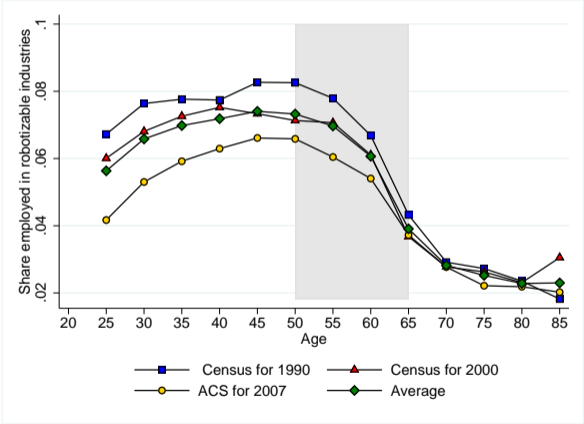
Figure: Share of employees working in industries with the greatest opportunities for the use of robots.

Age and Occupation Employment

▶ Middle-aged workers specialize in tasks that are more prone to industrial automation (machinist, craft production, material handling) than in service and white-collar jobs.
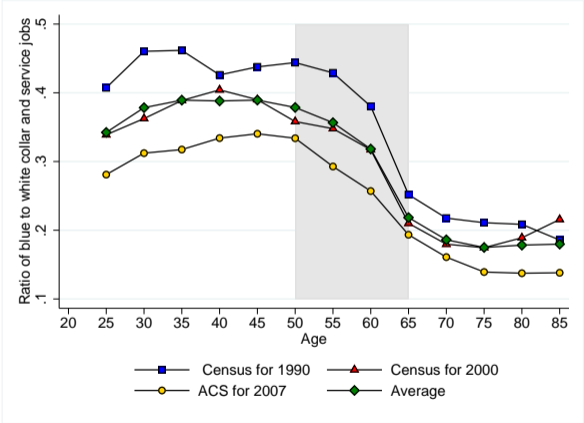
Figure: Ratio of the number of employees in blue-collar production jobs to the number of employees in white-collar and service jobs.

Estimating the Substitution Between Robots and Workers Directly

- ▶ We now estimate the impact of exposure to industrial robots on workers of different ages.
- ▶ Exposure to robots measure across commuting zones, z:

$$\text{Exposure to robots from 1993 to 2007}_z = \sum_{i \in \mathcal{I}} \ell_{zi}^{1970} \overline{APR}_i.$$

- ▶ For 10-year age bins, a, we estimate the impact of robots on the change in employment rates and the log of wages from 1990 to 2007:

$$\Delta L_{z,a} = \beta_a^L \; \text{Exposure to robots from 1993 to 2007}_z + \epsilon_{z,a}^L$$

$$\Delta \ln W_{z,a} = \beta_{z,a}^W \; \text{Exposure to robots from 1993 to 2007}_z + \epsilon_{z,a}^W.$$

- ▶ Unweighted regressions, and standard errors robust against correlation within US states.

Robots Substitute for Middle-Aged Workers
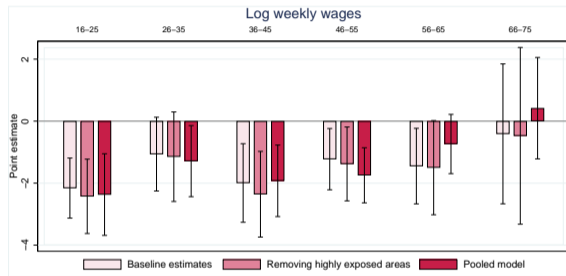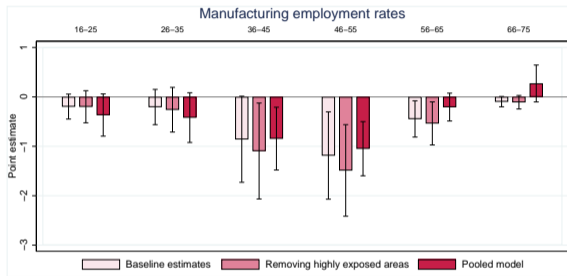
Figure: Estimated impact of one additional robot per thousand workers on employment (in p.p.) and wages (in log points).

