Automation, Market Concentration, and the Labor Share*

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Abstract

Since the early 2000s, a rising share of production has been concentrated in a small number of superstar firms. We argue that the rise of automation technologies and the cross-sectional variation of robot use rates have contributed to the increases in industrial concentration. Motivated by empirical evidence, we build a general equilibrium model with heterogeneous firms, endogenous automation decisions, and variable markups. Firms choose between two types of technologies, one uses workers only and the other uses both workers and robots subject to an idiosyncratic fixed cost of robot operation. Larger firms are more profitable and are thus more likely to choose the automation technology. A decline in the cost of robot adoption increases the relative automation usage by large firms, raising their market share of sales. However, the employment share of large firms does not increase as much as the sales share because the expansion of large firms relies more on robots than on workers. Our calibrated model predicts a cross-sectional distribution of automation usage in line with firm-level data. The model also implies that a decline in automation costs reduces the labor income share and raises the average markup, both driven by between-firm reallocation, consistent with empirical evidence.

Keywords: Automation, market concentration, labor share, markup, reallocation, heterogeneous firms.

JEL Codes: E24, L11, O33.

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1 Introduction

Industries have become increasingly concentrated, with each major sector in the US economy increasingly dominated by a small number of superstar firms. Autor et al. (2020) show that the rise of superstar firms has important consequences for the macro economy. In particular, it has contributed to the decline in the labor income share, since resources are reallocated to larger firms that use less labor-intensive technologies for production. It is less clear, however, what might explain the rise of the superstar firms. We argue that the rapid growth of industrial robots, and the rise of automation in general, since the early 2000s has played an important role in explaining the increases in market concentration, particularly in the manufacturing sector.

The connection between automation and concentration can be visualized from the time-series plots in Figure 1. The figure shows the average shares of sales and employment of the largest firms within four-digit manufacturing industries (Panel A).[1] The sales shares of the top 4 firms and the top 20 firms have increased steadily over time, especially after the early 2000s. The employment shares of those top firms have also increased, but at a slower pace. The rise in concentration coincides with the rise in automation, as shown in Panel B of the figure. Since the early 2000s, the relative price of robots has declined by nearly 40%, while the number of industrial robots per thousand US manufacturing employees has quadrupled.

The time-series correlation between automation and concentration is also present in cross-sectional data. We use Compustat firm-level data to construct industry concentration measures at the 2-digit industry level. We consider two alternative measures of concentration: share of top 1% firms and the Herfindahl–Hirschman Index (HHI), based on both sales and employment. To construct a measure for 2-digit industry-level robot density, we use the operation stocks of robots from the International Federation of Robotics (IFR) for each industry, combined with the manufacturing employment (or labor hours) in those industries from the Bureau of Labor Statistics. We obtain an unbalanced panel covering 13 industries for 12 years from 2007 to 2018.

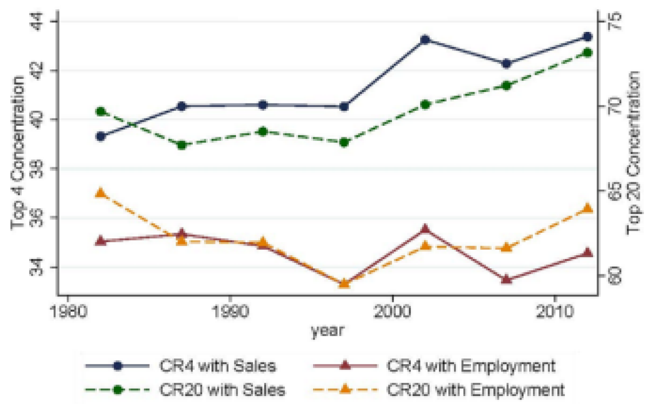
After controlling for industry and year fixed effects, we find that robot density is positively correlated with sales-based measures of industry concentration and the correlation is economically important and statistically significant. The correlation of robot density with employment-based concentration measures are also positive, although they are statistically insignificant and the magnitudes are much smaller than the correlations with sales-based measures. These cross-sectional correlations are consistent with the time-series patterns displayed in Figure 1.

The evidence suggests that automation may have led to concentration of production in a few superstar firms. To the extent that those superstar firms have lower labor shares

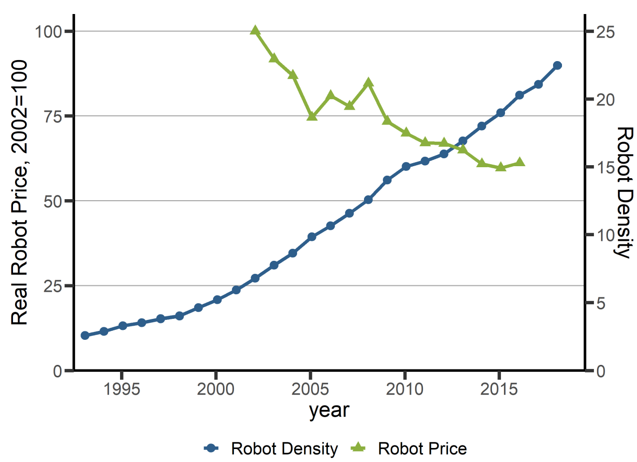
[1]The figure is taken from Figure IV in Autor et al. (2020) with permissions from the Oxford University Press (License Number 5241431011126).

Figure 1. Trends in industry concentration and automation.

(a) Panel A: Industry Concentration



(b) Panel B: Robot Price and Density



Note: Panel A is taken from Autor et al. (2020) and it shows the industry concentration measured by both the sales share and the employment share of the top 4 firms (the left scale) or the top 20 firms (the right scale) in a given industry. Panel B shows the unit value of newly shipped industrial robots deflated by the personal consumption expenditure price index (red line, left scale) and robot density measured by the operation stock of robots per thousand manufacturing workers (blue line, right scale). Both the series of robot price and the operation stock of industrial robots are taken from the International Federation of Robotics (IFR).

(Autor et al., 2020), an industry with greater exposures to automation should also have a lower labor share on average. This is indeed the case. We use an industry-level measure of the labor share constructed from the NBER-CES dataset and find that robot density is negatively and significantly correlated with the labor share at the 2-digit industry level.

To understand the connection between the rise of automation, market concentration, and the labor share, we construct a general equilibrium model featuring heterogeneous firms, variable markups, and endogenous automation decisions. Firms have access to two types of technologies for producing differentiated intermediate goods: one is the traditional technology that uses workers as the only input and the other is an automation technology that uses both workers and robots, with a constant elasticity of substitution. Operating the automation technology incurs a random fixed cost. Firms also face idiosyncratic and persistent productivity shocks. A firm's automation decision (i.e., whether to operate the traditional or the automation technology) depends on the realizations of the fixed cost relative to productivity. At a given fixed cost, larger firms are more likely to use robots in production because they have higher productivity and also higher market power and profits.

We calibrate the model parameters to match several moments in the data and in the empirical literature. To calibrate the fixed cost of operating the automation technology and the exogenous cost of new robot adoptions, we target the firm-weighted and the employment-weighted averages of robot adoption rates taken from the 2018 Annual Business Survey (ABS) conducted by the US Census Bureau (Zolas et al., 2020). The ABS covers a large and nationally representative sample of over 850,000 firms in all private non-farm business sectors. The calibrated model predicts that the automation probability increases with firm productivity and firm size, whereas the labor share decreases with firm productivity and size. Given a technology choice, higher productivity enables a firm to produce more output and to employ more workers (i.e., the firm is larger). With variable markup under the Kimball preferences (Kimball, 1995), larger firms face lower demand elasticities and charge higher markups. Thus, markup also increases with firm productivity.

The calibrated model does well in predicting the cross-sectional distribution of artificial intelligence (AI) usage observed in the firm-level data from the ABS. In particular, the usage of automation technologies is highly skewed towards large and high-productivity firms (Zolas et al., 2020), both in the model and in the data. Since this moment is not targeted in our calibration, the ability of the model to correctly predict the cross-sectional distribution of automation usage lends credence to the model's mechanism.

We use the calibrated model to examine the implications of an exogenous decline in the relative price of robots for market concentration and the labor share. The decline in robot prices raises the probability of automation through two channels. First, it reduces the user cost of robots, benefiting large firms that operate the automation technology (an intensive-margin effect). Second, it induces more firms to adopt the automation technology (an extensive-margin effect). Through the intensive-margin effect, the decline in robot prices enables large firms to become even larger, raising market concentration. At the same time, however, the extensive-margin effect implies that some smaller firms that operated the worker-only technology would switch to the automation technology when robot prices decline. This would reduce the production share of the superstar firms and lower market concentration.

Under our calibration, the intensive-margin effect dominates the extensive-margin effect, such that a decline in robot prices leads to an increase in market concentration. This result obtains because the calibrated model matches the cross-sectional distribution of the usage of automation technologies in the data, in which only a small fraction of firms automate and automation is highly skewed towards large firms (Zolas et al., 2020). A modest decline in robot prices would not induce a sufficiently large share of smaller firms to switch to the automation technology, while it enables large firms that already use the automation technology to expand further, raising market concentration of sales.

A decline in robot prices also increases the employment concentration, although the increase is smaller than that in sales concentration because the expansion of large firms relies more on robots than on workers. This model prediction is consistent with the empirical correlations between market concentration and automation from both the time-series evidence shown in Figure 1 and our cross-sectional evidence. Furthermore, since larger firms have higher markups and lower labor shares, the between-firm reallocation triggered by a decline in automation costs reduces the average labor share and increases the average markup, consistent with the reallocation channel documented by Autor et al. (2020) and Acemoglu, Lelarge and Restrepo (2020).

