Machines and Machinists: Incremental Technical Change and Wage Inequality

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Motivation

Inequality and polarization in the U.S. (Autor et al 2008)

FIGURE 1.—CHANGE IN LOG REAL WEEKLY WAGE BY PERCENTILE, FULL-TIME WORKERS, 1963–2005

Inequality and polarization in Germany (Dustmann et al 2009)

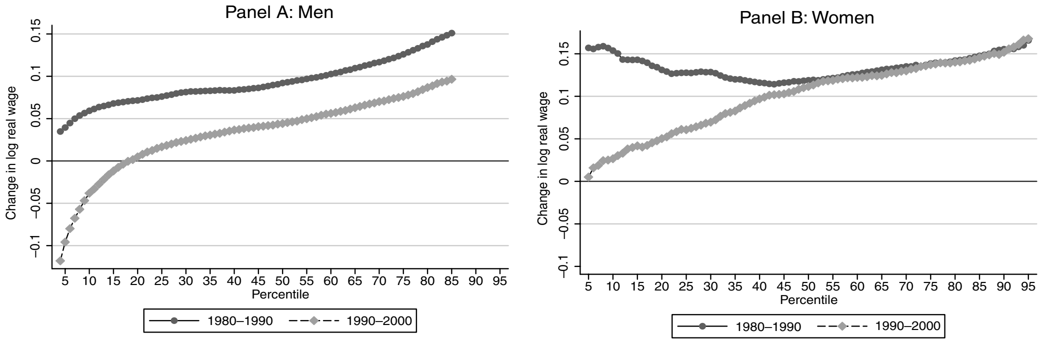


FIGURE III

Wage Growth by Percentile: The 1980s versus the 1990s

Source. 2% IABS Sample for full-time workers between 21 and 60 years of age. The figures plot wage growth by percentile from 1980 to 1990 and from 1990 to 2000. Due to censoring, we plot wage growth for men up to the 85th percentile only.

Wage inequality has increased in many countries

- U.S. (Katz, Loveman & Blanchflower 1995, Autor, Katz & Kearney 2008)
- U.K. and Japan (Katz et al. 1995)
- Germany (Dustmann, Ludsteck & Schönberg 2009), Poland (Rutkowski 1996, Rutkowski 1997)
- Czech Republic, Hungary, Romania and Slovenia (Rutkowski 1997)

Is technology to blame?

Emergence of radically new technologies favors some groups over others

- steam engines (Katz & Margo 2014, Franck & Galor 2015)
- electrification (Goldin & Katz 2008, Chapter 3)
- mass production and its dissolution (Piore & Sabel 1984)
- automation (Autor, Levy & Murnane 2003, Autor 2015, Acemoglu & Restrepo 2017)
- industrial robots (Acemoglu & Restrepo 2019, Dixon, Hong & Wu 2019, Koch, Manuylov & Smolka 2019, Graetz & Michaels 2018, Findeisen, Dauth, Suedekum & Woessner 2018)

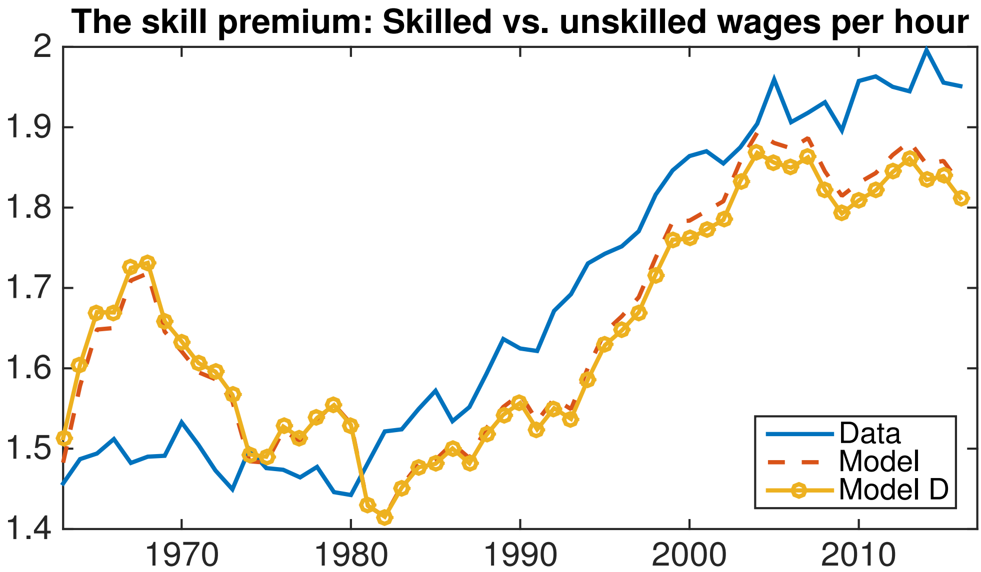
Two challenges to this explanation

1. Inequality increase is pervasive, even within narrow skill and occupation groups.
2. Technical revolutions are rare (in time, across countries).

Another explanation: capital-skill complementarity

Krusell et al (2000): lower relative price of capital goods can quantitatively explain the rise in the skill premium.

Model fits well after 20 more years (Maliar et al 2022)



This paper

1. A novel theoretical mechanism of capital-*quality*-skill complementarity: *incremental* improvement of machine quality differentially affect workers with *similar* skills.
2. Direct micro evidence for this mechanism from Hungarian industry 1988–2003.
3. Access to better machines can explain about half of the increase in within-occupation wage inequality in this period.

Machine-worker productivity across countries and over time

Clark 1987

"In 1910 one New England cotton textile operative performed as much work as 1.5 British, 2.3 German, and nearly 6 Greek, Japanese, Indian, or Chinese workers."

Bessen 2012

"A typical weaver in the United States in 1902 produced over *50 times* as many yards of cloth in an hour of weaving as did a weaver a century earlier producing a comparable cloth. [. . .] The weaver in 1902, however, achieved that output using *eighteen* power-driven looms while the weaver of 1802 used a single handloom."

Sutton 2001

"On technical performance, there was a small but significant quality gap in favour of the imported [rather than Indian] machine."

Outline

An engineering production function

Standard model

$$Y = AF(K, L)$$

What is the shape of F?

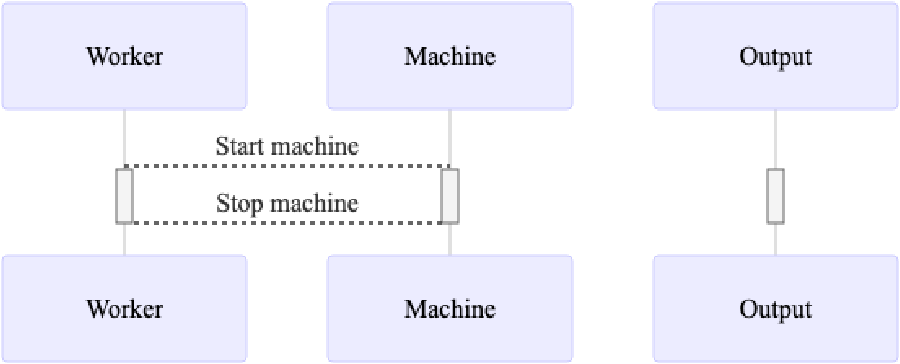
How do machines and people work together?

Tool model A worker feeds material into a metal press (both worker and machine busy) to produce.

Operator model A power loom produces in an autonomous fashion (worker idle), until a problem arises. The operator fixes it (machine idle) to get it back to work as fast as possible.

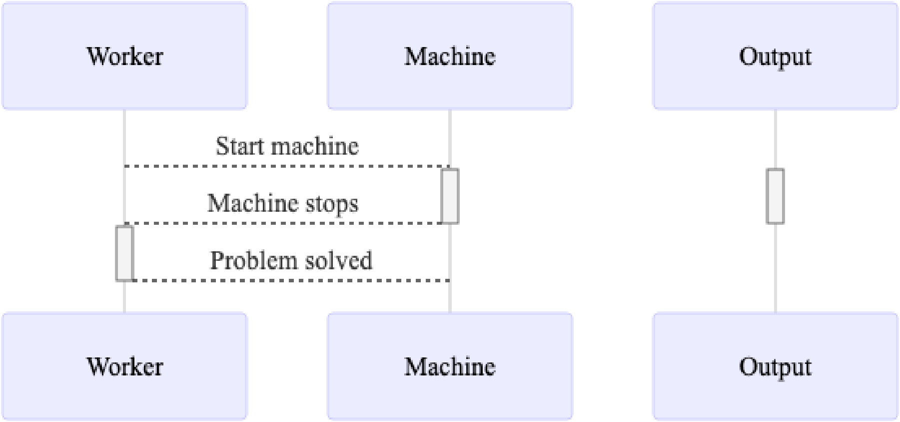
This paper: while the tool model assumes Leontief production, the operator model leads to non-trivial patterns of complementarity.