The Effects of Aging on the Adoption of Robots

▶ We start with the regression equation

$$\Delta \frac{R_c}{L_c} = \beta_m \Delta \ln \text{Pop}_c^{21-55} + \beta_o \Delta \ln \text{Pop}_c^{\geq 56} + \Gamma X_{c,1990} + \varepsilon_c,$$

▶ $\Delta \frac{R_c}{L_c}$ is the (annualized) change in the stock of robots per thousand workers between 1993 and 2014 in country c.

▶ The right-hand side variables are the changes between 1990 and 2025 in the log population of three age groups:
  1. between the ages of 21-55, Pop_c^{21-55};
  2. above the age of 56, $\text{Pop}_c^{\geq 56}$.

▶ Robots depreciate in 10-15 years, so current adoption decisions should take into account population trends at least until 2025.

▶ Unweighted estimates and robust standard errors.

The Effects of Aging on the Adoption of Robots

▶ Adoption of robots negatively affected by the population of 21-55-year-olds; positively affected by older population.

Table: OLS estimates of the impact of population change.

	Full sample			OECD sample
	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)			
	(1)	(2)	(3)	(4)
Change in the log of population aged 20-55 years	-0.451	-0.510	-0.538	-0.971
	(0.148)	(0.286)	(0.292)	(0.477)
Change in the log of population ≥ 56 years	0.366	0.368	0.307	0.312
	(0.190)	(0.203)	(0.202)	(0.368)
Robots per thousand workers in 1993			0.080	0.058
			(0.014)	(0.030)
Observations	52	52	52	30
R-squared	0.47	0.59	0.71	0.72
Covariates included:				
Country covariates		✓	✓	✓

▶ Country covariates: log GDP per capita, log population, average schooling, initial demographic structure, and log value added in manufacturing.

The Effects of Aging on the Adoption of Robots

▶ The previous exercise underscores the importance of aging, as opposed to changes in the population.

▶ We explore the role of aging in a more parsimonious specification:

$$\Delta\frac{R_c}{L_c} = \beta\text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c,$$

▶ **Aging**$_c$ is the change between 1990 and 2025 in the ratio of "older" workers (above 56 years of age) to middle-aged workers (those between 21 and 55).

▶ We present unweighted estimates and robust standard errors.

The Effects of Aging on the Adoption of Robots

Table: OLS estimates of the impact of aging on the adoption of robots.

| | Dependent variable: Change in the stock of industrial robots per thousand workers (annualized) | | | |
| | Full sample | | | OECD sample |
	(1)	(2)	(3)	(4)
Aging between 1990 and 2025	0.769	0.712	0.567	0.711
	(0.252)	(0.237)	(0.241)	(0.311)
log of GDP per capita in 1993		0.032	-0.005	-0.112
		(0.030)	(0.050)	(0.081)
Robots per thousand workers in 1993			0.077	0.065
			(0.013)	(0.026)
Observations	52	52	52	30
R-squared	0.47	0.59	0.70	0.64
Covariates included:				
Country covariates		✓	✓	✓

- Adoption of robots strongly associated with aging.
- Country covariates: (1990) log GDP per capita, log population, average schooling, initial demographic structure, and log value added in manufacturing.

The Effects of Aging on the Adoption of Robots
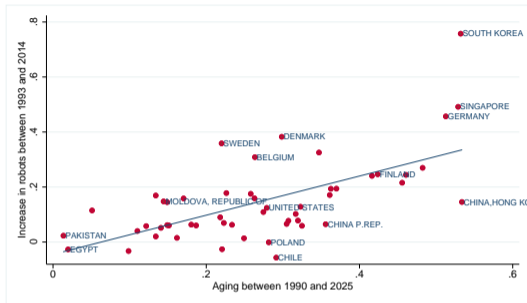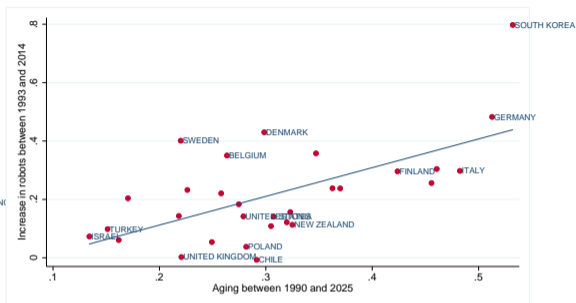
Full sample   OECD countries

Figure: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The plots partial out country covariates.

