Machines and Machinists: Incremental Technical Change and Wage Inequality

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Motivation

Motivation

1. Wage inequality in past decades
2. Technological revolutions

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."

Not all of it is *quantity* of capital

Bessen, 2012

"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 model of machines and machinists
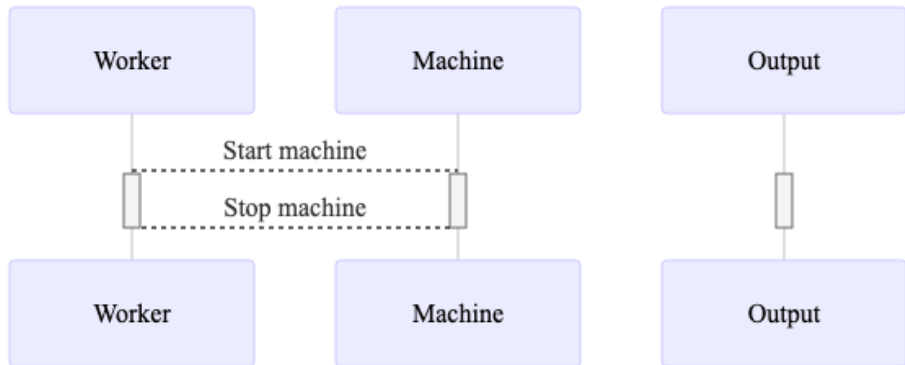
Standard model

$$Y = K^{\alpha}L^{1-\alpha}$$

How do machines and people work together?

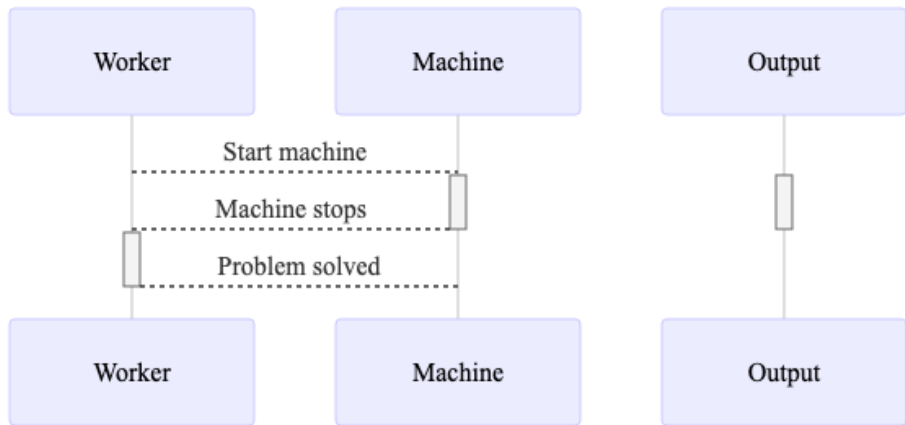Tool model
A worker feeds material into a metal press (both worker and machine busy) to produce.

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.

Tool model

Operator model

Two measures of quality

machine quality Expected autonomous uptime θ

worker quality Speed of fixing problems h

Machine busy for θ, idle for $1/h$.

Expected fraction of time working : $\theta h/(1 + \theta h) \equiv x$.

Worker busy $(1 - x)$ fraction of the time.

Production function

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

Markov chain for machine uptime

Kolmogorov equation:

$$\dot{\pi}_1(t) = -\frac{1}{\theta}\pi_1(t) + h\pi_0(t).$$

Ergodic distribution

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

The steady-state probability is the solution to $-\frac{1}{\theta_m}\pi_1(t) + h_i\pi_0(t) = 0$,
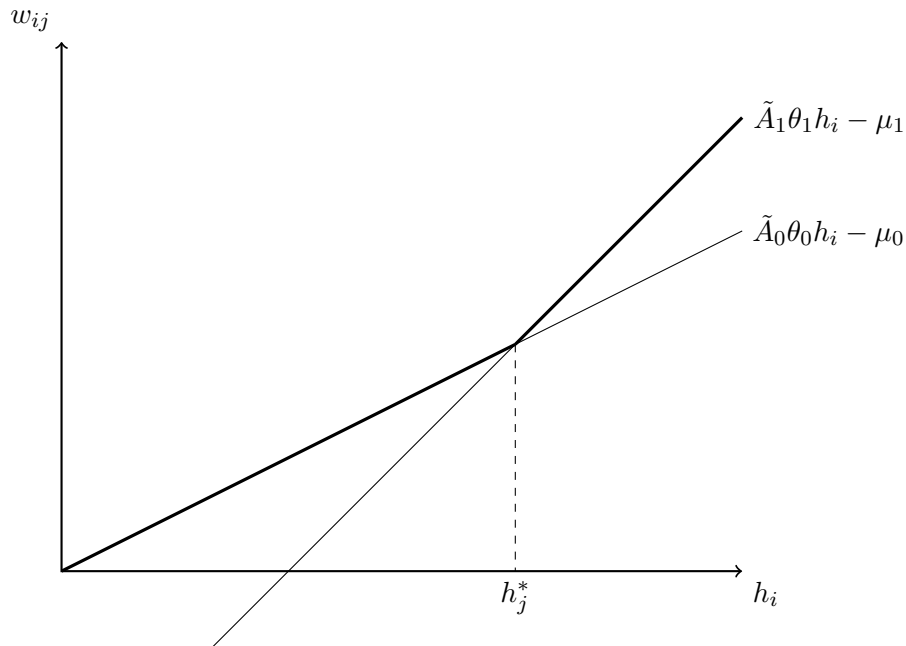
$$\pi_1^* = \frac{\theta_m h_i}{1 + \theta_m h_i}.$$

