Firms That Automate: Theory and Evidence

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Facts on Automation

- New technologies have replaced workers:
    - Robots displaced 400,000 U.S. jobs (Acemoglu and Restrepo, 2020)
    - Robots destroyed 275,000 German manuf. jobs (Dauth et al., 2021)
    - 5% fall in global employment due to robots (Carbonero et al., 2020)
- But heterogeneity is important - some industries expand while others contract.
- So on aggregate, not ex-ante clear impact of automation.
- Little work exploring the micro-macro automation relationship.

Overview

Data

- Insights from unique Italian firm survey data:
    1. Wide range of automation technologies
    2. Panel of large sample
    3. Track *when* firms automate

Results

- Automaters are larger, more productive & grow faster.
- Adoption of automation technology boosts firm employment.

Model

- *Why?* To understand aggregate effects.
- *What?* Hopenhayn (1992) with skilled/unskilled labour and automation technology.
- *Findings?* Reconcile firm-level and aggregate findings.

Roadmap

Empirical Research on Automating Firms

The little research on firm-level automation is limited:

1. Time periods (Bartelsman et al., 1998; Dinlersoz and Wolf, 2018; Kwon and Stoneman, 1995; Zator, 2019)
2. Automation technologies (Zator, 2019; Acemoglu et al., 2020; Stapleton and Webb, 2020; Koch et al., 2019; Cheng et al., 2019)
3. Sample of firms (Dinlersoz and Wolf, 2018; Kromann and Sorensen, 2019; Doms et al., 1997; Bartel et al., 2007)

I use a novel dataset which asks about **many automation technologies** in **recent years**, across a **panel** of nationally **representative** firms.

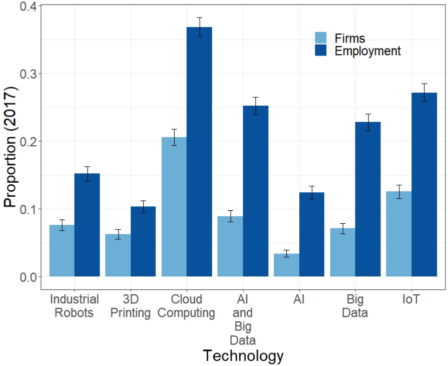
Survey of Industrial and Service Firms (Banca d'Italia)

- Around 4,500 firms in each year.
- Approx. 3,500 firms in panel, 2010 - 2018.
- Firms employed across services and manufacturing.
- Representative of population of firms, with weights to adjust.
- **Crucial:** information on automation across firms.
- Great data because:
    1. Depth of automation technologies
    2. Timing of automation behaviour
    3. Panel component - can track firms over time
    4. Size of sample

Questions on Automation

1. Firms asked in 2015 and 2017 about the use of:
    - Artificial Intelligence
    - Big Data
    - Internet of Things
    - Cloud Computing
    - Industrial Robotics
    - 3D Printing
2. Firms asked *when* they adopted each technology.
3. Share of investment in automation technologies.

Automation Adopters Are Larger

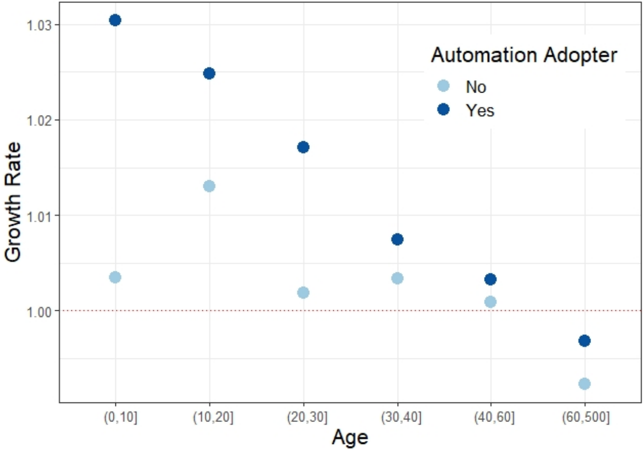


Further Evidence Across Size Distribution

Less Clear Variation in Adoption by Age

Growth Rates

Firms that automate generally **grow faster** than non-adopters:



Growth Rates by Technology

Matching Automating Firms and Non-Adopters

Firms matched to compare size across 'similar' firms that did/did not adopt automation technologies:

Table 1: Propensity Score Matching Regression Results, 2015

	Dependent variable: *Log Employment*					
	Any Tech.	*Cloud*	*AI & Big Data*	*IoT*	*Industrial Robotics*	*3D Printing*
Tech. Adoption (nearest)	0.461*** (0.06)	0.822*** (0.07)	0.623*** (0.11)	0.475*** (0.08)	0.370*** (0.10)	0.330** (0.11)
N	1914	1376	674	1042	720	524
Tech. Adoption (full)	0.586*** (0.05)	0.400*** (0.06)	0.818*** (0.07)	0.583*** (0.06)	0.535*** (0.07)	0.537** (0.08)
N	2554	2580	2547	2541	2544	2538

Automating Firms Over Time

Leverage panel component of data to ask: what happens to automating firms over time, and what is the impact of automation?

1. *Two-Way Fixed-Effects (TWFE):*

$$\ln \underbrace{Y_{it}}_{\substack{\text{Employment}\\\text{Productivity}}} = \alpha_i + \gamma_t + \delta \underbrace{X_{it}}_{\substack{\text{Age}\\\text{Sector}\\\text{Region}}} + \beta \mathbb{1} \underbrace{\text{Tech}_i}_{\text{Tech Adoption}} + \epsilon_{it}$$

Table

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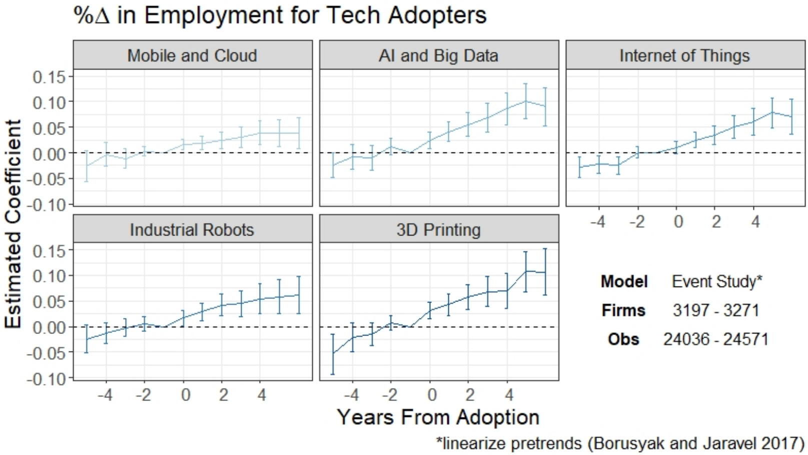
2. *Event Studies:*

$$\ln \underbrace{Y_{it}}_{\substack{\text{Employment}\\ \text{Wages}\\ \text{Turnover}}} = \alpha_i + \gamma_t + \delta X_{it} + \sum_{j=\underline{j}, j \neq -1}^{\bar{j}} \beta_j \mathbb{1} \underbrace{(D_{it} = j)}_{\substack{\text{Relative time}\\ \text{from adoption}}} + \epsilon_{it}$$

Event Study Estimates

Plots of estimated β_j for employment regressions.



More regressions

What Have We Learned?

The following facts will be critical to the model:

1. Automating firms are larger, more productive and pay higher wages.
2. Adopters grow faster across age and size distributions.
3. Firms expand when adopting automation technologies.

Why do we need a model?

- Aggregate impact of automation (productivity and employment)
- General equilibrium effects (via prices and wages)

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Basic Intuition: the incentive to automate rises in the savings to MC, falls in the automation FC, and rises in firm productivity. Simple Model

Model Outline

Standard heterogeneous firm dynamics model:

- Hopenhayn (1992).
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Automating firms are larger and more productive, pay higher wages, grow faster, employ more skilled workers.

Model in Words

- Firms produce with decreasing returns to scale.
- Heterogeneous in productivity z, which follows AR(1) process.
- Firms face fixed costs to enter and produce.
- There is a productivity cut-off, below which firms exit.
- Furthermore, firms can choose to automate, paying a fixed cost.
- A subset of firms endogenously choose to automate *if they are very productive*.

