Robots For Economic Development

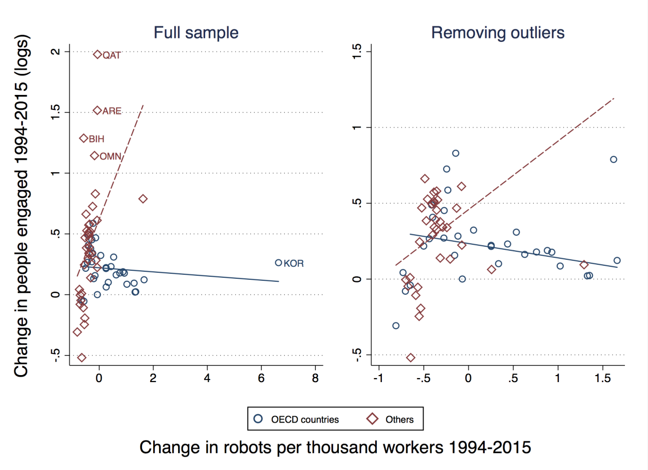
Massimiliano Calì [1]   Giorgio Presidente [2]

[1]World Bank

[2]Oxford Martin School, Oxford University

November 2021

Robot penetration and employment changes: OECD vs non-OECD countries



The figure plots the correlation between the change in residuals from a regression of log-employment on the share of population above 55 years old over population between 20 and 49 years old, and changes in robot penetration over the same period. Robot penetration is defined as the stock of industrial robots per thousand employed workers.
Sources: IFR; PWT; World Bank.

Do automation technologies present an opportunity or a threat to developing economies?

- Productivity / employment trade-off documented in advanced and emerging economies
- USA, France, Spain, Germany; Mexico, China

What about developing countries?

- Strong investment in automation technologies
- Premature de-industrialisation?

This paper

- Document a robust positive employment impact of robots at the local labor market-level in Indonesia (LFS data)
- Study underlying micro-level mechanisms (plant-level data)

Can diminishing productivity returns from automation explain the positive employment impact *vs* negative in advanced economies?

Diminishing productivity returns from automation

The task-based production framework (Acemoglu and Restrepo 2018)

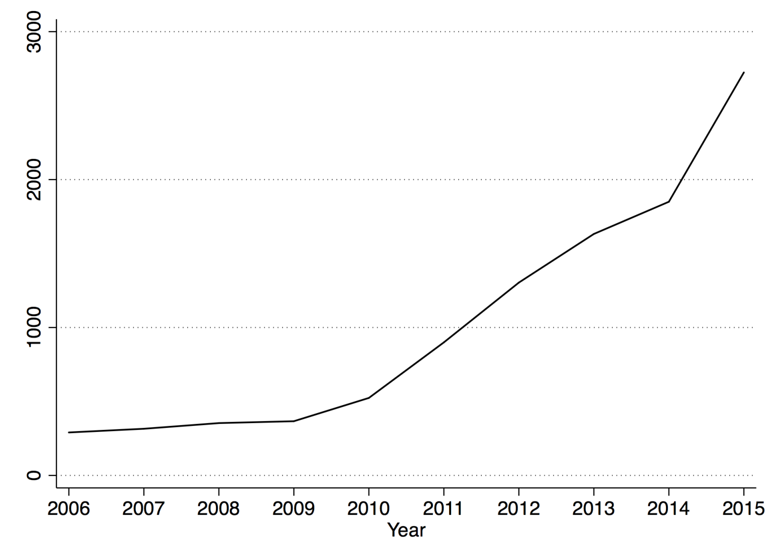
- Employment effect = productivity effect - displacement effect
  MODEL
- *Low* initial levels of automation: productivity effect is larger, displacement effect is smaller
- *High* initial levels of automation: only marginal productivity effect ("so-so technology"), large displacement effect