Tool model



Worker
Machine
Output
Start machine
Stop machine
Worker
Machine
Output

Operator model



Production function

A machine produces A units per time:

$$dY = \begin{cases} A dt & \text{if machine running, } s = 1 \\ 0 & \text{if not, } s = 0 \end{cases}$$

The need for human intervention

Machine breaks down with Poisson arrival $1/\theta$.

Worker fixes it with Poisson arrival h.

Markov chain:

$$\begin{pmatrix} d\pi_1 \\ d\pi_0 \end{pmatrix} = \begin{bmatrix} -1/\theta & h \\ 1/\theta & -h \end{bmatrix} \begin{pmatrix} \pi_1 \\ \pi_0 \end{pmatrix} dt$$

Two measures of quality

machine quality Expected autonomous uptime θ

worker skill Speed of fixing problems h

Ergodic distribution of machine runtime

$$\frac{1}{T}\int_{t=0}^{T} \pi_1(t)dt \approx \pi_1^*.$$

The steady-state probability is the solution to $-\frac{1}{\theta}\pi_1(t) + h[1 - \pi_1(t)] = 0$,

$$\pi_1^* = \frac{\theta h}{1 + \theta h}.$$

Expected output

A worker type h on a machine type (A, θ) produces, in expectation,

$$F(A, \theta, h) = A\pi_1 = A\frac{\theta h}{1 + \theta h}.$$

Are worker skill and machine quality complementary?

For sufficiently autonomous machines, they are **substitutes**

$$\frac{\partial^2 F(A, \theta, h)}{\partial \theta \partial h} < 0$$

iff

$$\frac{\theta h}{1 + \theta h} > 0.5.$$

Intuition: why bother with a good operator on a machine that does not stop frequently?

Are worker skill and machine quality complementary?

But this takes a **fixed number** of machines per worker. Pattern may be different if k can also adjust (Eeckhout and Kircher 2018).

Recall that worker is idle π_1 fraction of the time. She can operate $1/(1-\pi_1) = 1+\theta h$ machines.

At optimal *quantity* of machines

$$(1+\theta h)F(A,\theta,h) = A\theta h,$$

machine quality and worker skill are **complementary**.

1. Good workers can operate more machines (quality-quantity substitution).
2. Good machines have a higher shadow cost of downtime.

Equilibrium assignment of machines and machinists

Equilibrium assignment of machines and machinists

- There are two types of machines with $A_1\theta_1 > A_0\theta_0$ (for now).
- Available in quantity K_1 and K_0.
- Continuum of worker skills in inelastic supply, $h \in \mathbb{R}^+$ with continuous distribution $G(h)$.
- Frictionless capital and labor markets (for now).

Equilibrium

Assignment function $k_m(h) : \{0, 1\} \times H \to \mathbb{R}^+$ capturing machine m per worker h

Wage function $w(h) : H \to \mathbb{R}^+$

Rental rate of capital: R_1 and R_0 such that

1. $$w(h) + k_m(h)R_m \geq k_m(h)A_m\theta_m h$$

   for $m = 0, 1$ and $h \in H$ with equality if $k_m(h) > 0$ (non-positive profits)

2. $$\int_h k_m(h)dG(h) \leq K_m$$

   for $m = 0, 1$ with equality if $R_m > 0$ (machine markets clear)

3. $$\sum_{m=0}^{1} k_m(h)\frac{1}{1 + \theta_m h} \leq 1$$

   for all $h \in H$ with equality if $w(h)$ (labor markets clear)

Solution

Monge-Kantorovich duality

$$w(h) + (1 + \theta_m h)R_m \geq A_m \theta_m h$$

for all h and m, and $=$ if $k_m(h) > 0$

1. Each worker is only assigned to one type of machine: $k_0(h) \cdot k_1(h) = 0$.
2. Machine quantity uses all available worker time: $k_m(h) = 1 + \theta_m h$ if m is assigned to h

Assortative matching

- All skills above some h^* work type-1 machines.
- Equilibrium wage rate:

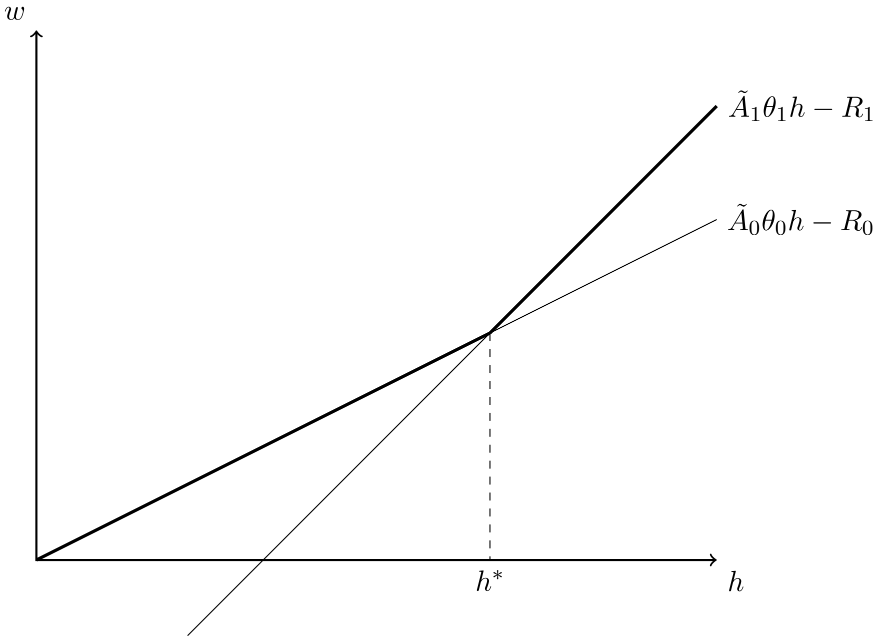
$$w(h) = \begin{cases} (A_1 - R_1)\theta_1 h - R_1 & \text{if } h > h^* \\ (A_0 - R_0)\theta_0 h - R_0 & \text{otherwise} \end{cases}$$

- Equilibrium rental rate such that

$$\int_0^{h^*} (1 + \theta_0 h) dG(h) = K_0$$

$$\int_{h^*}^{\infty} (1 + \theta_1 h) dG(h) = K_1$$

Machine assignment and wage setting by worker skill



A Pareto example

Suppose $G(h) = L[1 - (h/h_0)^{-\alpha}]$.

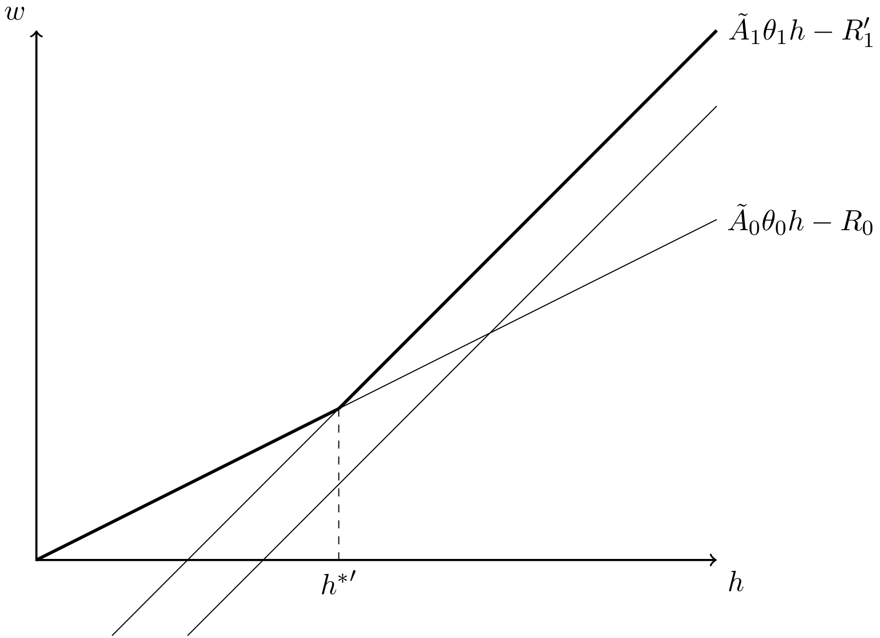
Market clearing for good machines

$$L\left(\frac{h^*}{h_0}\right)^{-\alpha}\left(1 + \frac{\alpha}{\alpha - 1}\theta_1 h^*\right) = K_1$$

pins down h^*.

