

Industrial Robots and Where to Find Them: Evidence and Theory on Derobotization

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Motivation

- Robots and automation have become a staple of production in the 21st century.
- The literature on automation is growing, especially in macroeconomics (Acemoglu and Restrepo).
- However, the literature (and conversation) on deautomation (at least within the macro- literature) is absent.

Motivation

- Robots and automation have become a staple of production in the 21st century.
- The literature on automation is growing, especially in macroeconomics (Acemoglu and Restrepo).
- However, the literature (and conversation) on deautomation (at least within the macro- literature) is absent.
- The prevailing assumption is of permanent automation.

Related literature

- Task-based production function to model automation. (Acemoglu and Restrepo, 2018).
- Robot adoption model and GE simulations. (Humlum, 2019)
 - Calibration on Danish manufacturing firms.
 - Baseline to our model (permanent adoption).
- Previous findings from Spanish manufacturing firms (Koch et al., 2019)
 - Larger and more productive firms adopt robots more frequently.
 - Robot adoption leads to net job creation for both low- and high-skilled workers.
 - Nearly 40% of adopters **derobotize** at some point.

Related literature

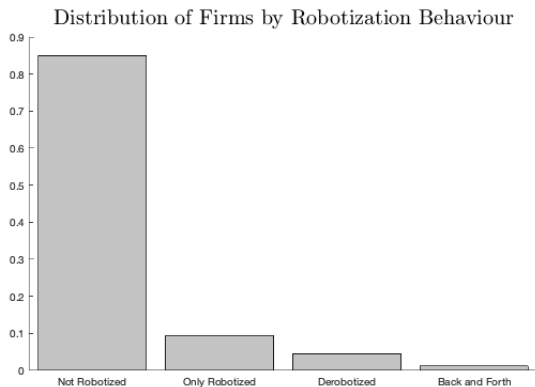


Figure: Koch et al (2019)

Kaplan-Meier estimates

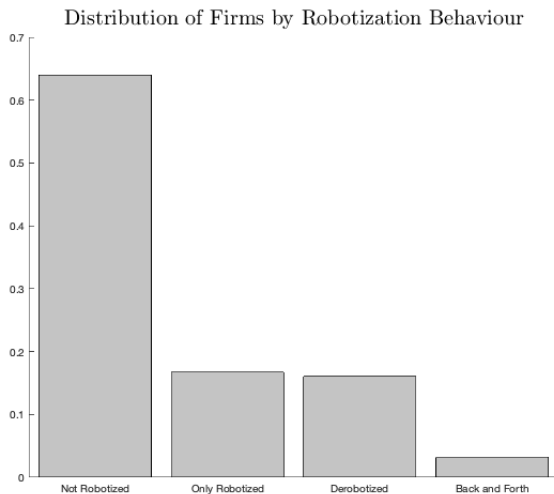


Figure: Camilo, Gokalp, Iurchenko, Klix, and Rubinoff (2020)

Data

- Annual survey of Spanish manufacturing firms from SEPI Foundation
 - Unbalanced panel from 1991-2014
 - Frequency: 4 years
 - Use of robots, firm size, capital, labor, and industry
- Data on 3,987 firms
 - 14,119 firm-year observations
 - 958 robotizations, and 755 derobotizations
- ESEE question:
"State whether the production process uses any of the following systems:
..
2. Robotics;
.."

Empirical investigation

- 1 When does derobotization happen?

Empirical investigation

- 1 When does derobotization happen?
- 2 Which firms derobotize?

Empirical investigation

- 1 When does derobotization happen?
- 2 Which firms derobotize?
- 3 What happens after derobotization?

Derobotization Timing

- When does derobotization happen?

Fact

Derobotization is most likely in the first periods after adoption.

- This fact is indicative of a learning process.

Derobotization Timing

- When does derobotization happen?

Fact

Derobotization is most likely in the first periods after adoption.

- This fact is indicative of a learning process.

Method:

- Kaplan-Meier estimator to adjust for censoring

Periods after Robotization	Derobotization % (KM)	Derobotization (Naive)
1	50.97%	64.64%
2	33.58%	26.62%
3	9.79%	5.56%
4	5.66%	3.18%

Derobotization and Size

- Which firms derobotize?

Fact

Larger firms are less likely to derobotize.

Derobotization and Size

- Which firms derobotize?

Fact

Larger firms are less likely to derobotize.

Method:

- Cox proportional hazards model on robot usage duration
- Negative effect of size on hazard ratio

Derobotization Outcomes

- What happens after derobotization?

Fact

Derobotization is correlated negatively with labor inputs and positively with capital-to-labor ratio.

Derobotization Outcomes

- What happens after derobotization?

Fact

Derobotization is correlated negatively with labor inputs and positively with capital-to-labor ratio.

Method:

- Measure changes in labor (hours), capital, and K/L ratio
- Sample: firms robotizing/derobotizing once
- Event study with two-way fixed effects

Robotization and the Model

Task-based framework: each factor completes a set of tasks for production.

Given a set of factors in production, robot adoption:

- Affects each factors productivity in production (productivity)
- Implies a reassignment of tasks between factors (substitution)
- Create new tasks (reinstatement)

Model

Then production can be formulated as:

$$Y_t(M_t, L_t | R_t, \varphi_t) := z_{Ht} \left(M_t^{\frac{\sigma-1}{\sigma}} + \sum_{o \in \{1,2\}} z_{ot}^{\frac{1}{\sigma}} L_{ot}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where $z_{xt}(R_t, \varphi_{xt}) := \exp(\varphi_{xt} + \gamma_x R_t)$ for $x \in \{H, 1, 2\}$.

$$\implies \pi_t(R, \varphi) \equiv \max_{X \in \mathbb{R}_+^3} \left\{ P_M Y_M^{\frac{1}{\varepsilon}} Y_t(X | R, \varphi)^{\frac{\varepsilon-1}{\varepsilon}} - w^T X \right\}$$

Firms maximize expected discounted value of all future profits.