Our Laboratory: Indonesia

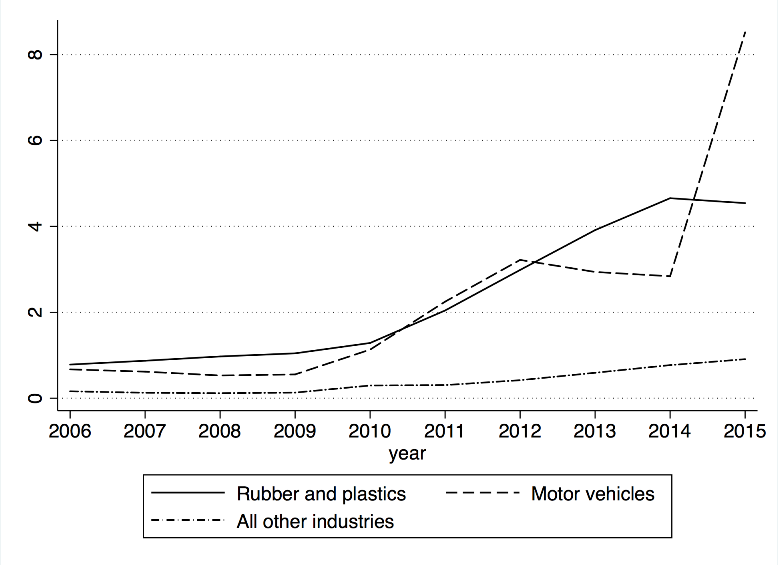
- Rapid increase of robots import after 2008 (led by global technology supply)
- Early adopter among developing countries - informative about future automation of others
- Rich availability of high quality data

Total number of robots shipped to Indonesia

Data on shipments of industrial robots from the International Federation of Robotics (IFR), by 2-digit industry and year



Robots per thousand workers



Local labor market analysis: data and setup

- Local labor market $\sim$ Indonesian regencies
- Labor Force Survey: employment by regency, 2-digit industry, year
- Regency dataset: 276 labor markets, 2008-2015 Summary statistics
- For all industries in the base year (2007), we compute industry i share of employment in regency r total employment:

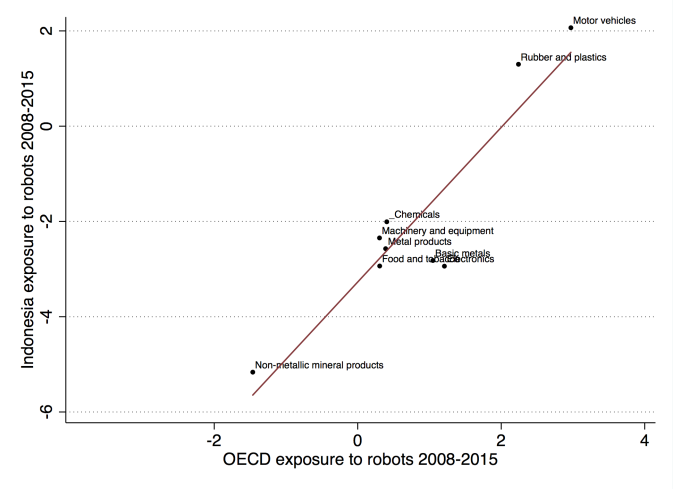
$$s_{i,r} = \frac{L_{r,i,2007}}{L_{r,2007}}$$

Regency-level exposure to robots:

$$ETR_r^{ID} \equiv \sum_{i \in r} s_{i,r} \frac{R_{i,2015}^{ID} - R_{i,2008}^{ID}}{L_{i,2007}^{ID}}$$

$$ETR_r^{OECD} \equiv \sum_{i \in r} s_{i,r} \frac{R_{i,2015}^{OECD} - R_{i,2008}^{OECD}}{L_{i,2007}^{OECD}}$$

Global supply shocks drive robot penetration



On the horizontal axis there is the change between 2007 and 2015, of the OECD region industry-average number of robots per thousand employees. On the vertical axis, there is the change between 2007 and 2015, of the industry-level number of robots per thousand employees in Indonesia. Sources: IFR, STAN, SI.

