Robot Adoption and Labor Market Dynamics

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1. Introduction

2. Data

2.1 Stylized Facts on Firm Robot Adoption

Fact 1. Robot Adoption Is Lumpy

- Table 1 reports summary statistics for the robot adoptions identified from firm customs records in Appendix A.2.
- The take-away from the table is that robot adoption is lumpy.
- Out of the sample adopters, 70.6 percent invest in a single year only, and the peak year of investment accounts on average for 90.7 percent of total firm robot expenditures.
- Adopting firms purchase robot machinery for an average of $311,000.
- This discrete nature of robot adoption motivates the choice in Section 3 to model robot adoption as a discrete choice problem.

Table 1: Firm Robot Investments

Adoptions (count)	454
Share of adopters with investments in one year only (percent)	70.6
Share of robot expenditures in max year (percent)	90.7
Robot machinery expenditures ($1,000)	311

Fact 2. Larger Firms Select into Robot Adoption

- Table 2 shows firm outcomes for the robot adopters in the year prior to adoption.
- Column 2 (“Industry”) reports average outcomes for non-adopters within the same two-digit industry year cells as the robot adopters.
- Robot adopters are different from non-adopters along several dimensions, but the key feature that sets robot adopters apart is that they are substantially larger.
- The model in Section 3 rationalizes the selection into robot adoption by combining firm heterogeneity with fixed costs of adoption, such that it is the firms with the largest expected efficiency gains from industrial robots that will choose to adopt the technology.

Table 2: Firm Outcomes in the Year Before Robot Adoption

	Adopters	Industry	Matches	P-value A-M
log Sales	18.28 (0.07)	16.35 (0.07)	18.19 (0.07)	0.37
log Wage Bill	16.93 (0.07)	15.15 (0.07)	16.89 (0.07)	0.66
log Employment	4.06 (0.06)	2.4 (0.06)	4.02 (0.06)	0.66
Wage bill shares (percent)				
– Managers	12.5 (0.5)	9.1 (0.7)	11.0 (0.4)	0.02
– Tech	16.0 (0.9)	6.9 (0.6)	14.3 (0.8)	0.14
– Sales	12.2 (0.4)	10.5 (0.6)	12.5 (0.5)	0.64
– Support	7.5 (0.4)	4.9 (0.5)	7.8 (0.5)	0.69
– Transportation/warehousing	5.9 (0.5)	3.6 (0.5)	6.8 (0.5)	0.23
– Line workers (mostly production)	39.9 (1.1)	47 (1.4)	40.7 (1.0)	0.61
Joint orthogonality (F test)				0.25
Observations	454	454	454	908

Note: "Joint orthogonality" represents a test of the joint hypothesis that all coefficients equal zero when the adopter indicator is regressed on the nine outcome variables in Table 2. Column 1 (Adopters) shows mean outcomes for robot adopters in the year before adoption. Column 2 (Industry) shows averages for randomly chosen non-adopters within the same industry-year cell as the adopters (one-to-one). Column 3 (Matches) shows averages for match firms within the same industry-year cell. These matches each have the minimum distance to an adopter with respect to log sales and production wage bill share (levels and two-year changes); see Appendix A.7.1 for details. Column 4 (P-value A-M) shows p-values for the null hypotheses that Adopters (column 1) and Matches (column 3) have the same population mean.

3. A Model of Firm Robot Adoption

3.1 Production Technology

A manufacturing firm j uses workers of different occupations $L \in \mathbb{R}_+^{|\mathcal{O}|}$ and intermediate inputs $M \in \mathbb{R}_+$ according to the CES production function

$$Y_{jt} = F(M_{jt}, L_{jt}|R_{jt}, \varphi_{jt}) = z_{Hjt} \left\{ M_{jt}^{\frac{\sigma-1}{\sigma}} + \sum_{o \in \mathcal{O}} z_{ojt}^{\frac{1}{\sigma}} L_{ojt}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} \quad \text{with} \tag{1}$$

$$z_{Hjt} = \exp(\varphi_{Hjt} + \gamma_H R_{jt}) \tag{2}$$

$$z_{ojt} = \exp(\varphi_{ojt} + \gamma_o R_{jt}) \tag{3}$$

Firms are heterogeneous with respect to a vector of exogenous baseline productivities $\varphi \in \mathbb{R}^{\mathcal{O}+1}$ and an endogenous robot technology state $R \in \{0, 1\}$. The parameter γ_H captures the effect of robot technology on firm Hicks-neutral productivity z_H, and the parameters γ_o govern how robot technology changes the relative productivities of worker occupations in production z_o (measured relative to intermediate inputs M).[1]

3.2 Demand and Flow Profits

The firm faces an iso-elastic demand curve

$$Y_{jt} = Y_{Mt} \times (P_{jt}/P_{Mt})^{-\epsilon}, \tag{4}$$

where Y_{Mt} is the aggregate manufacturing demand and P_{Mt} is the manufacturing price index. The firms takes the vector of factor prices w_t as given, such that the flow profit function reads

$$\pi_t(R,\varphi) = \max_X \left\{ P_{Mt} Y_{Mt}^{\frac{1}{\epsilon}} F(X|R,\varphi)^{1-1/\epsilon} - w_t^T X \right\} = \Omega_t C_t(R,\varphi)^{1-\epsilon}, \tag{5}$$

where C_t denotes the unit cost function, Ω_t is a common profit shifter, and the static inputs are stacked into the vector $X = (M, L)$.[2] By lowering production costs C_t, the robot technology allows firms to scale up output and increase flow profits.

3.3 Adoption of Robot Technology

The firm faces a dynamic decision about whether and when to adopt the robot technology R. The optimal adoption decision trades off a sunk cost of robot adoption with gains in future profits from being able to operate robot technology. The sunk adoption cost includes a common time-varying component c_t^R and an idiosyncratic component ε_{jt}^R. The adoption decision is essentially an optimal stopping problem that is reminiscent of the seminal work on bus engine replacement by Rust (1987). The value of a firm is represented by the Bellman equation

$$V_t(0,\varphi) = \max_{R\in\{0,1\}} \pi_t(0,\varphi) - (c_t^R + \varepsilon_{jt}^R) \times R + \beta \mathbb{E}_t V_{t+1}(R,\varphi') \tag{7}$$

$$V_t(1,\varphi) = \sum_{\tau=0}^{\infty} \beta^\tau \pi_{t+\tau}(1,\varphi_{t+\tau}). \tag{8}$$

Robot technology does not depreciate in the baseline specification of the model.[3]

Firm baseline productivities evolve according to the Markov process

$$\varphi_{jt+1} = g_t(\varphi_{jt}, \dots, \varphi_{jt-k}) + \xi_{jt+1}, \quad \xi_{jt+1} \perp (\varphi_{jt}, \dots, \varphi_{jt-k}), (\varepsilon^R_{jt}, \dots, \varepsilon^R_{jt-l}). \tag{9}$$

The idiosyncratic adoption cost shocks ε^R_{jt} are drawn i.i.d. from a cumulative distribution function F such that the probability that a firm adopts robot technology is

$$P_t(\Delta R_{jt+1} = 1) = F\left(\beta\left(\mathbb{E}_t V_{t+1}(1, \varphi_{jt+1}) - \mathbb{E}_t V_{t+1}(0, \varphi_{jt+1})\right) - c^R_t\right) \tag{10}$$

- The robot adoption model features two key simplifying assumptions about robot investment behavior.

- First, robot adoption is treated as a one-off decision. This assumption is motivated by the observed lumpiness (Fact 1 in Section 2.1) whereby most robot users invest entirely in a single year.

- Appendix C.5 estimates a model extension in which robots deteriorate at a fixed rate, thereby leaving scope for replacement investments. Second, firms cannot receive larger relative robot production effects g by spending more on robots.

- The structural estimation in Section 4 will provide empirical evidence in support of this homogeneity assumption on the treatment effects of robot adoption.

- Equation (7) entails a key timing assumption that robot adoption is decided one year in advance.

4. Structural Estimation of Firm Robot Adoption

4.1 Elasticity of Substitution between Production Tasks

In this section, I estimate the elasticity of substitution between production tasks, σ. I distinguish between labor tasks of production workers, tech workers, and other workers.[6] To preview, I use the model structure to derive an instrumental variables strategy, and I estimate that tasks are complements in firm production.

The first-order conditions for cost minimization in Equation (5) imply that firm factor demands satisfy the following relationship

$$\log(L_{o'jt}) - \log(L_{ojt}) = -\sigma(\log(w_{o'jt}) - \log(w_{ojt})) + \log(z_{o'jt}) - \log(z_{ojt}) \tag{11}$$

I use the structure of the model in Section 3 to derive a rational expectations generalized method of moments (GMM) estimator that explicitly solves this simultaneity problem. The identification strategy builds on the insight of Doraszelski and Jaumandreu (2018) that the Markovian structure on firm productivities implies that past factor choices X_{jt-1} and prices w_{jt-1} must be uncorrelated with the current productivity innovations ξ_{jt}. This restriction allows me to estimate σ from the moment condition

$$\mathbb{E}\left[A_{oo'}(Q_{jt-1})(\xi_{ojt} - \xi_{o'jt})\right] = 0, \tag{12}$$

where $A_{oo'}$ is a vector function of the instruments Q_{jt-1}, including $\log(X_{jt-1})$ and $\log(w_{jt-1})$.

Table 3: Estimating the Elasticity of Substitution between Tasks in Production

	GMM
Elasticity of task substitution, σ	0.493 (0.092)

4.2 Robot Technology

This section describes my strategy for identifying the parameters of robot technology, γ. I first discuss the identification challenges that arise from the fact that firms endogenously select into robot adoption. I then use the adoption model developed in Section 3 to derive an identification strategy that deals with this selection problem.

First, from the invertibility of the factor demand system, I can recover firm productivities from the first-order conditions to Equation (5)

$$z_{ojt} = l_{ojt} - m_{jt} + \sigma(\log(w_{ojt}) - \log(w_{Mjt})) \tag{13}$$

$$z_{Hjt} = \frac{1}{\epsilon - 1} m_{jt} + \frac{\sigma}{\epsilon - 1} w_{Mjt} + \frac{(\sigma - \epsilon)}{(\sigma - 1)(\epsilon - 1)} \log \left\{ w_{Mjt}^{1-\sigma} + \sum_{o} z_{ojt} w_{ojt}^{1-\sigma} \right\} \tag{14}$$

where lower-case factor choices denote log transforms. With these productivities recovered, it is now tempting to use Equations (2)-(3) to run the regression

$$\log(z_{jt}) = \gamma R_{jt} + \varphi_{jt} \tag{15}$$

Identification Strategy (Parameters of Robot Technology γ).

