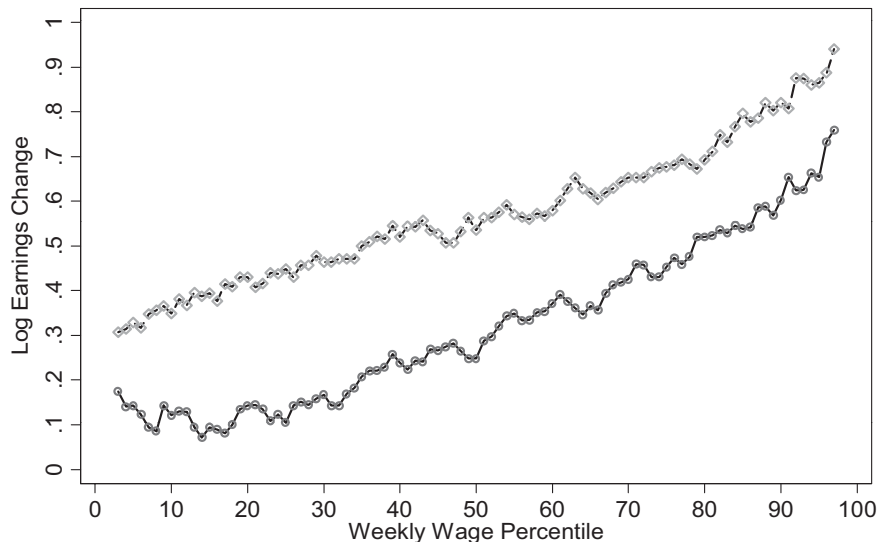# Machines and Machinists: Incremental Technical Change and Wage Inequality

Miklós Koren   Márton Csillag   János Köllő

Motivation

Inequality and polarization in the U.S.

Figure 1.—Change in Log Real Weekly Wage by Percentile, Full-
Time Workers, 1963–2005

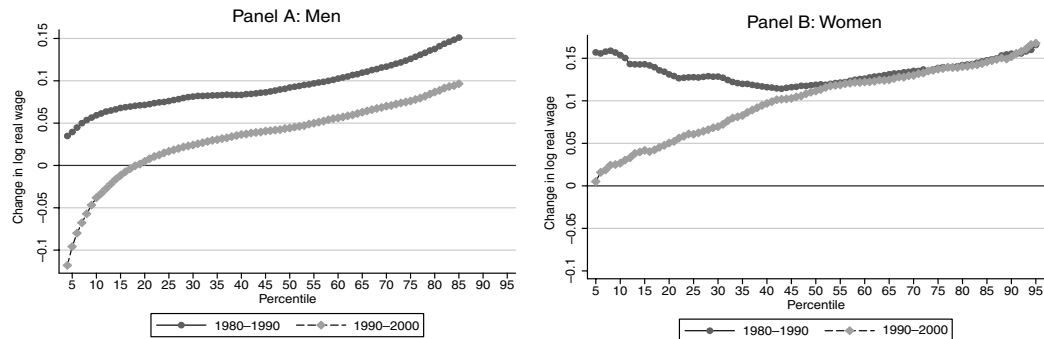# Inequality and polarization in Germany

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 in pervasive, even within well-defined 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

The skill premium: Skilled vs. unskilled wages per hour
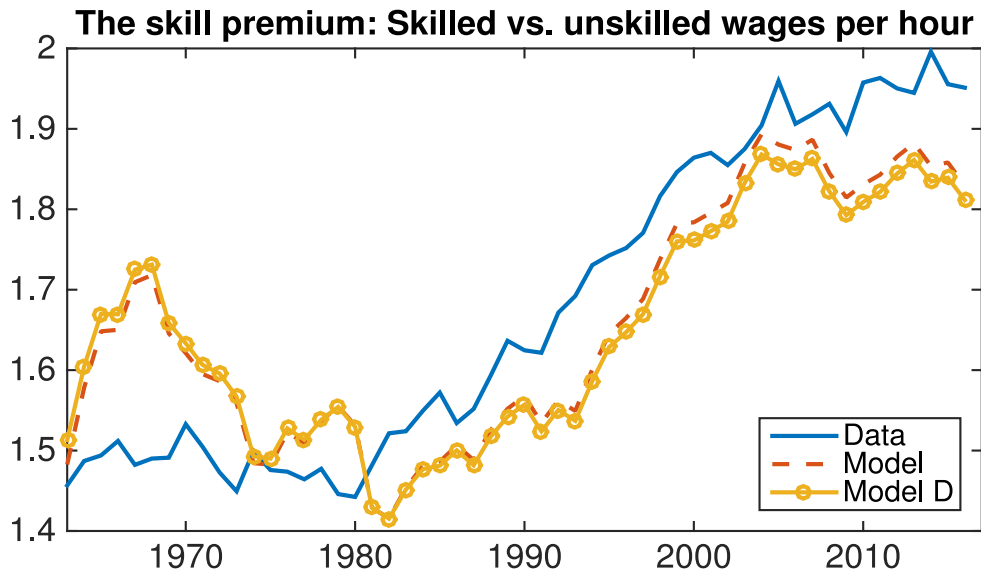
This paper

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.

Weaver 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
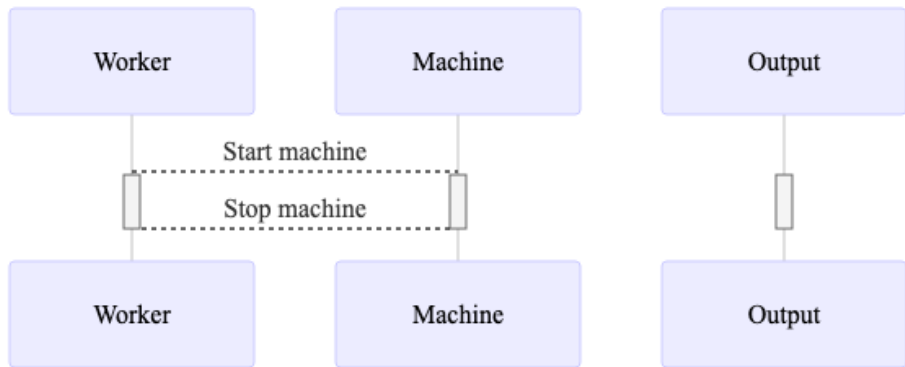
Operator model
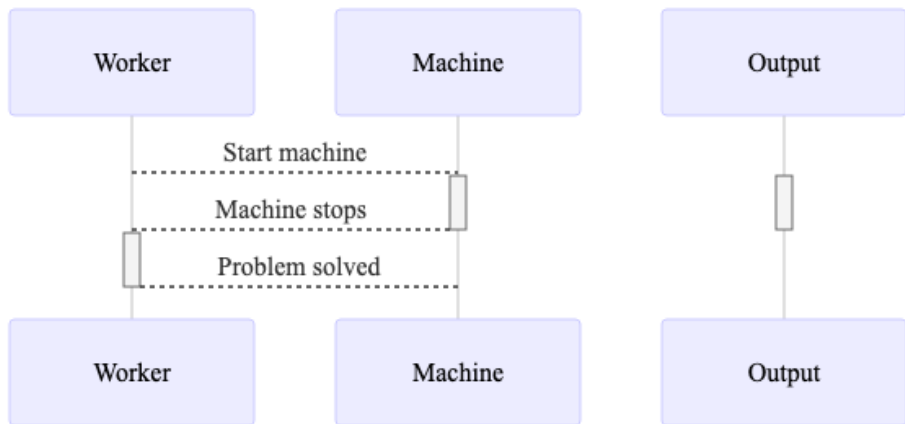
Production function