Comparative statics

When more good machines become available, skilled workers benefit



Cross sectional predictions

1. Conditional on machine productivity, wages increase in worker skill,
2. higher skilled workers are (weakly) more likely to use a good machine,
3. workers using a good machine earn higher wages,
4. the returns to skill are higher on good machines.

Technology upgrading

When K_1/K_0 increases, 1. a larger fraction of operators within the firm uses a good machine, 2. workers switching to a good machine receive a wage increase, 3. the wage of all existing good machine users increases, 4. the returns to skill increase.

A case study of a weaving mill

Data

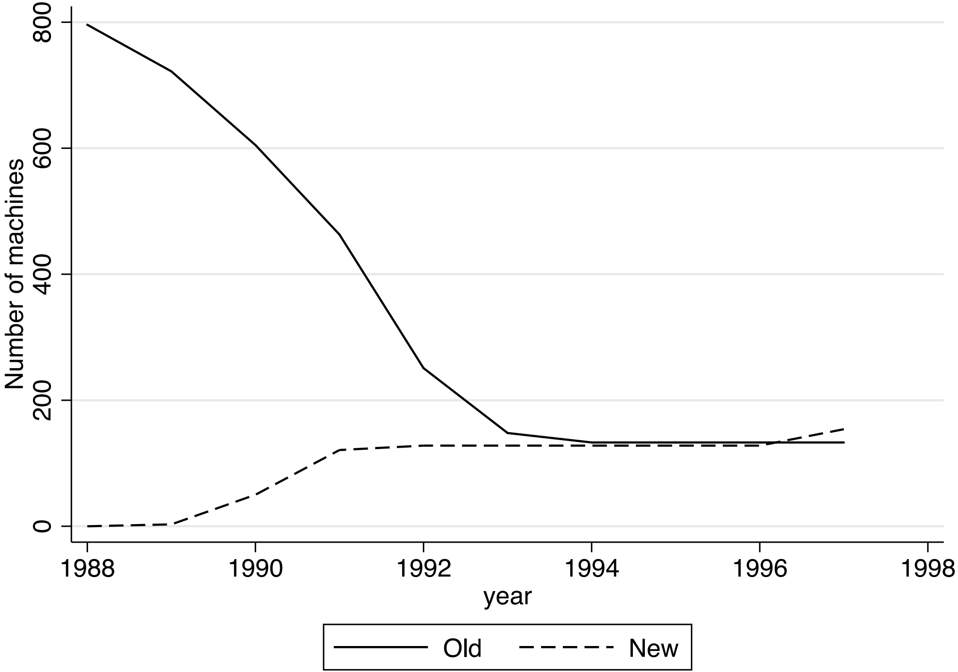
Hungarian cotton weaving mill. Soviet and Czechoslovakian (STB and UTAS) weaving machines, older Swiss-made (shuttle Rüti) looms in 1988. Starting in 1989, purchase modern looms from Switzerland (Rüti F and G) and Japan (Toyota).

Data: machines installed (type, properties, output, downtime). Workers on the floor (age, piece wage, machine assignment).

Show that

1. New machines have shorter downtimes.
2. Better workers are more likely to get a new machine.
3. Wages are higher on new machines.
4. The returns to skill are higher on new machines.

The number of old and new machines, 1988–1997

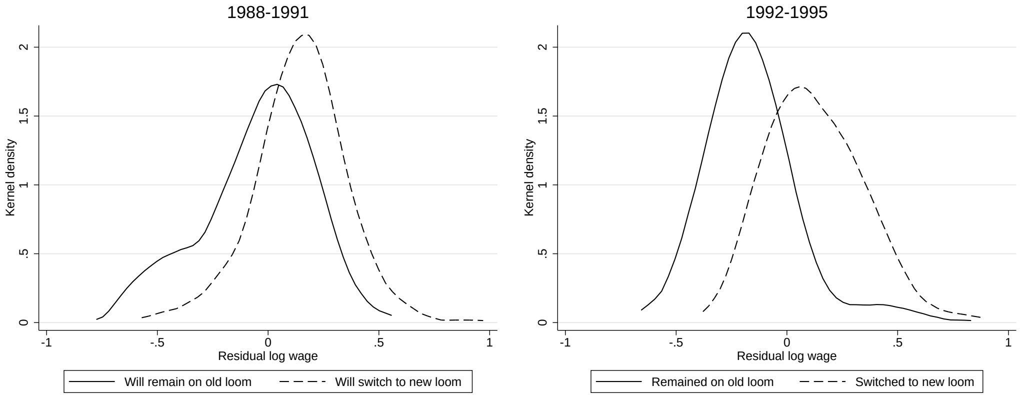


Differences between new and old machines—Regression estimates, 1991–1997

Dependent variable	Mean difference	Mean dep. var.	St. dev. dep. var.
Output (log)	0.820***	5.49	0.475
Potential output (log)	0.790***	5.94	0.449
Potential output/worker (log)	0.811***	3.52	0.845
Output/potential output (log)	0.031*	4.15	0.150
Percent downtime due to			
—scheduled maintenance	−3.20***	2.73	3.30
—troubleshooting	−1.68***	2.22	1.58
—change of warp	1.54**	8.33	5.97
—change of weft	0.940***	2.94	2.99
—other reasons	1.08	4.02	6.90
Total downtime	−0.961	20.38	9.74
Machine/worker	−2.64***	11.32	2.29
Interventions/hour	−1.64	45.26	9.46

Notes: Number of observations: 341 machine-months observed between May 1991 and August 1997.

Wage distribution before and after the adoption of new looms



Estimated kernel density of residual log wages relative to year mean. Bandwidth = 0.1. Left panel includes workers between 1988 and 1991 who do not yet work on a new loom (406 worker-years). Right panel includes workers between 1992 and 1995 (403 worker-years). Sample is limited to workers who appear in both time periods at least once.

Wage gain from moving from an old to a new machine

	(1) OLS	(2) Worker FE
New machine	0.167***	0.060***
	(0.021)	(0.020)
Age	0.075***	0.187***
	(0.007)	(0.021)
Age squared	-0.001***	-0.001***
	(0.000)	(0.000)
Number of observations	1,595	1,595
Number of workers	579	579
R^2	0.818	0.872

Notes: Dependent variable: log hourly wage. Sample: Person-years for continuing workers employed in the plant in 1989. Standard errors, clustered by worker, are reported in parantheses. Coefficients signifiantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

The effect of machine type and worker quality on log output per machine

	(1) Production function
Log number of weavers	0.109***
	(0.029)
New machine	-0.858**
	(0.335)
Log residual wage (as of 1989) of workers at the machine type	-9.91**
	(4.62)
New machine $\times$ log residual wage	38.53***
	(7.55)
Number of observations	261
R^2	0.733

Notes: Dependent variable: log output per machine. Sample: machine-months for five types of loom. Estimation: OLS.

Imported machines and wages in Hungary

Show that

1. Better workers are more likely to get an imported machine.
2. Wages are higher on imported machines.
3. The returns to skill are higher on imported machines.

Data

1. Linked employer-employee data (Bértarifa)
   - limit to machine operator occupations in industry (narrow skills)
   - drop firms with < 20 employees
   - repeated random sample of 6 percent (not a panel)
2. Hungarian Customs Statistics, 1992–2003
   - all *direct* exports and imports
   - detailed by product (HS6): specific machines

Compare operators of imported machine to other operators at the same firm.