Furthermore, the relation between robot prices and market concentration can be non-monotonic. We show that, in a counterfactual with a sufficiently large decline in the relative price of robots, the extensive-margin effect would become dominant, such that a sufficiently large number of (medium-sized) firms would switch technologies and expand production, reducing the sales share of top firms. Thus, in an economy with widely-spread automation technologies, a decline in automation costs may not lead to an increase in market concentration.[2]

Our work is motivated by the empirical evidence on market concentration documented by Autor et al. (2020). Their study highlights an important between-firm reallocation channel that connects the rise in product market concentration with the fall in the labor share. If an industry becomes increasingly dominated by superstar firms, which have high markups and low labor shares, then industries with a larger increase in concentration should

[2]Robots in our model are different from general capital equipment. Although both types of capital can substitute for workers, they differ in the sense that robot usage is highly concentrated in large firms, whereas equipment usage is much more widely spread. Our counterfactual simulation shows that, if the use rate of robots (i.e., the fraction of firms that operate automation technologies) is sufficiently high (e.g., bringing it to a level similar to the use rate of equipment), a decline in the relative price of robots would *reduce* market concentration because the extensive margin would dominate the intensive margin. Based on this finding, we conjecture that a decline in relative price of capital equipment, which is more widely used than robots, could reduce market concentration.

also have larger declines in the labor share. Autor et al. (2020) discuss a few potential drivers of the rise of superstar firms (what they call a “winner takes most” mechanism), such as greater market competition (e.g., through globalization) or scale-biased technological change driven by intangible capital investment and information technology. Our work complements that of Autor et al. (2020) by providing a formal theoretical framework for understanding what drives the “winner takes most” mechanism. Our model suggests that the rise in automation can contribute to the rise of superstar firms. Consistent with firm-level data, our model predicts that the adoption of automation technologies is highly skewed toward large and high-productivity firms. Our model also predicts that a decline in robot adoption costs benefit disproportionately large and high-productivity firms, increasing market concentration and reducing the labor share. To the extent that robots substitute for workers, a decline in robot costs raises sales concentration more than employment concentration, consistent with both the time-series evidence in Autor et al. (2020) and our own cross-sectional evidence.

Our work is related to the recent study of Aghion et al. (2019), who study the connection between the rise in firm concentration, the decline in the labor share, and the falling growth in the United States. Their theory suggests that, following a decline in the overhead costs, the most efficient firms (which are also large firms with high markups) spread into new product lines, raising market concentration, leading to a short-run burst in growth. Overtime, however, increased competition between efficient firms reduces within-firm markups and discourages innovation, and thus slowing aggregate growth. Their calibrated model can explain a significant portion of the long-run productivity slowdown. However, the model implies a much smaller decline in the labor share through between-firm reallocation than that in the data for the Manufacturing, Trade, and Service industries. Our paper complements theirs by highlighting the importance of automation as a potential driver of the observed changes in market concentration, labor productivity, and the labor share.

Our work contributes to the growing literature on the implications of automation for the labor market and income distribution. Automation has important implications for employment, wages, and labor productivity (Acemoglu and Restrepo, 2018, 2020; Arnoud, 2018; Aghion et al., 2021; Graetz and Michaels, 2018; Leduc and Liu, 2019). Automation has also contributed to wage inequality by displacing routine jobs in middle-skill occupations (Autor, Levy and Murnane, 2003; Autor, Dorn and Hanson, 2013; Jaimovich and Siu, 2020). Empirical evidence suggests that, at the firm level, robot adoptions are associated with declines in the labor share (Acemoglu, Lelarge and Restrepo, 2020). Our work suggests that automation has also important implications for the rise in market concentration and the decline in the labor share.

Our study is also related to the literature on the driving forces of the observed declines in the labor share in the past few decades. For example, Karabarbounis and Neiman (2013) argue that declines in the relative price of capital equipment in recent decades have led to capital deepening and declines in the labor share since capital and labor are substitutes in production. To the extent that robots can displace some tasks that used to be performed by workers, automation can also reduce the labor share. Autor and

Salomons (2018) use industry-level data from 18 OECD countries since 1970 to study the impact of automation on employment and the labor share. They find that although automation has not reduced employment on net, it has reduced labor's share in value-added, with the negative effects on the labor share becoming most substantial in the 2000s. Through a similar channel, increased globalization and offshoring of labor-intensive tasks has contributed to the declines in the labor share, as shown by Elsby, Hobijn and Sahin (2013). Since the global financial crisis in 2008-2009, however, the importance of offshoring seems to have peaked, with the ratio of imports to GDP staying flat in the 2010s while the labor share has continued to decline. In the same period, automation (measured by robot intensity) has increased steadily, suggesting that automation has played a more important role than offshoring for driving the recent declines in the labor share, consistent with our model's predictions.

2 Empirical Evidence

The time series in Figure 1 suggest that the rise in market concentration in the manufacturing sector is correlated with the rise in automation during the past two decades. We now provide some cross-sectional evidence that market concentration is also correlated with automation at the 2-digit industry level.

To measure industry-level market concentration, we use the firm-level data from Compustat. For each industry, we construct a sales-based measure of concentration, which is the sales share of the largest 1% firms in an industry. We also construct an employment-based measure of concentration, which is the employment share of the largest 1% firms. For robustness, we also consider the Herfindahl–Hirschman Index (HHI) for each industry based on sales and employment.[3] We measure the industry-level labor share using the NBER-CES Manufacturing Industry Dataset. For each industry, the labor share is measured by the ratio of payrolls to value added.

We use the IFR data to construct a measure of industry-level robot density. Specifically, for each 2-digit industry, the robot density is measured by the operation stock of robots per thousand workers. We consider an alternative measure of industry-level robot density based on labor hours, which is measured by the operation stock of robots per million hours. The data of industry-level employment (EMP) and labor hours (PRODH) are both taken from the NBER-CES Manufacturing Industry Dataset.[4] We obtain an unbalanced panel

[3] The HHI is defined as the sum of squared shares of sales (or employment, in percentage terms) across firms within the industry. When we compute the industry concentration measures, we require that each industry has at least 10 firms.

[4] The IFR uses the International Standard Industrial Classification (ISIC, Rev. 4) for industry classification, while NBER-CES and Compustat use the North American Industry Classification System (NAICS). We match the ISIC Rev. 4 industry codes with the NAICS2017US codes using the concordance table from the US Census Bureau.

Table 1. Summary Statistics

	#obs	mean	min	p25	p50	p75	max	s.d.
robots/thousand employees	151	31.43	0.001	0.30	2.89	11.33	419.92	89.24
robots/million hours	151	20.23	0.001	0.21	2.21	8.39	243.54	53.16
top 1% share of sales	117	0.31	0.09	0.22	0.30	0.37	0.77	0.13
top 1% share of employment	104	0.27	0.11	0.21	0.28	0.32	0.46	0.08
HHI (sales)	137	1433.18	411.18	672.44	1443.19	2000.26	6194.02	787.93
HHI (employment)	135	1331.78	289.64	680.84	1483.42	1862.03	2651.94	676.61
labor share	151	0.29	0.13	0.24	0.30	0.35	0.44	0.08

Note: This table shows the summary statistics of the data that we use in the regressions. We consider two alternative measures of industry-level robot density: one is the operation stock of industrial robots per thousand employees, and the other is the operation stock of industrial robots per million labor hours. We also consider two measures of industry concentration. One measure is the sales or employment share of the top 1% firms in the industry, and the other is the Herfindahl-Hirschman Index (HHI) based on sales or employment. For both measures of concentration, we restrict our sample to those industries with at least 10 firms. The industry-level labor share is the ratio of payrolls to value added.
Source: Authors' calculations using IFR, Compustat, and NBER-CES.

with 13 industries covering the 12 years from 2007 to 2018.[5] Table 1 reports the summary statistics of variables.

Table 1 shows that robot density varies widely in our sample. For example, the interquartile range (IQR) of robots per thousand workers is about 11, which is about one-third of the sample mean. The standard deviation of robot density is also large (about three times the mean). These patterns reflect both within-industry changes in robot adoptions over time and across-industry heterogeneity in robot adoptions and the growth rates of robot use. Market concentration in our sample also displays large variations. For example, the sales share of the top 1% firms averages about 31%, with an IQR of about 14% and a standard deviation of 13%. The employment share of the top 1% firms averages about 28%, and it varies less than the sales share, with an IQR of about 10% and a standard deviation of about 8%. Market concentrations measured by the HHI of sales and employment display similar patterns as those measured by the top firms' market shares. The labor income share from the NBER-CES dataset averages about 30%, which is lower than aggregate labor share, partly because our dataset covers the manufacturing sector, which is less labor intensive than the services sector.

To examine the correlation between market concentration and automation at the industry level, we estimate the empirical specification

$$log(Y_{jt}) = \beta_0 + \beta_1 \log(robot_{jt}) + \gamma_j + \delta_t + \varepsilon_{jt}. \tag{1}$$

[5] Prior to 2007, the IFR data on industrial robots at the 2-digit industry level are very limited. The codes for the 13 industries included in our sample are 10-12, 13-15, 16&31, 17-18, 19-22, 23, 24, 25, 26-27, 28, 29, 30, D&E. The sample size is smaller than $12 \times 13 = 156$ because there are some missing values.