A machine produces A units per time:

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

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,

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

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**.

Intuition: 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

Monge-Kantorovich duality

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

for all h and m, and $=$ if h uses positive amounts of m
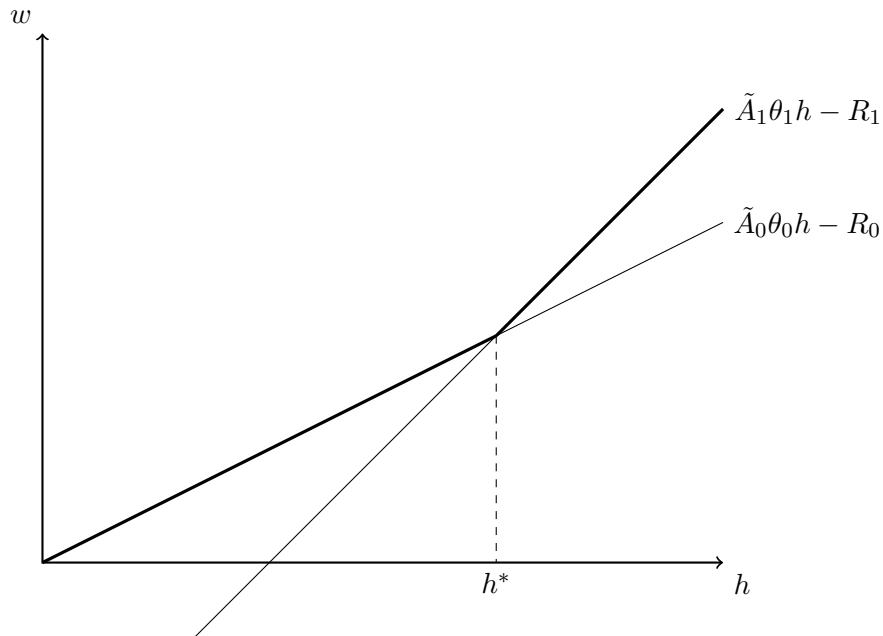
Assortative matching

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

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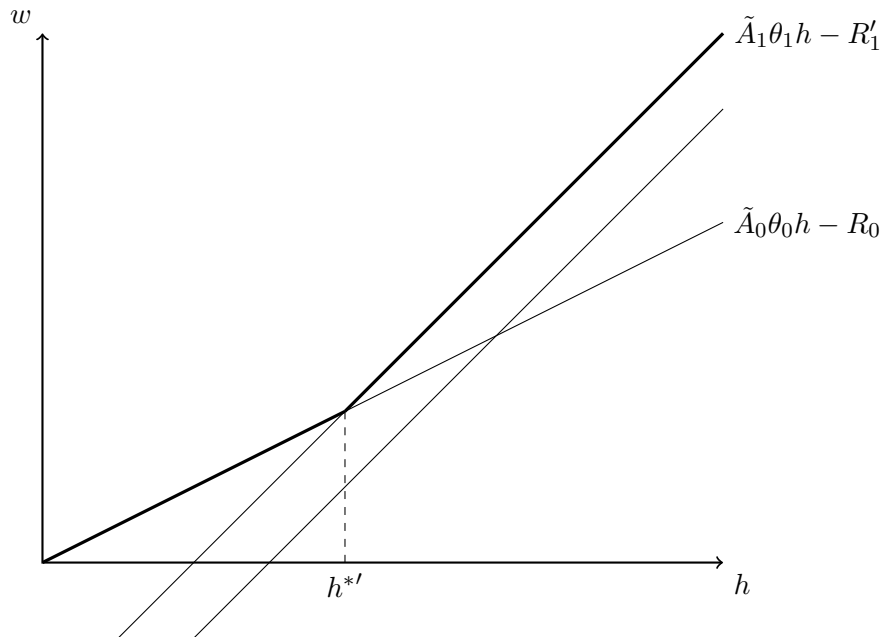
- Equilibrium rental rate such that

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

Machine assignment and wage setting by worker skill

Comparative statics

When more good machines become available, skilled workers benefit

Predictions

Cross sectional patterns

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 R_1/R_0 declines,

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).

# The number of old and new machines, 1988–1997
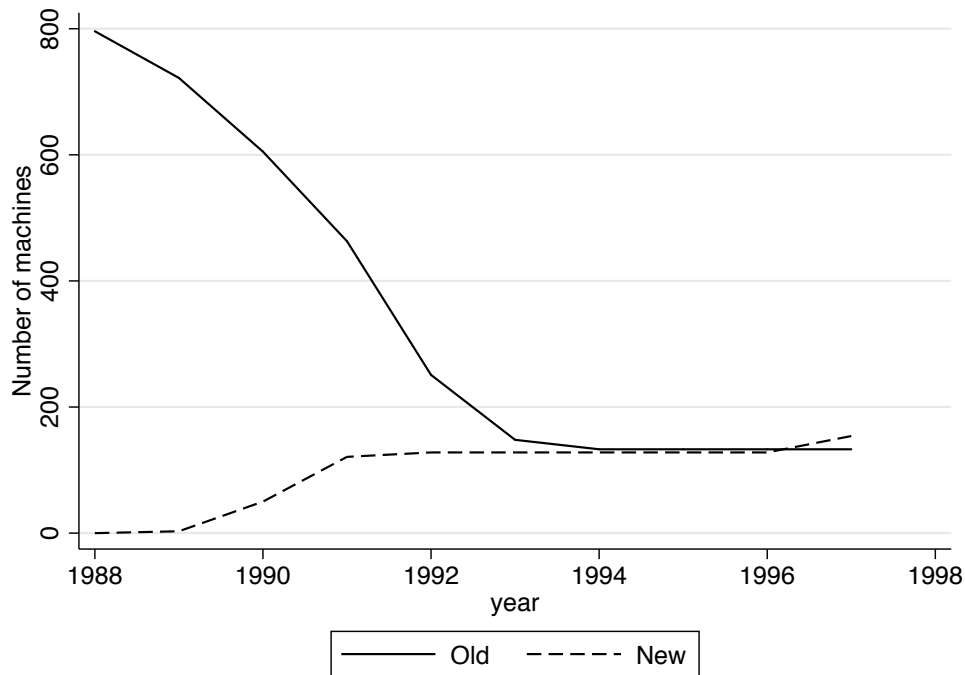
Differences between new and old machines—Regression estimates, 1991–1997