Machine operator occupations

FEOR code	Description
8131	Petroleum refinery and processing machine operators
8133	Basic chemicals and chemical products machine operators
8149	Building materials industry machine operators not elsewhere classified
8199	Processing machine operators, production line workers not elsewhere classified
8219	Mining-plant operators not elsewhere classified
8221	Power-production and transformation plant mechanics and operators
8222	Coal- or oil-fired power-generating plant operators
8223	Nuclear-fuelled power-generating plant operators
8224	Hydroelectric power-generating station mechanics and machine operators
8229	Power production and related plant operators not elsewhere classified
8231	Water works machine operators
8232	Sewage plant operators
8240	Packaging machine operators
8293	Agricultural machine operators, mechanics
8299	Other non manufacturing machine operators not elsewhere classified
8311	Agricultural engine drivers and operators
8319	Agricultural and forestry mobile-plant drivers, operators not elsewhere classified

Wage inequality over time

Year	High-school premium	90/10 inequality
1992	0.168	0.978
1993	0.161	1.02
1994	0.178	1.01
1995	0.167	1.01
1996	0.180	1.06
1997	0.184	1.15
1998	0.184	1.16
1999	0.206	1.15
2000	0.205	1.17

Notes: Table displays the wage gap between various groups of workers over time. The second column shows the wage difference (in log points) associated with a high-school degree (relative to primary school and vocational school), controlling worker gender, age and occupation. The third column shows the log point difference between the 90th and 10th percentile of the within-occupation wage distribution.

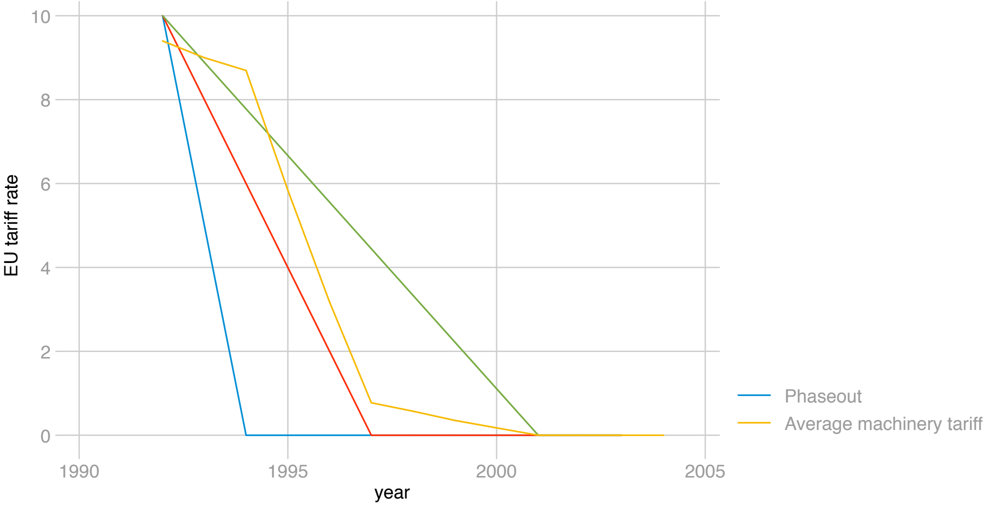
Imported machines became more prevalent

Imported machines became more prevalent

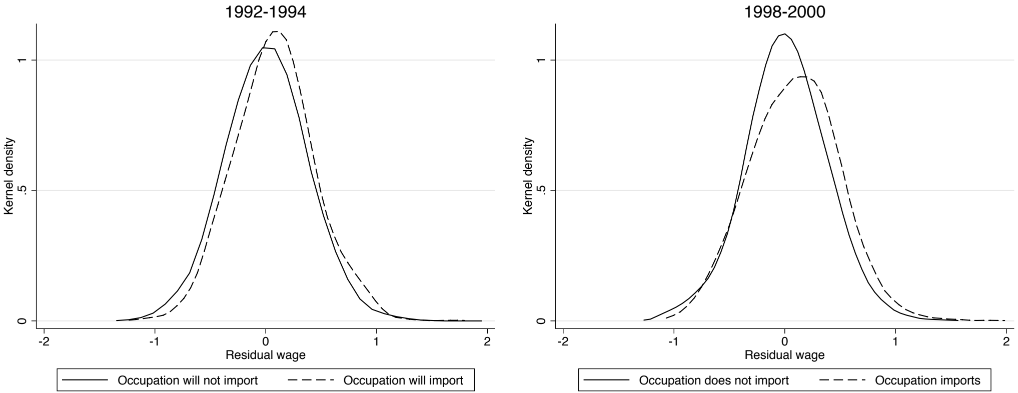
Year	Workers	Firms	Fraction importing (percent)	Import exposure (percent)
1992	10,853	1,823	35.27	16.57
1993	14,185	2,541	40.10	22.73
1994	14,695	2,773	39.07	27.26
1995	15,750	2,902	44.16	30.88
1996	15,419	2,775	48.74	34.35
1997	13,668	2,676	52.91	37.25
1998	15,239	2,754	55.22	40.04
1999	14,418	2,834	56.84	41.65
2000	14,805	2,966	55.89	43.44
2001	14,528	2,874	57.59	45.14
2002	15,907	2,345	53.40	45.99
2003	15,185	2,223	52.33	46.66
2004	15,261	2,281	49.86	46.66

Notes: "Fraction importing" denotes the fraction of workers in the sample in importer occupations and importer firms ($\chi_{jot} = 1$). "Import exposure" is defined on a balanced sample of firm-occupations and denotes the same importer fraction in this balanced sample.

Interim Agreement with EEA (1991) phased out tariffs



High-wage workers are more likely to import



Estimated kernel density of log wages relative to occupation-year mean. Bandwidth = 0.1. Sample includes only firm-occupations cells that have not imported in the early years, but whose firm will import in later years. Left panel includes workers between 1992 and 1994 (5342 worker-years). Right panel includes workers between 1998 and 2000 (7249 worker-ye

Estimation

Estimable equation

$$\ln w_{ijot} = \alpha_{ot} + \nu_{jt} + \gamma_h h_i + \gamma_m m_{jot} + \gamma_{mh} m_{jot} h_i + u_{ijot}$$

- α_{ot} occupation-year fixed effects capture machine prices and worker outside options
- ν_{jt} firm-year fixed effects capture differences in firm productivity and organization
- h_i worker i completed high school (dummy)
- m_{jot} occupation o at firm j has an imported machine by time t (dummy)

We expect $\gamma_m > 0$ and $\gamma_{mh} > 0$.

Identification

High-wage workers are more likely to receive new machines even within the same firm.

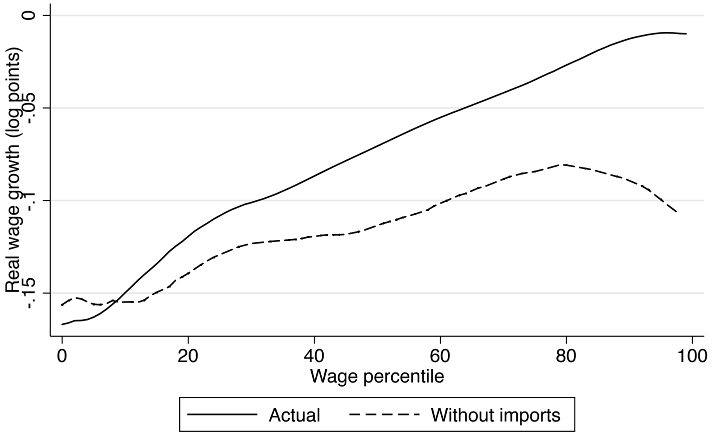
Instrument firm-occupation machine import with a Bartik instrument: aggregate Hungarian imports interacted by firm's share in that occupation.

The effect of import exposure on wages

	(1) OLS	(2) OLS	(3) IV	(4) IV
Importer firm-occupation (dummy)	0.028***	0.024***	0.093**	0.080*
	(0.007)	(0.007)	(0.046)	(0.045)
High school diploma (dummy)	0.089***	0.073***	0.089***	0.026**
	(0.007)	(0.007)	(0.007)	(0.013)
High school diploma at importer firm-occupation (dummy)		0.027***		0.105***
		(0.009)		(0.026)
R^2	0.771	0.771	0.087	0.085
Number of observations	184,048	184,048	183,714	183,714
F-test for 1st stage				

Notes: The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation-year and firm-year fixed effects. Worker controls include indicators for gender and schooling and a quadratic function of worker age. In columns 3 and 4, the importer dummy is instrumented by shift-share instruments, as explained in the main text. Standard errors, clustered by firm, are reported in parantheses. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

Actual and counterfactual wage change by wage percentile



Notes: Nonparametric estimates of log wage change between two periods by percentile of the wage distribution. Early period is 1992-1994 (15,205 worker-years), late period is 1998-2000 (17,475 worker-years). Firm-occupation cells that have already imported by 1994 are excluded. Counterfactua growth computed from firm-occupations cells that never import. Lowess curve with bandwidth of 0.33.