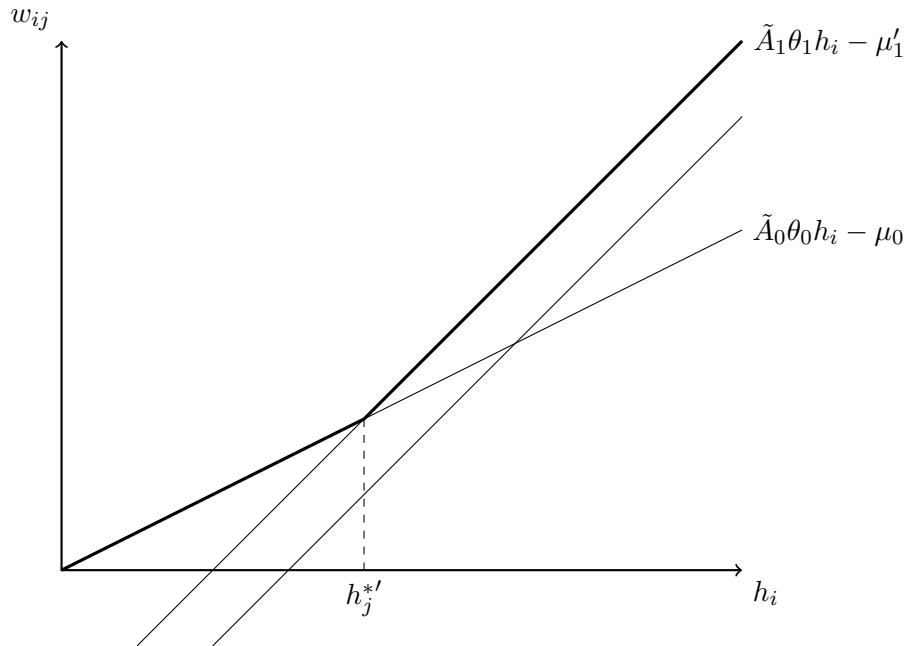A worker type h operating k units of a machine type θ produces, in expectation,

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

Machine assignment and wage setting by worker skill

Figure showing wage w_{ij} on the vertical axis and worker skill h_i on the horizontal axis. Two lines are drawn: the upper bold line labeled $\tilde{A}_1\theta_1 h_i - \mu_1$ and a thinner line labeled $\tilde{A}_0\theta_0 h_i - \mu_0$. The lines cross at h_j^*.

Technology upgrading by worker skill

Appendix

Worker wages

Workers earn w in agriculture. Large L number of workers, few K machines.