Table 2. Industry-Level Evidence

	(1)	(2)	(3)	(4)	(5)
	ln(top 1% share)		ln(HHI)		ln(labor share)
	sales	employment	sales	employment	
ln(robot/emp)	0.0737***	0.0135	0.0948**	0.0283	-0.0151*
	(0.0157)	(0.0504)	(0.0407)	(0.0299)	(0.00830)
Constant	-1.109***	-1.362***	6.978***	6.474***	-1.554***
	(0.0710)	(0.0674)	(0.101)	(0.0238)	(0.0167)
Observations	117	104	137	135	151
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Adjusted R^2	0.944	0.688	0.920	0.984	0.980

Note: This table shows the regression results from the empirical specification (1) that projects industry concentration measures and labor shares on robot density. The robot density is measured by the operation stock of industrial robots per thousand workers within the industry. The regressions weigh the industries by their sales share in the initial year (2007). All regressions control for industry and year fixed effects. The standard errors in the parentheses are clustered at the industry level. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Here, the dependent variable Y_{jt} is a measure of market concentration in industry j and year t (sales share of top 1% firms, employment share of top 1% firms, HHI based on sales, or HHI based on employment) or the labor income share. The key independent variable is $robot_{jt}$, which denotes the robot density in industry j and year t. In the regression, we control for the industry fixed effects (γ_j) and the year fixed effects (δ_t). The term ε_{jt} denotes the regression residual. The parameter β_0 is the intercept term.

The key parameter of interest is β_1, which measures the elasticity of market concentration (or labor share) with respect to robot density. For example, for the market concentration regression, if β_1 is estimated to be positive after controlling for industry fixed effects and time fixed effects, then it would suggest that an industry more exposed to automation than average (i.e., with a higher robot density) has also greater market concentration.[6]

Table 2 shows the estimation results under the empirical specification (1), where robot density is measured by the number of robots per thousand workers ($robot/emp$). In the regression, each industry-level variable is weighted by the industry's sales in the initial year (i.e., 2007), following Autor et al. (2020). The standard errors (i.e., the numbers in parentheses) are clustered at the industry level.

The regression results show that, controlling for industry and year fixed effects, robot

[6]The estimated β_1 from the regression reflects the correlation, but not necessarily a causal relation, between robot density and industry concentration (or labor share).

density is positively correlated with market concentration. However, the correlations of robot density with sales-based concentration are different from those with employment-based measures. The estimated coefficient in Column (1) of the table implies that, in an industry with robot density (in log units) that is one standard deviation higher than the mean, the sales share of the top 1% firms would be about 20 percent higher than average, or equivalently, about 6 percentage points higher than the sample mean (the average sales share of top 1% firms in our sample is about 31%).[7] This estimated coefficient is statistically significant at the one-percent confidence level. The correlation of robot density with the employment share of the top 1% firms, although positive, is small and statistically insignificant (Column (2)). A similar correlation pattern holds if we measure concentration using the HHI (see Columns (3) and (4)). These regression results from cross-sectional data corroborate well with the time-series correlations between automation and market concentration in Figure 1.

Table 2 further shows that robot density is negatively correlated with the labor share. After controlling for industry and year fixed effects, a higher robot density is associated with a lower labor share, and the correlation is statistically significant at the 10-percent level (see Column (5)).

The cross-sectional correlations of robot density with market concentration and the labor share are robust to alternative measures of robot density and alternative empirical specifications (such as a dynamic panel specification that included lagged dependent variables). We provide details of these robustness checks in Appendix A.

3 The Model

To understand the connection between the rise of automation, market concentration, and the labor share, this section constructs a general equilibrium model featuring heterogeneous firms, variable markups, and endogenous automation decisions.

3.1 Households

The economy is populated by a large number of infinitely-lived identical households with a unit measure. All agents have perfect foresight. The representative household has the utility function

$$\sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \chi \frac{N_t^{1+\xi}}{1+\xi} \right], \tag{2}$$

[7] The standard deviation of logged robot density is 2.71. The point estimate in Column (1) implies that a one standard deviation increase in logged robot density raises the sales share of the top 1% firms by $0.0737 \times 2.71 \approx 0.20$ log points, or about 20 percent in the level of the sales share.

where C_t denotes consumption, N_t denotes labor supply, $\beta \in (0,1)$ is a subjective discount factor, $\xi \geq 0$ is the inverse Frisch elasticity of labor supply, and $\chi > 0$ is the weight on the disutility from working.

The household faces the sequence of budget constraints

$$C_t + Q_{at} I_{at} \leq W_t N_t + r_{at} A_t + \pi_t, \tag{3}$$

where I_{at} denotes the investment in automation (i.e., robot adoption), A_t denotes the beginning-of-period robot stock, Q_{at} denotes the relative price of robots, W_t denotes the real wage rate, and π_t denotes the share of profit from the firms that the household owns. The stock of robots evolves according to the law of motion

$$A_{t+1} = (1-\delta_a) A_t + I_{at}, \tag{4}$$

where $\delta_a \in [0,1]$ denotes the robot depreciation rate.

The household takes the prices Q_{at}, W_t, and r_{at} as given, and maximizes the utility function (2) subject to the budget constraints (3) and the law of motion for robots (4). The optimizing consumption-leisure choice implies the labor supply equation

$$W_t = \chi N_t^{\xi} C_t. \tag{5}$$

The optimizing choice of robot adoptions implies that

$$Q_{at} = \beta \frac{C_t}{C_{t+1}} \left[r_{a,t+1} + Q_{a,t+1}(1-\delta_a) \right]. \tag{6}$$

3.2 Intermediate goods producers

There is a large number of monopolistically competitive firms with a unit measure indexed by $j \in [0,1]$. Firms have access to a constant returns technology for producing differentiated intermediate goods, with the production function

$$y_t(j) = \phi_t(j) \left[\alpha_a A_t(j)^{\frac{\eta-1}{\eta}} + (1-\alpha_a) N_t(j)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{7}$$

where $y_t(j)$ denotes the firm's output; $\phi_t(j)$ denotes an idiosyncratic productivity shock; and $A_t(j)$ and $N_t(j)$ denote the inputs of robots and workers, respectively. The parameter $\eta > 1$ is the elasticity of substitution between robots and workers. The parameter α_a measures the relative importance of robot input in production.

The idiosyncratic productivity shock follows a stationary AR(1) process

$$\ln \phi_t(j) = \gamma \ln \phi_{t-1}(j) + \varepsilon_t(j), \quad \varepsilon_t(j) \sim N(0, \sigma_\phi^2), \tag{8}$$

where $\gamma \in (0,1)$ measures the persistence of the productivity shock, and $\sigma_\phi > 0$ denotes the standard deviation of the innovation.

To use robots for production (i.e., to have $A_t(j) > 0$), a firm needs to pay a per-period fixed cost f_a, which is an i.i.d. random variable drawn from the distribution $F(\cdot)$. If the firm pays f_a, then it can hire both workers and robots from the representative household at the competitive wage rate W_t and robot rental rate r_{at}. Cost-minimizing leads to the conditional factor demand functions

$$r_{at} = \alpha_a \lambda_t(j) \phi_t(j)^{\frac{\eta-1}{\eta}} \left(\frac{y_t(j)}{A_t(j)} \right)^{\frac{1}{\eta}}, \tag{9}$$

$$W_t = (1-\alpha_a) \lambda_t(j) \phi_t(j)^{\frac{\eta-1}{\eta}} \left(\frac{y_t(j)}{N_t(j)} \right)^{\frac{1}{\eta}}, \tag{10}$$

where $\lambda_t(j)$ denotes the real marginal cost of production for firm j:

$$\lambda_t(j) = \frac{\left[\alpha_a^{\eta} r_{at}^{1-\eta} + (1-\alpha_a)^{\eta} W_t^{1-\eta} \right]^{\frac{1}{1-\eta}}}{\phi_t(j)}. \tag{11}$$

If the firm does not pay f_a, then the firm would not have access to the automation technology and it can hire workers only. In that case, the firm chooses $A_t(j) = 0$ and cost-minimizing implies the conditional labor demand function

$$N_t(j) = \frac{y_t(j)}{\phi_t(j)} (1-\alpha_a)^{\frac{\eta}{1-\eta}}. \tag{12}$$

The marginal cost of production in this case would be

$$\lambda_t(j) = \frac{(1-\alpha_a)^{\frac{\eta}{1-\eta}} W_t}{\phi_t(j)}. \tag{13}$$

3.3 Final good producers

Final good producers make a composite homogeneous good out of the intermediate varieties and sell it to consumers in a perfectly competitive market, with the final good price normalized to one. The final good Y_t is produced using a bundle of intermediate goods $y_t(j)$, according to the Kimball aggregator

$$\int_0^1 \Lambda\left(\frac{y_t(j)}{Y_t}\right) dj = 1, \tag{14}$$

where the intermediate varieties are denoted by j. For ease of notation, we suppress the time subscript t in what follows.