Conclusion

Conclusion

1. New production function to model quality-skill complementarity: relevant for small changes in quality and small differences in skill.
2. Data confirms, within narrow occupations:
   1. Assignment of better workers to better machines
   2. Higher wages on better machines
   3. Higher returns to skill on better machines
3. Mechanism has the potential to quantitatively explain a large fraction of the increase in wage inequality

Appendix

Complementarity and the quality-quantity trade-off

Complementarity and the quality-quantity trade-off

Eeckhout and Kircher (2018) study

$$F(\theta, h, K, L).$$

There is positive assortative matching iff

$$F_{\theta h} \geq \frac{F_{\theta L} F_{hK}}{F_{KL}}.$$

Frictional labor markets

Frictional labor markets

- Marginal product of labor:

$$\lambda(h) = (A_m - \mu_m)\theta_m h - \mu_m.$$

- Workers have upward-sloping labor supply curve at each employer (Card et al 2018). (Can be microfounded by a search model.)
- Wages are a weighted average of marginal product and outside option b,

$$w_{ijm} = \beta(A_m - \mu_m)\theta_m h_i - \beta\mu_m + (1-\beta)b, \tag{1}$$

Robustness

Alternative ways of capturing import exposure

	(1) No large occupations	(2) No new hires	(3) Intensive margin
Worker exposed to imported machine (dummy)	0.032***	0.031***	
	(0.006)	(0.007)	
Specific import per worker (1st quartile)			0.002
			(0.015)
Specific import per worker (2nd quartile)			0.037***
			(0.009)
Specific import per worker (3rd quartile)			0.044***
			(0.009)
Specific import per worker (4th quartile)			0.046***
			(0.009)
R^2	0.770	0.772	0.771
Number of observations	151,029	161,512	184,048

Notes: The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation-year and firm-year fixed effects, indicators for

Robustness to various firm controls

	(1) No firm controls	(2) Capital stock	(3) Vintage	(4) Full controls
Importer occupation	0.163***	0.084***	0.083***	0.049***
at importer firm (dummy)	(0.015)	(0.010)	(0.010)	(0.010)
Importer firm	0.170***	0.027***	0.027***	0.012
(dummy)	(0.012)	(0.010)	(0.010)	(0.010)
Book value of machinery		0.074***	0.074***	0.069***
(log)		(0.003)	(0.003)	(0.005)
Equipment bought 2–5			-0.054***	-0.042***
years ago (share)			(0.012)	(0.012)
Equipment bought 6 or			0.082**	0.067*
more years ago (share)			(0.032)	(0.037)
Firm is foreign owned				0.153***
(dummy)				(0.013)
R^2	0.381	0.459	0.460	0.479
Number of observations	172,212	172,212	172,212	172,212

Patterns of capital imports

Data

- Hungarian Customs Statistics, 1992–2003
  - all *direct* exporter and importer
  - detailed by product (HS6): capital goods
  - and country of origin
- Balance Sheet and Earnings Statement
  - revenue, employment, material cost
  - capital: book value of equipment

Stocks and flows

- Imports are flows, equipment value is stock.
- Gross investment *flow*:

$$\hat{I}_{it} = K_{it} - (1 - \delta_{it})K_{i,t-1}$$

  with $\hat{I}_{it} = \hat{I}^D_{it} + I^F_{it}$
- Imported equipment *stock*:

$$\hat{K}^F_{it} = (1 - \hat{\delta}_{it})\hat{K}^F_{i,t-1} + I^F_{it}$$

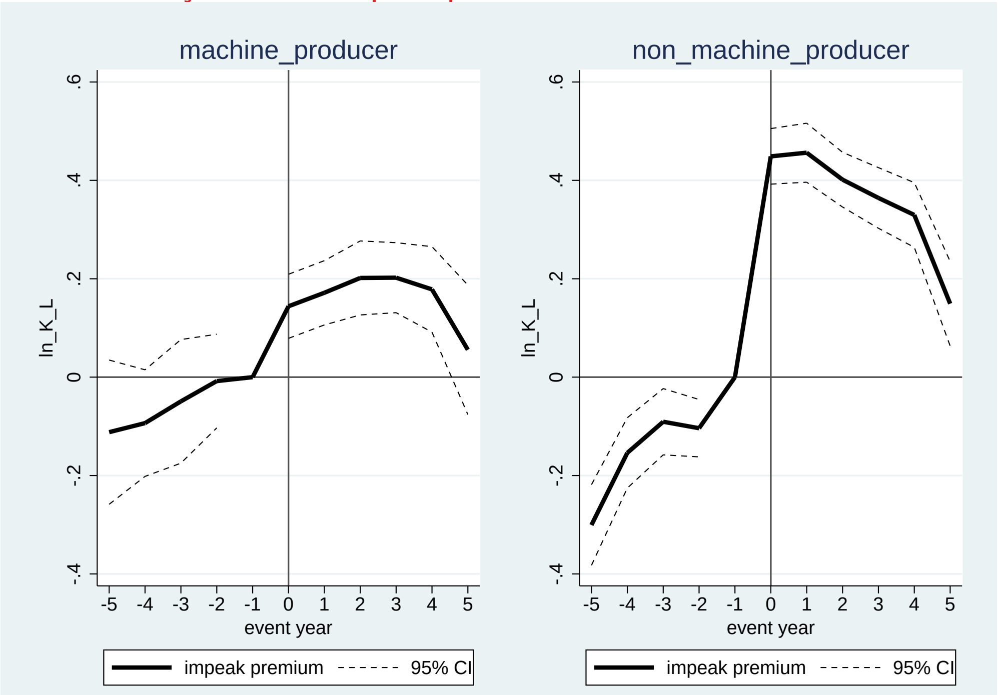
- Complications: what if $I^F_{it} > I_{it}$?

Distribution of investment rates (following Khan and Thomas, 2008)

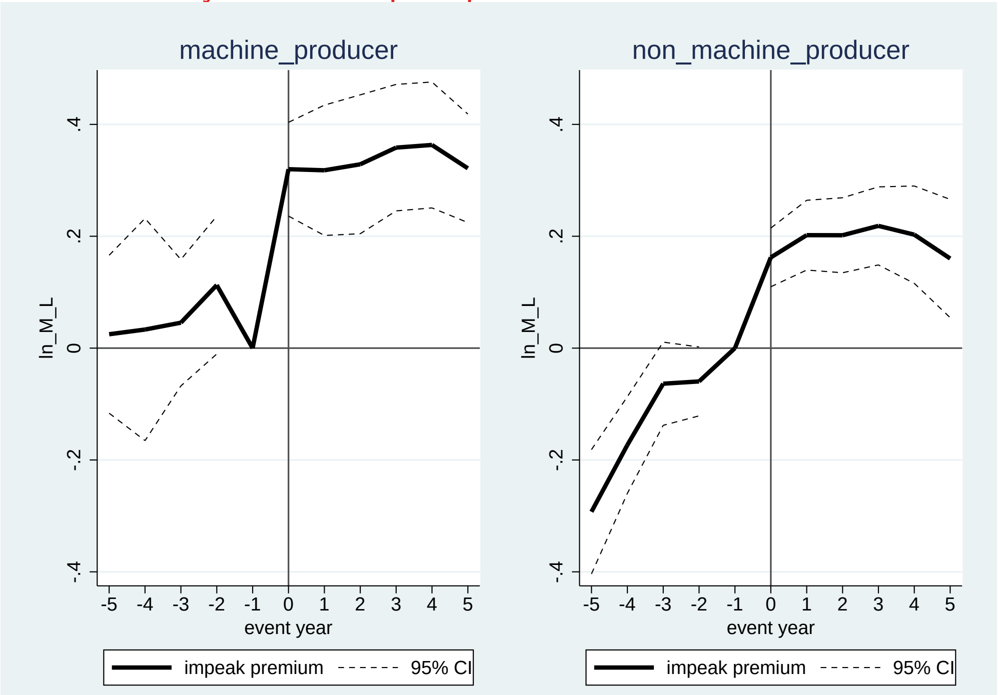
	Manufacturing 10+ employees	Non-machine manuf 10+ employees	Non-machine manuf all firm sizes
Average IR	0.321	0.270	-0.132
Average IR (winsor. 0.01)	0.378	0.335	0.338
Median IR	0.291	0.260	0.247
Inaction (%)	5.9	6.4	13.3
Positive investment (%)	85.9	85.0	77.0
Negative investment (%)	8.1	8.6	9.8
Positive spike (%)	59.9	56.9	54.1
Negative spike (%)	3.7	3.8	5.1
Observations	75,281	57,607	137,508

Notes: Inaction: abs(IR)$<$0.01, Positive spike: IR$>$0.2, Negative spike: IR$<$-0.2.
All samples exclude the first year of firms, where I_t equals K_t by construction.