Task-based Production Function with Automation

- Firm output depends on productivity and production over a set of tasks x of increasing 'difficulty':

$$\ln y = \ln z + \int_0^{\phi} \ln y(x) dx \quad \text{where } \phi < 1 \text{ for DRTS}$$

- Production of a task is determined:

$$y(x) = \begin{cases} r(x) = R(x) + n^r(x) & \text{for } x \in [0, \gamma) \\ n^n(x) & \text{for } x \in [\gamma, \phi) \end{cases}$$

- Assume $\frac{q}{w_r} < 1$ such that automating is beneficial. However firms must pay a fixed cost c_a to use automation technology R.
- Therefore

$$\ln y = \ln z + (\phi - \gamma) \ln n^n + \gamma \ln r$$

$$y = z(n^n)^{\alpha} r^{\gamma} \text{ where } r = (n^r + R)$$

$$\text{Where } \alpha = \phi - \gamma$$

Model with Automation

- Firms endogenously choose to automate.
- They do automate *if they are very productive*.
    - So additionally $\exists\ z^a : \forall z \geq z^a$, firms automate.

$$v_t^a(z_t, n_{t-1}) = \max_{R_t, n_t^n, n_t^r \geq 0} \{p_t z_t (n_t^n)^\alpha (n_t^r + R_t)^\gamma - w_t^n n_t^n - w_t^r n_t^r - q_t R_t - g(n_t, n_{t-1}) - c_f + \beta \max\{\int v_{t+1}^a(z_{t+1}, n_t) dF(z_{t+1}|z_t), -g(0, n_t)\}\}$$

$$v_t(z_t, n_{t-1}) = \max_{n_t^r, n_t^n \geq 0} \{p_t z_t (n_t^n)^\alpha (n_t^r)^\gamma - w_t^n n_t^n - w_t^n n_t^r - g(n_t, n_{t-1}) - c_f + \beta \max\{\int v_{t+1}(z_{t+1}, n_t) dF(z_{t+1}|z_t), -g(0, n_t)\}\}$$

$$\tilde{v}(z_t, n_{t-1}) = \max\{v_t^a(z_t, n_{t-1}) - c_a, v_t(z_t, n_{t-1})\}$$

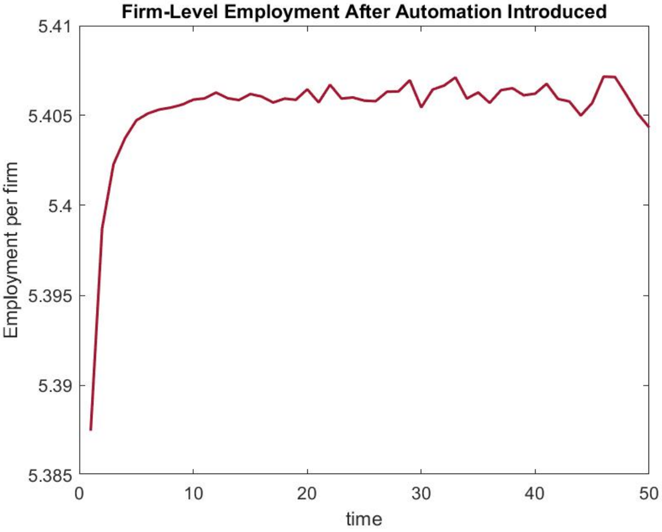
Calibrated Model

Introduction of automation technology leads to:

1. Productive firms automate, and expand due to low-cost input.
2. Reallocation towards more-productive firms raises output-weighted productivity.
3. GE effect: price falls and low productivity firms exit.
4. Overall fall in employment, skewed towards routine workers.