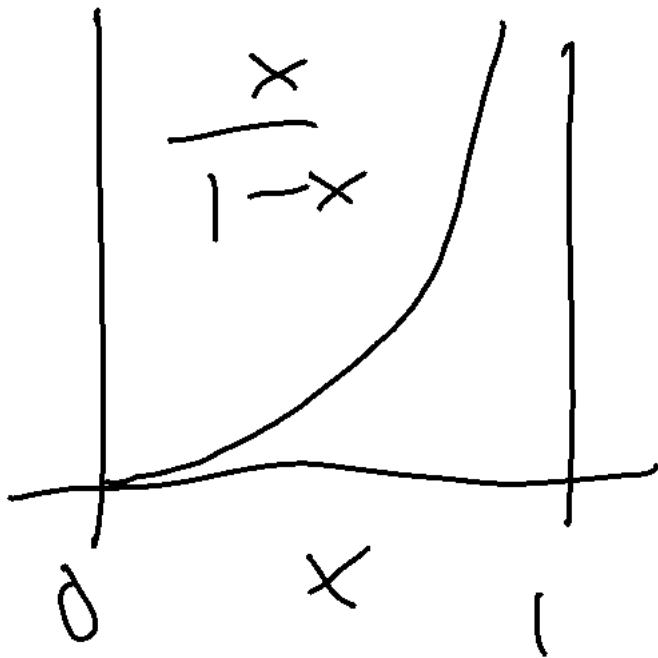# Net output over agriculture

$$x - w(1 - x) = x(1 + w) - w$$

Equilibrium

$$K(1 - x) \leq L$$

Output per worker hour

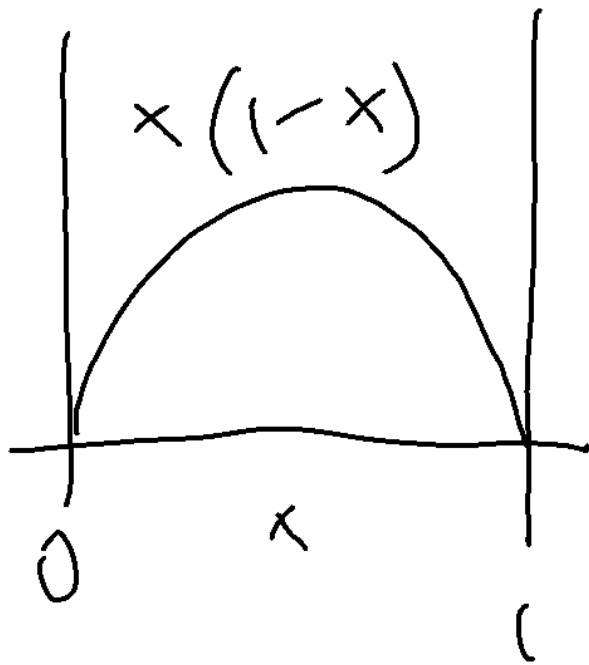$$\frac{x K_i}{L_i} = \frac{x}{1 - x}$$

Output per worker hour

$$\frac{x}{1-x}$$

0 x 1

Return to machine quality

$$\frac{\partial Q}{\partial \theta} = x(1-x)(1+w)$$

$x(1-x)$

x

0

1
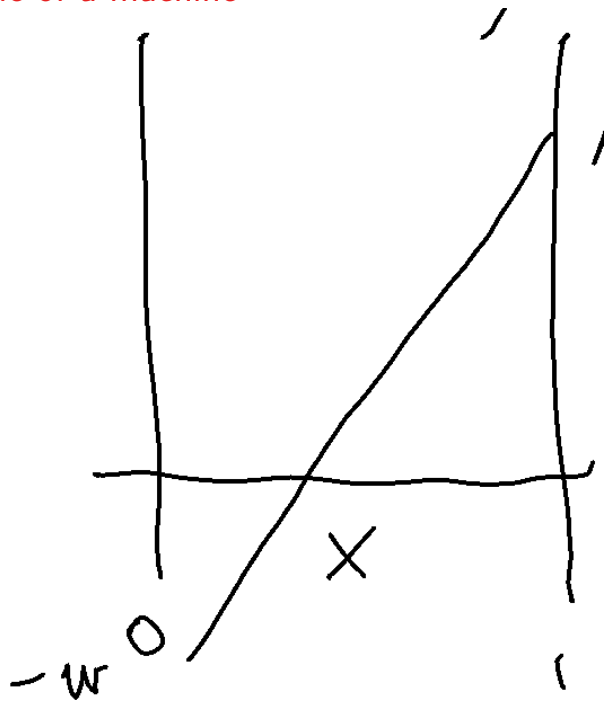
Value of a machine

$$Q_i - wL_i = x(1 + w) - w$$

Value of a machine

Innovation

Two types of innovation

1. Improve quality θ
2. Build more machines K

Suppose both cost the same amount of final goods.

Three epochs of innovation

1. Artisanal period. Labor is slack, wages are determined in agriculture. Improving machine quality has higher return. $x(1-x)(1+w) > x(1+w) - w$. x continues to increase.

2. Mass production. Value of a machine is high enough to produce more. K/L increases with constant x.

3. Automation. After all L has been absorbed from agriculture, wages start to rise. The returns to labor-saving machine quality improvement now exceed the value of an old machine. x keeps increasing.

Plus one

4 Singularity (never reached). As $x \to 1$, the ratio of machine time to worker time grows without bound. Nobody works, all work is done by robots. But to reach this state from a very large degree of automation (say, $x = 0.999$), labor has to capture almost all of the output, otherwise there is no incentive to innovate further.

Artisanal period

$$\frac{w}{1+w} \le x \le \sqrt{\frac{w}{1+w}}$$

Production function

Production function

$$Q_{it} = \Omega_{it}(\lambda K_{it}^F + K_{it}^D)^\alpha L_{it}^\beta M_{it}^\gamma$$

with $\lambda > 1$

$$q_{it} \approx \omega_{it} + \alpha k_{it} + \beta l_{it} + \gamma m_{it} + \alpha(\lambda - 1)\frac{K_{it}^F}{K_{it}}$$