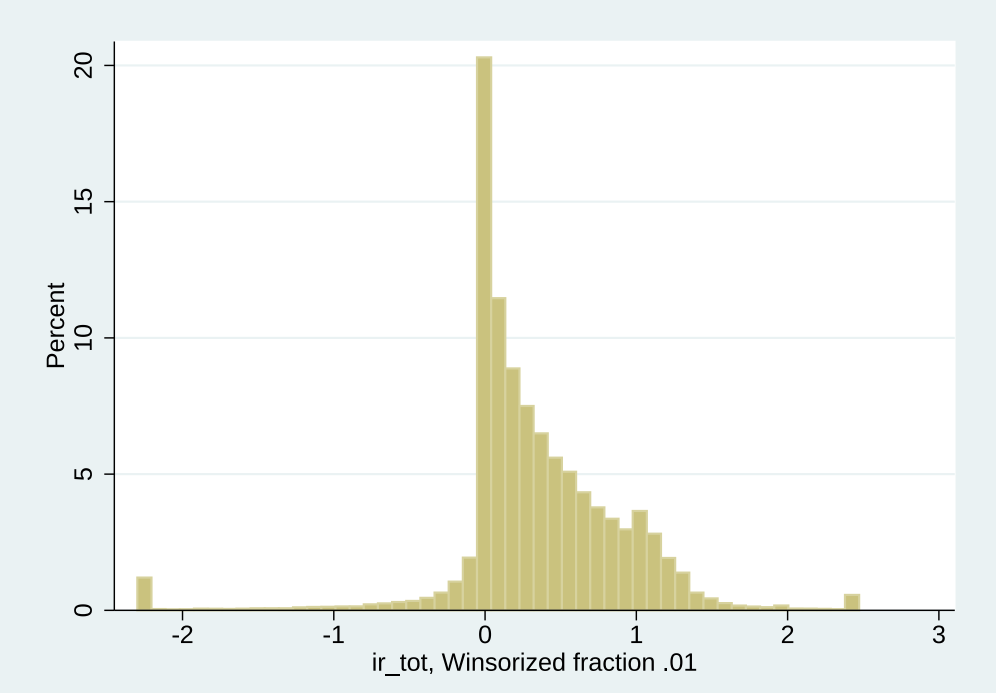
Capital intensity around import peaks



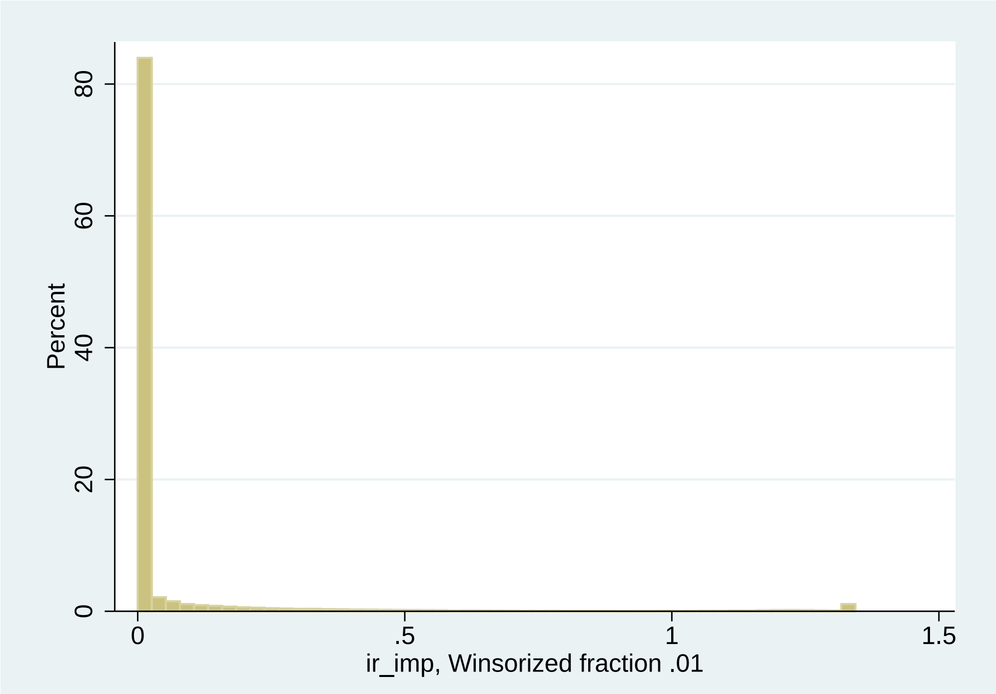
Material intensity around import peaks



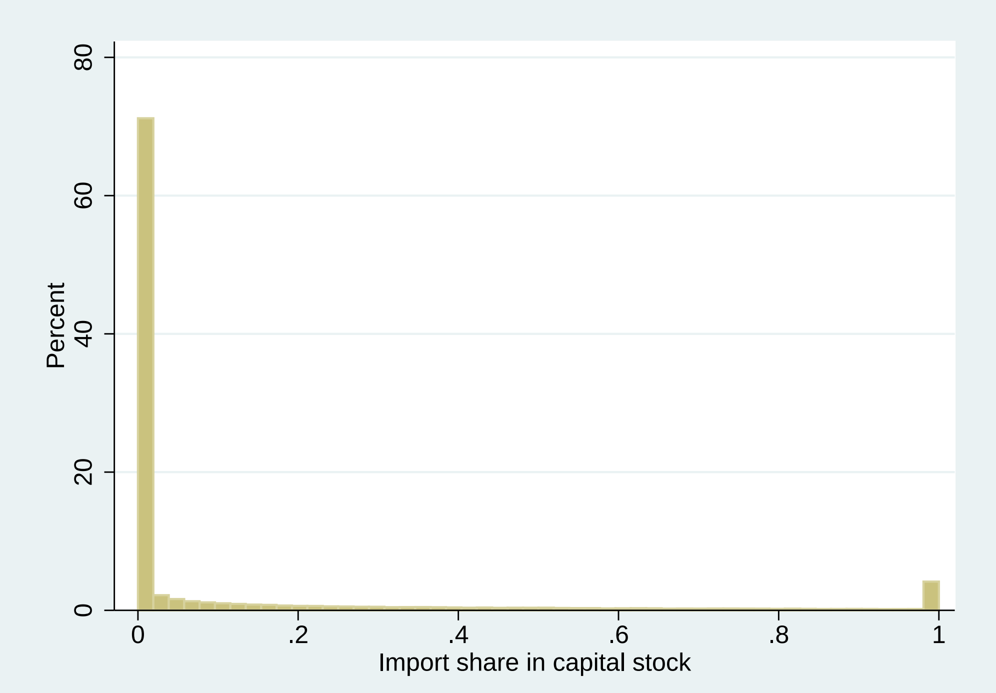
Investment rate distribution



Imported investment rate distribution

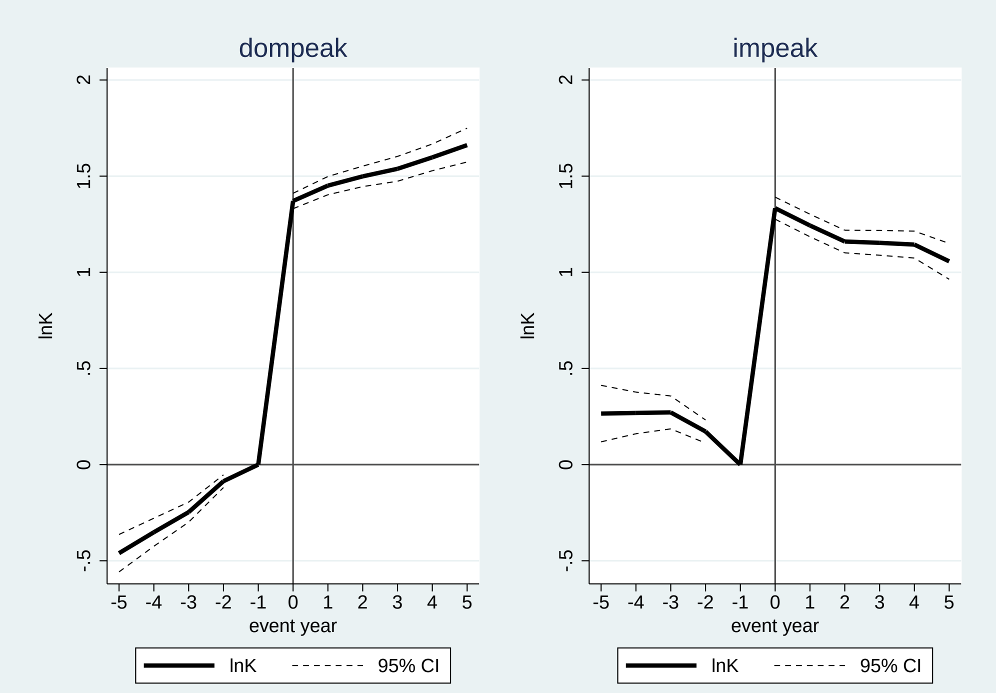