▶ About 50% of cross-country variation in robot adoption due to demographic factors.
▶ 20 p.p. increase in aging (difference between Germany and the US) leads to three more robots per thousand workers by 2007, closing more than 30% of the Germany-US gap.

The Effects of Aging on the Adoption of Robots: IV

▶ IV estimates using the average birth rates over five-year intervals from 1950-1954 to 1980-1984 as instruments. The results are very similar:

Table: IV estimates of the impact of aging on the adoption of industrial robots.

| | Dependent variable: Change in the stock of industrial robots per thousand workers (annualized) | | | |
| | Full sample | | | OECD sample |
	(1)	(2)	(3)	(4)
Aging between 1990 and 2025	0.874	0.767	0.714	0.901
	(0.263)	(0.241)	(0.251)	(0.323)
Observations	52	52	52	30
First-stage F stat.	25.2	17.8	15.2	8.7
Overid $p-$ value	0.67	0.66	0.09	0.10
Anderson-Rubin Wald test $p-$ value	0.02	0.03	0.00	0.00
Covariates included:				
Country covariates		✓	✓	✓
Robot density in 1993			✓	✓

Stacked Differences

- Split our sample from 1993 to 2015 into roughly two decades, 1993-2005 and 2005-2015, and estimate stacked differences models.
- Control for country effects; does robot adoption happen during time of rapid aging?

Table: Stacked-differences estimates of aging on adoption of robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)			OECD
	Full sample			
	(1)	(2)	(3)	(4)
	Panel A. OLS estimates			
Contemporary aging	0.843	0.552	0.448	0.583
	(0.291)	(0.207)	(0.206)	(0.323)
Observations	104	104	104	60
R-squared	0.28	0.49	0.13	0.13
	Panel B. IV estimates			
Contemporary aging	1.157	0.831	0.797	1.122
	(0.401)	(0.294)	(0.473)	(0.647)
Observations	104	104	104	60
First-stage F stat.	10.4	6.1	4.1	4.2
Overid $p-$ value	0.50	0.07	0.49	0.47
Anderson-Rubin Wald test $p-$ value	0.02	0.07	0.00	0.14
Covariates included:				
Country covariates		✓	✓	✓
Country trends			✓	✓

The Effects of Aging on Imports of Industrial Robots
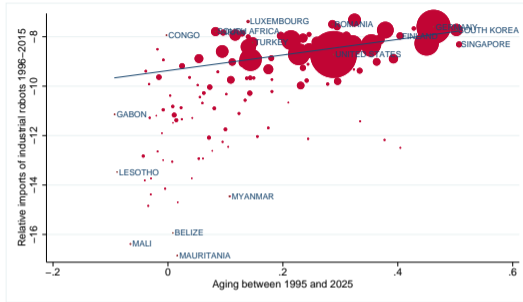
Full sample
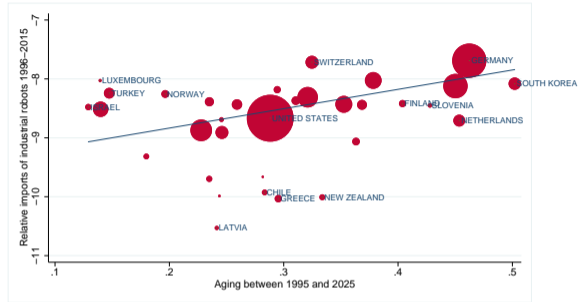
OECD sample

Figure: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1995 and 2025) and the log of imports of industrial robots between 1996 and 2015 (relative to total imports of intermediates).

▶ OLS estimates for full sample 1.8 (se=0.77) and OECD sample 2.2 (se=0.72).
▶ Quantitative importance: a 20 p.p. increase in aging leads to a 44% increase in robot imports (a third of the Germany-US gap).