Local labor market analysis: results

$+1$ R/L $\longrightarrow$ $+31$ percentage points over 2008–15

2X mean R/L $\longrightarrow$ $+5$ percentage points

	(1) Regency ETR	(2) Δ Total employment	(3) Δ Manufacturing employment	(4) Δ Services employment	(5) Δ Agr/Mining employment
Regency ETR (instrument)	0.440***				
	(0.082)				
Regency ETR		0.054	0.309***	0.023	-0.277**
		(0.039)	(0.105)	(0.057)	(0.137)
Observations	276	276	276	276	276
R-squared	0.472				
Province FE	yes	yes	yes	yes	yes
Regency demand shifter	yes	yes	yes	yes	yes
First stage F-stat	–	28.97	28.97	28.97	28.97

The table presents 2SLS estimates of the relationship between regency-level exposure to robots and employment. Exposure to robots is instrumented with the average exposure in the OECD region. The dependent variables are the 2008-2015 differences of log of employment (total or manufacturing) in each regency. The regency demand shifter aggregates global exports by industry (excluding Indonesia) using regency-level industry employment shares in the base year. Base year regency covariates include: i) population; ii) the shares of workers with tertiary and no education (separately); iii) real output per capita, and iv) the GDP share of agriculture and mining sectors. Standard errors are clustered at the regency-level. Weights are constructed using 2007 (base year) regency population. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.
The sample average value of ETR_r is 0.16. Therefore, $0.31 \times 0.16 = 0.05$.

Plant Level Data

- Plant level data from the Indonesian survey of manufacturing plants with at least 20 employees (Statistik Industri, SI)
- SI actual census in 2006: educational attainments of the workforce
- 8.5 percent of the plants switch industry: drop observations after switch / keep / fix initial industry / drop switching plants
- Plant (unbalanced) panel: 22,288 plants between 2008 and 2015; 13 2-digit manufacturing industries; 64,742 observations (1318 singletons)

Summary statistics

Estimation of Marginal Cost

- Plants output and inputs quantities and values
- Multi product plants: output and input price indexes (Eslava et al. 2004)
- Transmission bias (Ackerberg, Caves, and Frazer 2015)
- Robots affect the expected value of future productivity
- Estimation industry by industry
- Plants marginal cost (De Loecker and Warzynski 2012)

Measuring plant level exposure to robots

- Routine task-intensive occupations are the most likely to be automated (Autor, Levy, and Murnane 2003)
- Occupation *replaceability*: Graetz and Michaels 2018 (GM); Frey and Osborne 2017 (FO)
- Indonesian labor force survey data

	(1)	(2)
	FO	**GM**
Primary	.42	.39
Secondary	.56	.59
Tertiary	.02	.02

The table reports the share of employment in production occupations at high risk of automation, by the educational attainments of Indonesian workers in 2007. Primary education includes up to completed primary school. Secondary education includes junior and senior high-school. Tertiary education includes education levels from diplomas to PhD. FO indicates that the list of occupations at risk of automation is based on the methodology in Frey and Osborne 2017. GM indicates that the list of occupations at risk of automation is based on the methodology in Graetz and Michaels 2018. Sources: Sakernas (LFS); Frey and Osborne 2017; Graetz and Michaels 2018.