Import share in capital sock

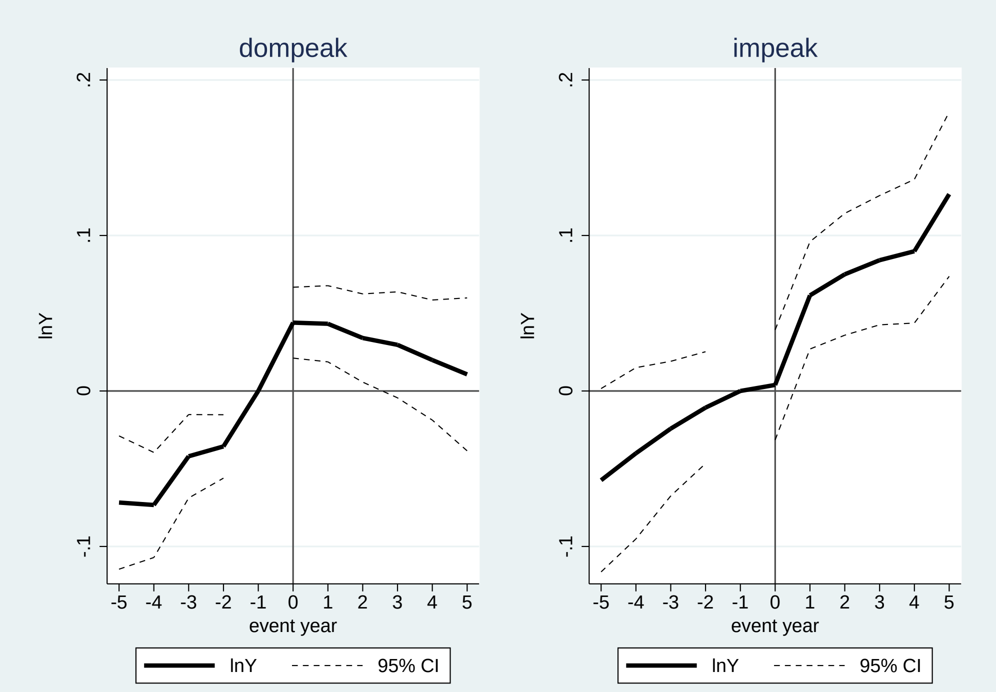


Event studies around large investments

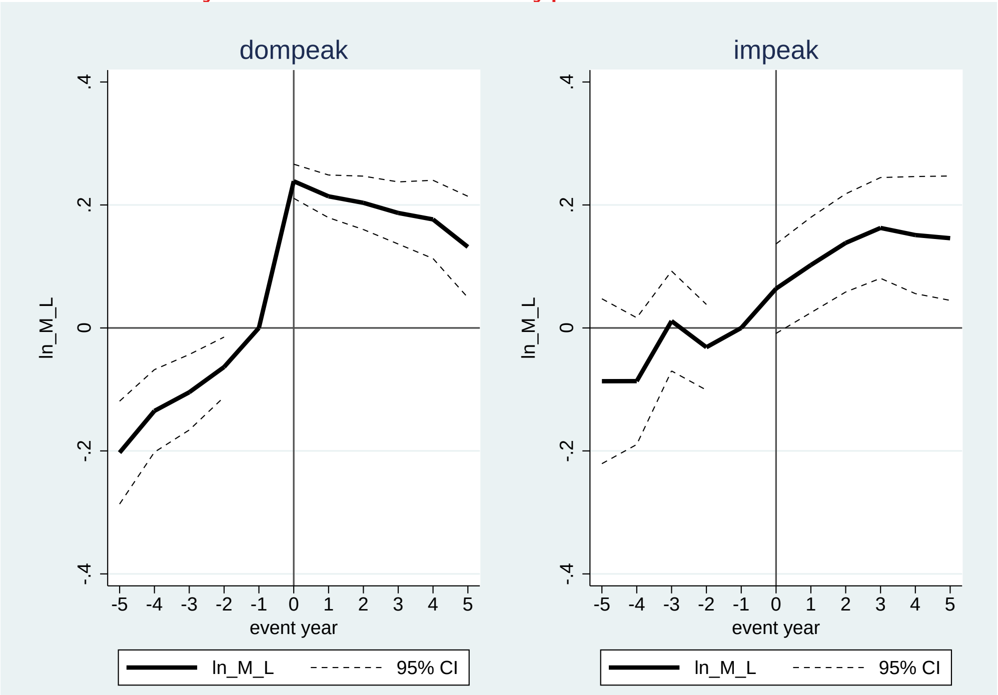
Capital stock increases by same amount (by construction)



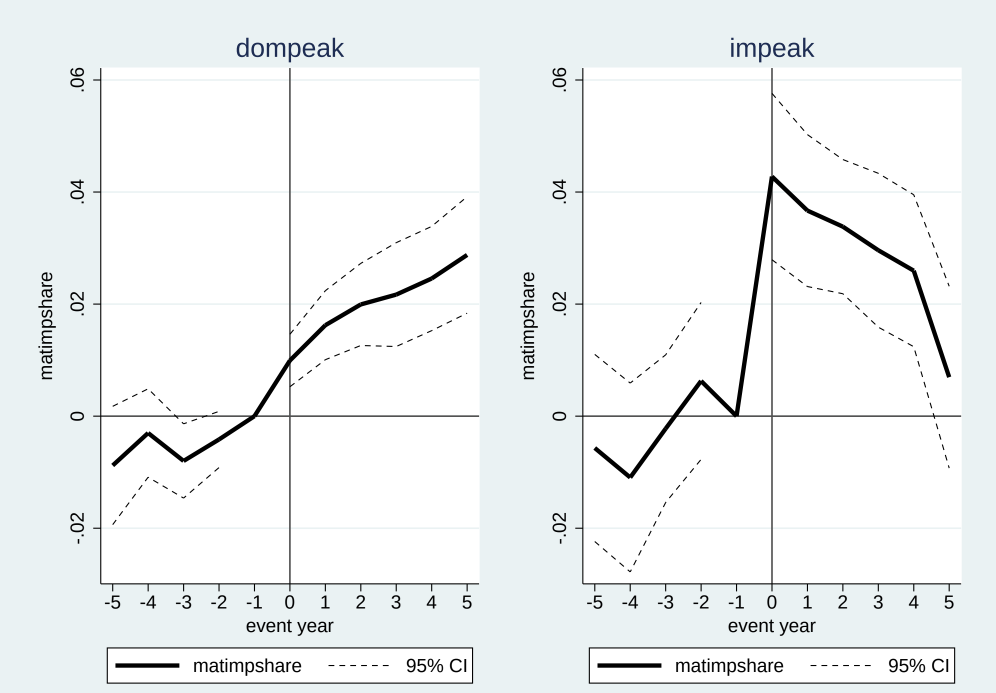
TFP improves more for imported investment