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

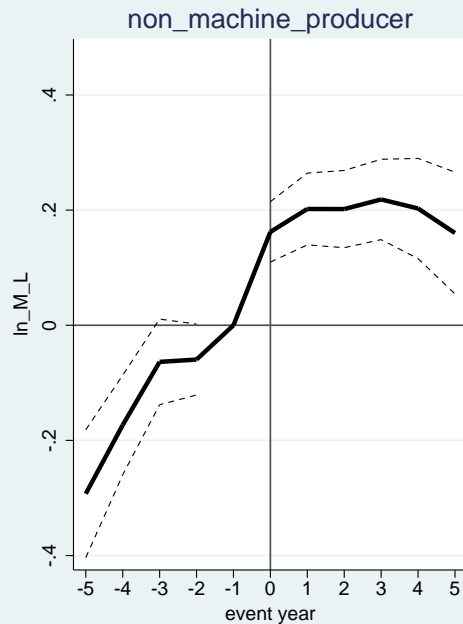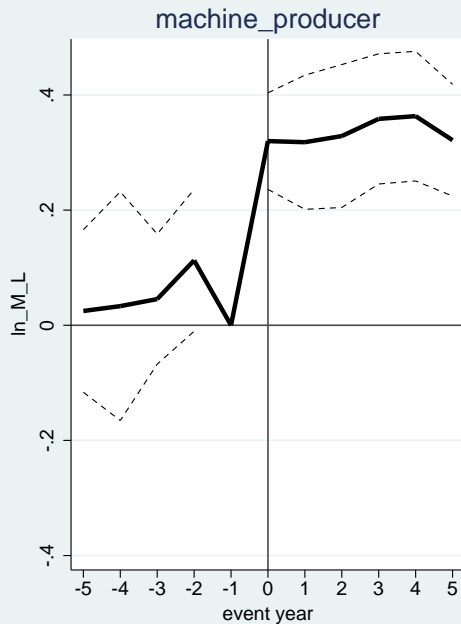Notes: Inaction: abs(IR)<0.01, Positive spike: IR>0.2, Negative spike: IR<-0.2.
All samples exclude the first year of firms, where I_t equals K_t by construction.
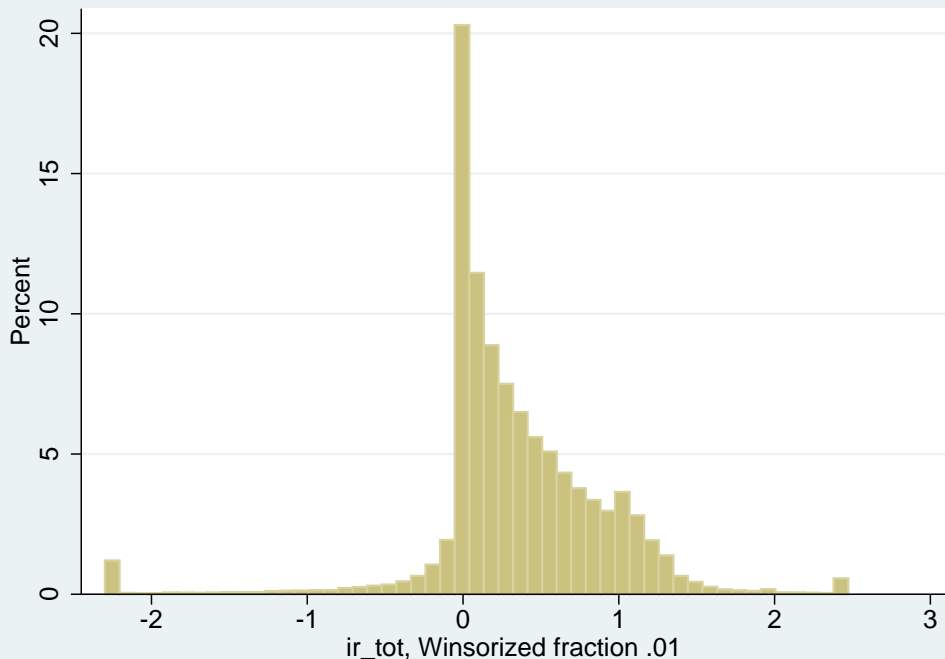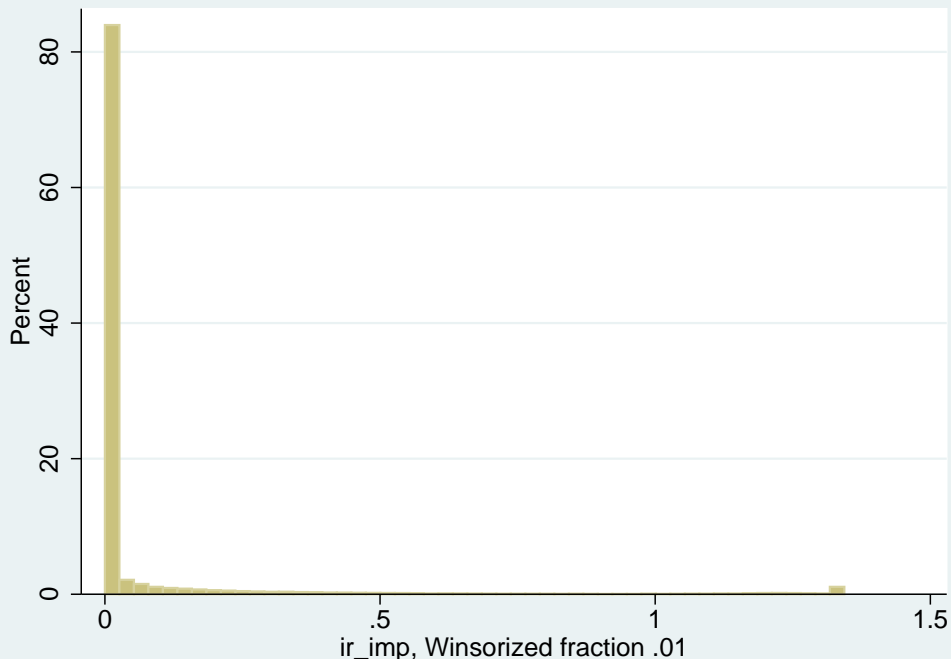
Capital intensity around import peaks
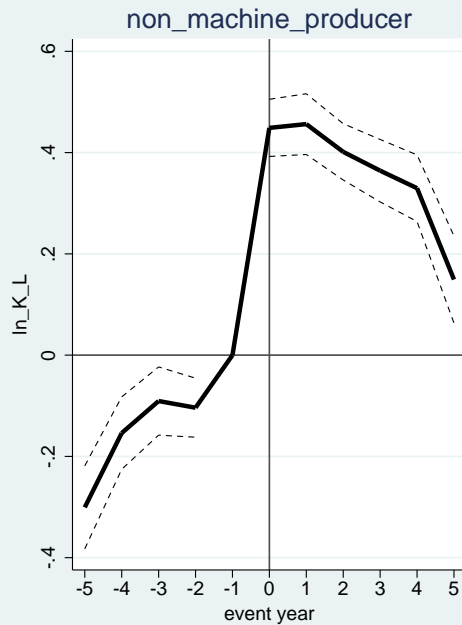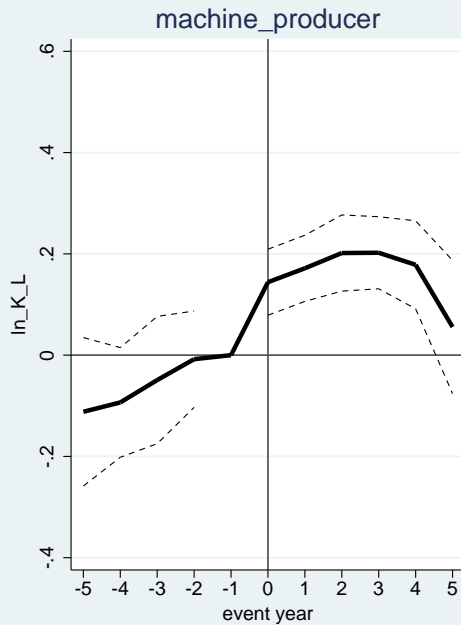
Material intensity around import peaks