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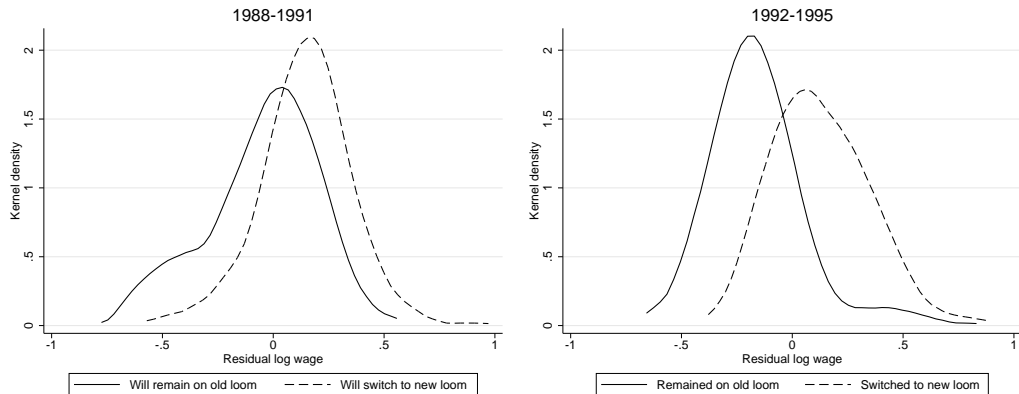
Estimated kernel density of residual log wages relative to year mean. Bandwidth = 0.1. Left panel includes workers between 1988 and 1991 who do not yet work on a new loom (406 worker-years). Right panel includes workers between 1992 and 1995 (403 worker-years). Sample is limited to workers who appear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

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)
2. Customs statistics

Sample

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

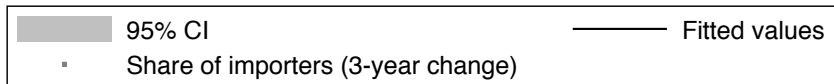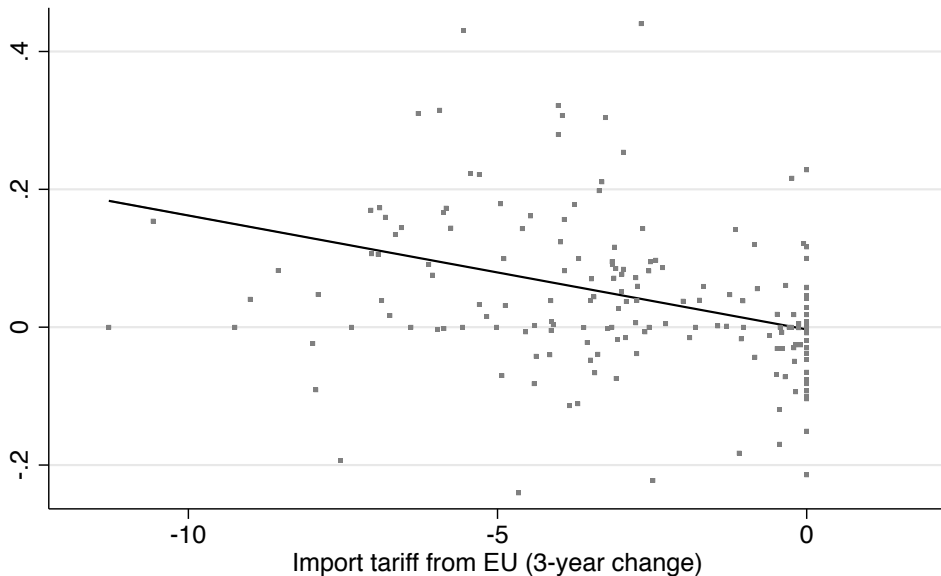| Year	Workers	Firms	Fraction importing (percent)	Import exposure (percent)
1992	10,853	1,823	35.27	16.57
1993	14,185	2,541	40.10	22.73
1994	14,695	2,773	39.07	27.26
1995	15,750	2,902	44.16	30.88
1996	15,419	2,775	48.74	34.35
1997	13,668	2,676	52.91	37.25
1998	15,239	2,754	55.22	40.04
1999	14,418	2,834	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.
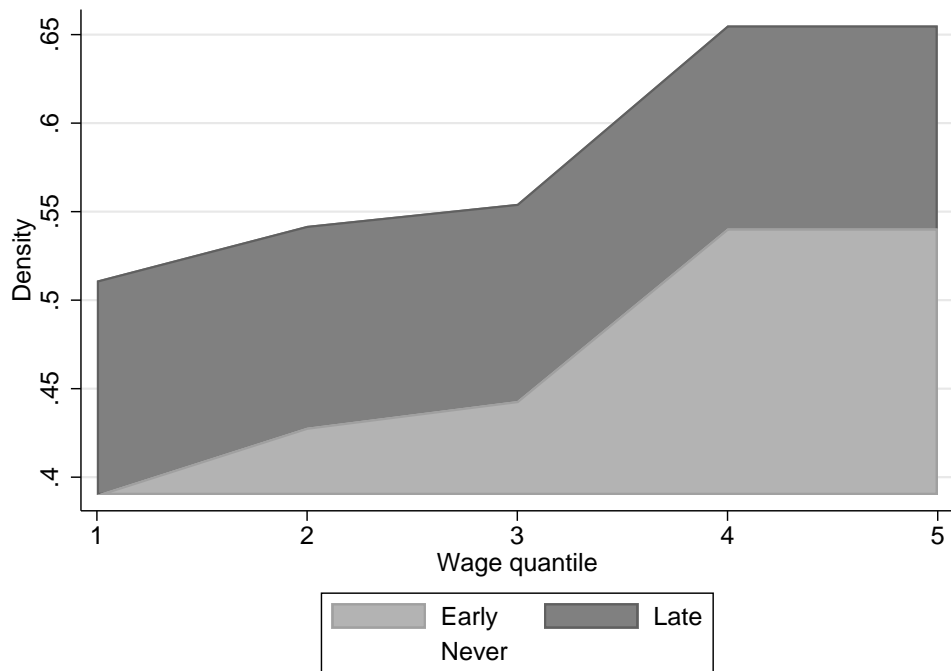
Average machinery tariffs