Timing and Structure

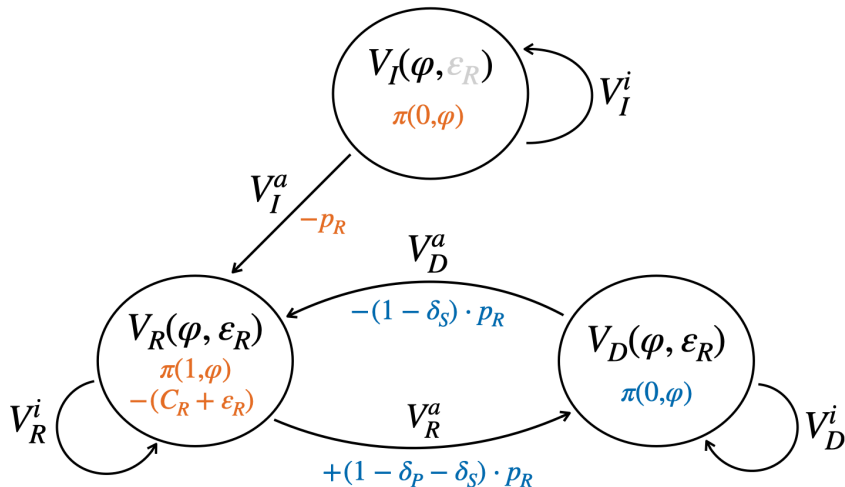


Figure: Value function structure

Robot adoption - Policy function

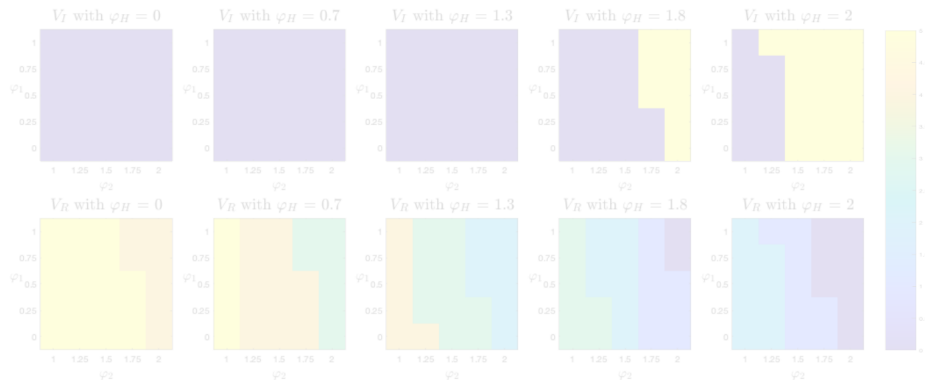


Figure: Action-Inaction regions by productivity φ and cost-type ε_R

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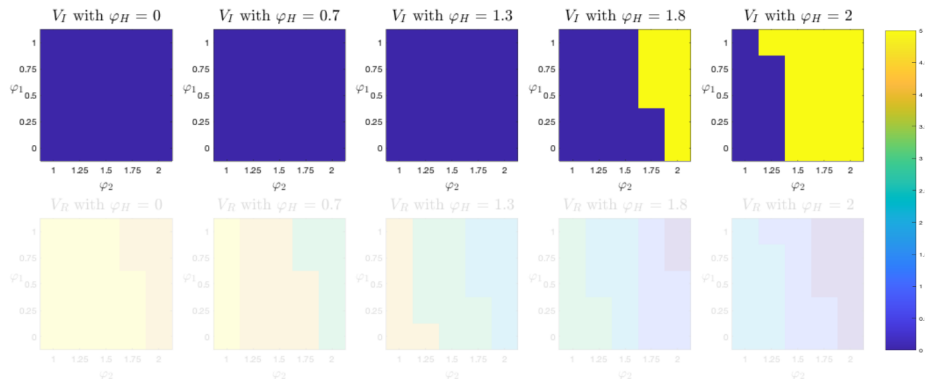


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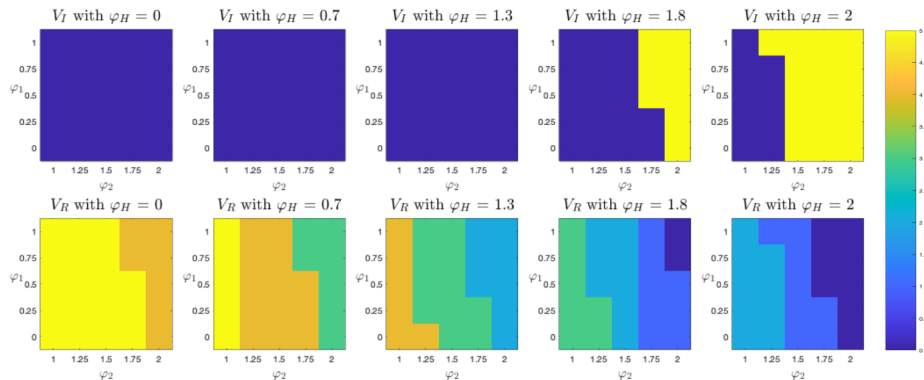


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Robot adoption - Policy function

- Determinants of derobotization
 - *Productivity effect*: Decrease in productivity
 - *Revelation effect*: Above-average robotization costs

Robot adoption - Policy function

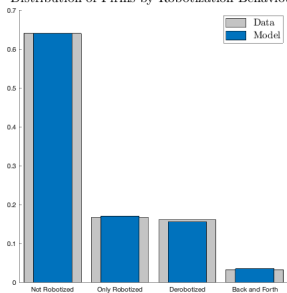
- Determinants of derobotization
 - *Productivity effect*: Decrease in productivity
 - *Revelation effect*: Above-average robotization costs
- φ_H indicates firm size (Humlum 2019)

Observation

Larger firms are less likely to derobotize.

Robotization behaviour

Distribution of Firms by Robotization Behaviour



Periods of Robotization before Derobotization

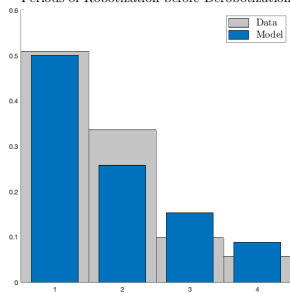


Figure: Adoption behaviour of firms in simulated time series.

Observation

Derobotization is most likely in the first periods after adoption.