Investment rate distribution

Imported investment rate distribution

Histogram with y-axis labeled "Percent" ranging from 0 to 80, and x-axis labeled "ir_imp, Winsorized fraction .01" ranging from 0 to 1.5.

Import share in capital sock
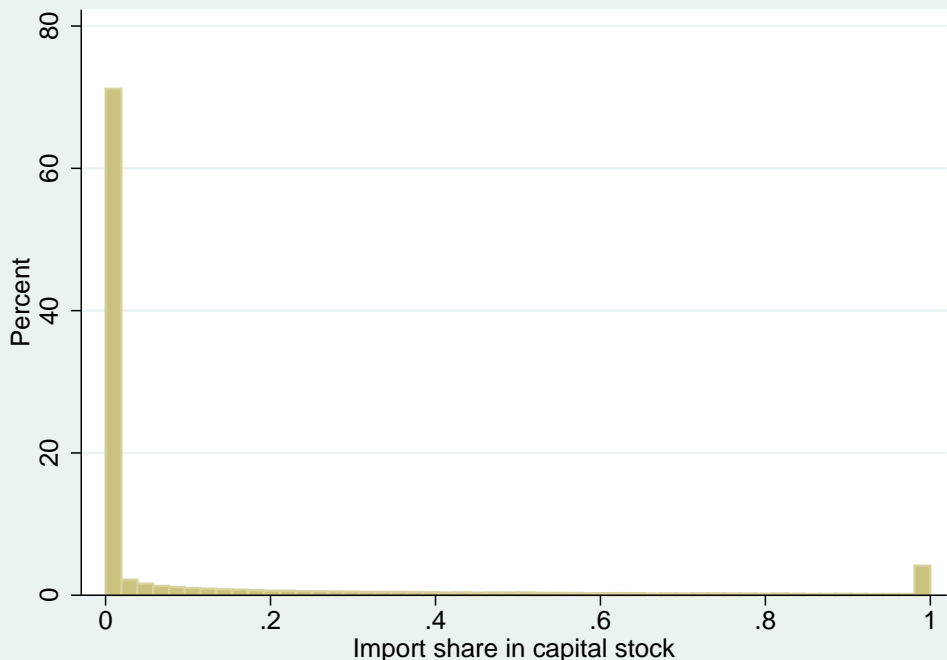
Event studies around large investments