Year	Tariff on EU imports	Column 2 tariff
1992	9.40	9.70
1993	9.00	9.61
1994	8.69	9.61
1995	5.84	9.23
1996	3.18	9.02
1997	0.774	8.80
1998	0.572	8.56
1999	0.354	8.34
2000	0.176	8.33
2001	0.000	8.31
2002	0.000	8.33
2003	0.000	8.31

Notes: Table reports the unweighted average of tariffs on machinery imports from the European Economic Community (EU, second column), as well as the unweighted average of Column 2 tariffs on machinery (third column). Tariff rates are ad valorem percentages.

Occupations with faster tariff cuts adopt imported machines faster

Import tariff from EU (3-year change)

| 95% CI | Fitted values |
| Share of importers (3-year change) | |

Among high-wage workers, early importers are overrepresented

Estimation

Estimable equation

$$\ln w_{ijot} = \alpha_{ot} + \nu_{jt} + \gamma_h h_i + \gamma_\chi \chi_{jot} + \gamma_{\chi h} \chi_{jot} h_i + u_{ijot}. \tag{2}$$

Creating a Bartik instrument

$$\hat{K}_{jot} = \frac{n_{jot} + n_{jo,t+1}}{\sum_l (n_{jlt} + n_{jl,t+1})} \times K_{jt}. \tag{3}$$

$$\hat{M}_{jot} = \frac{\hat{K}_{jot_0}}{\sum_l \hat{K}_{lot_0}} \times M_{ot}. \tag{4}$$

The effect of import exposure on wages

	(1) OLS	(2) OLS	(3) IV	(4) IV
Importer firm-occupation (dummy)	0.028*** (0.007)	0.024*** (0.007)	0.093** (0.046)	0.080* (0.045)
High school diploma (dummy)	0.089*** (0.007)	0.073*** (0.007)	0.089*** (0.007)	0.026** (0.013)
High school diploma at importer firm-occupation (dummy)		0.027*** (0.009)		0.105*** (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.

Robustness to various firm controls

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

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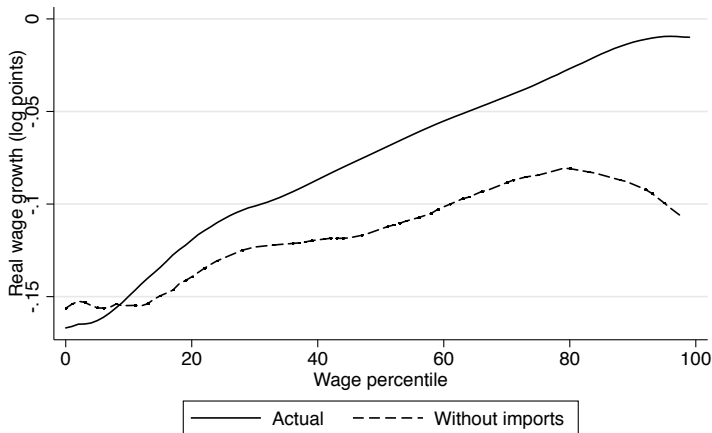
Notes: Nonparametric estimates of log wage change between two periods by percentile of the wage distribution. Early period is 1992-1994 (15,205 worker-years), late period is 1998-2000 (17,475 worker-years). Firm-occupation cells that have already imported by 1994 are excluded. Counterfactual growth computed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

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,

$$w_{ijm} = \beta(A_m - \mu_m)\theta_m h_i - \beta\mu_m + (1-\beta)b, \tag{5}$$

Robustness

Alternative ways of capturing import exposure

	(1) Weighted	(2) No large occupations	(3) $1/N_{fot}$	(4) No new hires	(Inte ma
Worker exposed to imported machine (dummy)	0.040*** (0.006)	0.032*** (0.006)		0.031*** (0.007)	
Worker exposed to imported machine $\times 1/n_{fot}$			0.016* (0.009)		
Specific import per worker (1st quartile)					0.0 (0.
Specific import per worker (2nd quartile)					0.03 (0.
Specific import per worker (3rd quartile)					0.04 (0.
Specific import per worker (4th quartile)					0.04 (0.
R^2	0.774	0.770	0.770	0.772	0.7

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 $\hat{I}_{it} = \hat{I}_{it}^D + I_{it}^F$
- Imported equipment *stock*:

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

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

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.
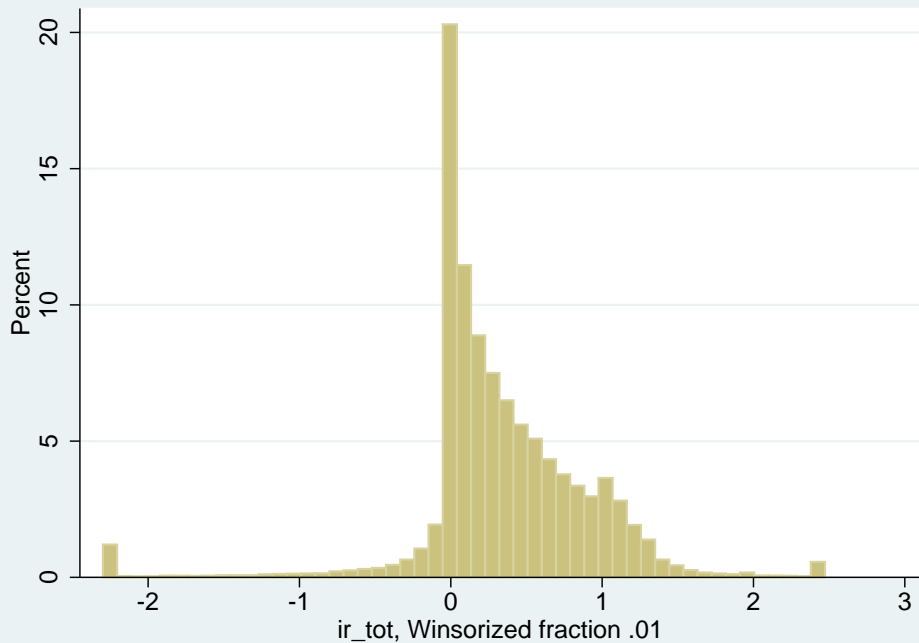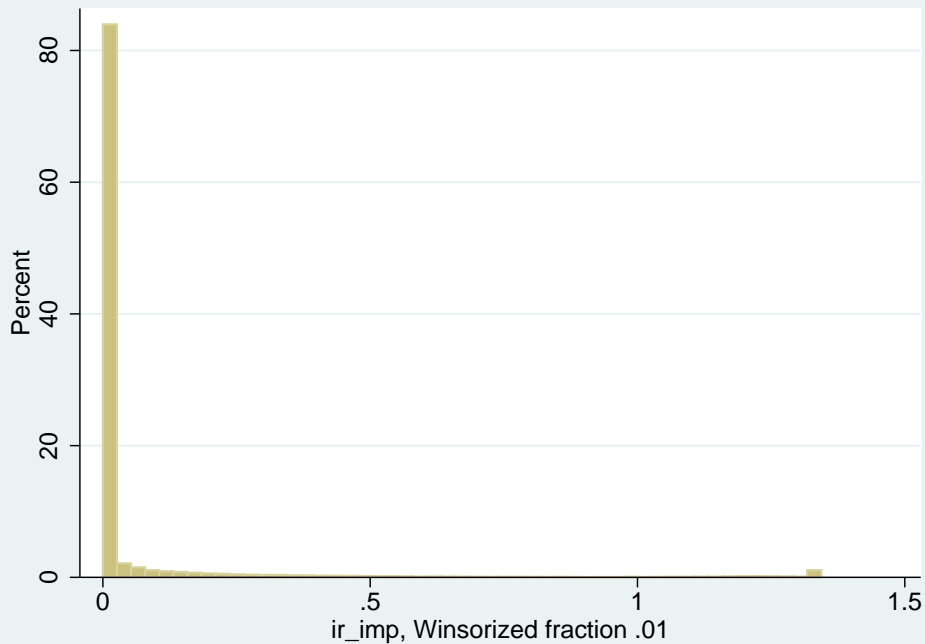
Capital intensity around import peaks
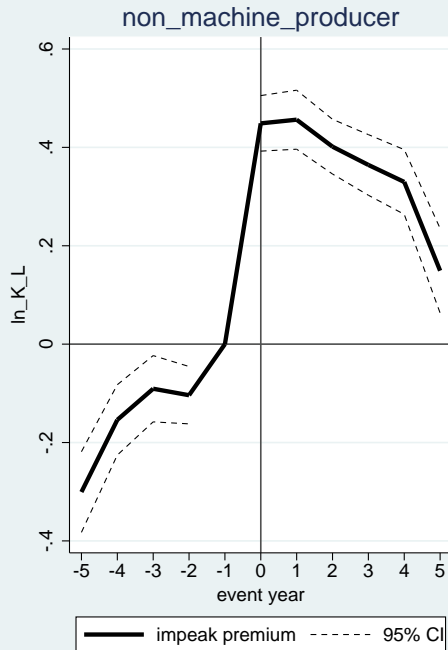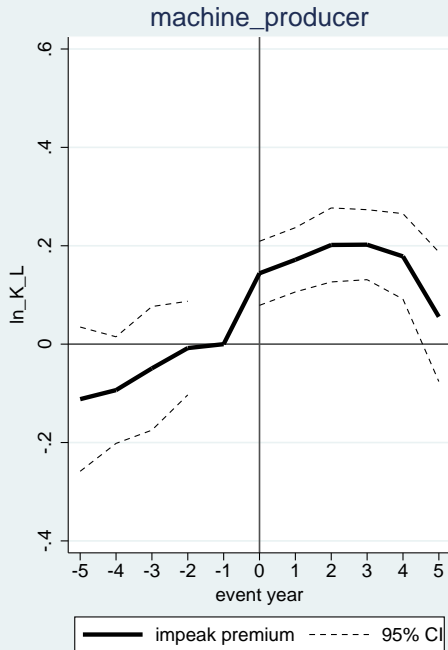
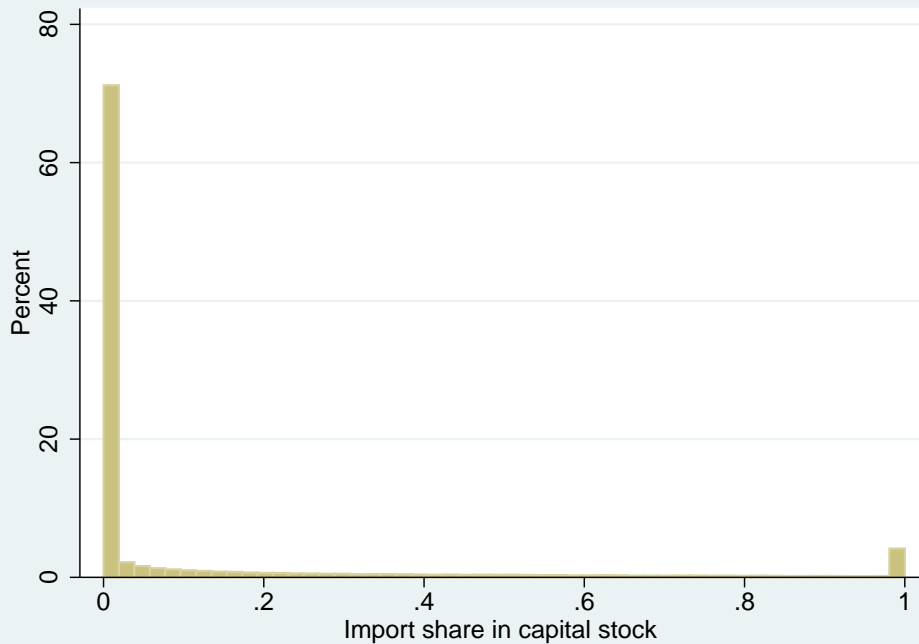# Material intensity around import peaks