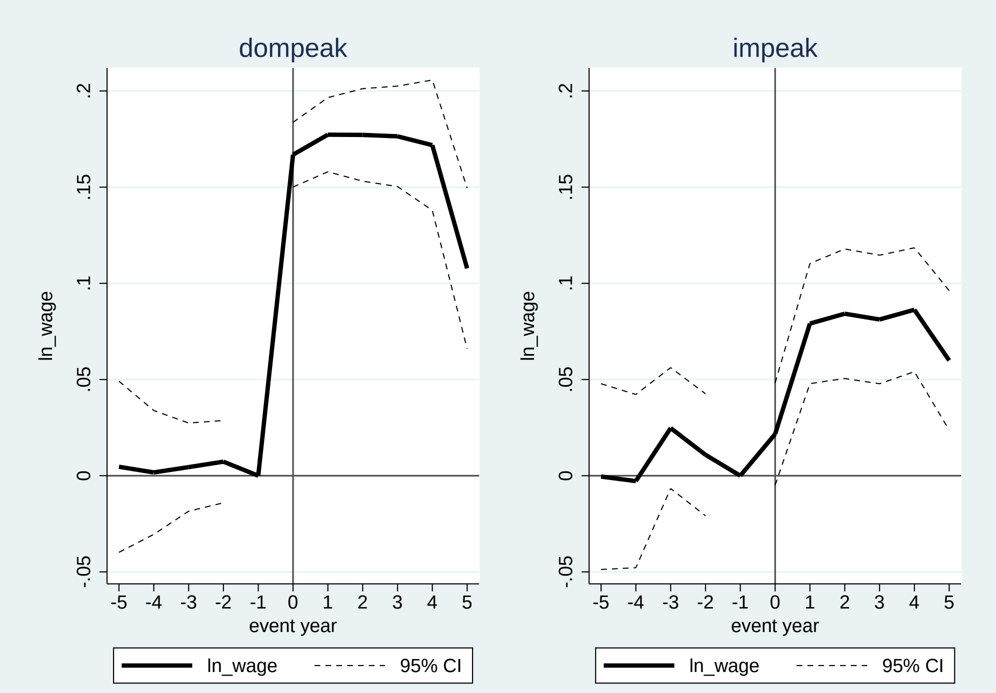
Material intensity increases for both types of investment



Material import intensity jumps more for imported investment



Average wage reacts to domestic investment



Identification

When do firms import?

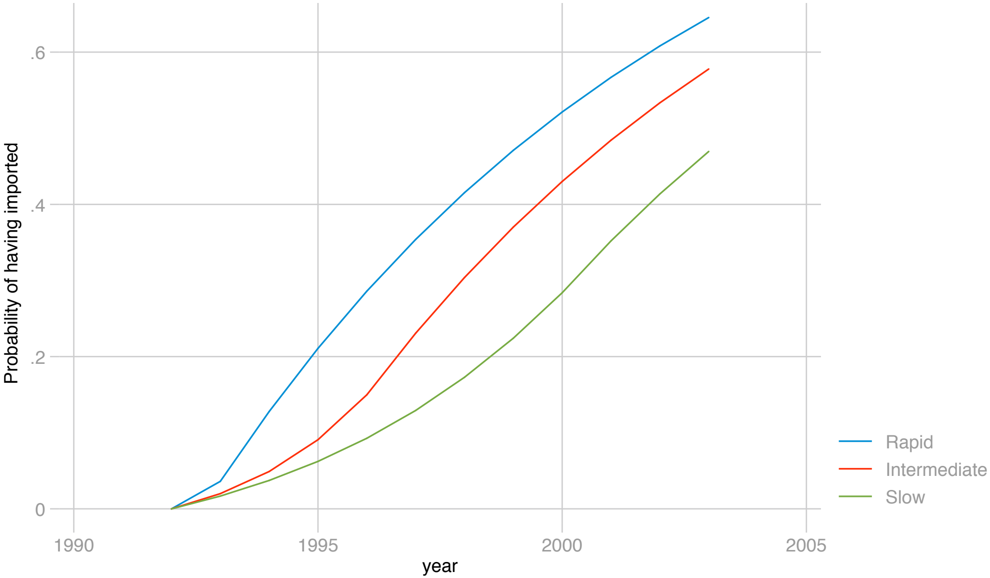
- Lumpy imported investment suggests fixed cost of importing (also see Halpern, Koren and Szeidl, 2015)
- Import if $p_t^F/p_t^D < f(L_{it})$.
- Hazard of *starting to import* (flow):

$$\Pr(K_{it}^F > 0 | K_{i,t-1}^F = 0) = \mu_{st} - \xi \Delta\tau_{st} L_{it}$$

- Probability of *having imported* in the past (stock):

$$\Pr(K_{it}^F > 0) \approx \tilde{\mu}_{st} - \xi L_{it-\mathsf{age}_{it}} \sum_{a=0}^{\mathsf{age}_{it}} \Delta\tau_{st-a}$$

Example of cumulated import hazards



Results

First stage

Depvar: having imported (dummy)	Pooled	Firm FE
cdtariffeu X size 0-10	-0.017***	0.009*
	(0.001)	(0.005)
cdtariffeu X size 10-50	-0.026***	-0.001
	(0.001)	(0.005)
cdtariffeu X size 50+	-0.046***	-0.019***
	(0.002)	(0.005)
lnK	0.048***	0.027***
	(0.002)	(0.001)
lnM	0.018***	0.007***
	(0.001)	(0.001)
lnL	0.008**	0.018***
	(0.003)	(0.003)
foreign (dummy)	0.321***	0.149***
	(0.011)	(0.022)
size dummies	yes	yes
age dummies	yes	yes
industry x year effects	yes	
year effects		yes
Observations	102,516	102,516
R-squared	0.296	0.211
Number of id		17,736
F-test	239.1	91.74

Notes: Robust standard errors (clustered by industry) are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Productivity

Depvar: lnY	Pooled		Firm FE	
	OLS	IV	OLS	IV
having imported (dummy)	0.199***	0.263***	0.086***	0.781***
	(0.015)	(0.075)	(0.012)	(0.112)
lnK	0.132***	0.129***	0.092***	0.073***
	(0.005)	(0.006)	(0.004)	(0.005)
lnM	0.413***	0.412***	0.297***	0.292***
	(0.009)	(0.010)	(0.010)	(0.010)
lnL	0.299***	0.299***	0.364***	0.353***
	(0.010)	(0.010)	(0.010)	(0.010)
foreign (dummy)	0.161***	0.140***	0.091**	-0.033
	(0.023)	(0.034)	(0.043)	(0.047)
size dummies	yes	yes	yes	yes
age dummies	yes	yes	yes	yes
industry x year effects	yes	yes		
year effects			yes	yes
Observations	102,516	102,516	102,516	102,516
R-squared	0.771	0.771	0.545	0.503
Number of id			17,736	17,736

Notes: Robust standard errors (clustered by industry) are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Complementarity

Complementarity

- Are imported machines complementary with other inputs?
- If so, can explain
  - large gaps
  - divergence
- Two ways to measure complementarity (Brynjolfsson and Milgrom, 2013):
  - performance: $f_{xy} > 0$
  - behavior: $\partial x / \partial y > 0$

Imported machines are more material intensive

Depvar: ln M/L	Pooled		Firm FE	
	OLS	IV	OLS	IV
having imported (dummy)	0.542***	0.706***	0.206***	1.218***
	(0.021)	(0.119)	(0.020)	(0.185)
foreign (dummy)	-0.032	-0.091*	0.109	-0.072
	(0.037)	(0.055)	(0.073)	(0.078)
size dummies	yes	yes	yes	yes
age dummies	yes	yes	yes	yes
industry x year effects	yes	yes		
year effects			yes	yes
Observations	102,516	102,516	102,516	102,516
R-squared	0.161	0.159	0.056	0.007
Number of id			17,736	17,736

Notes: Robust standard errors (clustered by industry) are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Imported machines are more *imported* material intensive

Depvar: matimpshare	Pooled		Firm FE	
	OLS	IV	OLS	IV
having imported (dummy)	0.127***	0.110***	0.042***	0.148***
	(0.005)	(0.026)	(0.004)	(0.034)
foreign (dummy)	0.138***	0.144***	0.032**	0.014
	(0.009)	(0.013)	(0.014)	(0.015)
size dummies	yes	yes	yes	yes
age dummies	yes	yes	yes	yes
industry x year effects	yes	yes		
year effects			yes	yes
Observations	102,516	102,516	102,516	102,516
R-squared	0.186	0.186	0.010	-0.023
Number of id			17,736	17,736

Notes: Robust standard errors (clustered by industry) are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Imported machines use higher quality labor

Depvar: ln wage	Pooled		Firm FE	
	OLS	IV	OLS	IV
having imported (dummy)	0.151***	0.586***	0.089***	0.796***
	(0.009)	(0.049)	(0.009)	(0.090)
foreign (dummy)	0.280***	0.125***	0.089**	-0.037
	(0.017)	(0.024)	(0.036)	(0.041)
size dummies	yes	yes	yes	yes
age dummies	yes	yes	yes	yes
industry x year effects	yes	yes		
year effects			yes	yes
Observations	102,516	102,516	102,516	102,516
R-squared	0.463	0.417	0.587	0.523
Number of id			17,736	17,736

Notes: Robust standard errors (clustered by industry) are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$