Robotization behaviour

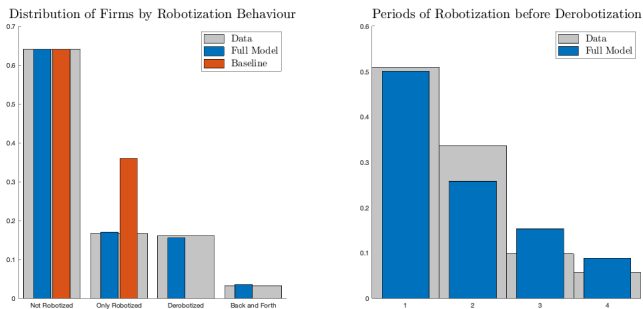


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Event Study: Derobotization Event

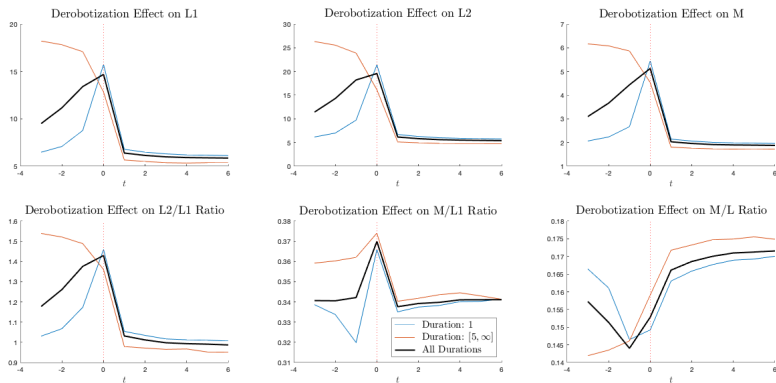


Figure: Derobotization event in the simulated time series

Event Study: Derobotization Event

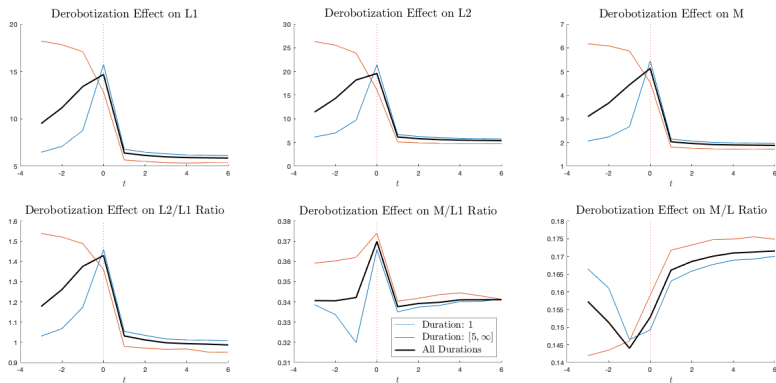


Figure: Derobotization event in the simulated time series

Observation

Derobotization causes a drop in labor demand. Furthermore it leads to an increase in the intermediate-to-labor ratio.

Event Study: Robotization Event

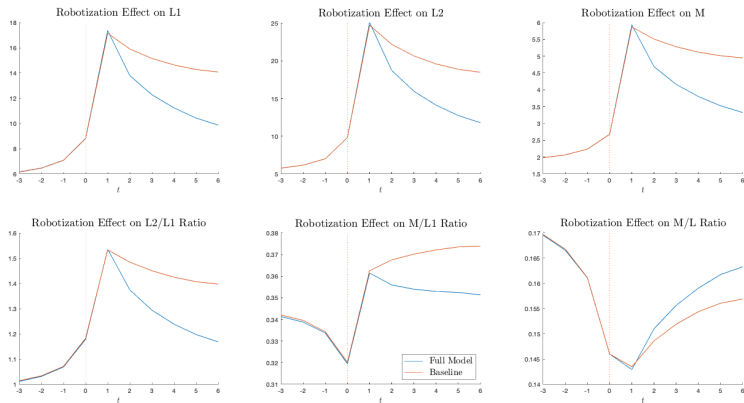


Figure: Robotization event in the simulated time series

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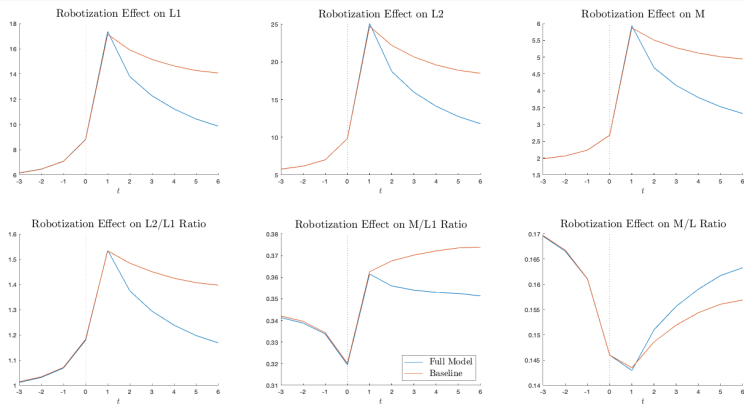


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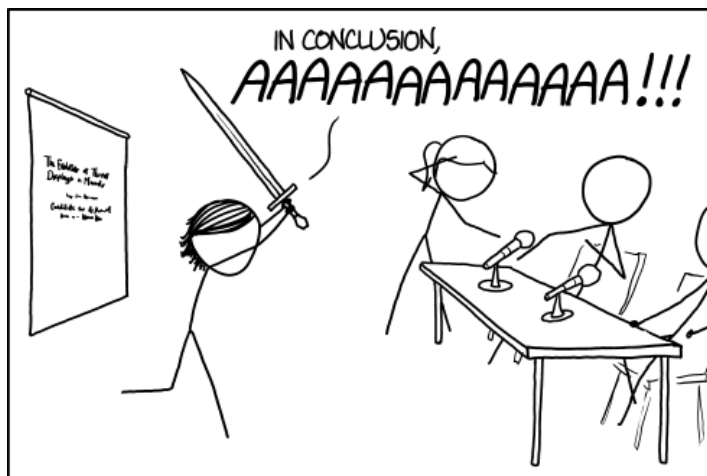
Observation

The permanent adoption model overestimates the effects of robotization.