Measuring plant level exposure to robots

$$ETR_{f,t} \equiv \frac{R_{i,t}}{L_{i,t_0}} \times secondary_{f,t_0}$$

- $secondary_{f,t_0}$ share of plant production employment with secondary education (base year)
- $R_{i,t}$ number of industrial robots in use in industry i (2-digit ISIC code) in year t
- Number of workers in industry i (in thousands, base year)

Plant-level analysis: econometric specification

$$Y_{f,i,t} = \gamma_0 + \gamma_1 ETR_{f,t} + \eta_f + u_{i,t} + \Gamma X_{f,t} + \epsilon_{f,t}$$

- $Y_{f,i,t}$ outcome of plant f in industry i at time t
- η_f plant fixed effects
- $u_{i,t}$ industry-year effects (2-digit ISIC code)

- Technological sophistication index (R&D units, product and process innovation, use of computers and the Internet)
- Share of high-skill employment
- Downstream automation spillovers (control group)

- Industry-year clustered errors (robust to alternatives)
- Normalise $ETR_{f,t}$ to have zero mean and unitary standard deviation

The employment effect

	(1) Employment	(2) Employment
ETR	0.010**	0.033***
	(0.005)	(0.012)
ETR $\times$ high-initial exposure		-0.025*
		(0.015)
Observations	65,573	65,573
R-squared	0.927	0.927
Plant FE	yes	yes
Industry-year FE	yes	yes
Other technologies	yes	yes
Downstream automation	yes	yes

The table presents OLS estimates of the relationship between plants' exposure to robots (ETR) and log-employment. ETR is defined as industry robot penetration times the plant-level share of secondary education employment in the base year. High-initial exposure plants are plants with base-year ETR larger than the 90th percentile of the ETR distribution in the base year. Other technologies are captured by: i) an index of plant innovation activities in the base year, interacted with year fixed effects, and ii) the plant share of tertiary education workers in the base year, interacted with year fixed effects. Downstream automation captures automation possibilities in downstream industries using 5-digit $\times$ 2-digit industry IO tables and average OECD robot penetration interacted with plant-level share of secondary education employment in the base year. Standard errors are clustered at the 2-digit industry-year-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

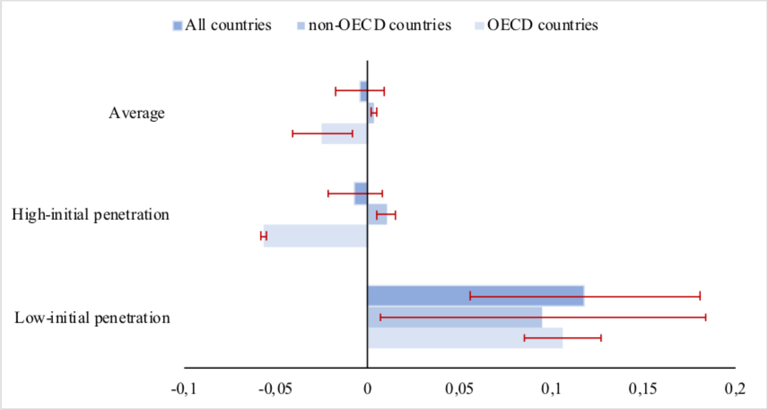
The productivity effect

	(1) TFP	(2) TFP	(3) Marginal cost	(4) Marginal cost
ETR	0.069*	0.168***	-0.101***	-0.283***
	(0.038)	(0.041)	(0.021)	(0.084)
ETR × high-initial exposure		-0.112**		0.200**
		(0.049)		(0.087)
Observations	62,066	62,066	54,683	54,683
R-squared	0.994	0.994	0.680	0.681
Plant FE	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Other technologies	yes	yes	yes	yes
Downstream automation	yes	yes	yes	yes

The table presents OLS estimates of the relationship between plants' exposure to robots (ETR) and alternative productivity measures. ETR is defined as industry robot penetration times the plant-level share of secondary education employment in the base year. High-penetration industries are 2-digit industries with base year average penetration larger than the 75th percentile of the distribution in the base year. Other technologies are captured by: i) an index of plant innovation activities in the base year, interacted with year fixed effects, and ii) the plant share of tertiary education workers in the base year, interacted with year fixed effects. Downstream spillovers are captured, for each 5-digit industry, by robot penetration in downstream industries (proxied by average penetration in the OECD). Standard errors are clustered at the 2-digit industry-year level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Robots For Economic Development

Employment impact of robots in 61 countries and 12 industries (2007-2015)



The figure shows 2SLS estimates of the impact of robot penetration and 90 percent confidence intervals in a sample of 61 countries and 12 industries, from 2007 to 2015. The complete estimation results are presented in Online Appendix Table ??.
Sources: authors' calculations based on IFR, STAN, SI.