3.4 Demand for intermediate goods

Denote the relative output of firm j by $q(j) := \frac{y(j)}{Y}$. Taking the intermediate goods prices $p(j)$ as given, the cost-minimizing decision of the final good producer leads to the demand schedule for the type j intermediate goods

$$p(j) = \Lambda'(q(j))D, \tag{15}$$

where D is a demand shifter given by

$$D = \left(\int \Lambda'(q(j))q(j)dj \right)^{-1}. \tag{16}$$

We follow Klenow and Willis (2016) and assume:

$$\Lambda(q) = 1 + (\sigma - 1)\exp(\frac{1}{\varepsilon})\varepsilon^{\frac{\sigma}{\varepsilon}-1}[\Gamma(\frac{\sigma}{\varepsilon}, \frac{1}{\varepsilon}) - \Gamma(\frac{\sigma}{\varepsilon}, \frac{q^{\varepsilon/\sigma}}{\varepsilon})], \tag{17}$$

with $\sigma > 1$ and $\varepsilon \geq 0$ and $\Gamma(s, x)$ is the upper incomplete Gamma function

$$\Gamma(s, x) = \int_x^\infty v^{s-1}e^{-v}dv. \tag{18}$$

With the specification for Λ, we get

$$\Lambda'(q(j)) = \frac{\sigma - 1}{\sigma}\exp(\frac{1 - q(j)^{\frac{\varepsilon}{\sigma}}}{\varepsilon}), \tag{19}$$

which, using the demand schedule (15), implies that the demand elasticity (i.e., price elasticity of demand) faced by firm j is

$$\sigma(q(j)) = -\frac{\Lambda'(q(j))}{\Lambda''(q(j))q(j)} = \sigma q(j)^{-\frac{\varepsilon}{\sigma}}. \tag{20}$$

Given this demand elasticity, the firm with relative production $q(j)$ charges the optimal markup

$$\mu(j) = \frac{\sigma(q(j))}{\sigma(q(j)) - 1}. \tag{21}$$

As a result, larger firms have more market power and charge higher markups.[8]

[8] We make the technical assumption that $q(j) < \sigma^{\frac{\sigma}{\varepsilon}}$ such that the effective demand elasticity is always greater than one. This assumption ensures a well-defined equilibrium under monopolistic competition. In our numerical solutions, we find that this constraint is never binding.

3.5 Automation decision

From hereon, we drop the firm index j and index firms by their idiosyncratic productivity ϕ. The firm with productivity ϕ takes as given aggregate output Y, the demand shifter D, and the downward-sloping demand schedule for its differentiated product in Eq. (15).

A firm first draws its idiosyncratic productivity ϕ according to the productivity process (8). Then, the firm draws its i.i.d fixed cost for using the automation technology, and decides which technology of production to use. If the firm pays the fixed cost f_a for using the automation technology, then the firm would choose its price $p(\phi)$, quantity $y(\phi)$, and inputs $N(\phi)$ and $A(\phi)$ to solve the profit-maximizing problem

$$\Pi^a(\phi) = \max_{p(\phi),y(\phi),N(\phi),A(\phi)} \Big[p(\phi)y(\phi) - WN(\phi) - r_a A(\phi) \Big], \tag{22}$$

subject to the constraints in equations (9), (10) and (15).

If the firm uses labor only, then it would solve the profit-maximizing problem

$$\Pi^n(\phi) = \max_{p(\phi),y(\phi),N(\phi)} \Big[p(\phi)y(\phi) - WN(\phi) \Big], \tag{23}$$

subject to the constraints in equations (12) and (15).

Since accessing the automation technology incurs an i.i.d. fixed cost, a firm would automate if and only if the net benefit of automation exceeds the fixed cost. Let $\bar{f}_a(\phi) \equiv \Pi^n(\phi) - \Pi^a(\phi)$. If a firm draws a fixed cost of automation f_a that is at or below $\bar{f}_a(\phi)$, then it would choose to automate. More formally, we have

$$f_a \leq \bar{f}_a(\phi) \Longleftrightarrow \mathbb{I}_a(\phi, f_a) = 1, \tag{24}$$

where $\mathbb{I}_a(\cdot)$ is an indicator of the automation decision, which is a function of the firm-level variables ϕ and f_a. It follows that, for a firm with productivity ϕ, the ex ante (i.e., before drawing the automation fixed cost) automation probability equals $F(\bar{f}_a(\phi))$, the cumulative density of the fixed costs evaluated at the indifference point.

3.6 Stationary equilibrium

We focus on a stationary equilibrium and thus drop the time subscript for all variables. The equilibrium consists of aggregate allocations C, I_a, A, N, and Y, aggregate prices W and r_a, firm-level allocations $A(\phi)$, $N(\phi)$, and $y(\phi)$ and firm-level prices $p(\phi)$ for all $\phi \in G(\cdot)$, where $G(\cdot)$ is the ergodic distribution implied by the productivity process (8), such that (i) taking all prices as given, the aggregate allocations solve the representative household's optimizing problem; (ii) taking the aggregate allocations and prices as given, the firm-level allocations and prices solve each individual firm's optimizing problem; and (iii) the markets for the final good, labor, and robots all clear.

The final good market clearing condition is given by

$$C + Q_a I_a + \int_\phi \int_0^{\bar{f}_a(\phi)} f_a \; dF(f_a) \; dG(\phi) = Y. \tag{25}$$

The labor market clearing condition is given by

$$N = \int_\phi N(\phi) dG(\phi). \tag{26}$$

The robot market clearing condition is given by

$$A = \int_\phi A(\phi) F(\bar{f}_a(\phi)) dG(\phi). \tag{27}$$

Appendix B outlines the solution algorithm.

4 Model mechanism

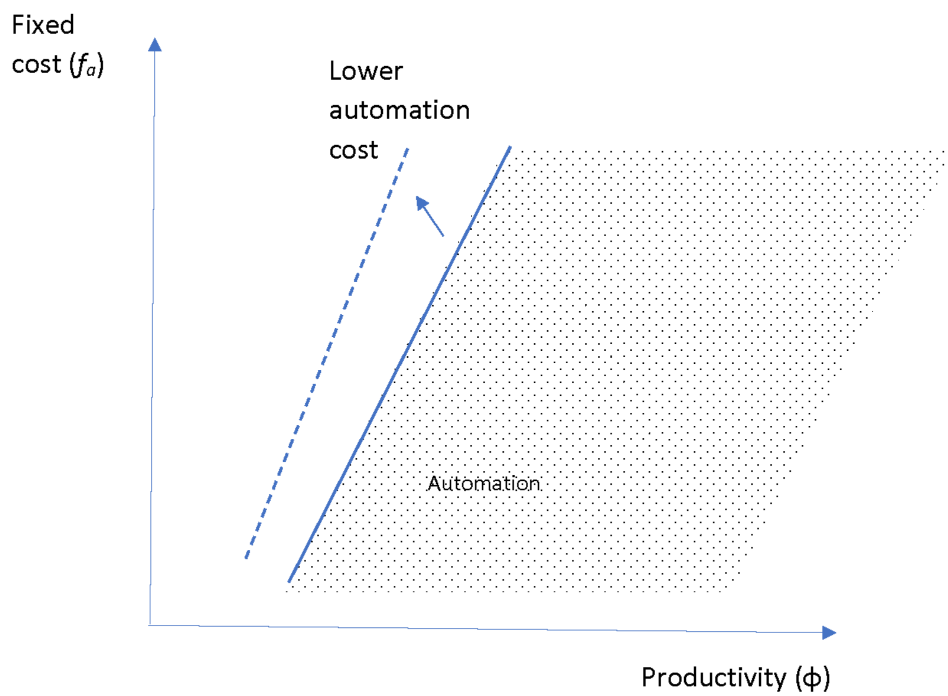
Firms are heterogeneous along two dimensions: they face idiosyncratic shocks to both productivity (ϕ) and the fixed cost of operating the automation technology (f_a). The automation decision depends on the combination of the realizations of ϕ and f_a. Firms face a trade-off when deciding whether to automate. On the one hand, firms need to pay a fixed cost f_a to automate. On the other hand, however, the marginal cost of production using the automation technology (equation (11)) is always smaller than that using the labor-only technology (equation (13)). Since higher-productivity firms are larger and charge higher markups, they earn higher profits and therefore are more likely to pay the fixed cost and automate.

Figure 2 illustrates the automation decision rules. For any given productivity ϕ, a firm will choose to automate if the realized fixed cost is sufficiently low. Similarly, for any given fixed cost f_a, a firm will automate if the realized productivity is sufficiently high. There is an upward slowing line that separates the technology choices. To the right of the line (high ϕ and low f_a), firms use the automation technology and to the left of the line, they use the labor-only technology. Firms with combinations of ϕ and f_a on the upward-sloping line are indifferent between the two types of technologies.

The location of the indifference line is endogenous, depending on aggregate economic conditions. A decline in the relative price of robots (Q_a), for example, will lower the robot rental rate r_a, reducing the marginal cost of using the automation technology. This would shift the indifference curve up (from the solid to the dashed line), such that more firms would choose to automate (the extensive margin) and those firms already operating the automation technology would increase their use of robots (the intensive margin).

For a given technology choice (labor only or automation), a high-productivity firm is also a large firm in terms of both employment and output, and is also more likely to use

Figure 2. Automation decision rules.



Note: This figure shows the automation decisions as a function of firm-level productivity (ϕ) and the fixed cost of operating the automation technology (f_a). Firms with (ϕ, f_a) to the lower-right of the solid line choose to automate (the shaded area) and those to the upper-left of the line choose to use the labor-only technology. A decline in the robot price shifts the indifference line upward (from the solid to the dashed line), inducing more use of the automation technology.

robots at any given fixed cost, as illustrated in Figure 2. A decline in the relative price of robots improves labor productivity, enabling those robot-using firms to become even larger and increasing the share of top firms in the product market (through the intensive margin). However, the decline in robot price also induces some less-productive firms to switch from the labor-only technology to the automation technology (through the extensive margin), partially offsetting the increase in the share of sales of the top firms. The net effect of the decline in the robot price on sales concentration can be ambiguous, depending on the relative strength of the extensive vs. the intensive margin effects. As we will show below, under our calibration the intensive margin effect dominates, such that a lower robot price leads to higher concentration of sales in large firms.