1. Take two firms with similar output and occupational wage bills in some initial k years.
2. In the following year, one of the firms adopts robots.
3. The differential paths of firm output and occupational wage bills identify the parameters of robot technology, γ .

In the model, a firm's factor demands $x_{jt} = (m_{jt}, l_{jt})$ can take two potential values, $(x_{jt}(0), x_{jt}(1))$, according to whether or not the firm has adopted robot technology. In the language of Rubin (1990), the two identifying assumptions are *unconfoundedness*

$$\{\Delta R_{jt+1} \perp (x_{jt+1}(1), x_{jt+1}(0))\} \mid (x_{jt-1}(0), .., x_{jt-k}(0)) \tag{A1}$$

and *overlap* in robot adoption

$$0 < P\left(\Delta R_{jt+1} = 1 \mid x_{jt-1}(0), .., x_{jt-k}(0)\right) < 1 \tag{A2}$$

On top of this, Assumption (A2) requires that I can find another firm that experienced the same initial sequence of factor choices but did not adopt robots in year t. Under Assumptions (A1) and (A2), the difference in sample means between adopter and match firms identifies the average treatment effect of robot adoption (see Imbens and Wooldridge (2007))

$$\bar{x}_{t+1}^{T} - \bar{x}_{t+1}^{C} \xrightarrow{p} \mathbb{E}\left[x_{jt+1}(1) - x_{jt+1}(0) \mid j \in T\right], \tag{16}$$

where $\bar{x}^{T}$ and $\bar{x}^{C}$ denote the sample means for adopter and match firms, respectively.

Second, the probability of robot adoption in the model is given by

$$P_t(\Delta R_{jt} = 1 | \varphi_{jt-1}, ..., \varphi_{jt-k}) = F\left(\beta\left(\mathbb{E}_t V_{t+1}(1, \varphi_{jt+1}) - \mathbb{E}_t V_{t+1}(0, \varphi_{jt+1})\right) - c_t^R\right) \tag{17}$$

which lies strictly within the unit interval as long as the distribution of idiosyncratic adoption costs F has full support. The adoption model thus also satisfies the *overlap* condition (A2). Put into words, the identification strategy relies here on firm heterogeneity in the costs of robot adoption ε_{jt}^R driving otherwise similar firms to make different decisions about robot adoption.

Equation (16) identify the parameters of the robot technology

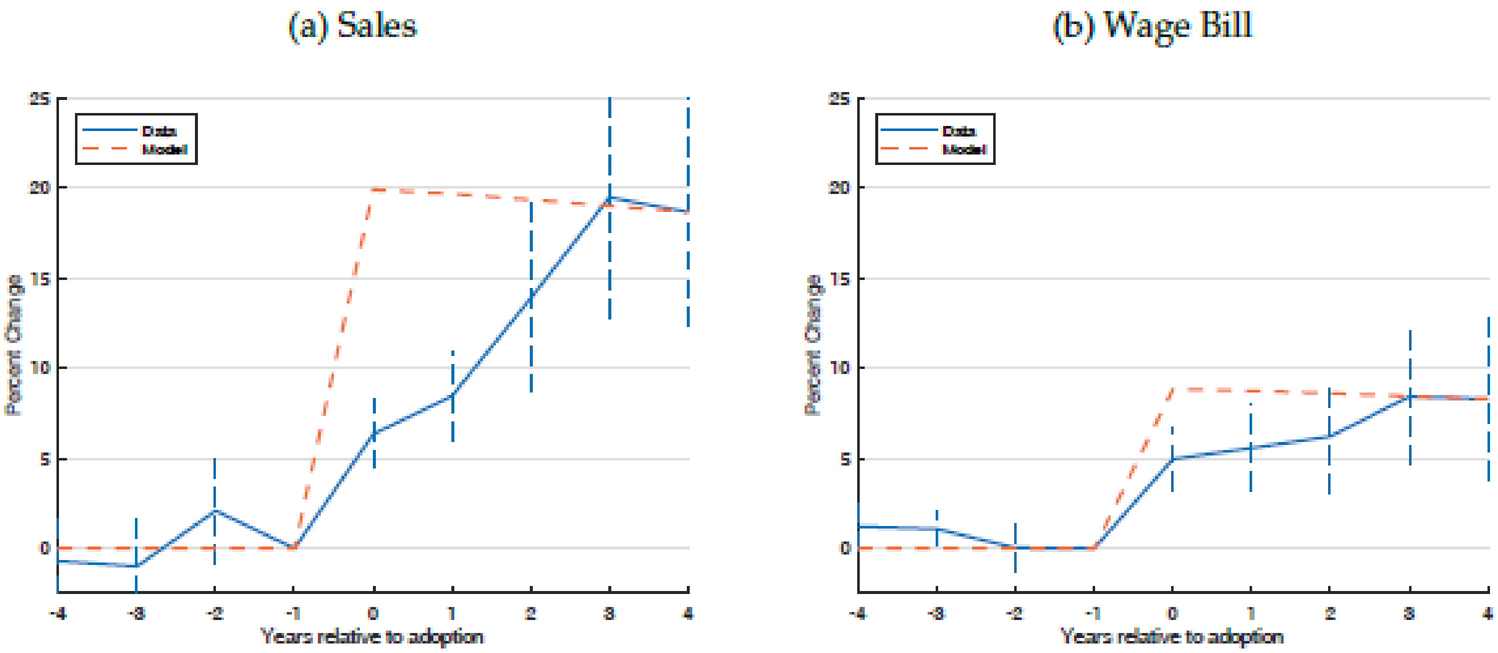
$$\gamma_o = z_{ojt}(1) - z_{ojt}(0) = \left(l_{ojt}(1) - l_{ojt}(0)\right) - \left(m_{jt}(1) - m_{jt}(0)\right) \tag{18}$$

$$\gamma_H = z_{ojt}(1) - z_{ojt}(0) \tag{19}$$

$$= \frac{1}{\epsilon - 1}\left(m_{jt}(1) - m_{jt}(0)\right) + \frac{(\sigma - \epsilon)}{(\sigma - 1)(\epsilon - 1)} \log \left\{ \frac{w_{Mjt}^{1-\sigma} + \sum_o z_{ojt}(1) w_{ojt}^{1-\sigma}}{w_{Mjt}^{1-\sigma} + \sum_o z_{ojt}(0) w_{ojt}^{1-\sigma}} \right\} \tag{20}$$

The identification of γ_H requires the values of the factor augmenting productivities z_{ojt} which at this point can be readily recovered from Equation (13).

Figure 1: Firm Outcomes Around Robot Adoption (Matching Diff-in-Diff)



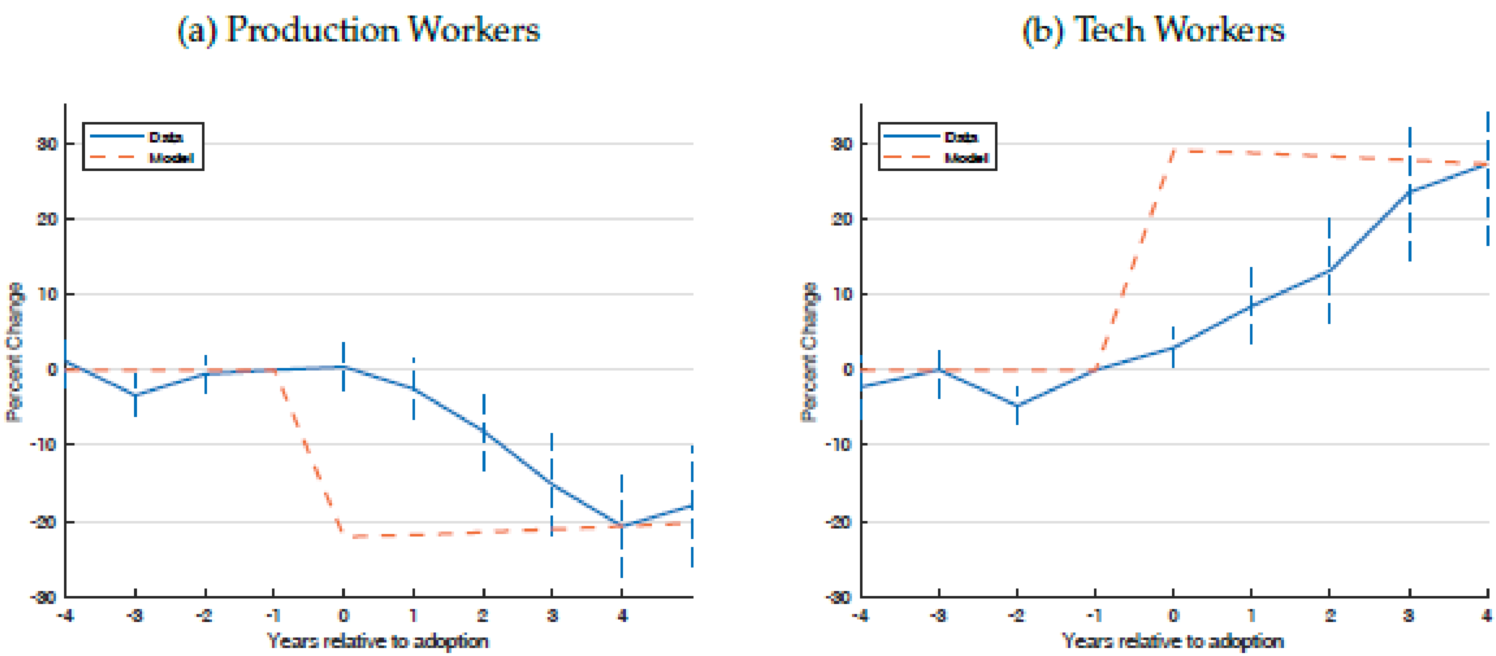
- Figure 1(a) shows that the average firm's sales increase 20 percent around robot adoption.

- Through the lens of the structural model, this sales effect implies that robot technology increases firm production efficiency by around 7 percent, given the calibrated elasticity of firm demand e.