Conclusion

- First paper (to our knowledge) to analyze this behaviour in depth
- Permanent adoption models are incomplete
- Our biggest contribution is opening avenues of future research:
 - Implications for business cycles
 - A repeat of our analysis in other countries (Acemoglu et al., 2020 but with deautomation)
 - An analysis on deautomation which includes depth (IFR data)

The End

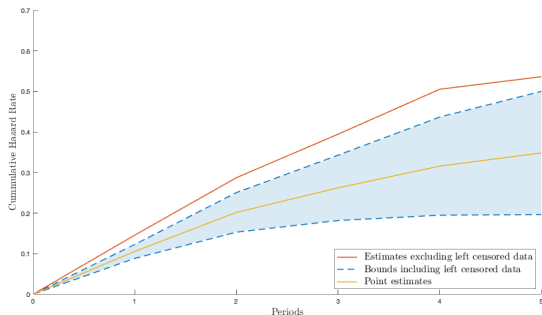


THE BEST THESIS DEFENSE IS A GOOD THESIS OFFENSE.

Appendix

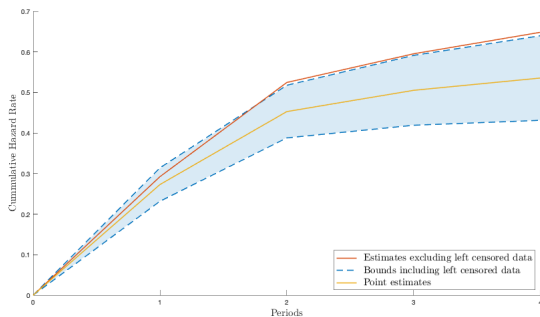
- KM: Robot. Classes
- KM: Derobotization
- Regression: Size
- Robustness Test: Size
- Regression: Inputs
- Microfoundations
- Value Functions
- Action-Region Graph
- Parametrization
- Determining Effects
- Policy functions
- CF: Certain Costs
- CF: No Setup Costs
- CF: Reversed Persistence
- Derobotization Event
- Robotization Event

Kaplan-Meier: Robotization Behaviour



- Kaplan-Meier estimation is used to adjust for right-censoring

Kaplan-Meier: Derobotization Behaviour



- Kaplan-Meier estimation is used to adjust for right-censoring
- The area in the bounds represents possible rates of derobotization
- We use the midpoint as our estimate

Appendix: duration model

$$\lambda(t_i|X_i) = \lambda_0(t_i) \times \exp\left(\beta_1 \text{size}_i + \beta_2 \text{prevrob}_i + \beta_3 \log(K/L)_i\right) \quad (1)$$

Table: Duration of robot usage and firm size

Specification	(1)	(2)
size		
from 100 to 500	-0.42*** (0.15)	-0.35** (0.15)
from 500	-0.47** (0.21)	-0.44** (0.22)
Controls		yes

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

Appendix: Robustness Test

$$\text{derobotization}_{it} = \beta_1 \text{size}_{it-1} + \beta_2 \log(K/L)_{it-1} + \beta_3' \times \text{industry}_{it} + \tau_t + \varepsilon_{it}. \quad (2)$$

Table: Robustness test: disaggregated data

	(1)	(2)	(3)	(4)
Size _{t-1}				
From 100 to 500	-0.09*** (0.02)	-0.08*** (0.02)	-0.08*** (0.02)	-0.06*** (0.02)
From 500	-0.17*** (0.02)	-0.16*** (0.02)	-0.16*** (0.02)	-0.14*** (0.03)
log(K/L) _{t-1}		-0.02* (0.01)	-0.02 (0.01)	-0.02** (0.01)
Time FE			yes	yes
Industry FE				yes
Observations	1560	1538	1538	1529

Appendix: Event Study

$$y_{it} = \beta_1 \text{derobotization}_{it} + \beta_2 \text{derobotization}_{it-1} + \mu_i + \tau_t + \varepsilon_{it}. \quad (3)$$

Table: Derobotization and Firm Outcomes

Specification	log(<i>capital</i>)		log(<i>hours</i>)		log(<i>K/L</i>)	
	(1)	(2)	(3)	(4)	(5)	(6)
derobotization _{<i>t</i>}	-0.00 (0.06)	-0.00 (0.06)	-0.09** (0.04)	-0.08** (0.04)	0.09* (0.05)	0.09* (0.05)
derobotization _{<i>t-1</i>}		0.02 (0.05)		-0.06 (0.03)		0.06 (0.04)
cumulative effect	0.00	0.02	-0.09**	-0.14**	0.09*	0.15**

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

Microfoundations for Task-Based model (1/3)

- Firm operates with a task-based production function [▶ back](#)

$$Y := \left(\int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \quad (4)$$

- Production of task i conditional on robotization:

$$y(i) := z_o(i, R)X_o(i). \quad (5)$$

- Firms solves the problem

$$\max_{\{X_o(i)\}_{o=1}^{|\{1,2\}|}} \left(\int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} - \sum_{o=1}^{|\{1,2\}|} \left(\int_0^1 p_o X_o(i) di \right), \quad (6)$$

Microfoundations for Task-Based model (2/3)

Given a set of factors in production, robot adoption:

- Affects each factors productivity in production (productivity)
- Implies reassignment of tasks between factors (substitution)
- Create new tasks (reinstatement)

Microfoundations for Task-Based model (3/3)

- The solution to this problem is given by: [▶ back](#)

$$Y \equiv \left\{ \sum_{o=1}^2 \left(z_o \mathbf{X}_o \right)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} \quad (7)$$

$$z_o := \left(\int_{A_o} z_o(i)^\sigma di \right) \left(\int_{A_o} z_o(i)^{\sigma-1} di \right)^{-1} \quad (8)$$

$$z_o = \exp(\varphi_o + R\gamma_o) \quad (9)$$

$$\varphi_o = \log \frac{\int_{A_o} z_o(i, 0)^\sigma di}{\int_{A_o} z_o(i, 0)^{\sigma-1} di} \quad (10)$$

$$\gamma_o = \log \frac{\int_{A_o} z_o(i, 1)^\sigma di}{\int_{A_o} z_o(i, 1)^{\sigma-1} di} - \log \frac{\int_{A_o} z_o(i, 0)^\sigma di}{\int_{A_o} z_o(i, 0)^{\sigma-1} di} \quad (11)$$

Model

Then production can be formulated as:

$$Y_t(M_t, L_t | R_t, \varphi_t) := z_{Ht}(\varphi_{Ht}, R_t) \left(M_t^{\frac{\sigma-1}{\sigma}} + \sum_{o \in \{1,2\}} z_{ot}(\varphi_{ot}, R_t)^{\frac{1}{\sigma}} L_{ot}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where

$$z_{Ht}(R_t, \varphi_t) := \exp(\varphi_{Ht} + \gamma_H R_t),$$

$$z_{ot}(R_t, \varphi_t) := \exp(\varphi_{ot} + \gamma_o R_t),$$

▶ back

▶ App.