Capital stock increases by same amount (by construction)

| dompeak | impeak |

lnK ——— 95% CI

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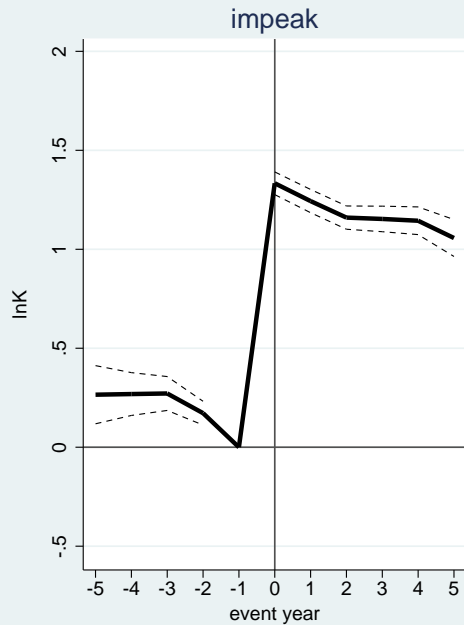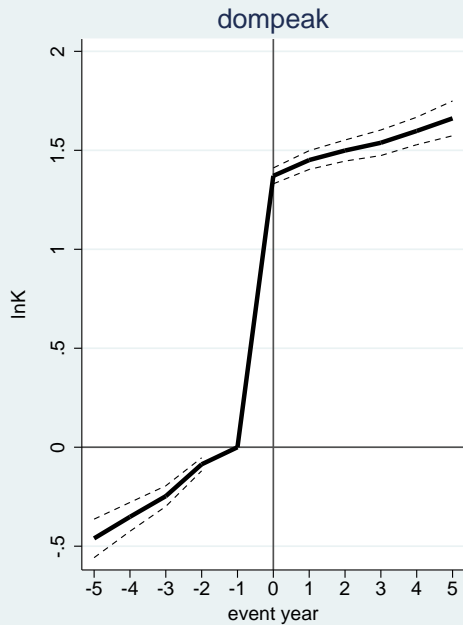
TFP improves more for imported investment
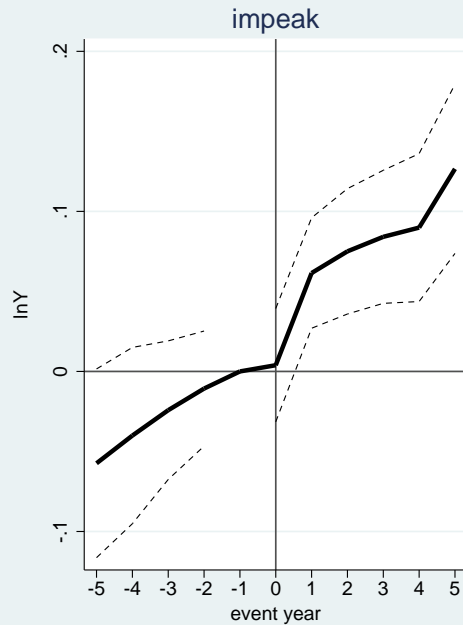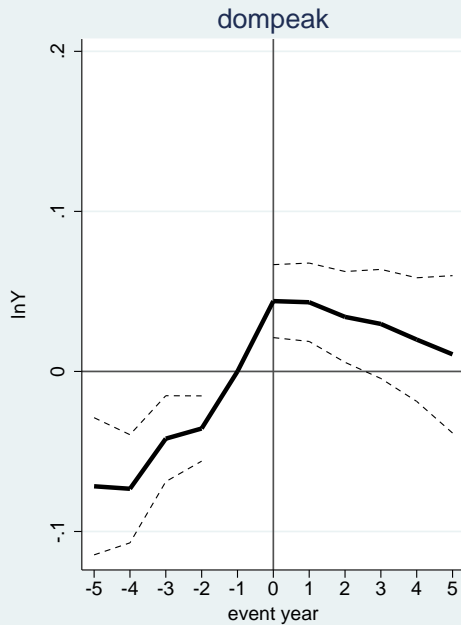
Material intensity increases for both types of investment
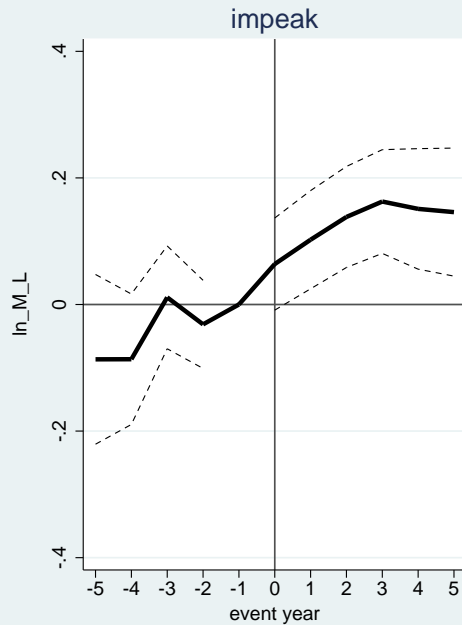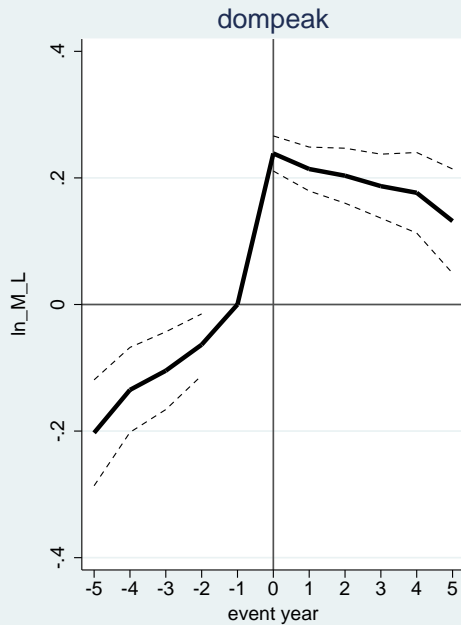
Material import intensity jumps more for imported investment
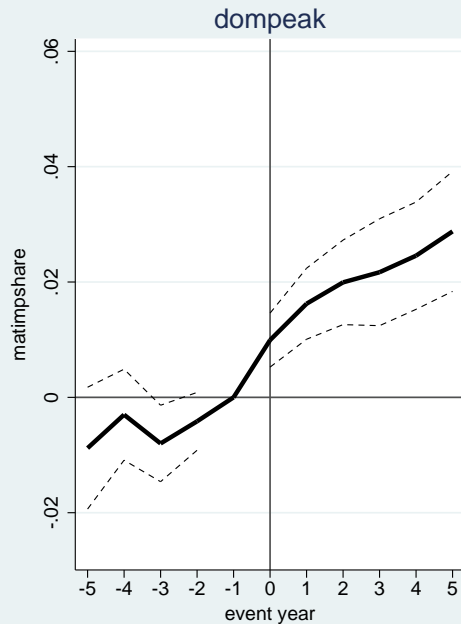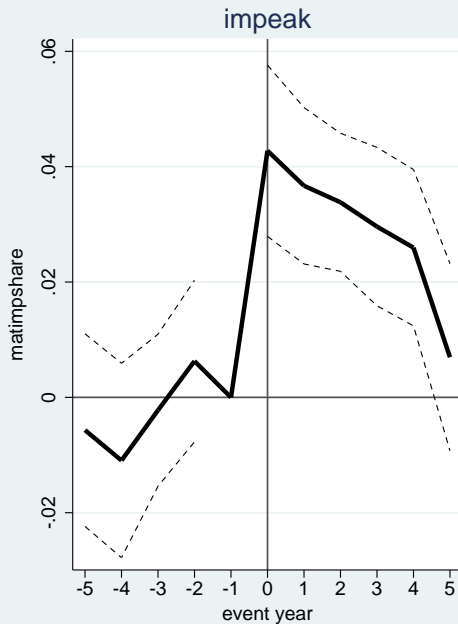
Average wage reacts to domestic investment
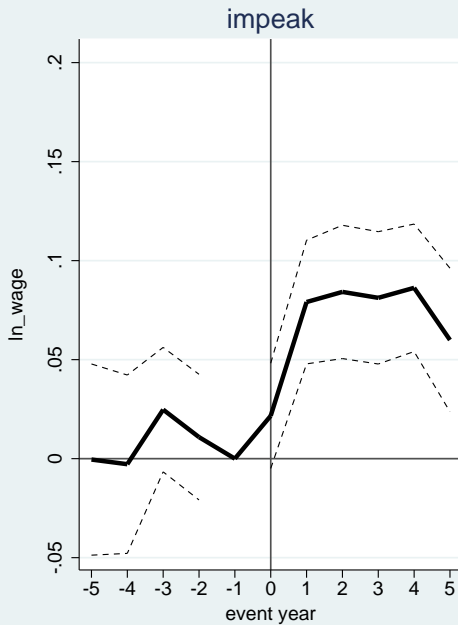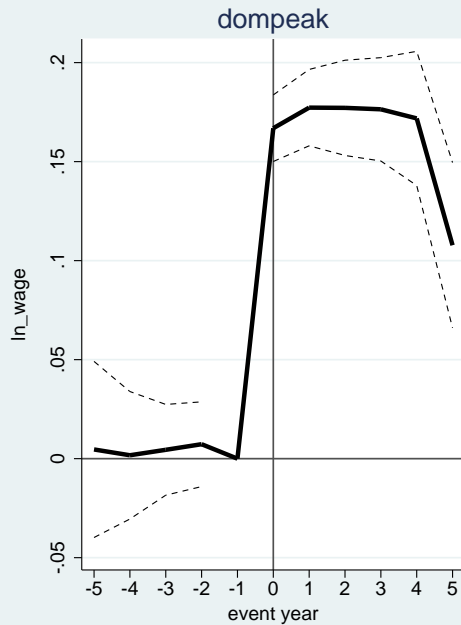
Identification