- Figure 1(b) shows that the wage bill increases by 8 percent around robot adoption.

- The wage bill increase is less than the 20 percent sales effect in Panel (a), and implies that the substitution effects of robot adoption on labor go on average are negative.

Figure 2: Firm Wage Bills Around Robot Adoption (Matching Diff-in-Diff)



- Figure 2 decomposes the wage bill effects in Figure 1(b) by occupations. Production workers include tasks from welding to assembly, while tech workers include engineers, researchers, and skilled technicians.

- Panel (a) of Figure 2 shows that the demand for production workers falls by around 20 percent around robot adoption, while Panel (b) shows that the demand for tech workers simultaneously increases by around 30 percent.

- This shift of labor demand away from the production line and toward the tech department implies that robot adoption lowers the relative productivity of production workers ($\hat{\gamma}_P = -0.461$) but increases the relative productivity of tech workers ($\hat{\gamma}_T = 0.043$).

- Table 4 summarizes the estimated parameters of robot technology.

Table 4: Estimated Parameters of Robot Technology

Parameter	Description	Estimated Value
γ_P	Production worker augmenting robot productivity	−0.461
γ_T	Tech worker augmenting robot productivity	0.043
γ_O	Other worker augmenting robot productivity	−0.115
γ_H	Hicks-neutral robot productivity (normalized)	0.066

Note: The relative productivity effects go are measured relative to intermediate inputs. The parameter gH is normalized such that a zero sales effect of robot adoption would imply a value gH of zero.

- The reduced-form effects in Figure 1 align well with Koch et al. (2019), who find that robot adoption increases output 20-25 percent and lowers labor costs per unit produced among Spanish manufacturing firms.

- It is worth keeping in mind that the reduced-form effects in Figures 1 and 2 only identify the partial effects of one firm adopting industrial robots, and that any general equilibrium effects of robotization are differenced out in the figures.

- The general equilibrium model in Section 6 will fit these partial effects but also take into account general equilibrium interactions in product and labor markets to be able to quantify what happens when many firms in the economy adopt industrial robots.

4.3 Baseline Technology

To solve their forward-looking problem of robot adoption, firms must form expectations about their future productivities. To estimate this robot adoption problem, I specify that firm productivities (Equation (9)) follow a first-order vector autoregression VAR(1) with Gaussian innovations.

$$\varphi_{jt} = \mu_t + \Pi \varphi_{jt-1} + \xi_{jt}, \quad \text{with} \quad \xi_{jt} \overset{iid}{\sim} \mathcal{N}(0, \Sigma). \tag{21}$$

The unknown parameters (μ_t, Π, Σ) in Equation (21) can readily be estimated using either maximum likelihood or three-stage least squares.

4.4 Robot Adoption Costs

I specify the idiosyncratic adoption cost shocks ε_{jt}^{R} to be drawn from a logistic distribution $F \sim \text{Logistic}(0, \nu)$ such that the probability that a firm adopts robot technology (Equation (10)) takes the form

$$P_t(\Delta R_{jt+1} = 1) = \frac{\exp(\frac{1}{\nu}(-c_t^R + \beta \mathbb{E}_t V_{t+1}(1, \varphi_{jt+1})))}{\exp(\frac{1}{\nu}(-c_t^R + \beta \mathbb{E}_t V_{t+1}(1, \varphi_{jt+1}))) + \exp(\frac{1}{\nu}\beta \mathbb{E}_t V_{t+1}(0, \varphi_{jt+1}))}. \tag{22}$$

To develop intuition for the estimation strategy that I adopt here, note that Equation (22) implies a linear relationship between the log odds ratio of robot adoption and the expected gain in future profits from operating industrial robots.

$$\log\left(\frac{P_t(\Delta R_{jt+1} = 1)}{1 - P_t(\Delta R_{jt+1} = 1)}\right) = -\frac{c_t^R}{\nu} + \frac{1}{\nu} \times \left(\beta \mathbb{E} V_{t+1}(1, \varphi_{jt+1}) - \beta \mathbb{E}_t V_{t+1}(0, \varphi_{jt+1})\right) \tag{23}$$

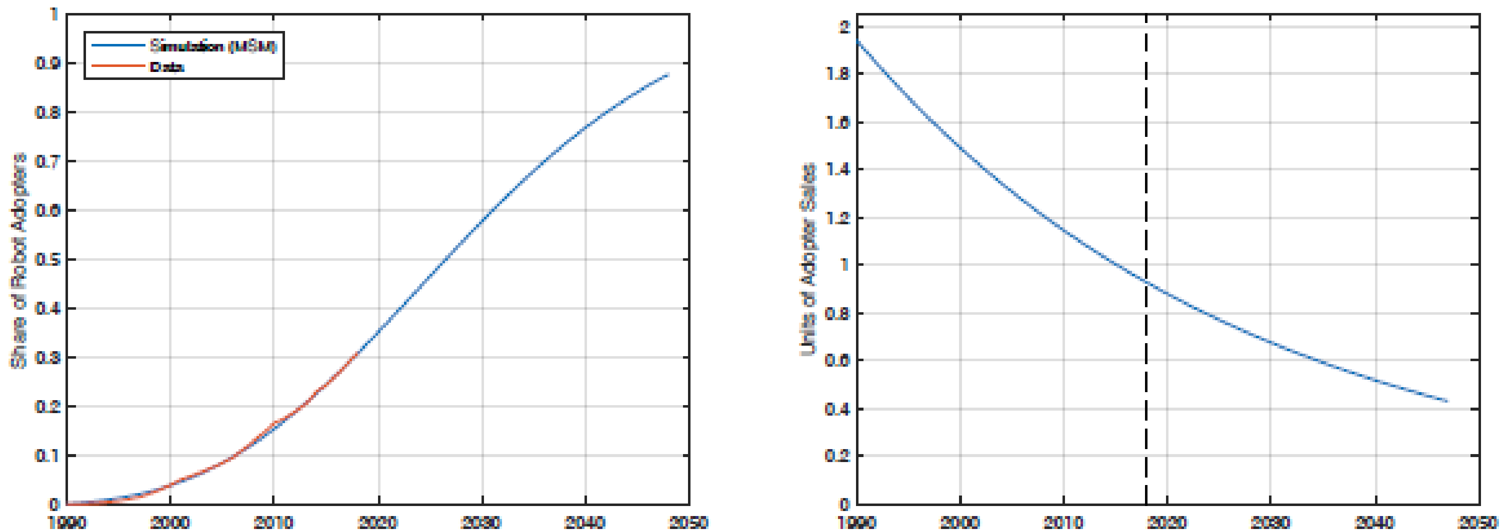
I estimate the path of common adoption costs $\{c_t^R\}_{t=0}^T$ to bring the model as close as possible to the observed robot diffusion curve. In particular, I parameterize the adoption cost schedule to be log-linear in time,

$$c_t^R = \exp(c_0^R + c_1^R \times t), \tag{25}$$

Figure 3: Estimating Adoption Costs on the Robot Diffusion Curve

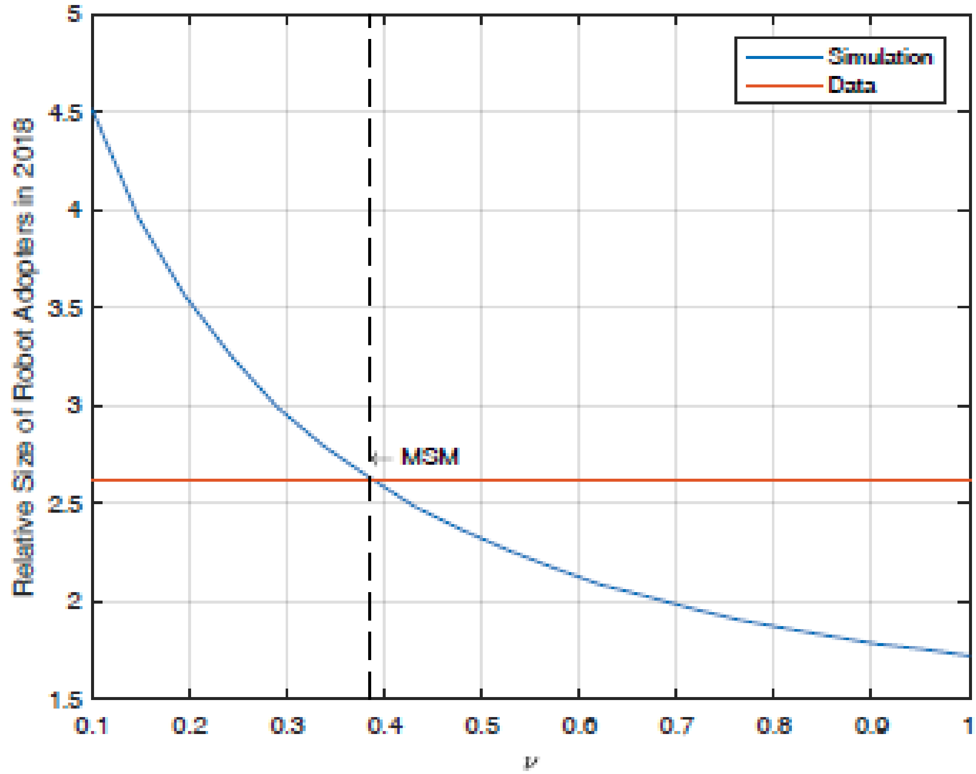
(a) Robot Diffusion Curve

(b) MSM Estimate of Adoption Costs
$\hat{c}_t^R = \exp(\hat{c}_0^R + \hat{c}_1^R \times t)$



Note: Firm sales (the units in Panel (b)) are an average of adopter sales measured over the full simulation period.

Figure 4: Size Premium of Robot Adopters for Varying Adoption Cost Dispersion *ν*



5. The Labor Supply Block

A worker i of age a in occupation o in year t earns the product of a competitive occupational skill price, w_{ot}, and her human capital, H_{oit}. Her occupational human capital is given by

$$\log(H_{oit}) = \beta_s^o s_{it} + \beta_1^o a_{it} + \beta_2^o a_{it}^2 + \beta_3^o \text{ten}_{oit} + \varsigma_{it} \tag{26}$$

where ten_o denotes tenure in occupation o, and $\varsigma_{it} \overset{iid}{\sim} \mathcal{N}(0, \sigma_h^2)$ is an ex-post productivity shock.