Value functions

Unrobotized: $V_I = \max\{V_I^a, V_I^i\}$

$$V_I^a(\varphi_t, \varepsilon_R) = \pi(0, \varphi_t) - p_R + \beta \mathbb{E}[V_R(\varphi_{t+1}, \varepsilon_R) | \varphi_t]$$

$$V_I^i(\varphi_t, \varepsilon_R) = \pi(0, \varphi_t) + \beta \mathbb{E}[V_I(\varphi_{t+1}, \varepsilon_R) | \varphi_t]$$

Robotized: $V_R = \max\{V_R^a, V_R^i\}$

$$V_R^a(\varphi_t, \varepsilon_R) = \pi(1, \varphi_t) - c_R + (1 - \delta)p_R + \beta \mathbb{E}[V_I(\varphi_{t+1}, \varepsilon_R) | \varphi_t, \varepsilon_R]$$

$$V_R^i(\varphi_t, \varepsilon_R) = \pi(1, \varphi_t) - c_R + \beta \mathbb{E}[V_R(\varphi_{t+1}, \varepsilon_R) | \varphi_t, \varepsilon_R]$$

$$\text{where } c_R = C_R + \varepsilon_R, \quad \delta = \delta_S + \delta_P$$

Derobotized $V_D = \max\{V_D^a, V_D^i\}$

$$V_D^a(0, \varphi_t, \varepsilon_R) = \pi(0, \varphi_t) - (1 - \delta_S) \cdot p_R + \beta \mathbb{E}[V(1, \varphi_{t+1}, \varepsilon_R) | \varphi_t, \varepsilon_R]$$

$$V_D^i(0, \varphi_t, \varepsilon_R) = \pi(0, \varphi_t) + \beta \mathbb{E}[V_R(0, \varphi_{t+1}, \varepsilon_R) | \varphi_t, \varepsilon_R]$$

Action-Inaction region

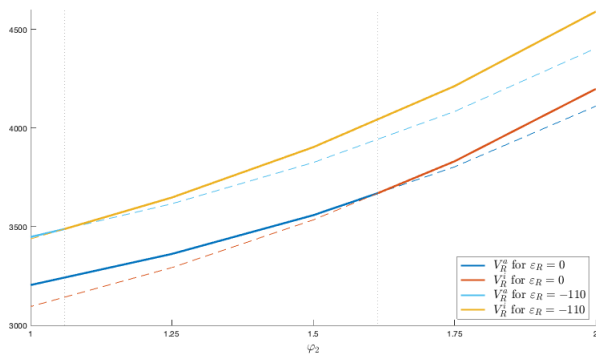


Figure: Action-Inaction regions of V_R at $(\varphi_H, \varphi_1) = (1.3, 1)$

▶ back

▶ App.

Parametrization

Table: Parametrization

Parameter	Full Model	Parameter	Full Model
β	0.8	C_R	500
σ	1.5	ρ_R	1260
γ_H	1.74	δ_P	0.03
γ_1	-0.1	δ_S	0.17
γ_2	0.2	φ_H	[0,0.7,1.3,1.8,2]
w_M	15	φ_1	[0,0.25,0.5,0.75,1]
w_1	10	φ_2	[1,1.25,1.5,1.75,2]
w_2	20	ε_R	[-220,-110,0,110,220]
ε	1.5	ρ_H	2/3
Y_M	10	ρ_1	0.3
P_M	10	ρ_2	0.5

Robot adoption - Determining Effects

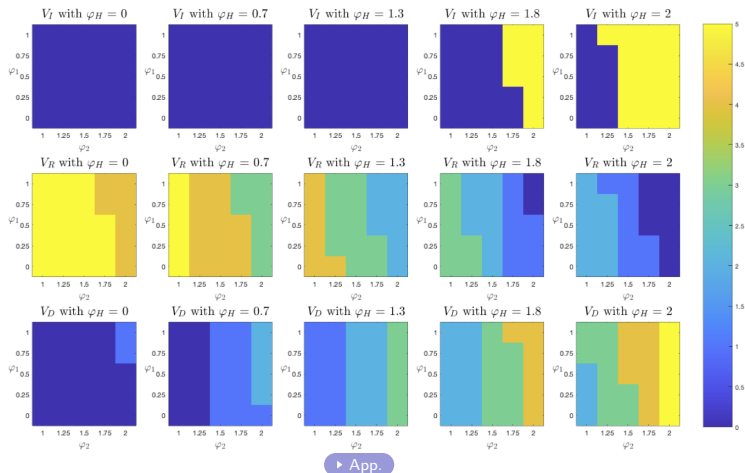


Figure: Action-Inaction regions by productivity φ and cost-type ε_R

Robot adoption - Determining Effects

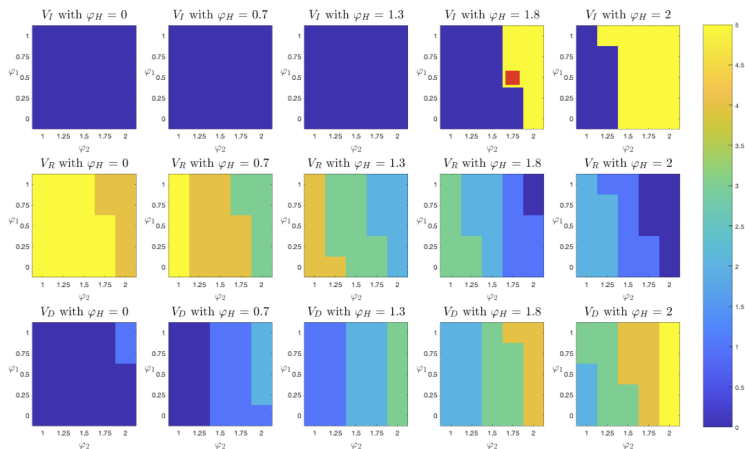


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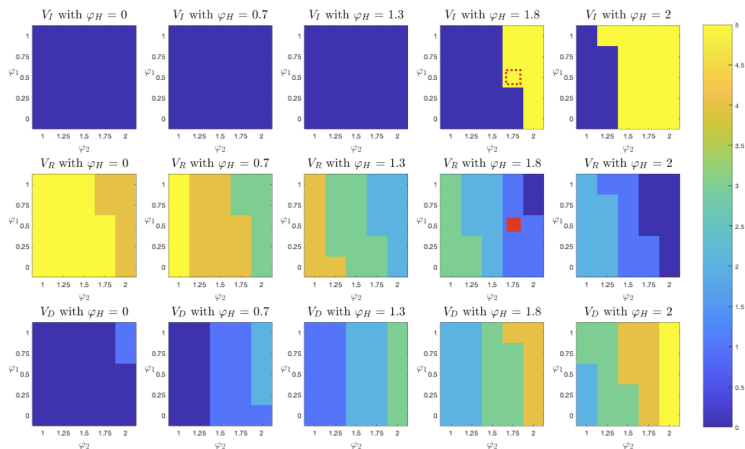