Table

Automation Boosts Firm-level Employment



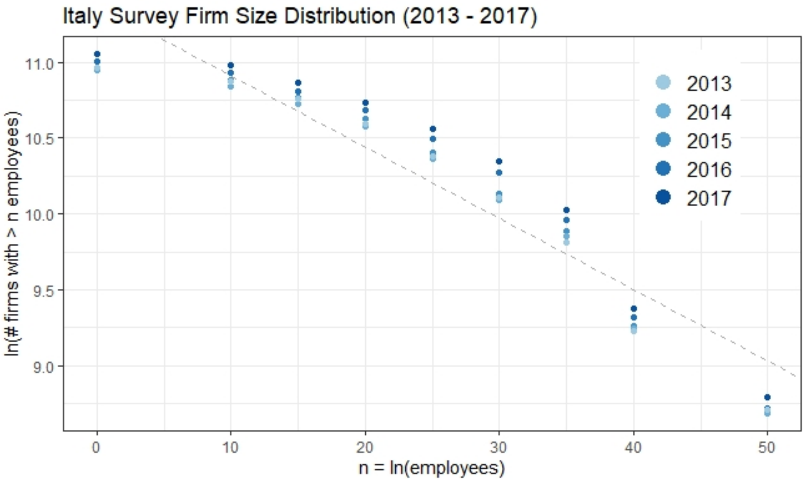
Extensions

Endogenous labour supply - what happens when wages adjust to respond to automation?

Conclusions

- Firms that automate are different ex-ante: larger, and more productive.
- Thus endogenous automation decision matters for aggregate outcomes.
- Automation boosts employment of skilled workers.
- Aggregate effects: reallocation towards more productive firms; exit of marginal firms; fall in total employment.

Firm Size Distribution



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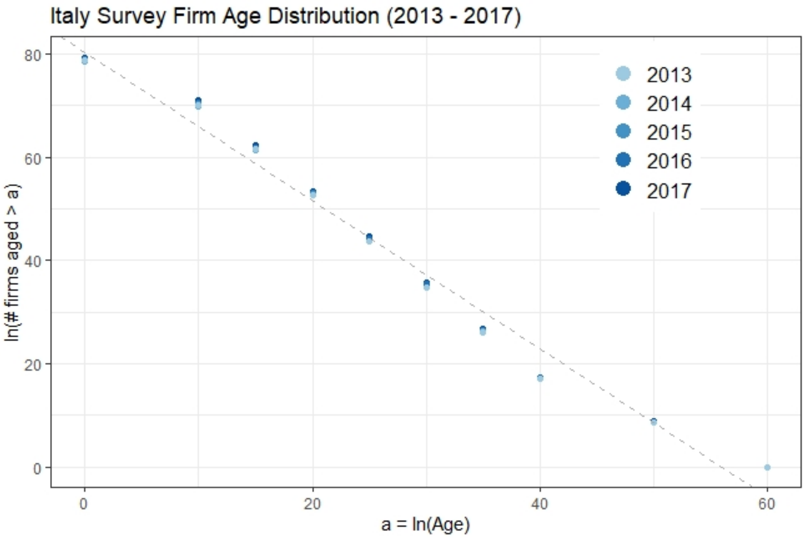
Firm Age Distribution



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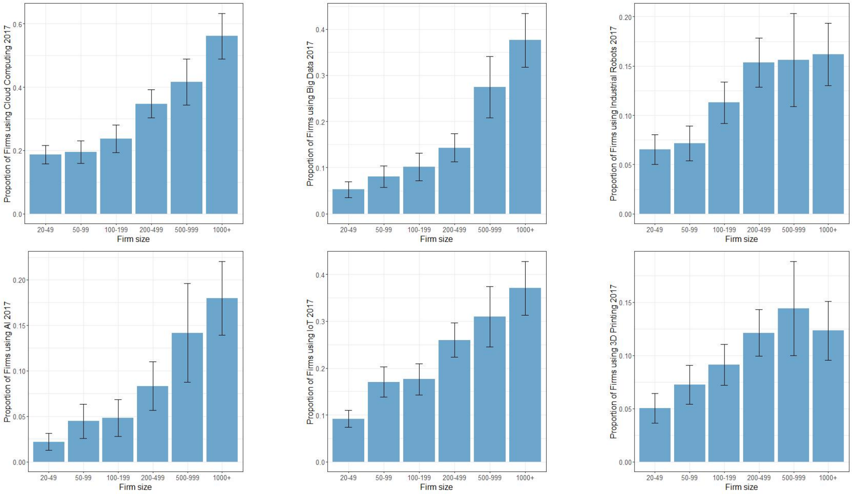
Adoption More Common in Larger Firms