The worker's choice of occupation is an investment decision that trades off a sunk cost of switching occupations with future gains in wages and amenities of being employed in a new occupation. The occupational choice problem is represented by the Bellman equation

$$v_t(o, s, a, \text{ten}) = \max_{o' \in \mathcal{O}} \quad \log(w_{ot} H_o(s, a, \text{ten})) + \eta_{ot} - (c_{oo'}(s, a) + \varepsilon_{o'}) \tag{27}$$

$$+ \mathbf{1}_{\{a<65\}} \beta \mathbb{E}_t v_{t+1} \left(o', s, a+1, \mathbf{1}_{\{o'=o\}} (\text{ten}+1) \right) \tag{28}$$

where η_{ot} is a non-monetary amenity of working in occupation o, and $\varepsilon_o \overset{iid}{\sim} \text{GEV1}(\rho)$ is an idiosyncratic occupational switching cost shock. Income is implicitly assumed to be fully consumed in each period, and workers receive logarithmic flow utility of consumption. The occupational switching cost depends on the bilateral pair of current and prospective occupations, as well as the worker's age and skill

$$c_{oo'}(s, a) = c_{oo'} \exp \left\{ \alpha_s s + \alpha_1 \times a + \alpha_2 \times a^2 \right\} \tag{29}$$

I stack the worker state variables into the vector $\omega = (s, a, \text{ten}, o)'$.

5.1 Estimation of Labor Supply Parameters

I estimate the human capital function in Equation (26) using a Mincer regression of log earnings on worker skill, age, and occupational tenure.

$$\log(\text{Earnings}_{it}) = \log(w_{ot}) + \beta_s^o s_{it} + \beta_1^o a_{it} + \beta_2^o a_{it}^2 + \beta_3^o \text{ten}_{oit} + \varsigma_{it}, \tag{30}$$

where Earnings_{it} denotes labor earnings of worker i in year t, and w_{ot} is an occupation-time fixed effect. The key model assumption that enables me to identify the human capital parameters β in this regression is that workers cannot select on the productivity shock ς when choosing occupation or education. Appendix Table D.1 provides the OLS estimation results, which align with estimates from the existing literature (Ashournia, 2017; Dix-Carneiro, 2014; Traiberman, 2019).

$$\log \frac{\pi_t(oo'|\omega)}{\pi_t(oo|\omega)} + \beta \log \frac{\pi_{t+1}(o'o''|\omega')}{\pi_{t+1}(oo''|\omega'')} = -\frac{1}{\rho} c_{oo'}(\omega) - \frac{\beta}{\rho}(c_{o'o''}(\omega') - c_{oo''}(\omega'')) \tag{31}$$

$$+ \frac{\beta}{\rho}\left(\log(w_{o't+1} H_{o'}(\omega')) - \log(w_{ot+1} H_o(\omega''))\right) \tag{32}$$

$$+ \frac{\beta}{\rho}(\eta_{o'} - \eta_o) + \zeta_{oo'o''t} \tag{33}$$

where $\pi_t(oo'|\omega)$ is the transition rate from occupation o to o' of workers with characteristics ω, H_o and w_{ot} are the human capital function and occupational skill prices estimated in Equation (30), and ξ is a mean-zero expectational error that is uncorrelated with the remaining RHS variables.

6. Counterfactual Experiments

6.1 Closing the General Equilibrium Model

The economy consists of a manufacturing sector and a service sector. The manufacturing sector consists of a mass $\mu_t^F(R,\varphi)$ of firms that are monopolistically competitive in product markets, pricetakers in factor markets, and otherwise operate as specified in Section 3.[18] Services are produced with a Cobb-Douglas technology and supplied competitively,

$$Y_{st} = z_{st} M_{st}^{\alpha_M^s} \prod_{o \in \mathcal{O}} L_{ost}^{\alpha_o^s} \tag{34}$$

The economy is populated by a mass $\mu_t^W(\omega)$ of workers who supply labor as specified in Section 5, and consume the final output bundle

$$Y_t = Y_{Mt}^{\mu} Y_{St}^{1-\mu} \quad \text{with} \quad Y_{Mt} = \left[\int Y(R,\varphi)^{\frac{\epsilon-1}{\epsilon}} d\mu_t^F(R,\varphi) \right]^{\frac{\epsilon}{\epsilon-1}} \tag{35}$$

I model Denmark, a country of less than 6 million people located in the European free trade zone, as a small open economy. Intermediate inputs M are imported at world price w_{Mt}, which the Danish economy takes as given, and trade is balanced. The robot adoption cost c_t^R is determined on the world market for industrial robots and is thus exogenous to local conditions in Denmark. The general equilibrium of the economy is defined as follows.

Definition 1 (Dynamic General Equilibrium). A dynamic general equilibrium of the economy is a path of factor prices $\{w_t\}_t$, distributions of firm and worker states $\{\mu_t^F(R,\varphi), \mu_t^W(\omega)\}_t$, and policy functions $\{R_t(0,\varphi)\}_t, \{o_t'(\omega)\}_t$, such that taking the schedule of adoption costs $\{c_t^R\}_t$ and the price of intermediate inputs $\{w_{Mt}\}_t$ as given

1. Firms adopt robots to maximize expected discounted profits (Equation (7)) and demand static inputs to maximize profits period-by-period (Equation (5)).
2. Workers choose occupations to maximize expected present values (Equation (27)).
3. Labor markets clear (segmented by occupations and sectors)

$$\int L_{ot}(R,\varphi)d\mu_t^F(R,\varphi) = \int_\omega H_o(\omega)d\mu_t^W(\omega|M) \tag{36}$$

$$L_{ost} = \int_\omega H_o(\omega)d\mu_t^W(\omega|S), \tag{37}$$

where $L_{ot}(R,\varphi)$ is the static labor demand function satisfying Equation (5).

4. Firm output markets clear and trade is balanced.

$$Y_t = C_t + w_M M_t \tag{38}$$

where $M_t = \int M_t(R,\varphi)d\mu_t^F(R,\varphi) + M_{st}$ and $C_t = \sum_o w_{ot} L_{ot}^S + \Pi_t$. Equation (38) states that expenditures on intermediate input imports equal revenues from final goods exports.

5. The evolution of the distributions of firm and worker states $\{\mu_t^F, \mu_t^W\}_t$ is consistent with the policy functions $\{R_t(0,\varphi), o_t'(\omega)\}_t$.

6.2 The Distributional Impact of Industrial Robots

Figure 5: Robot Diffusion Curve

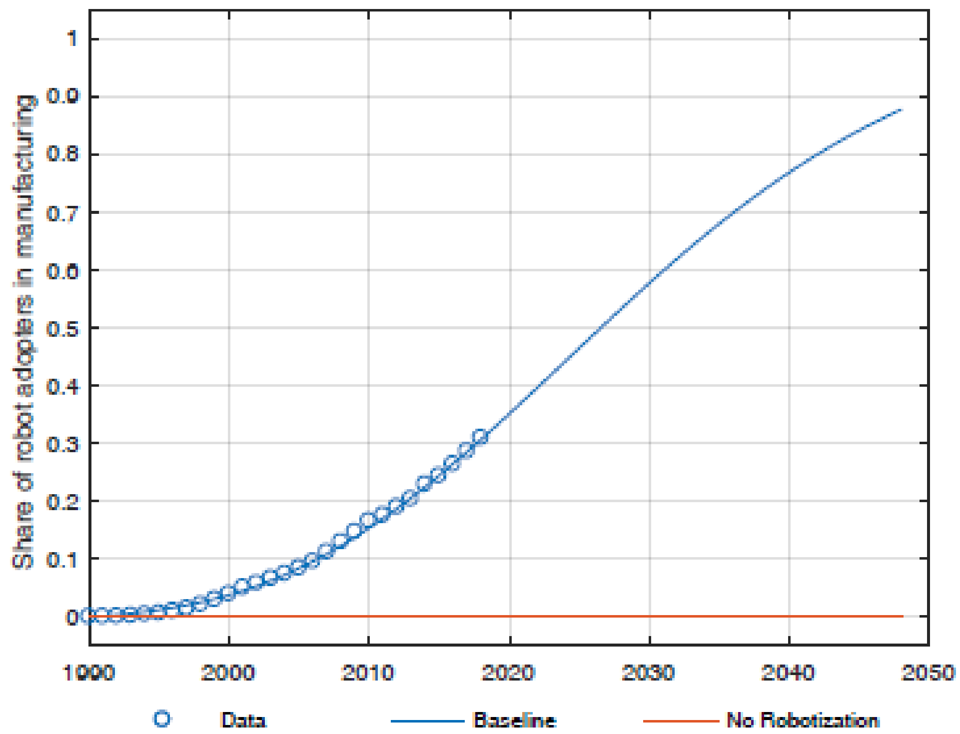


Figure 6: Real Wage Effects of Industrial Robots
(Weighted Average in 2019: +0.76 percent)