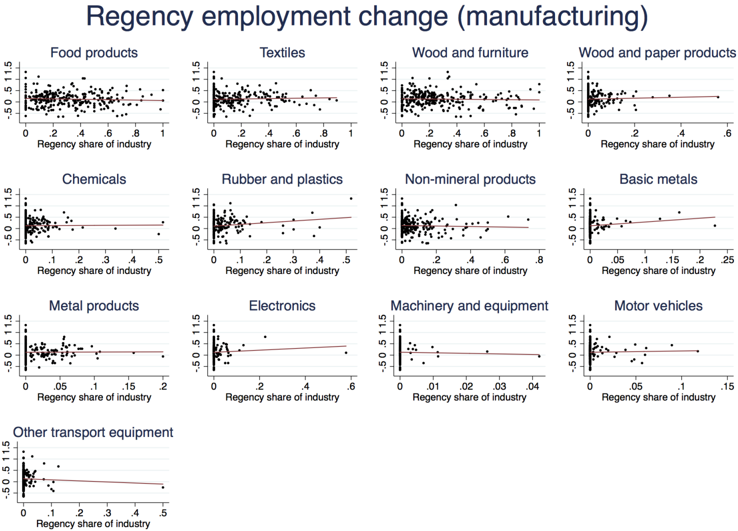
Summary statistics (regency-level)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Regency Δ ETR	284	0.165	0.316	-0.278	2.243
Regency Δ ETR (instrument)	284	0.504	0.524	-3.162	1.990
Change in total employment (log)	284	0.122	0.128	-0.178	0.615
Change in manufacturing employment (log)	284	0.121	0.376	-2.839	1.325
Change in services employment (log)	284	0.276	0.210	-0.176	1.373
Change in agriculture and mining employment (log)	284	-0.0920	0.273	-1.400	0.869
Change in RoW export by regency (log)	276	0.0771	0.380	-2.913	0.829
Population in 2007	281	793,849	704,630	29,682	5.756e+06
Share of workers with tertiary education in 2007	281	0.0482	0.0324	0.00898	0.206
Share of workers with no education in 2007	281	0.113	0.0459	0.0178	0.270
Natural resources share of output in 2007	281	0.495	0.233	0.0392	0.983
Share of employment at risk of computerisation	284	0.0138	0.0110	0	0.0856
Change in real capital stock (log)	277	1.188	0.475	-0.594	2.536
GDP per capita in 2007 (log)	281	2.934	0.638	1.757	5.518

Back

Exogeneity of local industry shares and changes in employment

Goldsmith-Pinkham, Sorkin, and Swift 2020 Back



Summary statistics (plant-level)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Real expenditure on domestic inputs (log)	64,742	9.695	2.164	-4.034	19.47
Industry number of robots (1000s of workers)	64,742	0.160	0.713	0	14.08
Innovation-intensity (index)	64,742	0.212	0.273	0	1
Share of secondary education workers	64,742	0.611	0.362	0	1
Share of primary education workers	64,742	0.376	0.369	0	1
Share of tertiary education workers	64,742	0.0127	0.0436	0	1
Downstream exposure to robots (index)	64,742	0.0874	0.356	-0.311	8.996
Downstream exposure to robots (index, OECD)	64,742	1.224	3.575	-29.45	35.75
Real investment in machinery and equipment (log)	64,742	1.717	3.541	0	19.64
Employment (log)	64,742	3.951	0.954	2.197	9.458
Real marginal cost (log)	64,742	-0.767	1.522	-16.92	5.714
Real revenue (log)	64,742	13.71	1.987	6.961	31.82
TFP (index)	64,742	-0.150	1.945	-293.2	32.42