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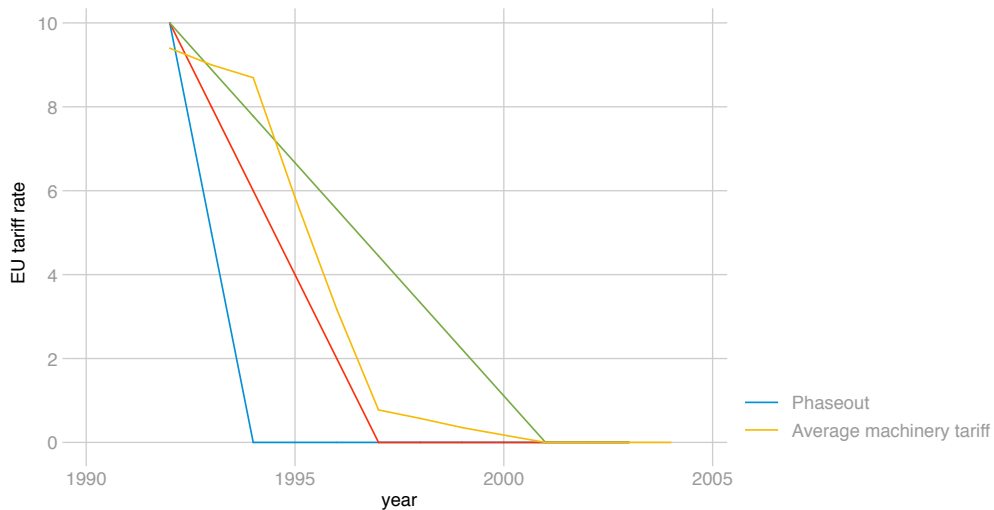
Faster phaseout results in faster imports (Koren, Csillag and Köllő, 2019)