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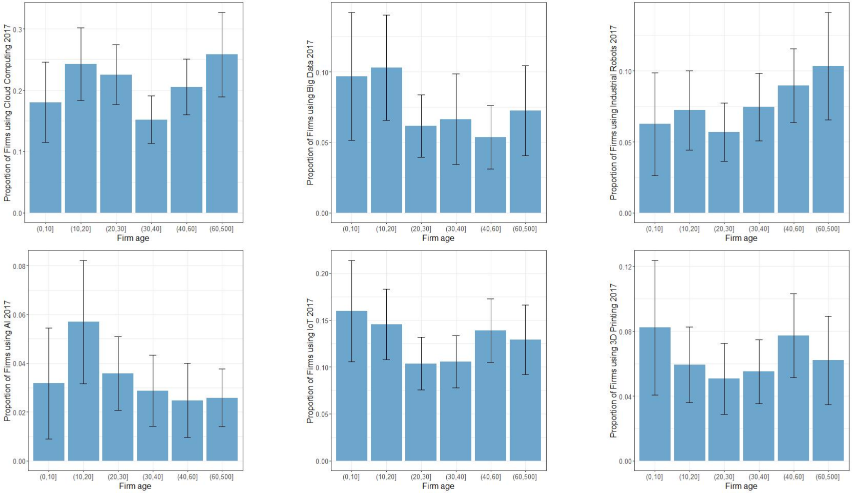
Less Systematic Variation in Adoption by Age



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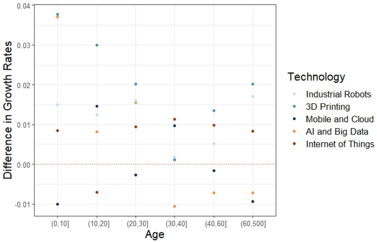
Regressions: Automation Investment Share

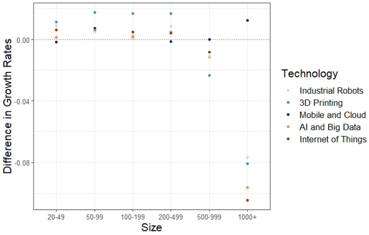
Table 2: Estimated Coefficients from Advanced Tech. Investment Regressions

	Dependent variable: *Share of Investment in Advanced Tech.*					
	2016			2017		
log(Emp.)	0.279***	0.278***	0.254***	0.337***	0.329***	0.299***
	(0.025)	(0.025)	(0.026)	(0.028)	(0.028)	(0.028)
Age		−0.0000004	0.0002		0.0034**	0.0026*
		(0.001)	(0.001)		(0.001)	(0.001)
Sector FE			✓			✓
Region FE			✓			✓
N	3756	3749	3749	3926	3926	3926

Estimates are significant at levels of 0.1%: ***, 1%: **, 5%: *. Return

Growth Rates by Technology





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Simple Static Theoretical Framework

Consider simple production function with single input and DRS $y = zx^\alpha$. The optimal choice of the input is $x = \left(\frac{z\alpha}{w}\right)^{\frac{1}{1-\alpha}}$. A firm can choose labour n with wage w or robots R with unit cost $q < w$ but fixed per-period cost c.

For a firm with productivity z, the optimal profit functions are:

$$\pi = z\left(\frac{z\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}} - w\left(\frac{z\alpha}{w}\right)^{\frac{1}{1-\alpha}}$$

$$\pi^a = z\left(\frac{z\alpha}{q}\right)^{\frac{\alpha}{1-\alpha}} - q\left(\frac{z\alpha}{q}\right)^{\frac{1}{1-\alpha}} - c$$

A firm will automate if $\pi^a > \pi$ (see next slide).

Return

Simple Static Theoretical Framework

Incentive to automate if:

$$z^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha}{1-\alpha}} q^{\frac{-\alpha}{1-\alpha}} - z^{\frac{1}{1-\alpha}} \alpha^{\frac{1}{1-\alpha}} q^{\frac{-\alpha}{1-\alpha}} - c > z^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha}{1-\alpha}} w^{\frac{-\alpha}{1-\alpha}} - z^{\frac{1}{1-\alpha}} \alpha^{\frac{1}{1-\alpha}} w^{\frac{-\alpha}{1-\alpha}}$$

$$\implies q^{\frac{-\alpha}{1-\alpha}} - \frac{c}{z^{\frac{1}{1-\alpha}}} \frac{1}{\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}} > w^{\frac{-\alpha}{1-\alpha}}$$