A higher share of sales of the large firms does not directly translate into a higher share

Table 3. Parameters

Parameter	Notation	Value	Sources/Matched Moments
Panel A: Assigned Parameters			
Discount factor	β	0.99	4% annual interest rate
Inverse Frisch elasticity	ξ	0.5	Rogerson and Wallenius (2009)
Working disutility weight	χ	1	Normalization
Elasticity of substitution	η	3	Eden and Gaggl (2018)
Robot input weight	α_a	0.465	Eden and Gaggl (2018)
Robot depreciation rate	δ_a	0.02	8% annual depreciation rate
Productivity persistence	γ	0.95	Khan and Thomas (2008)
Productivity standard dev.	σ_ϕ	0.1	Bloom et al. (2018)
Demand elasticity parameter	σ	10.86	Edmond, Midrigan and Xu (2021)
Super-elasticity	ϵ/σ	0.16	Edmond, Midrigan and Xu (2021)
Panel B: Parameters from Moment Matching			
Relative price of robots	Q_a	50.1	Fraction of automating firms
Automation fixed cost	F_a	1.5	Employment share of automating firms

Note: This table shows the calibrated parameters in the model. Panel A reports the externally assigned parameters and their sources. Panel B shows the parameters calibrated by moment matching.

of employment of those firms. A decline in the price of robots improves labor productivity for firms that use robots, allowing those firms to expand. Since larger firms are more likely to use robots, they also benefit more from the declined rental costs of robots. Since robots substitute for workers, large firms can increase production without proportional increases in labor input, and they also charge higher markups as they get larger. Thus, the share of employment of large firms increases by less than their sales share. Furthermore, the labor share falls because production reallocates from firms using the labor-only technology to those using the automation technology. This is the key model mechanism to generate a positive correlation between automation and market concentration, but a negative correlation between automation and the labor share. The model mechanism also implies a larger correlation of automation with market concentration measured by the share of sales of top firms than that measured by the share of employment.

5 Calibration

Table 3 displays the calibrated parameters. We calibrate a subset of parameters based on the literature (Panel A). One period in the model corresponds to a quarter of a year. We set the subjective discount factor to $\beta = 0.99$, implying an annual real interest rate of 4%. We set the inverse Frisch elasticity to $\xi = 0.5$, following Rogerson and Wallenius (2009).

Table 4. Matched Moments

Moments	Data	Model
Fraction of automating firms	1.3%	1.2%
Employment share of automating firms	13.4%	13.4%

Note: This table shows the targeted data moments and the simulated moments by the model. The data moments are from the ABS data (from Zolas et al., 2020).

We normalize the disutility from working to $\chi = 1$. We set the elasticity of substitution between robots and workers in the automation technology to $\eta = 3$, and the input weight of robots to $\alpha_a = 0.465$ following the study of Eden and Gaggl (2018).[9] We calibrate the quarterly robot depreciation rate to $\delta_a = 0.02$, implying an average robot lifespan of about 12 years, in line with the assumption made by the International Federal of Robotics in imputing the operation stocks of industrial robots.

We set the persistence of idiosyncratic productivity shocks to $\gamma = 0.95$ following Khan and Thomas (2008). We set the standard deviation of productivity shocks to $\sigma_\phi = 0.1$, consistent with Bloom et al. (2018).[10] To calibrate the elasticity parameters σ and ϵ in the Kimball preferences, we follow Edmond, Midrigan and Xu (2021) and set $\sigma = 10.86$ and $\epsilon/\sigma = 0.16$.

We calibrate the remaining parameters to match some key moments in the micro-level data. These parameters include the steady-state relative price of robots Q_a and the parameters in the distribution of the fixed cost of automation. We assume that the fixed cost of automation follows a uniform distribution $U(0, F_a)$, and we calibrate F_a, the upper bound of the uniform distribution. The calibrated values are shown in Panel B of Table 3.

The relative price of robots Q_a affects the fraction of firms that use the automation technology (i.e., the automation probability), which is given by

$$\int_\phi F(\bar{f}_a(\phi))\, dG(\phi).$$

We calibrate Q_a to target the observed fraction of firms that use robots in the micro-level data. In particular, we target this moment to match that in the ABS survey, which shows that the fraction of firms that use robots is about 1.3% in 2018 (Zolas et al., 2020).

The parameter F_a in the distribution of fixed costs of automation affects the relation between the firm size and automation decisions. Under a larger F_a, small firms would be

[9] Cheng et al. (2021) estimate the firm-level elasticity of substitution between labor and automation capital in China ranging from 3 to 4.5, with their preferred estimate being 3.8. Therefore, the elasticity of $\eta = 3$ is conservative relative to their benchmark estimate.

[10] Bloom et al. (2018) estimate a 2-state Markov switching process of firm-level volatility. They find that the low standard deviation is 0.051 and the high value is 0.209. Also, according to their estimated transition probabilities, the unconditional probability of the low standard deviation is 68.7%. Therefore, the average standard deviation is 0.1 (=0.051*68.7%+0.209*(1-68.7%)).

less likely to cover the fixed cost of automation. As a result, the employment share of firms that choose to automate would rise. Therefore, to calibrate F_a, we target the employment share of firms that automate, which in our model equals

$$\frac{\int_\phi F(\bar{f}_a(\phi))N(\phi)\ dG(\phi)}{\int_\phi N(\phi)\ dG(\phi)}. \tag{28}$$

In the ABS survey, the employment share of automating firms is about 13.4% (Zolas et al., 2020). By matching the fraction of automating firms and the employment share of those firms in the ABS data, we obtain $Q_a = 50.1$ and $F_a = 1.5$, as shown in Panel B of Table 3. The calibrated model matches the targeted moments closely, as shown in Table 4.

6 Model Implications

We solve the model's steady-state equilibrium based on the calibrated parameters. We now report the model's quantitative implications.

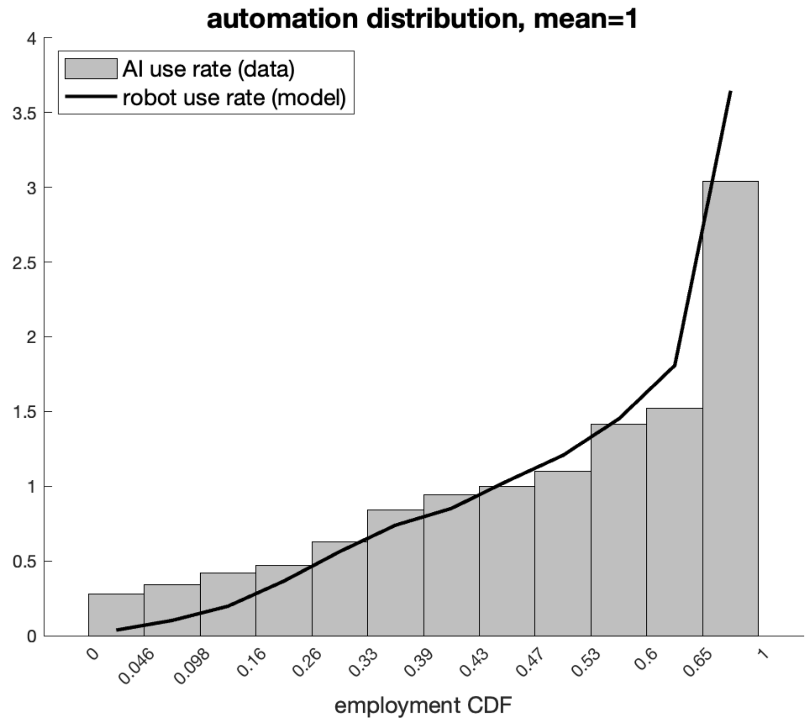
The calibrated model does well in generating the observed distribution of automation in the ABS data. Figure 3 plots the distribution of AI use rate (i.e., fraction of firms that use AI in their production) in the data (from Zolas et al., 2020) and the fraction of firms with robots in the model.[11] The model closely matches this non-targeted distribution of robot use rates.

To further examine the automation mechanism, we plot in Figure 4 the firms' decision rules as a function of the idiosyncratic productivity level ϕ. In each panel, we show two lines, one in the baseline model with calibrated parameters (black solid line) and the other in a counterfactual with a lower robot price (low Q_a, red dashed line). The figure shows that the automation probability increases with productivity, and thus more productive firms are more likely to pay the fixed costs to access the automation technology. In addition, a non-degenerate set of firms with sufficiently low productivity do not use robots and they operate the worker-only technology. A decline in the robot price boosts the automation probabilities, with a larger effect on more productive firms. It also reduces the productivity cutoff for accessing the automation technology.

The figure also shows the decision rules for firms that use robots and those who don't at each level of productivity. In the baseline model, the decision rules are qualitatively similar between the two types of firms. In particular, higher-productivity firms are larger,

[11] In Figure 8 of Zolas et al. (2020), they show the share of firms that use AI technologies for each size category, e.g., 1-4 employees, 5-9 employees, or 10,000+ employees. To make a fair comparison between the data and the model, we use the 2017 County Business Patterns and Economic Census to obtain the number of employees for each firm size category to compute the cumulative distribution function (CDF) of employment-based firm sizes in the data. Now we have the AI use rates with respect to the employment CDF in the data. Then we calculate the robot use rates with respect to the employment CDF in the model in the same way. In Figure 3, we normalize their mean to one for comparison.