x-axis: Import tariff from EU (3-year change)

Legend: 95% CI   Fitted values

Share of importers (3-year change)
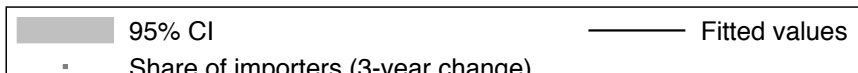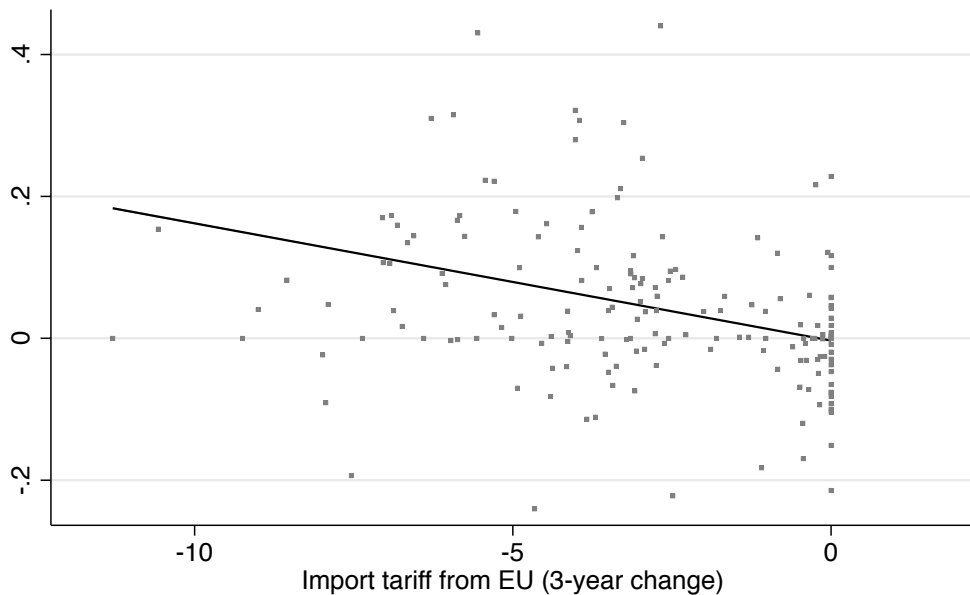
When do firms import?

- 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):

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

Example of cumulated import hazards
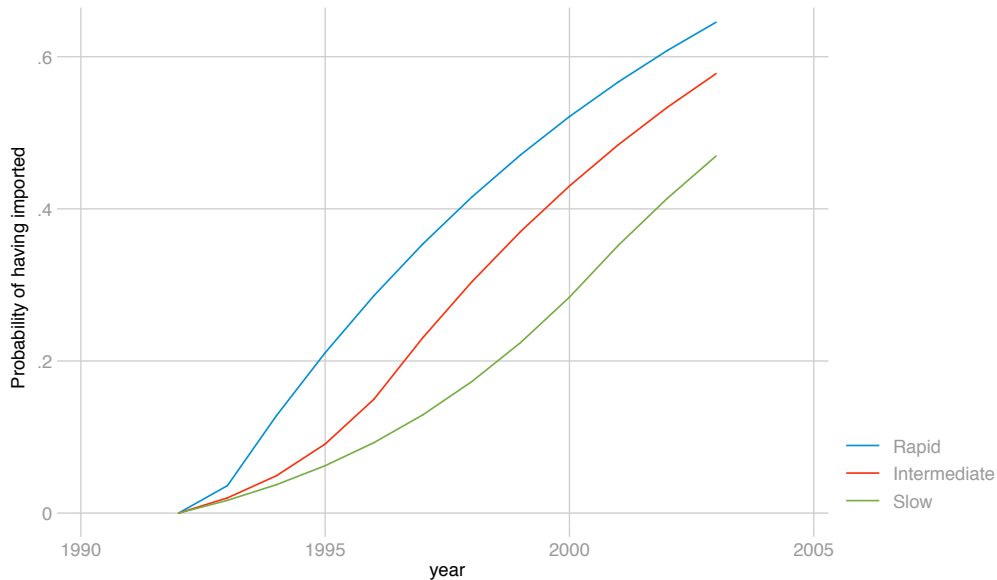
Results

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

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

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

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