$$\implies \frac{-\alpha}{1-\alpha} \ln\left(\frac{q}{w}\right) > \ln\left(\frac{c}{z^{\frac{1}{1-\alpha}}} \frac{1}{\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}}\right)$$

$$\implies \underbrace{\ln\left(\frac{w}{q}\right)}_{\text{Automation saving to MC}} > \frac{1-\alpha}{\alpha} \underbrace{\ln c}_{\text{Automation FC}} - \frac{1}{\alpha} \underbrace{\ln z}_{\text{Productivity}} - \frac{1-\alpha}{\alpha} \ln A(\alpha)$$

Therefore, the incentive to automate rises in the savings to MC, falls in the automation FC, and rises in firm productivity.

Return

Model Results

Table 3: Percentage point change relative to 'No Automation' model

Aggregates:	Price	-3.2
	# firms	-9.0
	Output	+3.7
	Employment	-25.5
	Output-weighted productivity	+6.7
	Share routine employment	-10.0
Firm Level:	Employment per firm	+2.5
	Output per firm	+7.5
	% firms that automate	+24.0

Return

Industry Breakdown of Technology Adopters

Table 4: Technology Adoption by Industry 2017 Graphs

Technology	High Adoption	Low Adoption
Cloud Computing	Real Estate Transport & Comms.	Hotels & Restaurants
AI	Metal Manuf.	Chems, Rubber & Plastics Other Manuf.
Big Data	Real Estate Transport & Comms. Energy & Extraction	Hotels & Restaurants
Internet of Things	Metal Manuf. Energy & Extraction	Hotels & Restaurants Real Estate
Industrial Robotics	Metal Manuf.	Hotels & Restaurants
3D Printing	Metal Manuf. Other Manuf.	Wholesale & Retail Hotels & Restaurants

Industry Breakdown

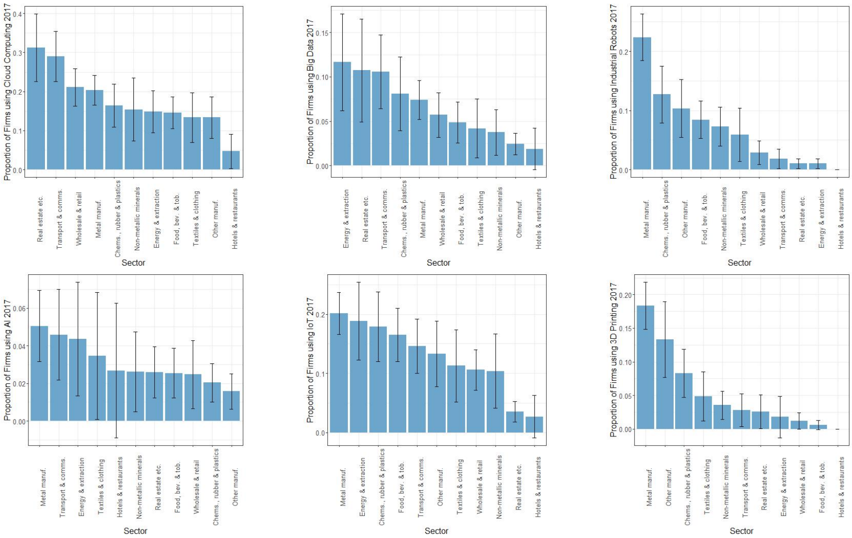

Figure 1: Technology Adoption by Industry 2017

Return

Exporting Behaviour of Tech Adopters

Table 5: Average proportion of sales from exports by group, 2015

Technology	*Cloud Computing*	*AI & Big Data*	*IoT*	*Industrial Robotics*	*3D Printing*
Adopters	0.09	0.06	0.04	0.05	0.11
Non-Adopters	0.11	**0.10**	**0.11**	**0.10**	0.10

Notes: Summary statistics from 2015 for firms that do and don't use advanced technologies. All values are weighted means. Bold values are the larger of the two, if there is a significant difference between adopters and non-adopters at the 1% level, computed with Welch's t-test and the Welch-Sattherwaite equation for degrees of freedom.