Figure 3. Automation Distribution

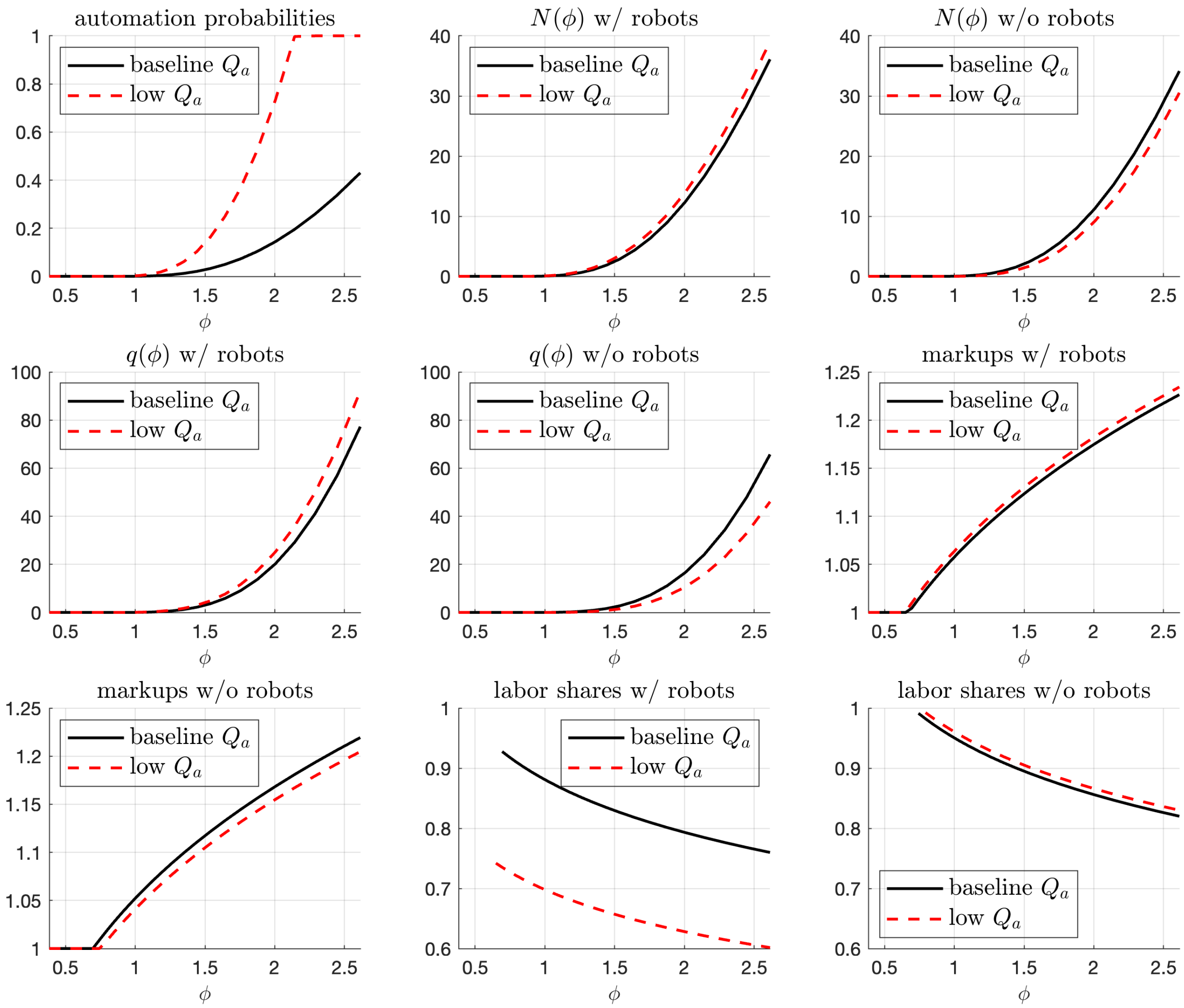


Note: This figure plots the distribution of AI use rate (i.e., fraction of firms that use AI in their production) in the ABS data (from Zolas et al., 2020) and the fraction of firms with robots in the model.

with higher employment ($N(\phi)$), higher relative output ($q(\phi)$), and higher market power measured by the markup; and those firms have also lower labor shares. Larger firms have lower labor shares for two reasons. First, larger firms charge higher markups, reducing the share of labor compensation in value-added. This force is at play for all firms, regardless of whether they use robots. Second, larger firms are more likely to automate, and as a result have lower labor shares. This effect is working only for the firms that use robots.

The figure further shows that the impacts of a decline in the robot price on the firms' decisions rules depend on whether the firm uses robots. For robot-using firms, a decline in the robot price raises employment, output, and markup at each level of productivity. A reduction in robot price activates two competing forces on the employment for the firms with robots. On the one hand, these firms substitute away from workers to robots, which tends to reduce employment at these firms. On the other hand, however, these firms gain market share and become larger, and therefore, will employ more workers. As figure 4 shows, the latter effect dominates and firms with robots employ more workers after the reduction in robot price. The labor shares of the firms with robots decline despite the increases in employment, reflecting the substitution of robots for workers and also the increase in markups as those firms expand production.

Figure 4. Firms' Decision Rules



Note: This figure shows firms' decision rules for the firms that automate (w/ robots) and those that do not automate (w/o robots). The solid-black lines are associated with our baseline calibration, while red-dashed lines show the results for a counterfactual in which robot price Q_a falls by 50%.

For firms without robots, the decline in the robot price has the opposite effects on their decision rules. In particular, a decline in Q_a reduces employment, output, and markups and increases the labor share at any given level of productivity. These changes in the decision rules reflect the reallocation of labor from non-automating firms to automating firms. As the non-automating firms become smaller, their market power declines, resulting in lower markups and higher labor shares.

The reallocation mechanism has important implications for the response of the aggregate economy to exogenous changes in the robot price, as shown in Figure 5. The figure plots the steady-state relations between several key macroeconomic variables and the relative price of robots. To illustrate, we consider a range of robot price variations, from 15 to 75 (relative to the calibrated level of $Q_a = 50.1$).

At a lower robot price, more firms would find it profitable to automate, raising the aggregate share of automating firms. Since larger firms are more likely to automate, they benefit more than smaller firms from a reduction in the robot price. As a result, the product market becomes more concentrated and the share of the top 1% firms rises. Importantly, the sales-share of the top firms rises more than the employment-share when Q_a declines, because those top firms that use robots can expand production without proportional increases in their labor input, and also because as they get larger they charge higher markups.

As Q_a falls, large firms become even larger, raising the average markup (both sales- and cost-weighted).[12] Moreover, as Figure 4 shows, a reduction in Q_a reallocates production and employment towards automating firms, who have lower labor shares in the original steady state and even lower labor shares with a reduction in Q_a. Therefore, as Q_a falls, the labor share in the aggregate economy declines. Our model's implication that the decline in the aggregate labor share is mainly driven by the between-firm reallocation channel is consistent with the empirical evidence in Autor et al. (2020) and Acemoglu, Lelarge and Restrepo (2020).

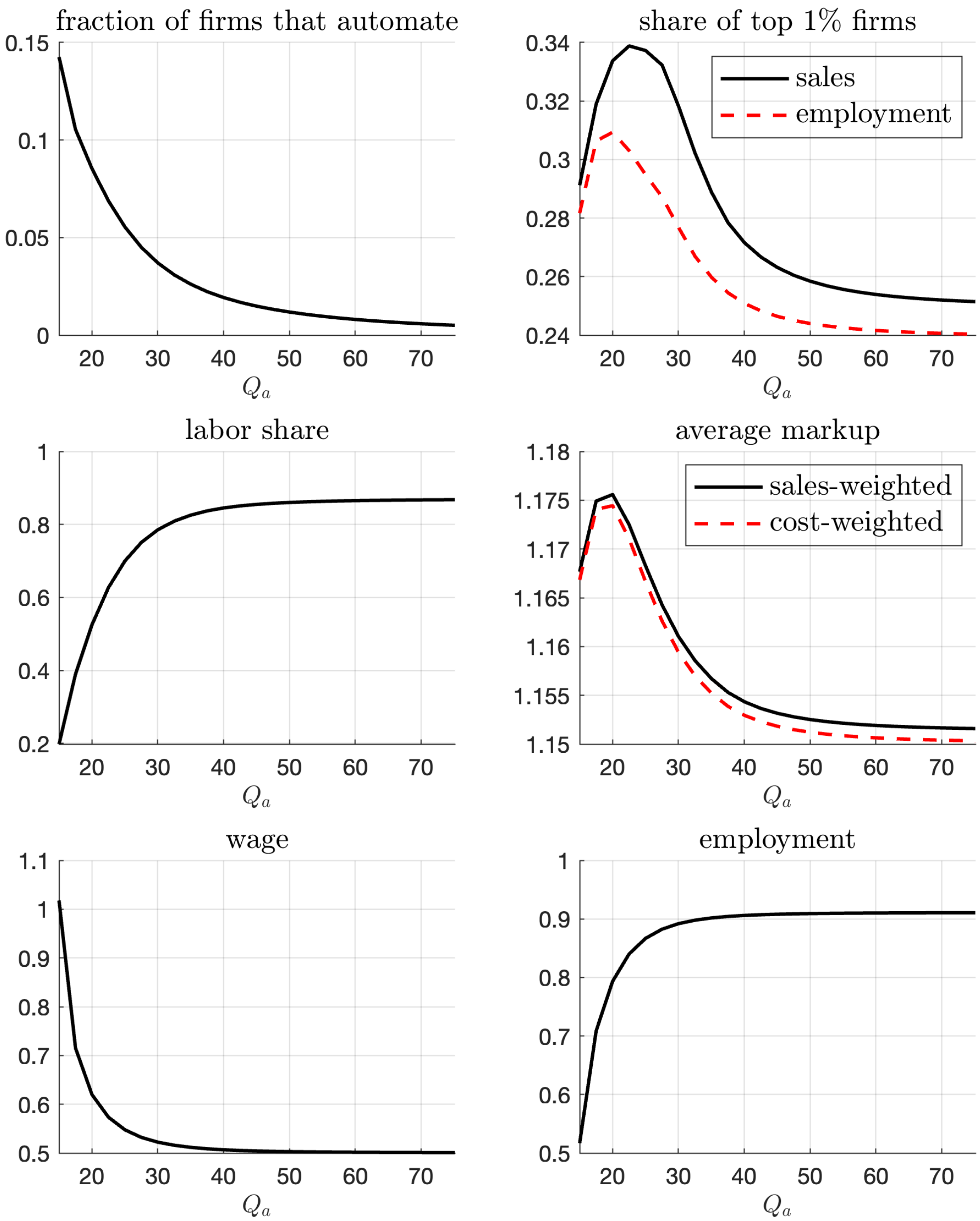
The relation between robot prices and market concentration can be non-monotonic. If the fraction of automating firms in the original steady state is low, as in our calibrated model, then a reduction in the robot price would increase market concentration. In an economy with relatively wide-spread automation, however, a reduction in the robot price may not increase market concentration as much, and it could even reduce concentration. This possibility is illustrated in Figure 5. The figure shows that, if Q_a starts from a sufficiently low level, a further decline in Q_a would still increase the fraction of automating firms, but it would reduce the share of the top 1% firms in both sales and employment. For similar reasons, the relation between average markup and the robot price is also non-monotonic, as shown in the figure.