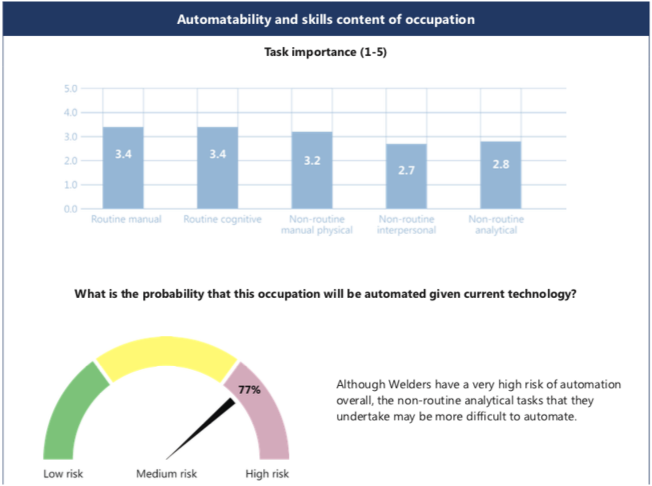
Back

Welders and Flame Cutter

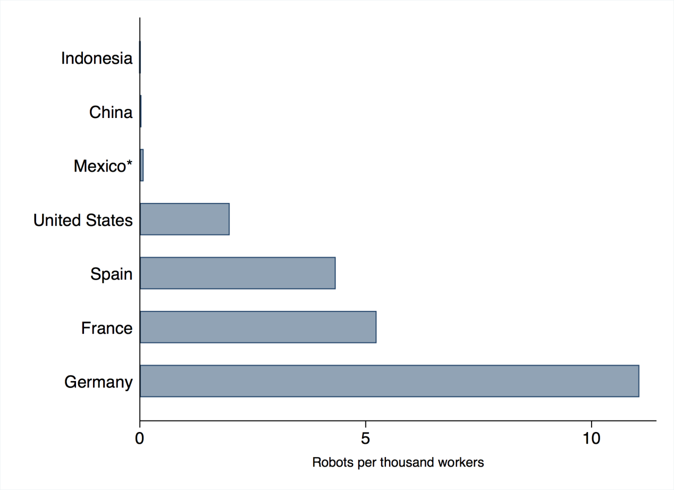
Summary	
KBJI title:	Welders and Flame Cutter
KBJI code:	7212
Job description:	Workers in this group weld and cut metal parts using gas flamesor electric flares and melt and unify the metal. Tasks include: to weld parts of metal using gas or electric flares, thermite compounds, or other methods; operate resistance welding machines; use a welding torch to make and repair important layers, pipes, floors, and other equipment; solder metal parts; cut metal plates with fire or electric incandescent; combine metal parts with hand soldering.
Position includes:	Welder (with specification on underwater welders and welders for food and beverage manufacturing)
Statistics	
Gender:	1% female
Age:	33-38 years old
Monthly wage:	IDR 1,800,000 – 2,375,000
Working hours:	47-48 hours per week
Typical education:	Junior High School and Vocational High School
Field of study:	N/A
Most common sector of employment:	Manufacturing
Most common employer type:	Individual/Household business

Back

Sources: World Bank Occupation Profiles



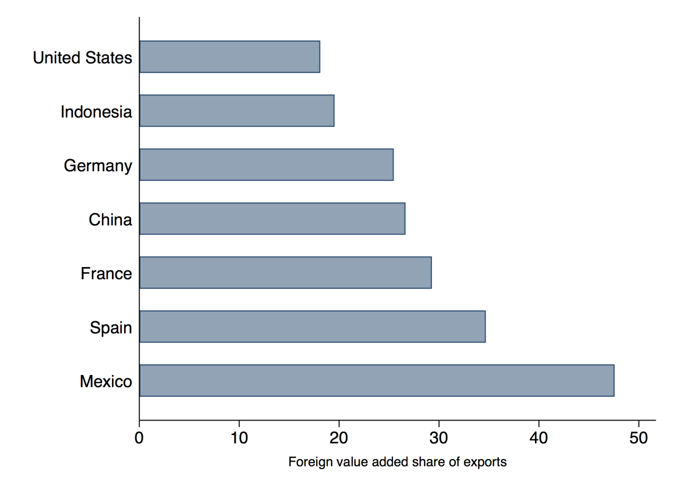
Back Sources: World Bank Occupation Profiles