The Effects of Aging on Imports of Other Automation Technologies

A. Log imports

Figure: Estimates of the relationship between aging and the log of imports of intermediate goods 1990-2015 (normalized by the total intermediate imports).

Innovation: The Effects of Aging on Exports of Robots

Full sample   OECD sample
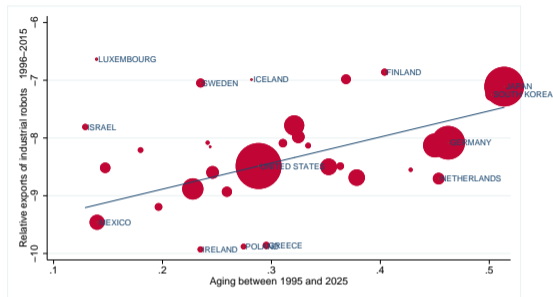
Figure: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of exports of industrial robots between 1996 and 2015 (relative to total exports of intermediates).

- OLS estimates for full sample 4.7 (se=0.98) and OECD sample 4.1 (se=1.2).
- Quantitative importance: a 20 p.p. increase in aging leads to a 82% increase in robot exports (roughly the Germany-US gap).

Innovation: The Effects of Aging on Other Automation Technologies
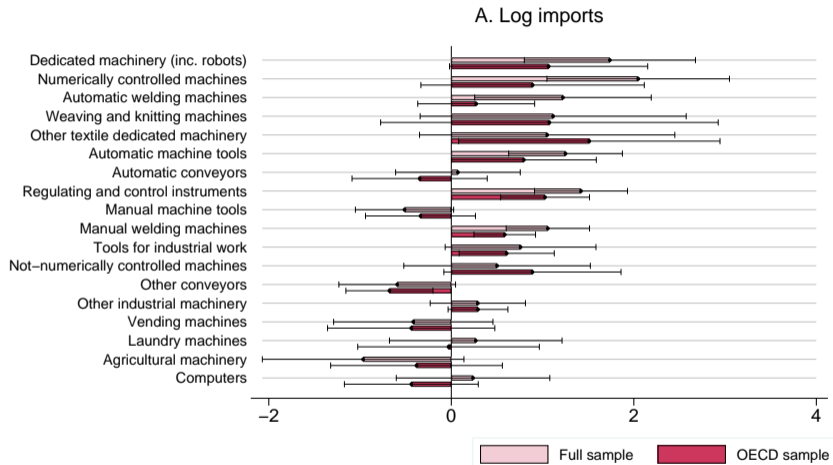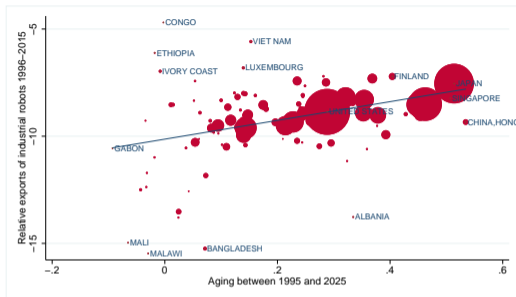

B. Log exports
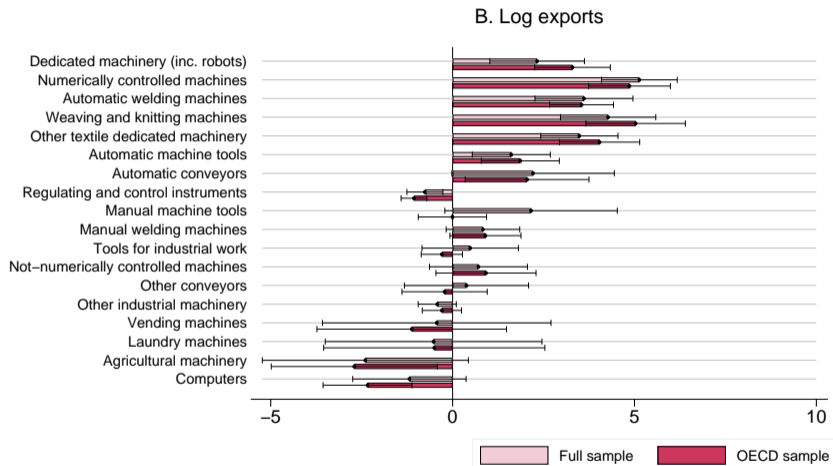
Figure: Estimates of the relationship between aging and the log of exports of intermediate goods 1990-2015 (normalized by the total intermediate exports).