These finding suggests that the relations between automation and market concentration and markup stem from robot usage that is highly skewed towards a small number of large firms, which is different from general capital equipment that is widely used by many firms in the economy.

Although a reduction in Q_a lowers the aggregate labor share, it raises equilibrium wages and reduces aggregate employment. In our model, workers are mobile across all firms. For automating firms, the decline in Q_a boosts the usage of robots, raising the marginal product of workers if the marginal cost is held constant (see Eq. (10)). The increased labor demand by the automating firms therefore drives up equilibrium wages for all firms. Of

[12] To derive the cost-weighted average markup, we use total variable costs at each firm, as in Edmond, Midrigan and Xu (2021).

Figure 5. Aggregate Variables



Note: This figure shows the effects of counterfactual changes in the robot price Q_a on the fraction of firms that automate, share of top 1% firms, labor share, average markup, wage and employment. We vary the robot price Q_a in the range between 15 and 75.

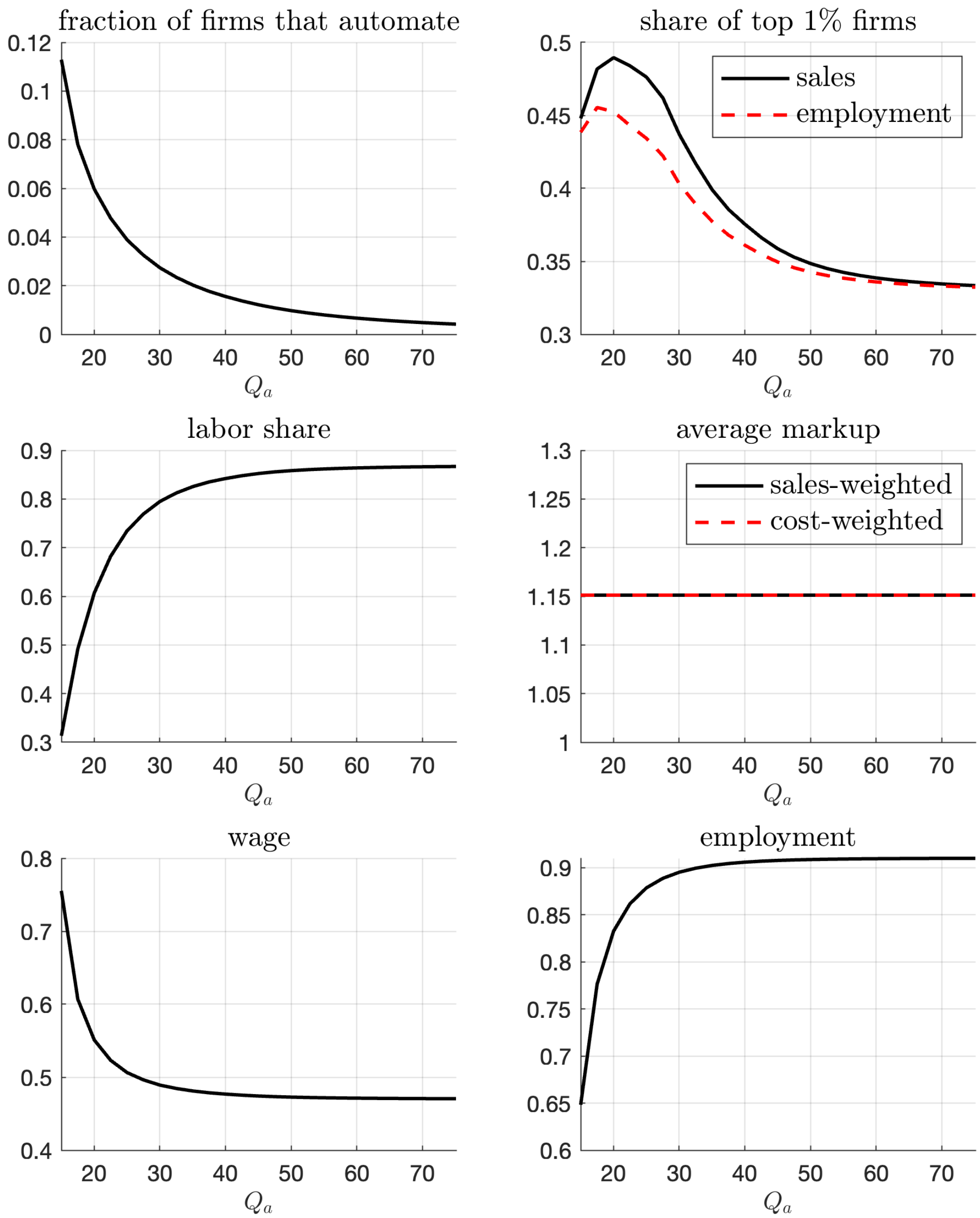
course, when the automating firms expand production, they gain market powers and their markups would rise. An increase in markups would mitigate the increase in labor demand, dampening the increase in wages. The reduction in Q_a also creates a positive wealth effect: by raising consumption, the household is willing to supply less labor at each given wage level. In equilibrium, a reduction in Q_a leads to an increase in wages and a decline in aggregate employment.[13]

To examine the role of variable markups in generating the results, we consider the constant-markup version of the model in which we replace the Kimball aggregator (14) with a Constant Elasticity of Substitution (CES) aggregator. Appendix C oulines this model and its solution algorithm. We use a CES elasticity that generates the same cost-weighted average markup as in our baseline variable-markup model (i.e., the average markup equals 1.15). Our calibration shows that the CES model is not able to match the fraction of firms that automate and employment share of firms that automate at the same time. Indeed, while we match the former, the latter moment will be too high. This is because the distribution of firm size is too skewed to the right when we use the empirically estimated productivity process from Bloom et al. (2018) and CES production function at the same time.

In the CES model, we perform the same counterfactual exercise as in the baseline model by varying Q_a in the range between 15 and 75 (relative to the baseline value of 50.1). Figure 6 shows that, in the CES economy, a reduction in the robot price leads to a more muted increase in the fraction of automating firms and a more muted decline in the labor share than in the economy with variable markups. To elaborate, since larger firms in the CES economy do not charge higher markups, they have less incentive to pay the fixed cost of automation than large firms in the variable-markup economy. In the CES economy, production and employment are more concentrated in the top 1% firms than in the variable-markup economy, because all firms in the CES economy charge the same markup, such that large firms produce more than that in the variable-markup economy (in which large firms need to refrain from production expansion to maintain high markups). As the robot price declines, the sales share and the employment share of the top 1% firms both increase, as in the variable-markup economy. However, the gap between the two measures of market concentration is smaller than that in the variable-markup economy, because the top firms cannot increase their markups by expanding production through increased use of automation.

[13]Our model's prediction that a reduction in the robot price raises worker wages seems to be at odds with the empirical evidence documented by Acemoglu and Restrepo (2021), who find substantial declines in the relative wages of workers specialized in routine tasks in industries experiencing rapid automation. This is perhaps not surprising because we focus on studying the relation between automation and market concentration and abstract from labor market frictions in our model. In a model with elaborated labor market frictions, such as the business cycle model with labor search frictions and automation studied by Leduc and Liu (2019), an increase in automation threat effectively reduces workers' bargaining power in wage negotiations, and it can lower equilibrium wages. Incorporating labor market frictions into our framework is potentially important for understanding the connection between automation and a broader set of labor market variables (including wages). We leave that important task for future research.

Figure 6. Aggregate Variables in the CES Economy



Note: This figure shows the effects of counterfactual changes in the robot price Q_a in the CES version of the model on the fraction of firms that automate, share of top 1% firms, labor share, average markup, wage, and employment. We vary the robot price Q_a from 15 to 75 (relative to the steady-state value of 50.1).

7 Conclusion

We study how increased automation may have contributed to the rise in industrial concentration and the decline in the labor share since the early 2000s. For this purpose, we build a general equilibrium model with heterogeneous firms, variable markups, and endogenous automation decisions. Our calibrated model does well in matching the cross-sectional distribution of automation usage observed in the firm-level data. The model implies that larger firms with higher productivity and higher markups are more likely to use the automation technology. A decline in automation costs (e.g., robot prices) intensifies the automation usage by large firms, improving labor productivity of those firms and enabling them to expand the market share of their production. Since robots substitute for workers, the decline in automation costs leads to a sharper increase in market concentration measured by sales than that measured by employment. The relative expansion of large firms also leads to a decline in the aggregate labor share through a between-firm reallocation channel. These model predictions are consistent with empirical evidence.