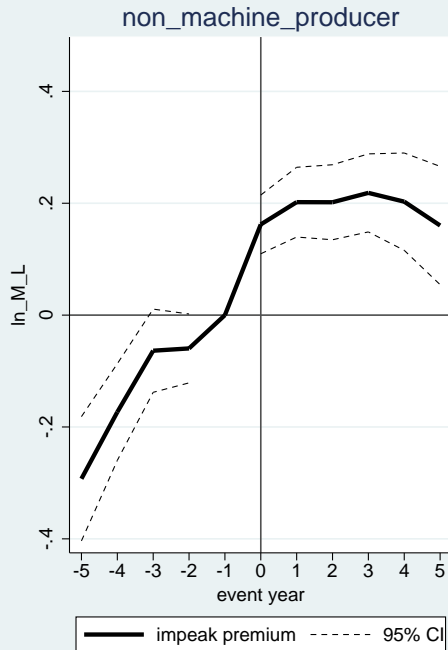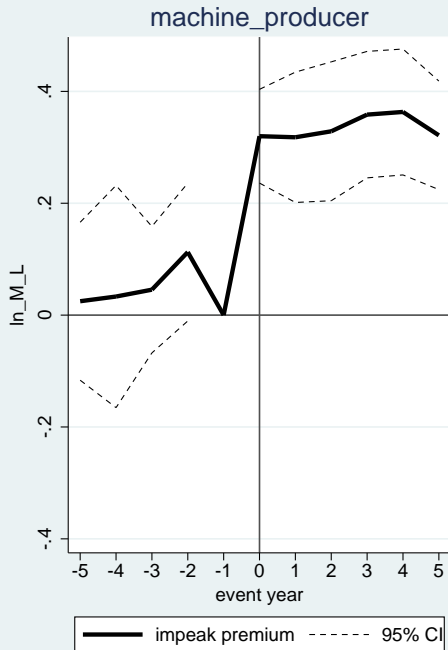
Investment rate distribution
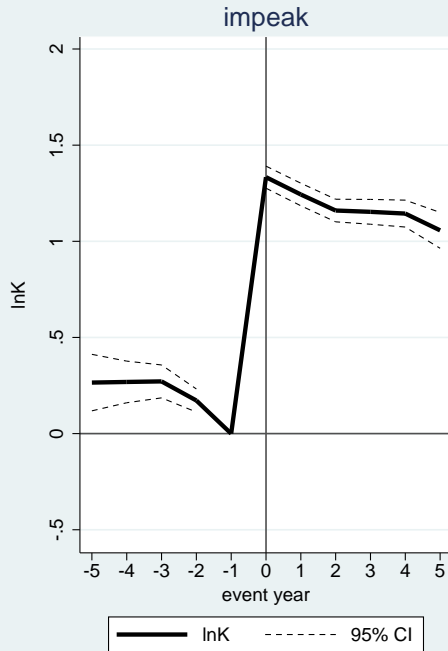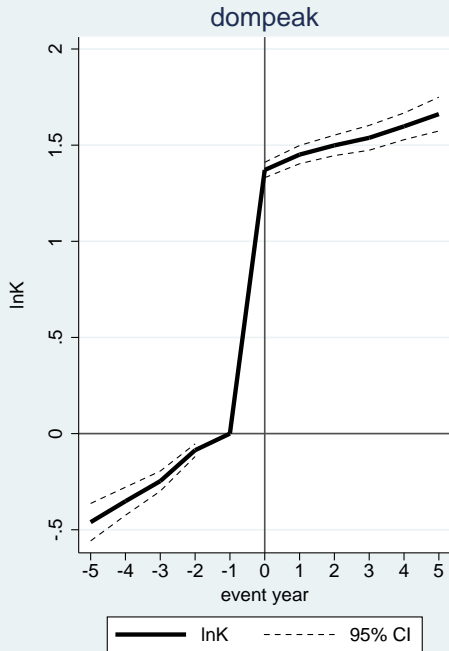
Imported investment rate distribution
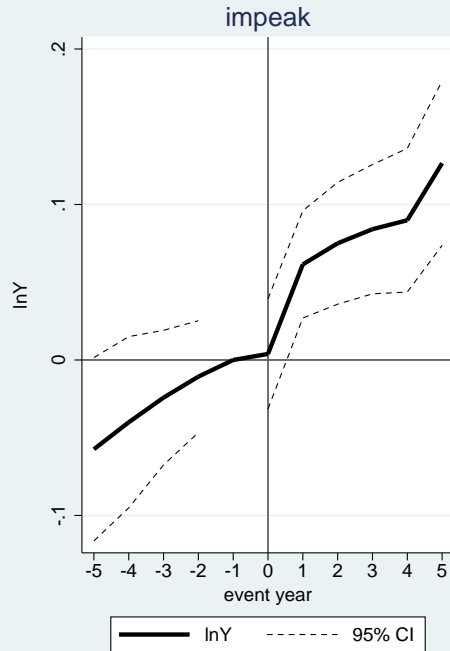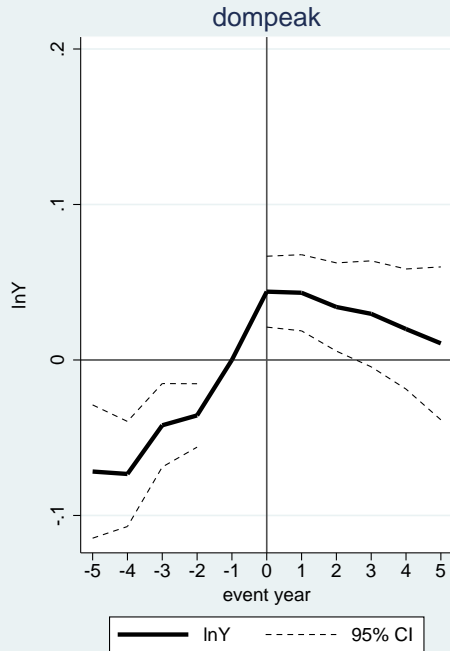
Import share in capital sock
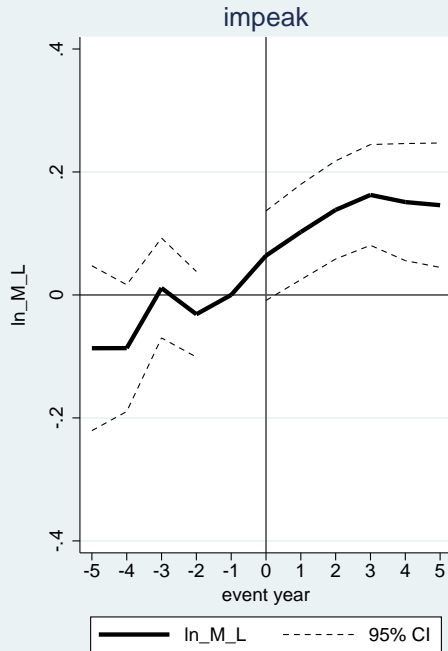
Event studies around large investments