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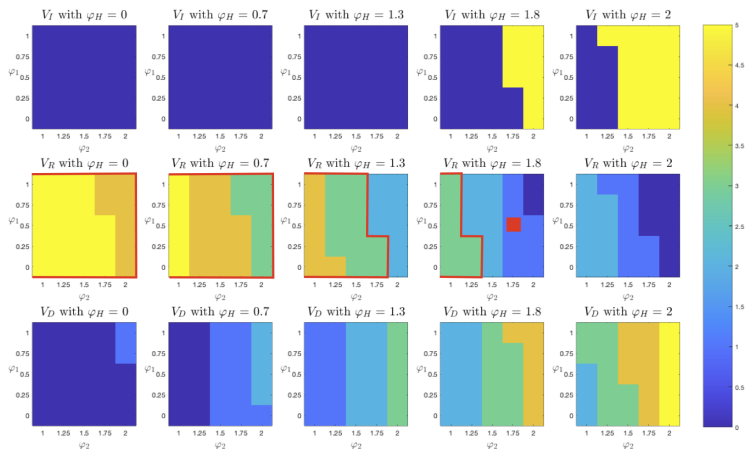


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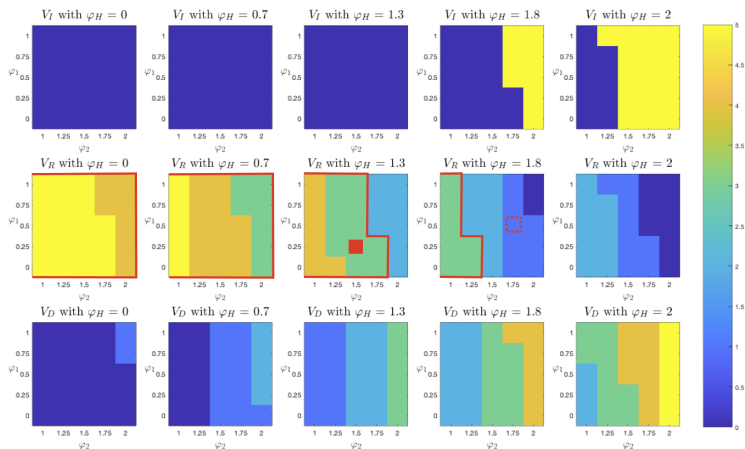


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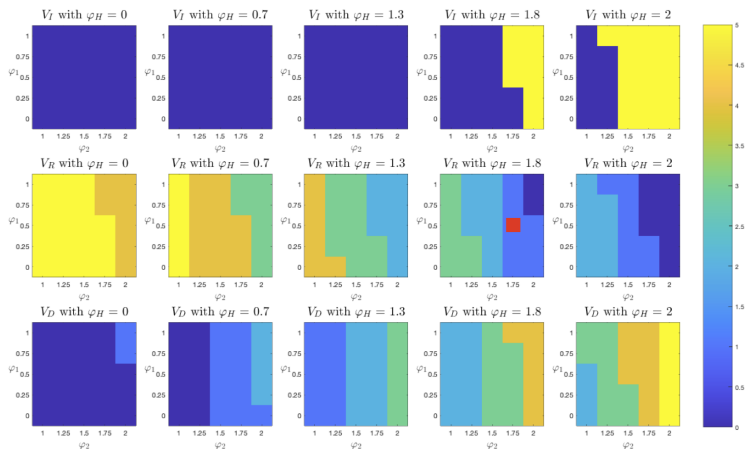


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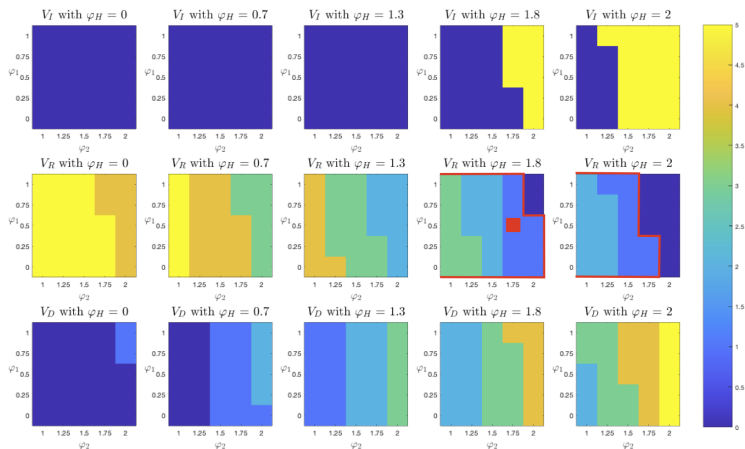