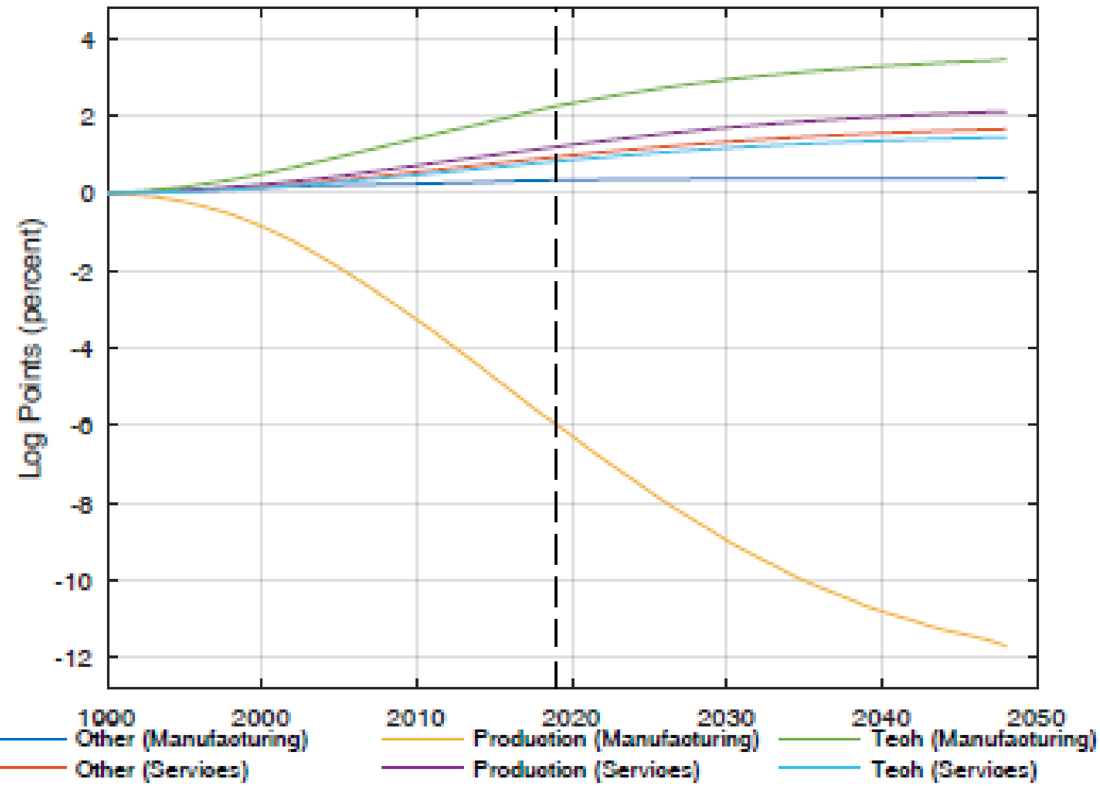
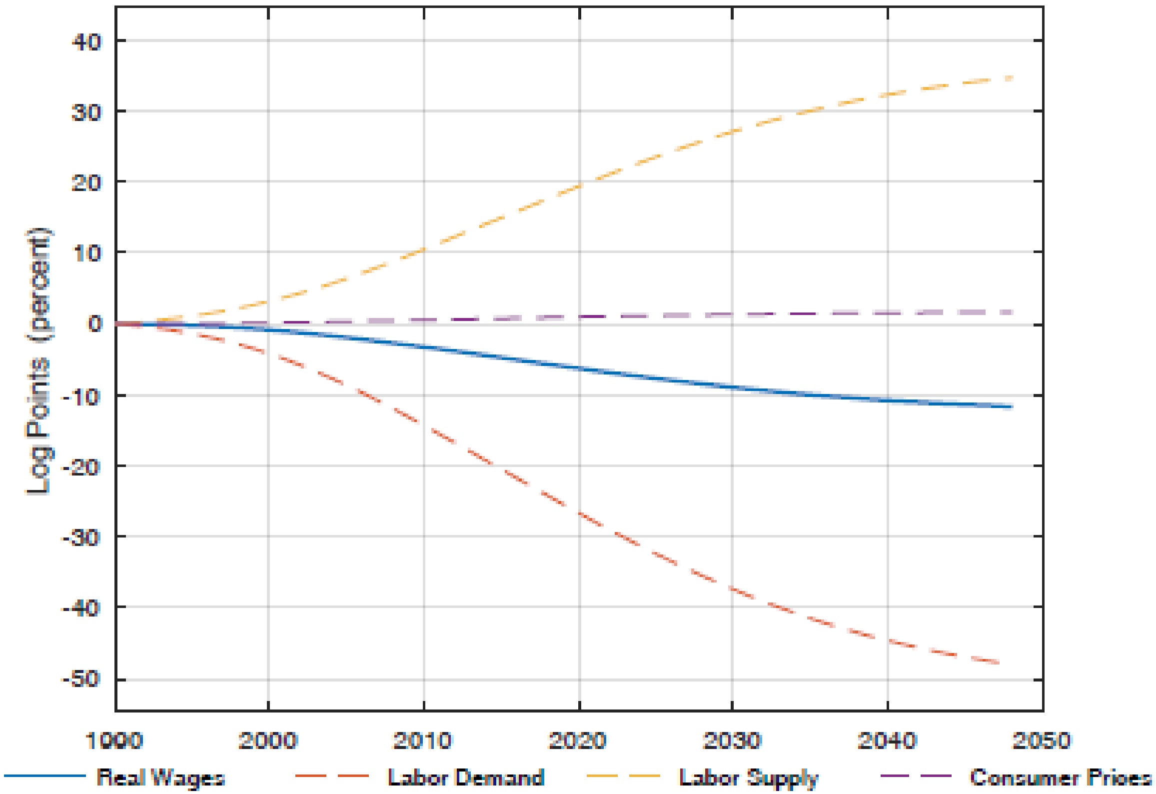
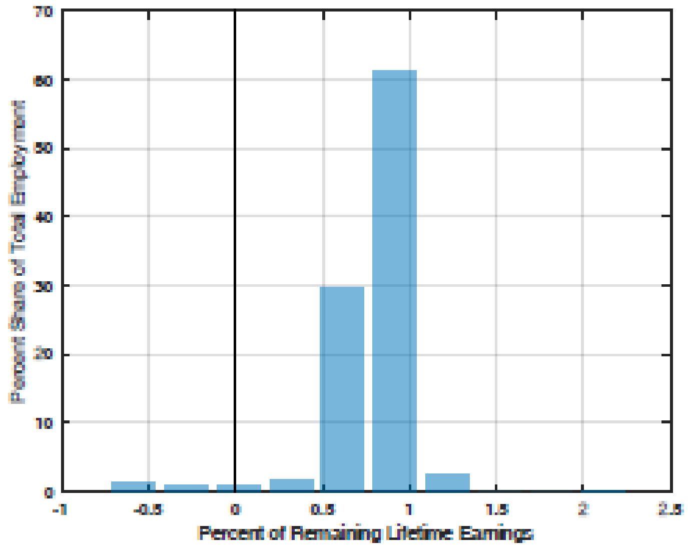


Figure 7: Decomposition of the Production Wage Effect

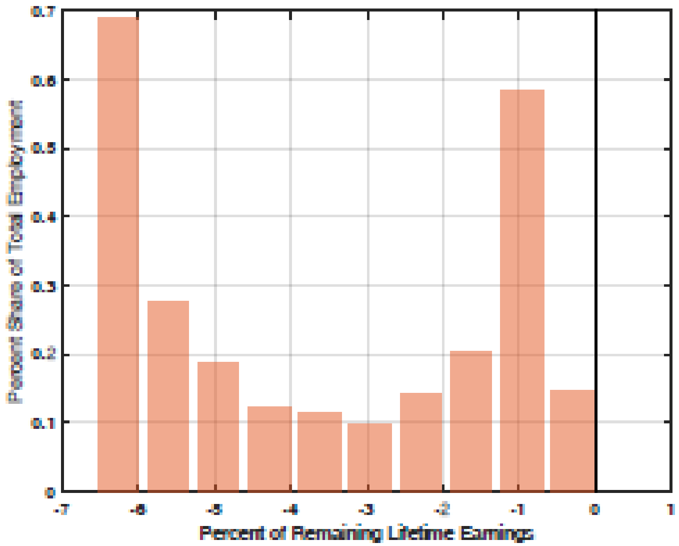


Note: Labor demand effects are measured relative to the “Other Workers” occupation in the services sector.

Figure 8: Welfare Effects for Workers in 2019
(Average: +0.85 percent)



(a) All Workers Excl. Manufacturing Production



(b) Manufacturing Production Workers

Note: Labor demand effects are measured relative to the “Other Workers” occupation in the services sector.

- Figure 9 shows that the welfare losses in Figure 8(b) are concentrated on older workers.

- Younger production workers, with less specific skills and a long career ahead of them, are less affected by the arrival of industrial robots, as wage losses in their current occupation are offset by gains in the option value of switching into occupations whose premiums rise as robots diffuse in the economy.

- The flip side of the labor supply responses found in Figure 7 is that industrial robots have contributed to employment polarization as documented in Autor and Dorn (2013) and Goos et al. (2014).

- Figure 10 shows that industrial robots can account for 25 percent of the fall in the employment share of manufacturing production workers and 8 percent of the rise in the employment share of tech workers in manufacturing since 1990.