Back

* The figure refers to 2007, except for Mexico, which due to data availability can only be computed for 2011. The figure shows the number of industrial robots per thousand workers in manufacturing. We approximate manufacturing employment by multiplying total employment from PWT to ILO estimates of the share of manufacturing employment in total employment. Sources: IFR; PWT; ILO.

Back



* The figure refers to 2007 and shows the share of foreign value added embedded in gross manufacturing exports.
Source: OECD TiVA

Model setup

The final good is produced by a representative firm combining a continuum of varieties of total measure equal to 1. Each variety is produced by an intermediate good-producing firm f:

$$Y = \left[\int_0^1 y_f^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}}$$

with $\sigma > 1$.
We use the price of the final good as the numeraire $P \equiv 1$. Thus, each firm faces a constant elasticity demand function:

$$y_f = p_f^{-\sigma}$$

Firms

The firm produces the variety combining a unit measure of tasks, each indexed by z, through the production function

$$y_f = \exp\left(\int_0^1 \ln x_f(z)dz\right)$$

where $x_f(z)$ is the quantity of task z demanded by the firm. Since all firms are identical and face the same problem, we can suppress f subscripts.

Tasks can be performed by human workers or machines with the following task production functions:

$$x(z) = \begin{cases} \gamma(z) \cdot n(z) & \text{if performed with labor} \\ \eta(z) \cdot k(z) & \text{if performed with capital} \end{cases} \tag{1}$$

where $n(z)$ and $k(z)$ are labor and capital allocated by the firm to the production of task z. We assume labor and capital to be fully flexible across tasks and firms.

where $\gamma(z)/\eta(z) \equiv \tilde{\gamma}(z)$ is increasing in z (higher-ordered tasks are harder to automate).

Consumers

The consumers side of the economy is composed by a representative household with quasi-linear preferences:

$$U(C, n, k) = C - \frac{n^{1+\frac{1}{\varepsilon_n}}}{1+\frac{1}{\varepsilon_n}} - \frac{k^{1+\frac{1}{\varepsilon_k}}}{1+\frac{1}{\varepsilon_k}}$$

where C denotes consumption of the final good, ε_n is the inverse labor supply elasticity, which fully parametrizes the disutility of supplying labor.

In order to avoid introducing dynamics in the model, we assume that the household transforms the consumption good into capital at some cost, which is parametrized by the inverst capital supply elasticity, ε_k.
The budget constraint of the household is given by

$$C = wn + rk$$

where w is the wage rate and r the price of capital.

Productivity effect in partial equilibrium

(a) The productivity effect of automation is given by

$$\frac{\partial \ln y}{\partial \kappa} = \sigma \left[\ln \left(\frac{w}{\gamma(\kappa)} \right) - \ln \left(\frac{r}{\eta(\kappa)} \right) \right]$$

(b) Automation has diminishing productivity returns:

$$\frac{\partial^2 \ln y}{\partial \kappa \partial \kappa} = -\sigma \tilde{\gamma}'(\kappa) < 0$$

where $\tilde{\gamma}(\kappa) \equiv \frac{\gamma(\kappa)}{\eta(\kappa)}$

Employment impact in general equilibrium

The employment impact of automation is given by

$$\frac{\partial \ln n}{\partial \kappa} = \frac{\sigma - 1}{\sigma} \frac{\partial \ln y}{\partial \kappa} - \frac{1}{1 - \kappa}$$

Back