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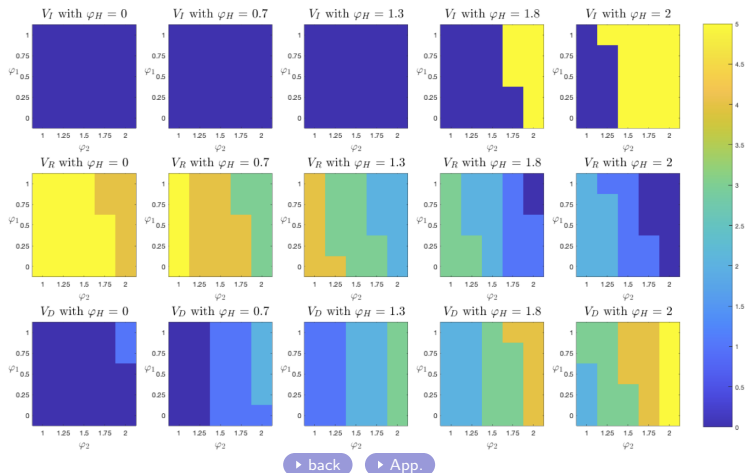
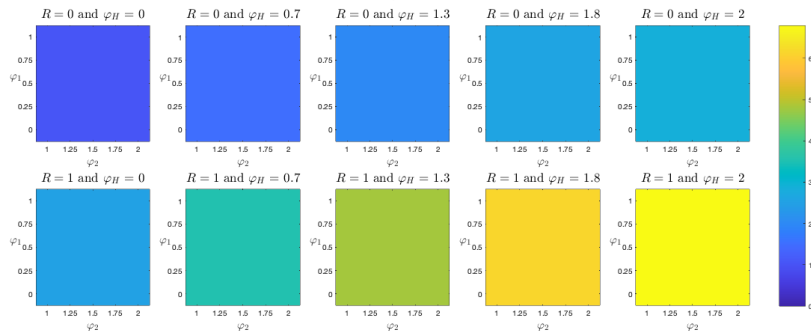


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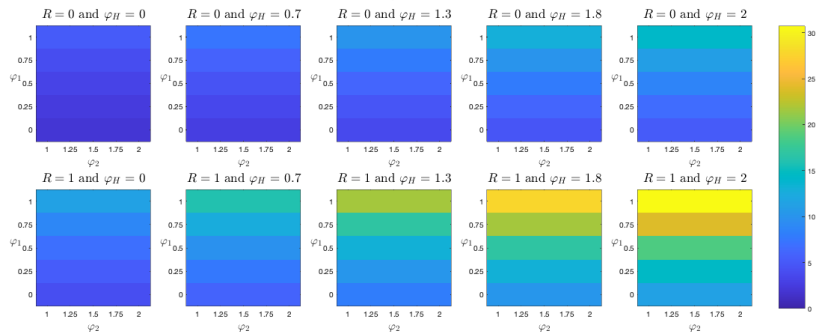
Policy functions

Heatmaps of Policy Function M



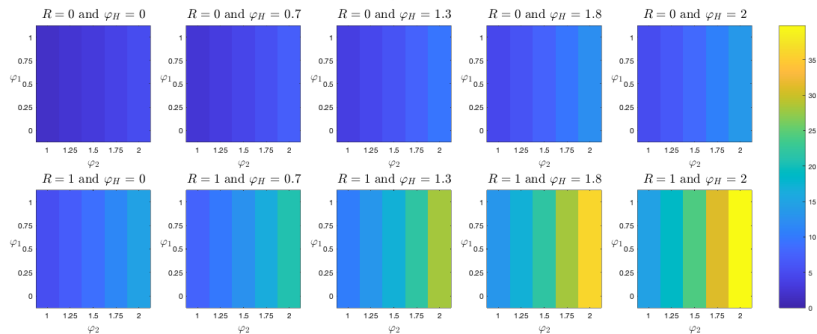
Policy functions

Heatmaps of Policy Function L1



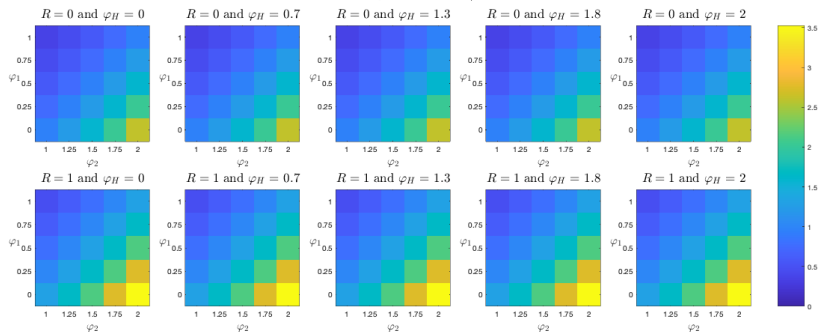
Policy functions

Heatmaps of Policy Function L2

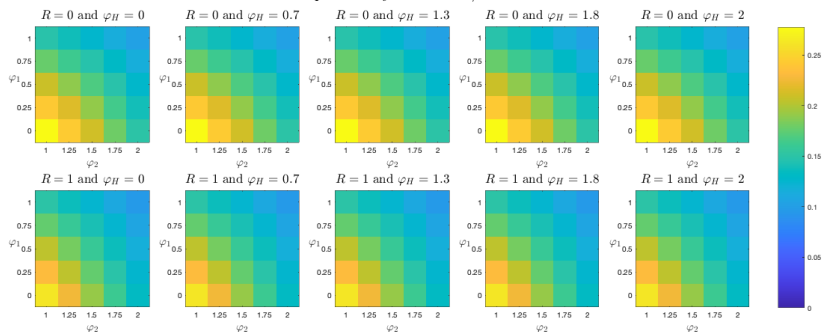


Policy functions

Heatmaps of Policy Function L2/L1



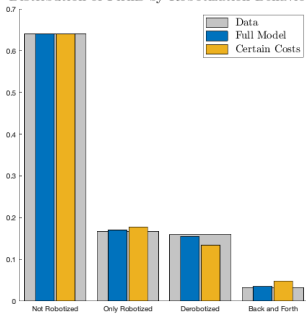
Policy functions

Heatmaps of Policy Function M/L 

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Counterfactuals: Certain Costs

Distribution of Firms by Robotization Behaviour



Periods of Robotization before Derobotization

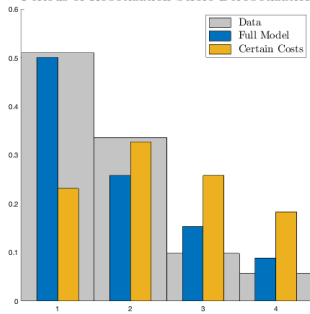


Figure: Adoption behaviour of firms in simulated time series with Certain Costs

▶ back

▶ App.