Graphs Return

Exporting Behaviour of Tech Adopters

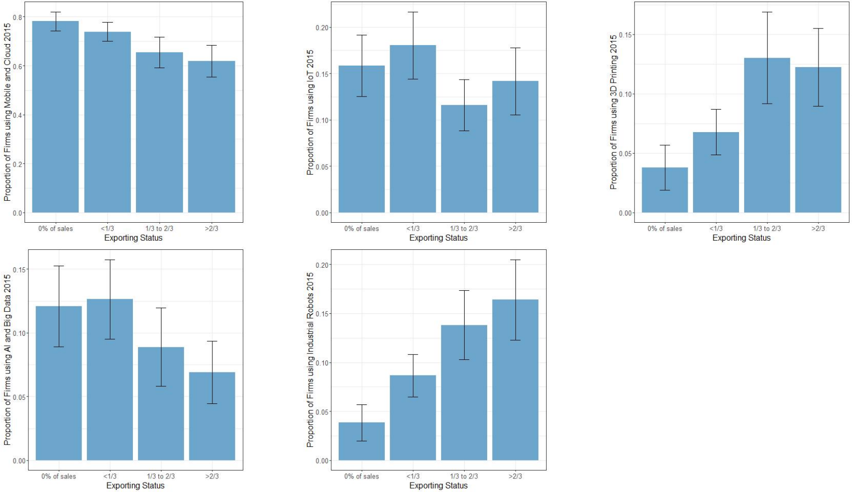

Figure 2: Tech Adoption by Exporting Status 2015 Return

TWFE Estimates

The set of β are shown for total employment, blue-collar employment, and turnover per worker.

Table 6: Estimates of β from homogeneous effect TWFE model: the % change in variables when adopting technology, relative to non-adopters

		Cloud Computing	*AI & Big Data*	*IoT*	*Industrial Robotics*	*3D Printing*
Employment	Coeff	0.020***	0.052***	0.051***	0.042***	0.056***
	SE	(0.0043)	(0.0061)	(0.0048)	(0.0062)	(0.0066)
Blue-collar Emp.	Coeff	−0.036*	−0.030	0.0008	0.048	−0.025
	SE	(0.015)	(0.027)	(0.021)	(0.027)	(0.028)
Turnover per worker	Coeff	0.0057	−0.017	0.017*	0.065***	0.019
	SE	(0.0066)	(0.0096)	(0.0075)	(0.0097)	(0.010)

Notes: Robust standard errors clustered at firm level. Coefficients labelled by statistical significance at: *** 0.1%, ** 1%, * 5%.

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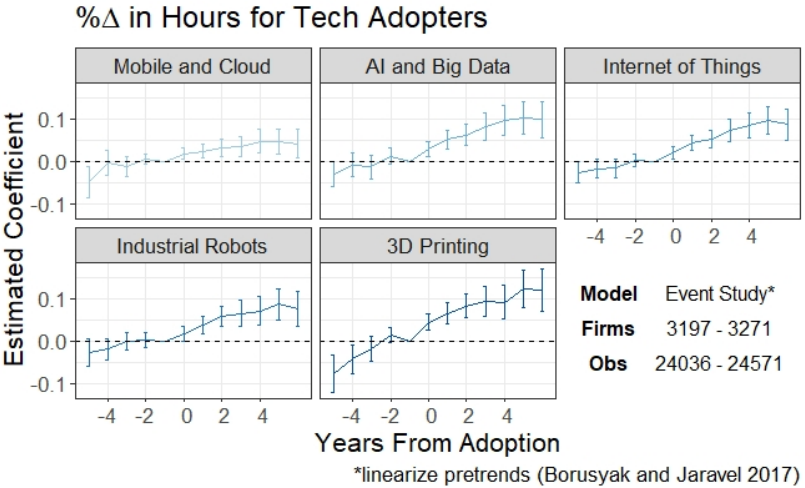
Further Event Study Estimates

Plots of estimated β_j for hours regressions.