Figure 9: Welfare Effects for Manufacturing Production Workers in 2019

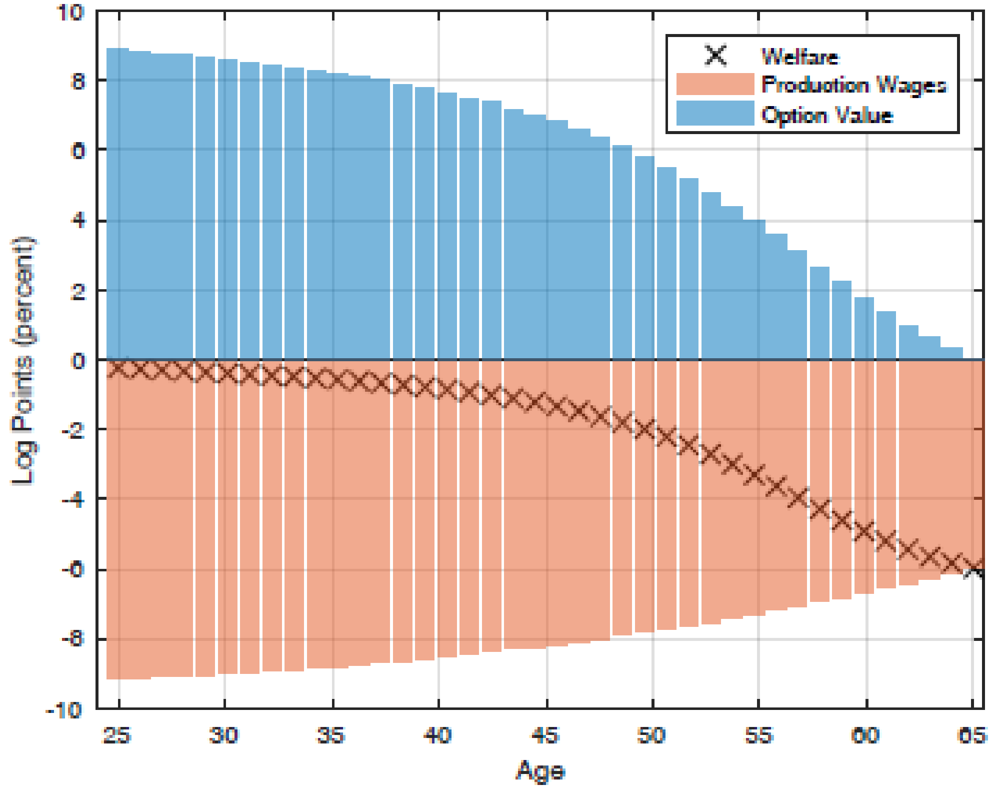
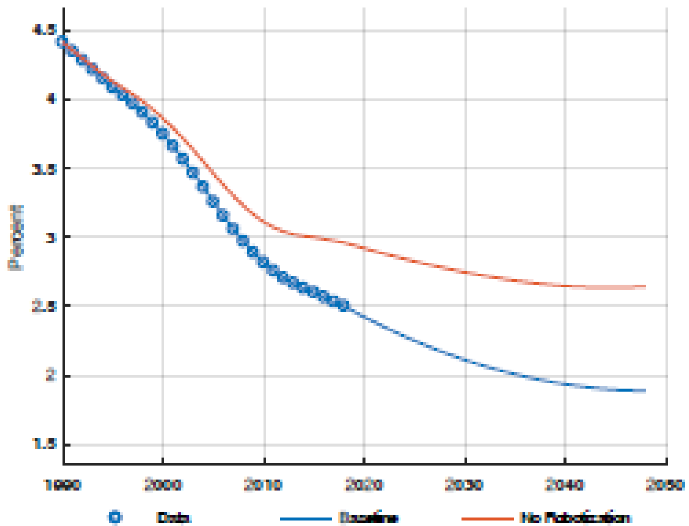
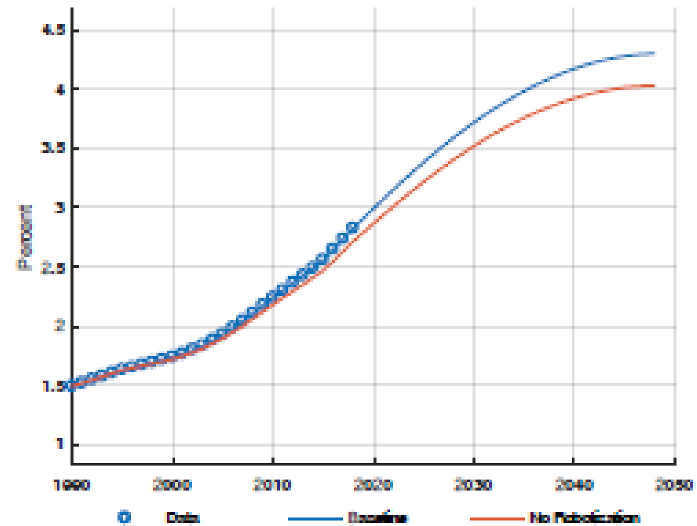


Figure 10: The Effect of Industrial Robots on Employment Shares



(a) Production Workers in Manufacturing



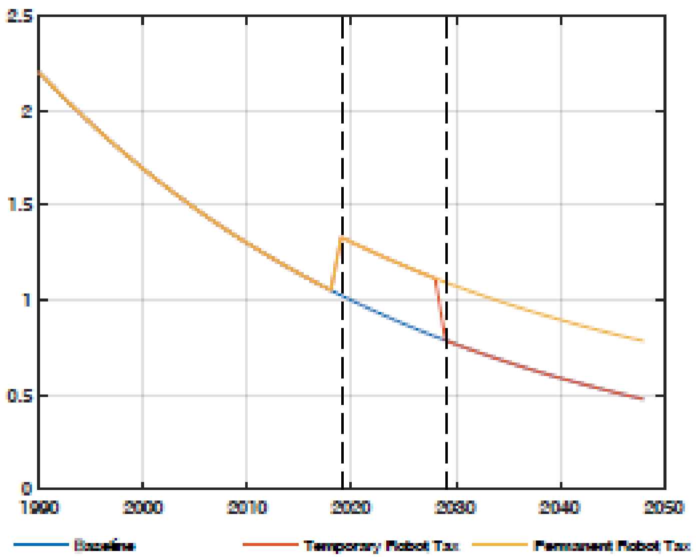
(b) Tech Workers in Manufacturing

6.3 Policy Counterfactuals: The Dynamic Incidence of a Robot Tax

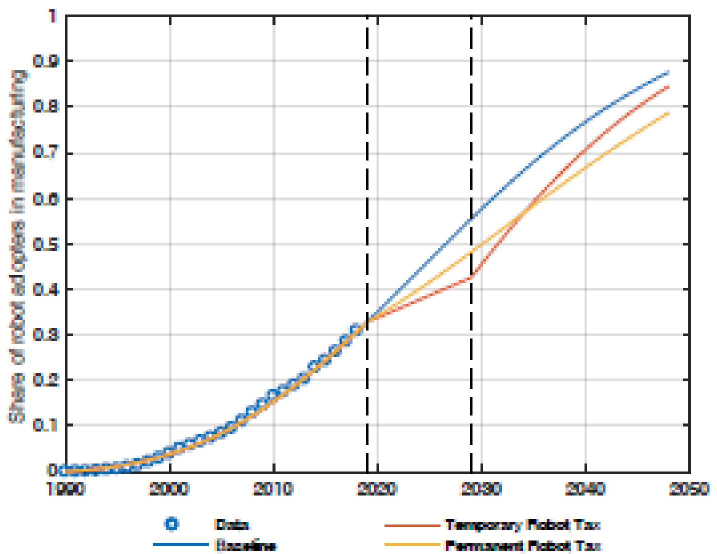
- To map out the potential policies, I evaluate both a temporary and a permanent tax, each of 30 percent.
- The policies are announced and implemented in 2019, and the temporary tax is put in place for 10 years.
- Figure 11(a) shows the path of robot adoption costs under the tax policies.
- I assume that a robot tax in Denmark does not alter the pre-tax price for robots which is determined on world markets.
- Panel (b) of Figure 11 shows the first key result from the robot tax counterfactuals: The temporary tax is more effective in slowing down the diffusion of industrial robots while it is put in place.

- With the temporary tax, only 43 percent of manufacturers will have adopted robots by 2029, compared to 48 percent with the permanent tax and 56 percent in the baseline scenario.
- The larger short-term effects of the temporary tax reflect the forward-looking nature of adoption, where firms foresee that the robot tax will expire and postpone adoption until then.
- The flip side of these delays is that the adoption of robots accelerates beyond its baseline speed after the temporary tax expires in 2030.

Figure 11: Robot Tax Counterfactuals



(a) Robot Adoption Costs



(b) Robot Diffusion Curve

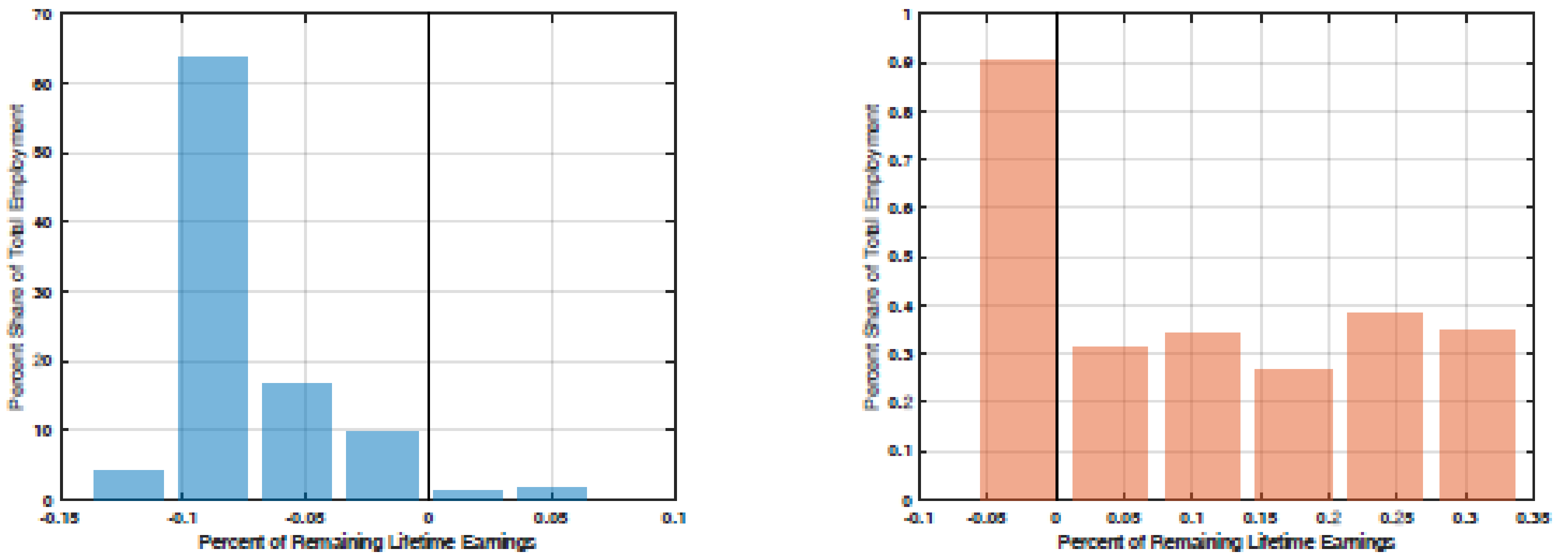
- Figure 12 shows how the temporary robot tax affects the welfare of workers in 2019.

- The temporary tax lowers average welfare by 0.05 percent of lifetime earnings but benefits a group of older production workers employed in manufacturing by 0.2 to 0.3 percent.

- Table 5 shows how the burden of the robot taxes falls on workers and firms in the economy.

- Measured in presented discounted terms, the robot taxes redistributes a total of 0.01 to 0.02 percent of GDP to production workers currently employed in manufacturing at the expense of a total welfare loss for workers of around 1 percent of GDP.

Figure 12: The Impact of a Temporary Robot Tax on the Welfare of Workers in 2019 (Average: -0.054 percent)



(a) All Workers Excl. Manufacturing Production

(b) Manufacturing Production Workers

- The robot taxes do, however, generate substantial amounts of tax revenue, whose burdens are primarily borne by manufacturing firms.
- As Table 5 shows, the tax revenues are sufficient to make all workers better off from the robot taxes, insofar as the revenues can be rebated appropriately and the planner does not care about firm profits.
- One should be cautious about drawing such a conclusions, however, as I do not model firms’ entry decisions.
- If the robot taxes would cause some manufacturing firms to go out of business, these profit losses would be passed on to lower worker welfare.