Capital stock increases by same amount (by construction)

TFP improves more for imported investment

Material intensity increases for both types of investment
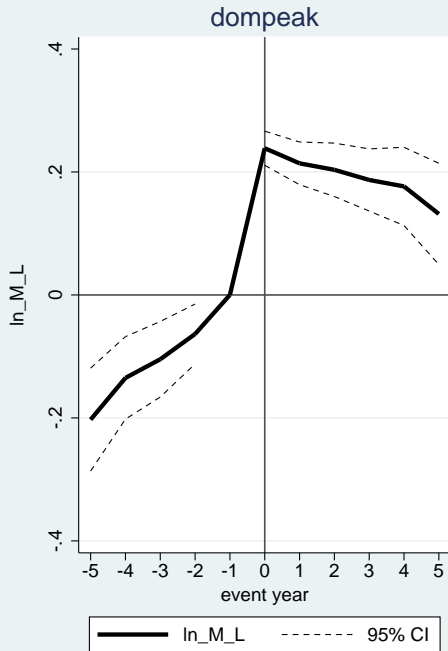
Material import intensity jumps more for imported investment
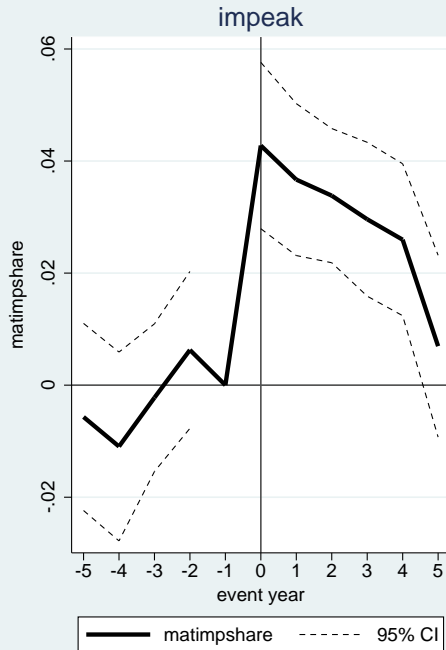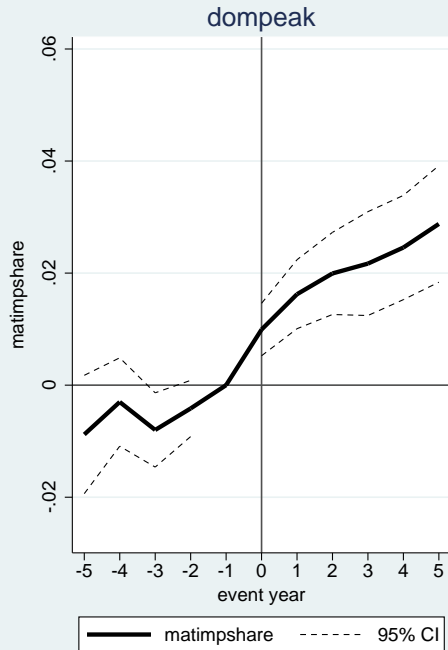
Average wage reacts to domestic investment
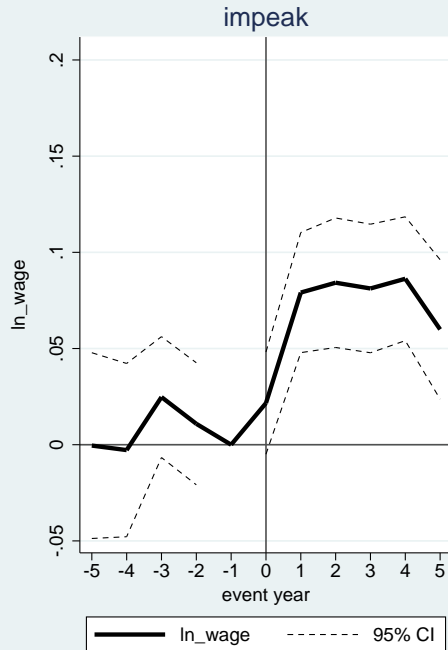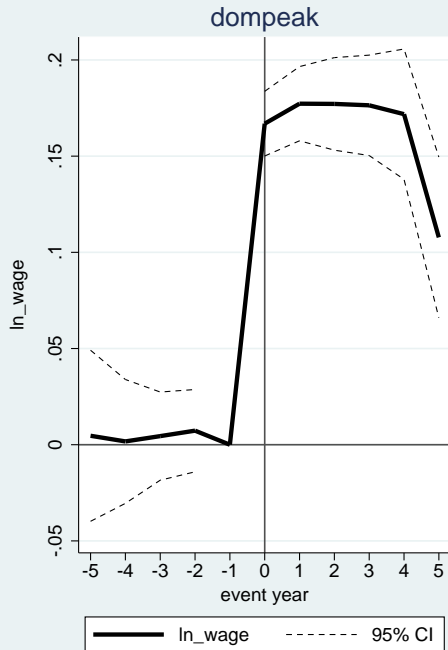
Identification

Interim Agreement with EEA (1991) phased out tariffs
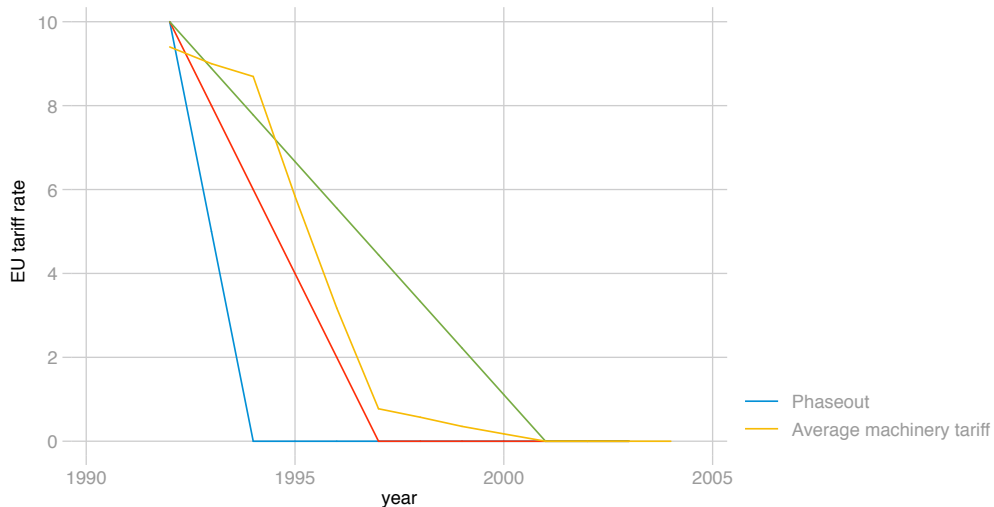
Faster phaseout results in faster imports (Koren, Csillag and Köllő, 2019)