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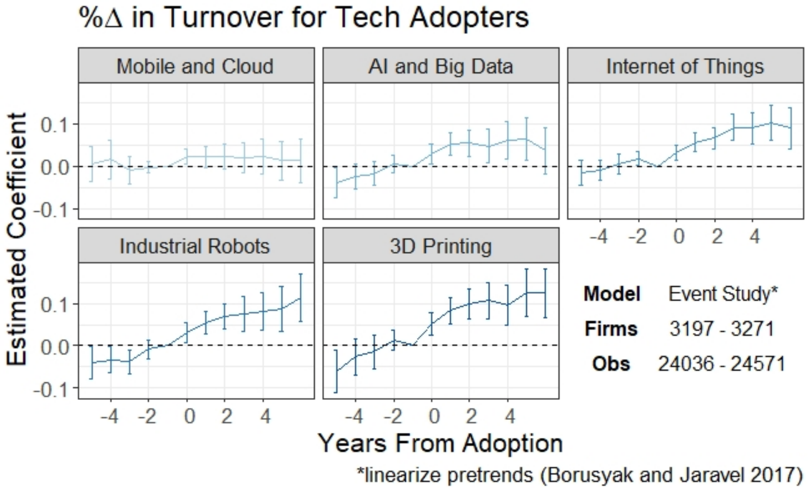
Further Event Study Estimates

Plots of estimated β_j for turnover regressions.



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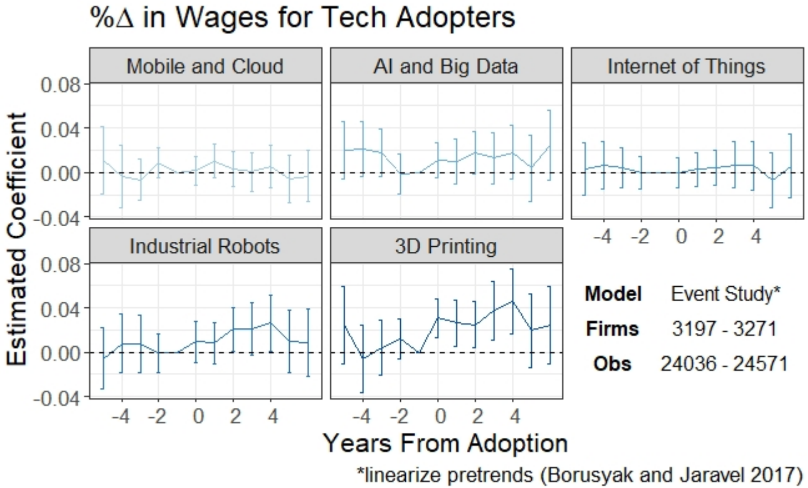
Further Event Study Estimates

Plots of estimated β_j for wages regressions.



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Value Function Plots

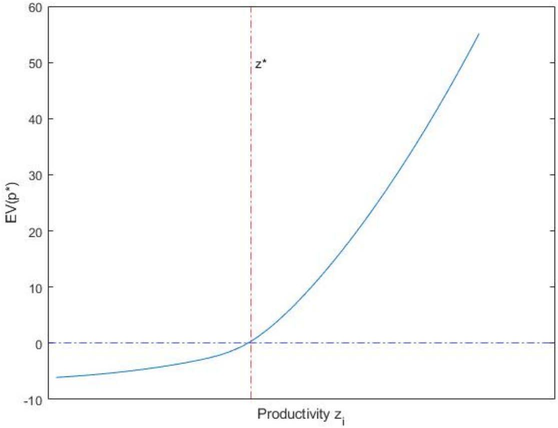

Figure 3: Entry cut-off Return

Value Function Plots

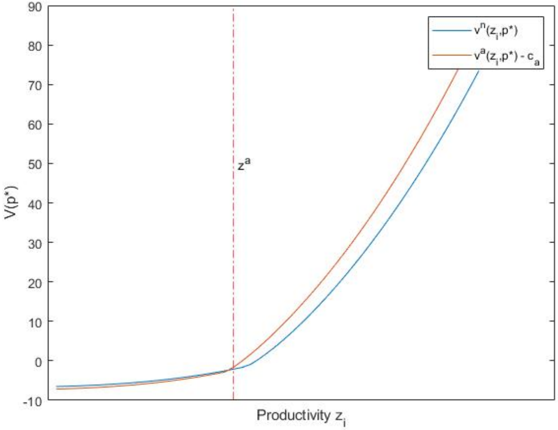

Figure 4: Automation cut-off Return

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