Counterfactuals: No Setup Costs

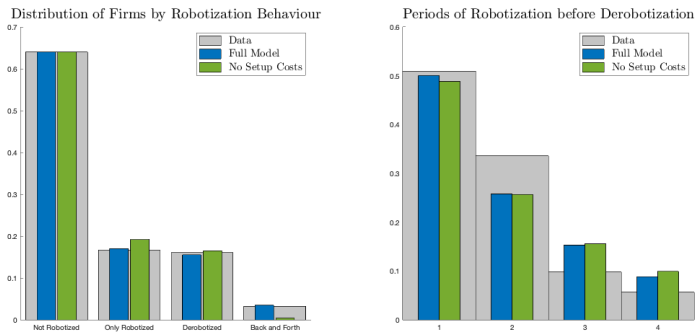
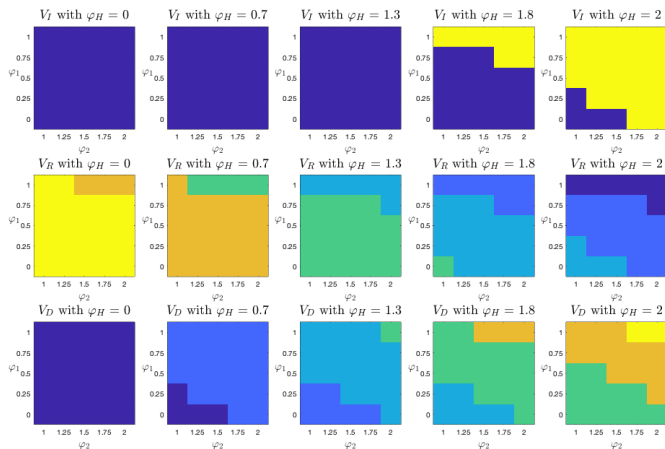


Figure: Adoption behaviour of firms in simulated time series with No Setup Costs

Counterfactuals: Reversed Persistences

Figure: Heatmaps of policy function R with reversed persistences

Event Study Appendix: Derobotization Event

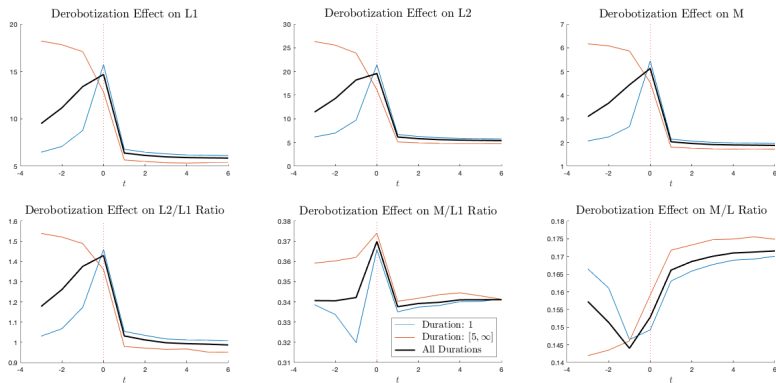


Figure: Derobotization event in the simulated time series

Observation

Long term adopters exhibit lower L_2/L_1 ratios prior to derobotization.

Event Study Appendix: Derobotization Event

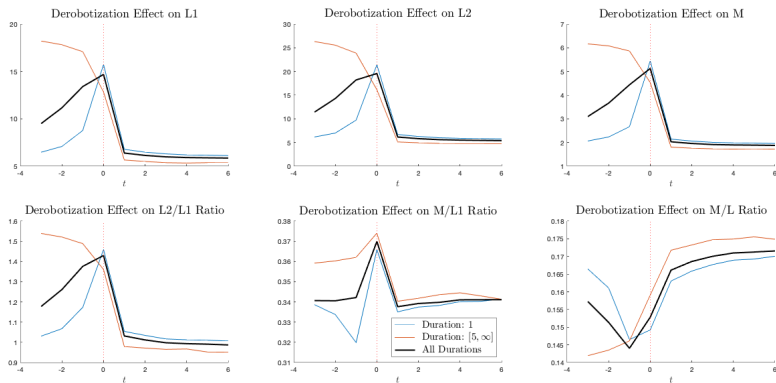


Figure: Derobotization event in the simulated time series

Observation

Long term adopters exhibit higher M/L_1 ratios prior to derobotization.

Event Study Appendix: Derobotization Event

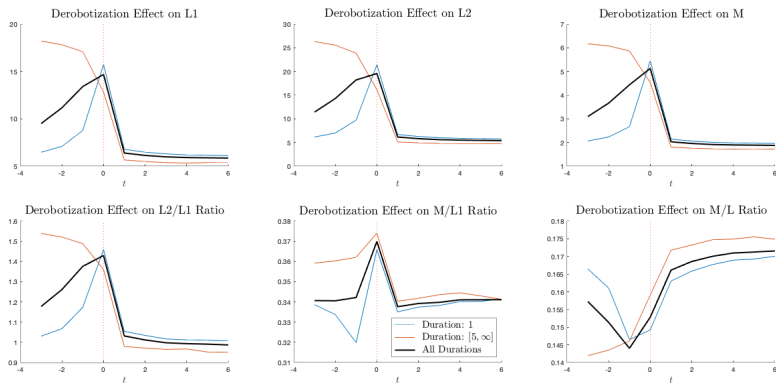


Figure: Derobotization event in the simulated time series

Observation

Those firms which take longer to derobotize do so following a sequence of low productivity shocks. [▶ back](#) [▶ App.](#)

Event Study: Robotization Event

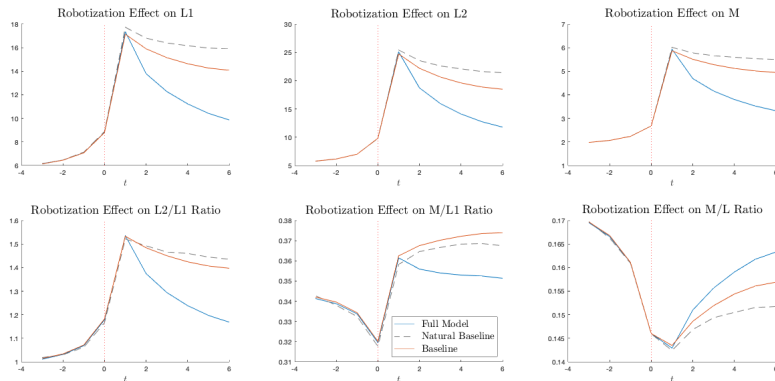


Figure: Robotization event in the simulated time series

Observation

Robotization increases high-skill labor and intermediate demand more than it increases low-skill labor demand. [▶ back](#) [▶ App.](#)