Innovation: The Effects of Aging on Robotics Patents
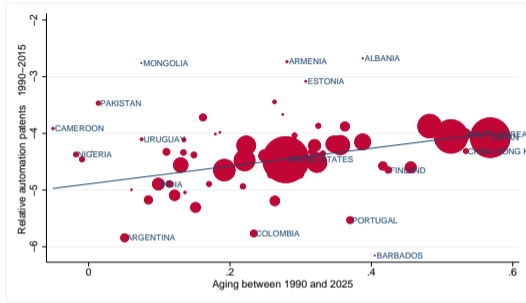
Full sample   OECD sample
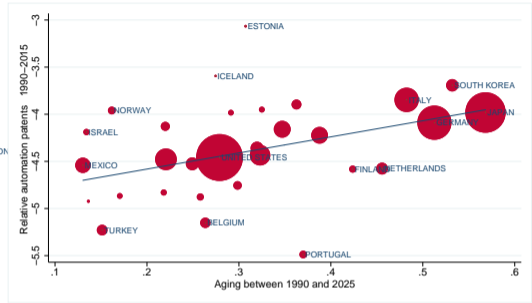
Figure: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of automation patents granted to a country between 1990 and 2016 (relative to total patents at the USPTO). Marker size indicates total patents.

▶ OLS estimates for full sample 1.4 (se=0.44) and OECD sample 1.6 (se=0.55).
▶ Quantitative importance: a 20 p.p. increase in aging leads to a 32% increase in robotics patents (half of the Germany-US gap).

Innovation: The Effects of Aging on Patents

Classes related to 901	
901 USPTO class	
Classes citing 901 class (25% threshold)	
Classes citing 901 class (10% threshold)	
Words related to robots	
Words related to industrial robots	
Words related to robots and manipulators	
Words related to numerical control	
Classes related to computers	
Words related to computers	
Classes related to software	
Words related to software	
Classes related to nanotechnology	
Words related to nanotechnology	
Classes related to pharmaceuticals	
Words related to pharmaceuticals	

Full sample   OECD sample

The Effects of Aging on Robots in the United States

▶ We now estimate the relationship between aging and robot-related activities across US commuting zones.

▶ We use Leigh and Kraft's (2017) data on the location of robot integrators as a proxy of robots-related activity.

▶ We estimate:

$$\text{Integrators}_z = \beta \text{Aging}_z + \Gamma X_{z,1990} + \upsilon_z$$

across 722 US commuting zones, z. Here Integrators$_z$ is a dummy variable for the presence of integrators.

▶ We measure aging between 1990 and 2015 using the NBER-SEER data, and instrument for it using past birthrates from 1950 to 1985.

▶ Control for the exposure to robots, Census division, demographic characteristics, industry shares, and trade shocks.

The Effects of Aging on Robots in the United States

▶ Focus on IV (given importance of migration within US) — similar results to cross-country.

Table: IV Estimates of the impact of aging on location of integrators in the US.

	(1)	(2)	(3)	(4)
	Dependent variable: Dummy for presence of robot integrator			
Aging between 1990 and 2015	1.338	0.642	0.530	0.879
	(0.581)	(0.224)	(0.218)	(0.240)
Exposure to robots			0.042	0.042
			(0.021)	(0.020)
Observations	722	722	722	722
First-stage F stat.	4.2	21.5	20.0	22.9
Overid $p-$ value	0.00	0.52	0.19	0.65
Regional dummies	✓	✓	✓	✓
Baseline covariates		✓	✓	✓
Industry composition			✓	✓
Additional covariates				✓

▶ Baseline covariates: (1990) log income per capita, log population, education and demographic structure. Additional covariates: (1990) shares of population by race, gender, living in urban areas, and employed in routine jobs, as well as exposure to Chinese imports.