Table 5: Robot Tax Incidence
(Discounted Present Values in Percent of GDP in 2019)

	Temporary Tax	Permanent Tax
Workers	-1.21	-1.00
Workers in 2019	-0.62	-0.47
– Manufacturing Production	0.02	0.01
Future Workers	-0.59	-0.53
Tax Revenues	2.39	9.41
Mechanical Effect	5.57	11.02
Behavioral Effect	-3.18	-1.61
Profits (excl. predatory externalities)	-4.14	-10.58

Note: Workers represent compensating variations; see Appendix G.1.1 for details. Profits (excl. predatory externalities) represent the effect on manufacturing firm values (Equations (7)-(8)) in 2019, holding constant pecuniary externalities of robot adoption in output markets; see Appendix G.2.1 for details. Mechanical Effect is the tax revenues collected if robot adoption did not respond to the tax.

7. Conclusion

- This paper makes two methodological contributions in order to study the distributional impact of industrial robots.

- First, I develop a dynamic firm model that can rationalize the selection into and reduced-form responses to robot adoption.

- Second, I model both firm and worker dynamics in general equilibrium.

- I use administrative data that link workers, firms, and robots in Denmark to structurally estimate a dynamic general equilibrium model that can account for event studies of firm robot adoption, the observed diffusion of industrial robots, and worker transitions in the labor market.

- The model fits the labor demand responses to robot adoption but also takes into account how production efficiency gains from robots are passed through to lower consumer prices as well as the ability of workers to reallocate between occupations in response to industrial robots.

Appendix

A. Data

Figure A.1: Firm Questionnaire on Firm Robot Adoption

Robot Technology

An industrial robot is an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications.

A service robot is a machine that has a degree of autonomy and is able to operate in complex and dynamic environment that may require interaction with persons, objects or other devices, excluding its use in industrial automation applications.

Software robots (computer programs) and 3D printers are out of the scope of the following questions.

18. **Does your enterprise use any of the following types of robots?**	**Yes**	**No**
- Industrial robots E.g. robotic welding, laser cutting, spray painting, etc.	○	○

Table A.1: Identifying Robot Adoption in Customs Records

Step	Sample at End of Step		
	Imports (million USD)	Import events (firm-year)	Firms
Raw imports	3291.9	14355	4839
1. Pre-data coverage	1457.7	5936	2594
2. Exclude wholesalers	826.5	2016	1048
3. Exclude integrators	535.0	1375	754
4. Survey-validated industries	247.6	776	416
5. Single production establishment	91.1	454	293

Table A.2: Robot Adoption Across Industries: Comparison of Data Sources

	Data Sources		
	Robot Survey (StatDK)	Robot Stock (IFR)	Robot Imports (Customs)
Share in Total Adoptions (%)			
Manufacturing	79.1	85.9	83.5
Share in Manufacturing Adoptions (%)			
Food and beverages	7.2	18.3	7.2
Textiles	1.1	2.8	0.0
Wood and furniture	6.4	4.7	3.5
Paper	2.2	1.4	0.0
Plastic and Chemicals	14.0	22.0	32.3
Glass, stone, minerals	5.0	3.7	1.9
Metal	51.1	34.1	31.7
Electrical and Electronics	10.9	8.4	23.5
Automotives and vehicles	1.9	4.7	0.0

Note: "Robot Survey" indicates the share in total firm robot adopters. "Robot Stock" specifies the share in total robot stock. "Robot Imports" is the share in total firm robot import events (firm-year observations). Robot Imports represents the 454 adoption events identified in Table A.1.

Figure A.2: Robot Adoption Across Time: Comparison of Data Sources

Table A.3: Import Share in Robot Investments, Denmark 1993-2015 (percent)

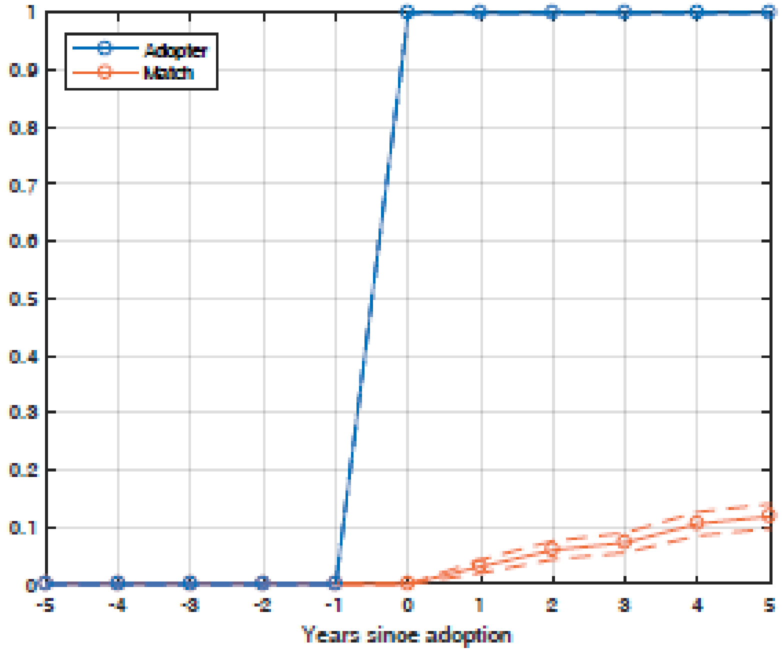
Average	1993-2004	2005-2015
94.9	98.5	90.9

Figure A.2: Robot Adoption Across Time: Comparison of Data Sources

B. A Model of Firm Robot Adoption

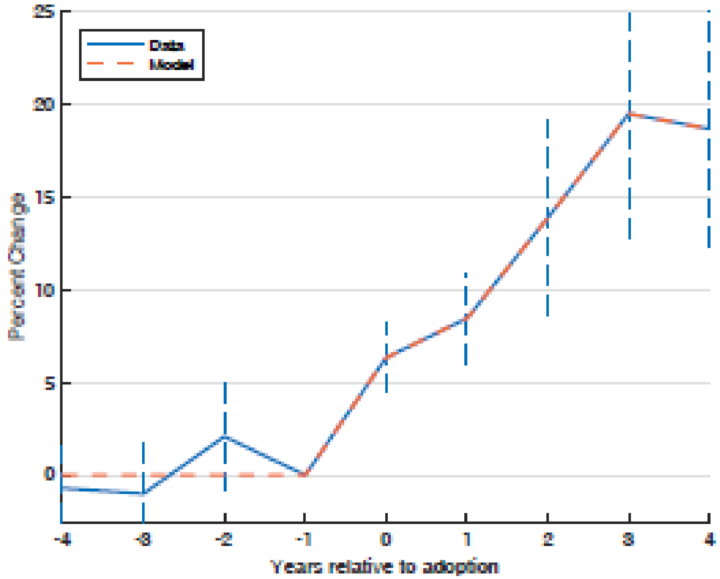
C. Structural Estimation of Firm Robot Adoption

Figure C.1: Firm Robot Adoption Around the Event Year

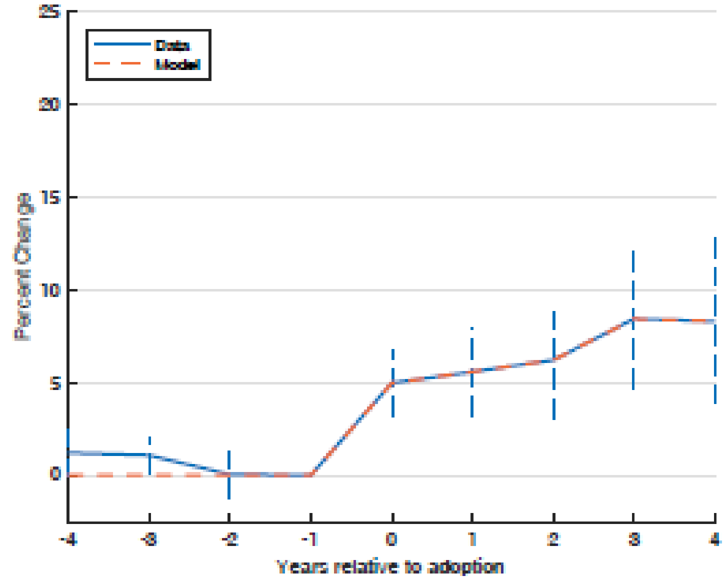


Note: The figure shows separately the shares of firms in the treatment and control groups that have adopted robots around the event year.

Figure C.2: Distributed Lag Model for Robot Productivities

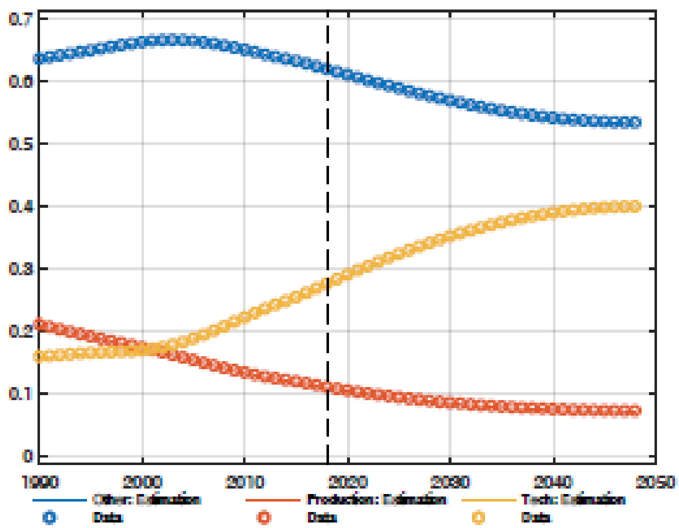


(a) Sales

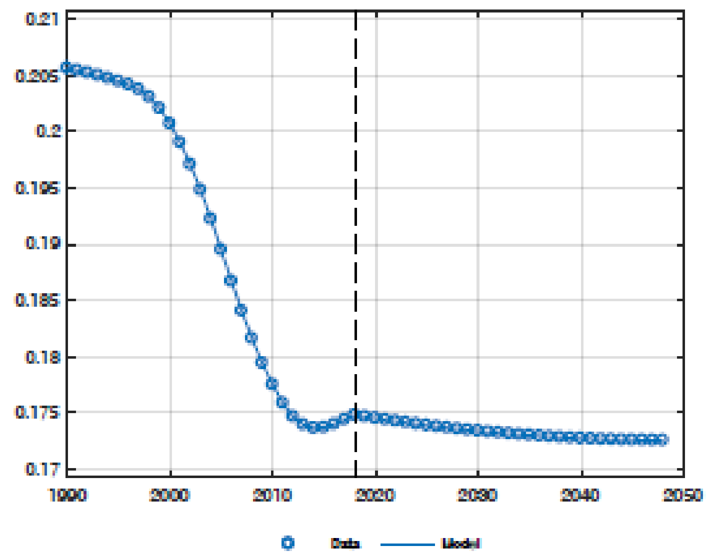


(b) Wage Bill

Figure C.3: Aggregate Factor Shares in Manufacturing Production



(a) Wage Bill Shares



(b) Wage Bill Share in Manufacturing Sales

Table C.1: Baseline Productivity Parameters

Parameter	Description	Estimated Value
$\hat{\rho}_z$	Persistence of firm productivity	0.901 (0.062)
$\hat{\sigma}_z$	Standard deviation of firm productivity innovations	0.140