- 95% CI
- Fitted values
- Share of importers (3-year change)

x-axis: Import tariff from EU (3-year change)
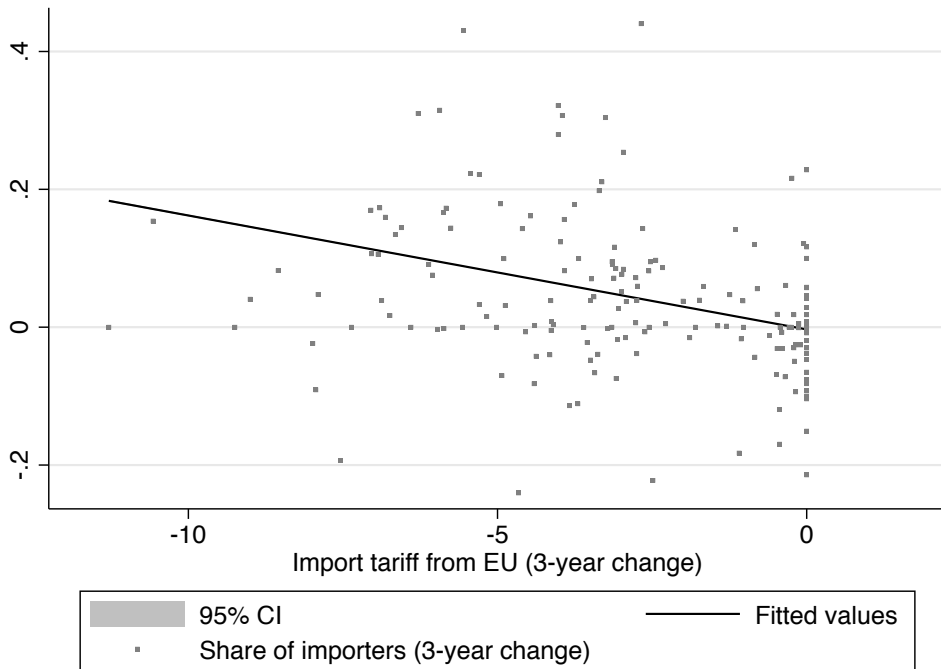
When do firms import?

- 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):

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

Example of cumulated import hazards
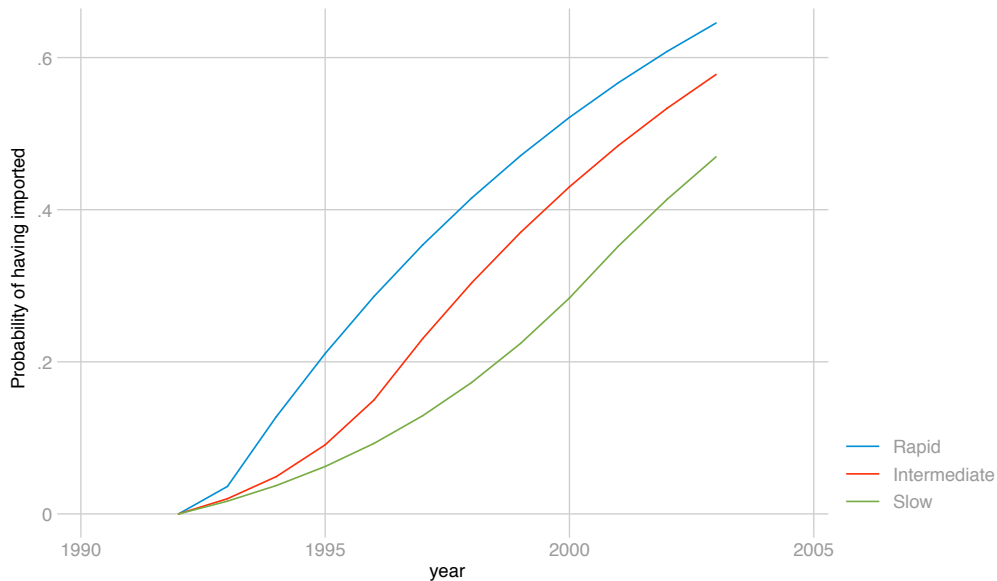
Results

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: $\partial x / \partial y > 0$

Positive cross derivative of output (Koren, Csillag and Köllő, 2019)

Table 4: 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 × log residual wage	38.53***
	(7.55)
Number of observations	261
R^2	0.733
Effect of the new machine at 25th percentile of the 1989 residual wage	-0.747
Effect of the new machine at 50th percentile of the 1989 residual wage	1.20
Effect of the new machine at 75th percentile of the 1989 residual wage	1.47

Notes: Dependent variable: log output per machine. Sample: machine-months for five types of loom. Estimation: OLS. The average residual wage was measured by regressing individual log annual earnings (based on payment by results) in 1989 on age, age squared and type of machine fixed effects, and averaging the residual for workers employed at the given type of machine in the given month. Output is measured in million pics/month. Standard errors (in parentheses) are calculated from a 200-repetition bootstrap. Coefficients

Assortative assignment (Koren, Csillag and Köllő, 2019)

Table 2: The effect of worker quality on the probability that a worker was matched to a new machine

	(1) Machine-worker assignment
Log residual wage in 1989	2.63***
	(0.645)
Age	0.231**
	(0.100)
Age squared	-0.004***
	(0.001)
Tenure (years)	0.051***
	(0.015)
Number of observations	519
Pseudo-R^2	0.233
Standard deviation of the residual wage	0.128
Mean dependent variable	0.299

Notes: Dependent variable: 1 if the worker is assigned to a new machine, and 0 otherwise. Sample: person-years for continuing workers employed in the plant in 1989. Estimation: Probit. The residual wage was measured by regressing log payments by results in 1989 on age, age squared and type of machine fixed effects. Standard errors (in parentheses) are calculated from a 200-repetition bootstrap. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by *** ** and * respectively

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 × 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 × 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$