▶ So why isn't this "good automation"? What is the difference from Germany?

Industry-Level Effects of Aging

- To explore the industry implications, we estimate

$$\frac{IR_{i,c,t}}{L_{i,c,1990}} = \beta \mathsf{Aging}_c + \beta_R \, \mathsf{Aging}_c \times \mathsf{Reliance\ on\ Middle\text{-}Aged\ Workers}_i$$
$$+ \beta_P \mathsf{Aging}_c \times \mathsf{Opportunities\ for\ Automation}_i$$
$$+ \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t},$$

- Opportunities for automation:
  - "replaceability" index constructed by Graetz and Michaels (2018).
  - Dummy variable for automobiles, electronics, metal products, metal machinery, and chemicals, plastics and pharmaceuticals (BCG, 2015).
- We proxy the reliance on middle-aged workers using the age composition of employees in an industry in the 1990 U.S. Census.
- Standard errors robust against heteroscedasticity and correlation at the country level.

Industry-Level Effects of Aging

- More pronounced effects for industries with greater opportunities for automation and greater reliance on middle-aged workers.
- Main effect: 95th percentile of reliance on middle-aged workers and 95th percentile opportunities for automation.

Table: IV estimates of the impact of aging by industry.

| | | Potential for the use of robots | | | |
| | | Replaceability index | | BCG measure | |
	(1)	(2)	(3)	(4)	(5)
	Dep. variable: Installation of robots in country-industry-year cells				
Aging between 1990 and 2025	1.430	3.780	2.992	6.585	5.246
	(0.477)	(1.254)	(1.025)	(2.175)	(1.768)
Aging × reliance on middle-aged		0.958	0.682	0.327	0.193
		(0.318)	(0.247)	(0.112)	(0.094)
Aging × opportunities for automation		4.919	4.597	5.902	4.835
		(2.228)	(1.883)	(1.986)	(1.594)
Observations	10,602	10,602	10,602	10,602	10,602
Countries in sample	50	50	50	50	50
Country covariates, industry and year fixed effects	✓	✓	✓	✓	✓
Robot density in 1993			✓		✓

Implications for Industries: Labor Productivity

▶ More positive productivity effect for industries with greater opportunities for automation.

▶ Main effect: 5th percentile of reliance on middle-aged workers and 95th percentile opportunities for automation.

Table: IV estimates of the impact of aging on labor productivity by industry.

| | | Potential for the use of robots | | | |
| | | Replaceability index | | BCG measure | |
	(1)	(2)	(3)	(4)	(5)
		Dependent variable: Change in log labor productivity 1995-2007				
Aging between 1995 and 2025	-1.707	1.432	1.768	1.138	1.534
	(0.595)	(1.149)	(0.978)	(1.224)	(1.059)
Aging × reliance on middle-aged		-0.566	-0.645	-0.538	-0.622
		(0.258)	(0.239)	(0.263)	(0.246)
Aging × opportunities for automation		4.782	5.119	1.450	1.617
		(1.334)	(1.459)	(0.430)	(0.419)
Observations	399	399	399	399	399
Countries in sample	21	21	21	21	21
Country covariates and industry fixed effects	✓	✓	✓	✓	✓
Initial value added in 1995			✓		✓

Conclusion: Implications for the Future of Work

▶ We have seen the two faces of automation.

▶ Good automation — high-productivity automation technology developed because of skill shortages — is a potent force combating the potential negative effects of demographic change already affecting many countries around the world.

▶ But bad or so-so automation reduces employment growth and worsens the distribution of income — esp. when there is excessive automation due to policy or vision distortions.

▶ The problem is even worse when automation is not counterbalanced by new tasks.

▶ If the future is one of ceaseless automation and nothing else, then the future of work will not be bright. There would be lower and lower labor share across industries and in national income. And there would be no guarantee of sufficient job growth.

▶ Improving labor market institutions, by itself, cannot be the solution — if we push wages up, this will cause more automation, unless technology becomes more "human-friendly".

▶ But good automation, particularly when combined with rapid creation of new tasks for workers, can be powerful engine of growth and prosperity.

▶ **Which future will it be?**