Table C.2: Robot Adoption Cost Parameters (MSM)

Parameter	Description	Estimate
c_0^R	Intercept of the common adoption cost schedule over time	1.155
c_1^R	Slope of the common adoption cost schedule over time	-0.026
ν	Dispersion in idiosyncratic adoption costs	0.384

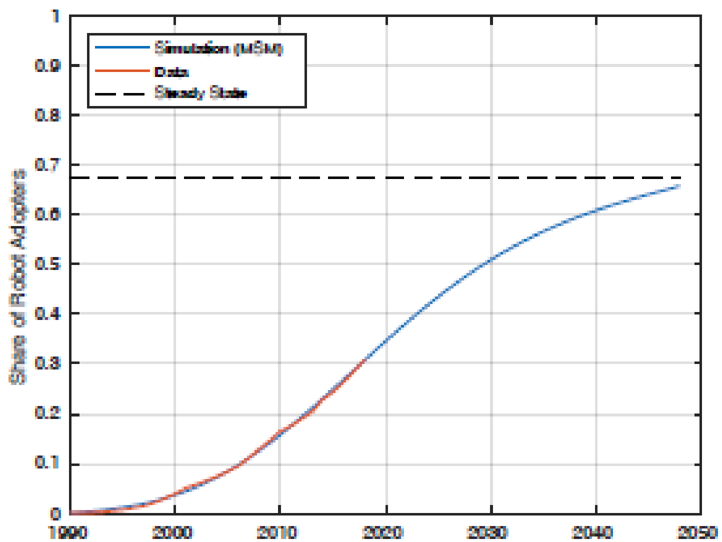
Table C.3: Rate of Change in Robot Adoption Costs: Model Estimates vs. External Measures

	Lower Bound (95% CI)	Point Estimate	Upper Bound (95% CI)
MSM Estimate ($\hat{c}_1^R$)		-0.0264	
Customs Expenditures 1	-0.1158	-0.0693	-0.0229
Customs Expenditures 2	-0.0661	0.0179	0.1019

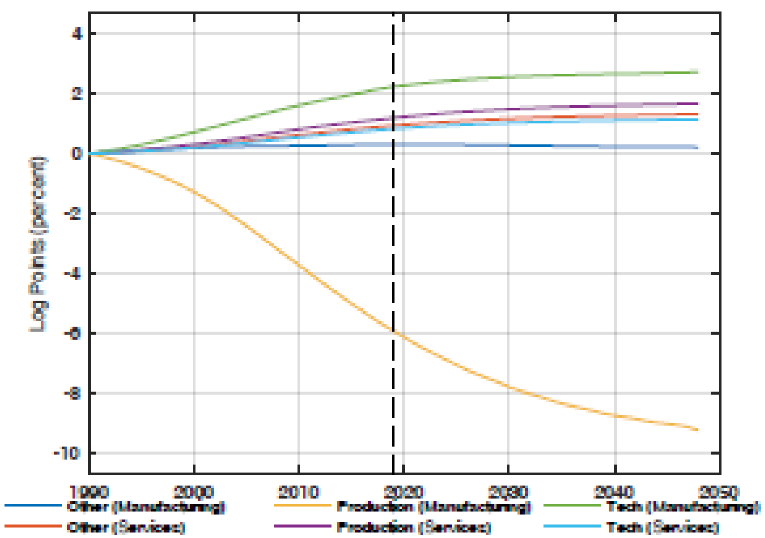
Note: The first row is the MSM estimate of $\hat{c}_1^R$. The second row (Customs Expenditures 1) is the OLS estimate of β_1 in $log(Y_{jt}) = \beta_0 + \beta_1 t$ (reweighted to the yearly level). The third row (Customs Expenditures 2) is the OLS estimate of β_1 in $\log(\bar{Y}_t) = \beta_0 + \beta_1 t$. I deflate the customs expenditures with the consumer price index.

Figure C.4: Effect of Industrial Robots with Depreciation of Robot Technology

(a) Robot Diffusion Curve



(b) Real Wage Effects



D. The Labor Supply Block

Table D.1: Human Capital Function

	Tech (services)	Tech (manuf)	Production (services)	Production (manuf)	Other (services)	Other (manuf)
Age β_1^o	0.0285	0.0265	0.0096	0.0055	0.0124	0.0139
	(0.0010)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0010)
Age-Squared β_2^o	-0.0590	-0.0543	-0.0236	-0.0171	-0.0266	-0.0301
	(0.0016)	(0.0013)	(0.0011)	(0.0014)	(0.0014)	(0.0023)
Tenure β_3^o	0.0300	0.0153	0.0277	0.0234	0.0537	0.0307
	(0.0018)	(0.0010)	(0.0012)	(0.0016)	(0.0030)	(0.0012)
Mid Skill β_M^o	-0.0428	0.0028	0.1025	0.1168	0.0537	0.1165
	(0.0015)	(0.0028)	(0.0015)	(0.0025)	(0.0012)	(0.0018)
High Skill β_H^o	0.1671	0.2958	0.0997	0.1629	0.2502	0.5108
	(0.0016)	(0.0022)	(0.0103)	(0.0061)	(0.0037)	(0.0053)
Observations	2147314	602741	1029836	681133	17176380	2780515

Note: SD of income shock: Tech (services): .118, Tech (manufacturing): .077, Production (services): .096, Production (manufacturing): .077 Others (services): .148, Others (services): .133. Standard errors are clustered at the occupation-year level. Coefficient on Age Squared is presented $\times 10^2$.

Table D.2: Bilateral Switching Costs

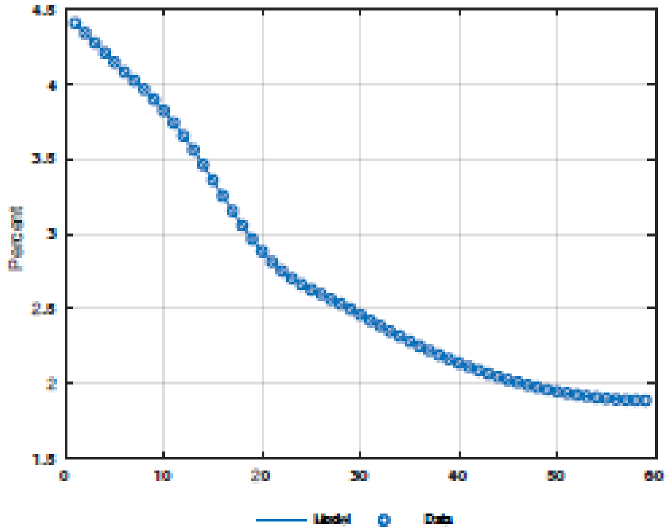
	Tech (serv)	Tech (manuf)	Production (serv)	Production (manuf)	Other (serv)	Other (manuf)
Tech (services)	0	4.71	1.7	5.04	1.17	4.64
Tech (manufacturing)	0.76	0	3.49	0.58	2.51	0.01
Production (services)	5.9	11.12	0	2.73	3.78	6.6
Production (manufacturing)	9.24	8.79	2.75	0	6.35	4.28
Other (services)	3.8	8.44	1.87	3.9	0	2.97
Other (manufacturing)	6.6	5.94	3.68	1.27	2.19	0

Table D.3: Switching Cost Parameters

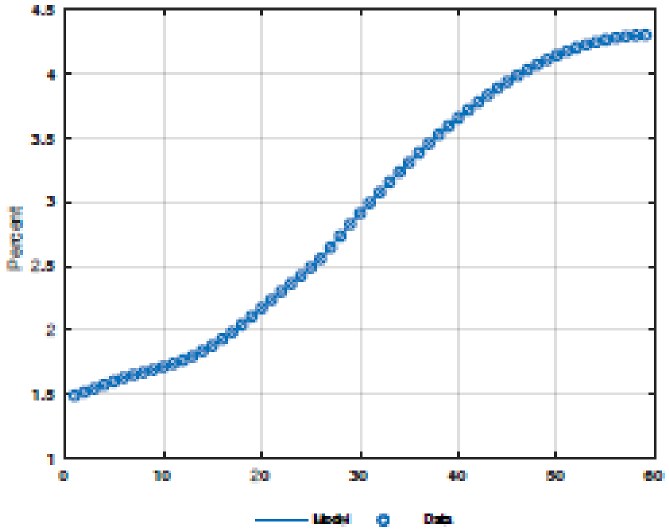
Parameter	Description	Estimate
α_1	Semi-elasticity of switching costs with respect to age (linear term)‡	13.86
α_2	Semi-elasticity of switching costs with respect to age (quadratic term)‡	−0.14
α_M	Semi-elasticity of switching cost with respect to mid skill	0.01
α_H	Semi-elasticity of switching cost with respect to high skill	0.00
ρ	Occupational preference shock variance†	2.00

Note: ‡ Coefficients of age polynomial are presented $\times 10^3$. †Parameter value of ρ used in Section 6.

Figure D.1: Employment Shares Across Occupations (Manufacturing)



(a) Production Workers



(b) Tech Workers

E. Model Extension to Firm-Specific Wages