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Appendices

A Robustness of cross-sectional empirical evidence

In the main text, we present evidence that industries with higher robot density have also higher levels of market concentration and lower labor shares. Furthermore, the sales-based measures of industry concentration have a larger and more significant correlation with robot density than employment-based measures. Here, we provide further evidence showing that these correlation patterns are robust to alternative measurements of robot density and alternative empirical specifications.

Table A.1 shows the regression results from the baseline empirical specification (1), where we replace the measure of robot density by the operation stock of industrial robots per million labor hours (instead of per thousand workers). The estimated correlations of this alternative measure of robot density with market concentration and labor shares are qualitatively the same as in the baseline regression reported in Table 2.

To further examine the correlations between robot density and industry concentration and labor shares, we have estimated a dynamic panel that includes the lagged dependent variable to capture some unobserved time-varying industry characteristics. In particular, we consider the empirical specification

$$\log(Y_{jt}) = \beta_0 + \beta_1 \log(Y_{j,t-1}) + \beta_2 \log(robot_{jt}) + \delta_t + \varepsilon_{jt}, \tag{29}$$

where the dependent variable Y_{jt} denotes market concentration (or the labor share) of industry j and year t and the key independent variable $robot_{jt}$ is the robot density of industry j in year t. The specification includes year fixed effects (δ_t). Unlike the baseline specification (1), this alternative specification includes the lagged dependent variable $\log(Y_{j,t-1})$.

We implement the estimation of the empirical specification (29) using the Arellano-Bond estimator. Table A.2 displays the estimation results, with the robot density measured by the stock of robots per thousand workers. The results show that an increase in robot density is associated with a significant increase in sales-based industry concentration measured by both the top 1% firm share and by the HHI (Columns (1) and (3)). The correlations between robot density with employment-based industry concentration are more mixed: while higher robot density is associated with a significantly higher employment-based HHI (Column (4), it has a slightly negative (and insignificant) correlation with the top 1% firms' share in employment (Column (1)). Overall, as in the baseline regressions, robot density is more positively correlated with sales-based measures of concentration than employment-based measures. Higher robot density is also negatively correlated with labor shares (Column (5)). These correlation patterns are consistent with those obtained from the baseline regressions. The estimation results from the dynamic panel specification are

Table A.1. Industry-Level Evidence by Hours

	(1)	(2)	(3)	(4)	(5)
	ln(top 1% share)		ln(HHI)		ln(labor share)
	sales	employment	sales	employment	
ln(robot/hours)	0.0734***	0.0133	0.0961**	0.0284	-0.0143*
	(0.0156)	(0.0501)	(0.0410)	(0.0297)	(0.00800)
Constant	-1.086***	-1.358***	7.009***	6.483***	-1.559***
	(0.0731)	(0.0629)	(0.111)	(0.0244)	(0.0159)
Observations	117	104	137	135	151
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Adjusted R^2	0.943	0.688	0.921	0.984	0.980

Note: This table shows the regression results for the empirical specification (1) that projects industry-level concentrations or labor shares on robot densities. The robot density is the operation stock of robots per million hours within the industry. The regressions weight industries by their sales share in the initial year, i.e., 2007. All regressions contain the industry and year fixed effects. Standard errors in parentheses are clustered at the industry level. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

similar when we measure robot density by the stock of robots per million labor hours, as shown in Table A.3.

Table A.2. Industry-Level Evidence; Arellano-Bond linear dynamic panel regression

	(1)	(2)	(3)	(4)	(5)
	ln(top 1% share)		ln(HHI)		ln(labor share)
	sales	employment	sales	employment	
ln(robot/emp)	0.0880***	-0.0243	0.0374***	0.0257***	-0.0111*
	(0.0199)	(0.0240)	(0.0124)	(0.00797)	(0.00567)
L.ln(top 1% share of sales)	0.283***				
	(0.0705)				
L.ln(top 1% share of employment)		0.0208			
		(0.0958)			
L.ln(HHI of sales)			0.734***		
			(0.0510)		
L.ln(HHI of employment)				0.568***	
				(0.0523)	
L.ln(labor share)					0.312***
					(0.0767)
Constant	-1.026***	-1.243***	1.691***	2.773***	-0.985***
	(0.102)	(0.140)	(0.337)	(0.341)	(0.113)
Observations	102	83	136	135	151
Year FE	✓	✓	✓	✓	✓

Note: This table shows the regression results for the Arellano-Bond linear dynamic panel regression that projects industry-level concentrations or labor shares on robot densities and the lagged dependent variables. The robot density is the operation stock of robots per thousand workers within the industry. L. denotes the lagged variable. The regressions weight industries by their sales share in the initial year, i.e., 2007. All regressions contain the year fixed effects. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Industry-Level Evidence by Hours; Arellano-Bond linear dynamic panel regression.

	(1)	(2)	(3)	(4)	(5)
	ln(top 1% share)		ln(HHI)		ln(labor share)
	sales	employment	sales	employment	
ln(robot/hours)	0.0855***	-0.0259	0.0372***	0.0258***	-0.0103*
	(0.0199)	(0.0240)	(0.0124)	(0.00799)	(0.00567)
L.ln(top 1% share of sales)	0.283***				
	(0.0709)				
L.ln(top 1% share of employment)		0.0208			
		(0.0957)			
L.ln(HHI of sales)			0.733***		
			(0.0513)		
L.ln(HHI of employment)				0.567***	
				(0.0523)	
L.ln(labor share)					0.314***
					(0.0768)
Constant	-0.994***	-1.233***	1.714***	2.786***	-0.987***
	(0.0982)	(0.136)	(0.340)	(0.342)	(0.114)
Observations	102	83	136	135	151
Year FE	✓	✓	✓	✓	✓

Note: This table shows the regression results for the Arellano-Bond linear dynamic panel regression that projects industry-level concentrations or labor shares on robot densities and the lagged dependent variables. The robot density is the operation stock of robots per million hours within the industry. L. denotes the lagged variable. The regressions weight industries by their sales share in the initial year, i.e., 2007. All regressions contain the year fixed effects. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Solution Algorithm

Out of iterations

1. Given the relative price of robots Q_a, the rental rate of robots r_a is determined by (6): $r_a = Q_a/\beta - Q_a(1-\delta_a)$.
2. The distribution of firms is the stationary distribution of the productivity process because there is no entry or exit.

There are three loops to solve the problem. Y loop is outside W loop. And W loop is outside q oop.

Y loop: use bisection to determine the aggregate final goods and other aggregate variables

1. Guess a Y.
2. Compute W and firms' relative production $q(j)$ in the W loop as explained below.
3. Given the equilibrium wage rate, compute other aggregate variables by finding Y using the bisection method:
   (a) Given the solved relative production $q(j)$, we have $y(j) = q(j)Y$.
   (b) Given the known r_a and W, compute the marginal costs $\lambda(j)$ by eq. (11) and (13), and we can get $A(j)$ and $N(j)$ from eq. (9) and (10).
   (c) The aggregate labor and robot demand are determined by eq. (26) and eq. (27).
   (d) Consumption C is determined by (5).
   (e) The steady state I is from (4).
   (f) Compute Y^{new} using the resource constraint (25). Stop if Y converges.
      i. If $Y = Y^{\text{new}}$, Y and all other aggregate variables are found.
      ii. If $Y > Y^{\text{new}}$, lower Y. Go back to Step 1.
      iii. If $Y < Y^{\text{new}}$, increase Y. Go back to 1.

W loop: use bisection to determine the wage rate

1. Guess a wage W.
2. Compute firms' relative production $q(j)$ in the q loop as explained below.
3. Check whether the Kimball aggregator (14) holds.
   (a) If LHS = RHS, the wage rate is found and jump out of W loop to Y loop.

(b) If LHS > RHS, increase the wage rate to lower $q(j)$ according to eq. (15). Go back to Step 2.

(c) If LHS < RHS, lower the wage rate to raise $q(j)$ according to eq. (15). Go back to Step 2.

q loop: find the relative production

1. Given the factor prices r_{at} and W_t, the marginal cost of production is determined by eq. (11) with robots and (13) without robots.

2. Guess a demand shifter D.

3. Use eq. (15) to solve the market shares $q(\phi)$ for each ϕ with and without robots.

   (a) The right-hand side of (15) is a function of q by plugging in (19).

   (b) The price in the left-hand side is the marginal cost in (11) or (13) times the markup in (21), which is also a function of q.

   (c) Use the bisection method to solve for q in eq. (15).

4. Compute the automation decisions.

   (a) Compute $y(j) = q(j)Y$ with and without robots.

   (b) Compute the demand for $A(j)$ and $N(j)$ with and without robots from (9), (10), and (12).

   (c) Compute the profits with and without robots and thus get the automation cutoffs $\bar{f}_a$ according to (24) and thus the automation probabilities $F(\bar{f}_a)$.

5. Given the automation decisions, compute D^{new} by (16). Stop if D converges. Otherwise, go back to Step 2 and repeat until D converges.

   (a) If $D = D^{\text{new}}$, D and $q(j)$ are found and jump out of q loop to W loop.

   (b) If $D > D^{\text{new}}$, lower D. Go back to Step 2.

   (c) If $D < D^{\text{new}}$, increase D. Go back to Step 2.

C The CES Model

Final good producers make a composite good out of the intermediate varieties and sell it to consumers. The final good Y is produced using a bundle of intermediate goods $y(j)$, according to the following commonly available CES aggregator:

$$Y = \left[\int_0^1 y(j)^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}} \tag{30}$$

where the intermediate varieties are denoted by j.

Given the prices for intermediate varieties $p(j)$, final good producers minimize their cost, which gives the following demand for each intermediate good:

$$y(j) = \left(\frac{p(j)}{P}\right)^{-\sigma} Y \tag{31}$$

where P is the CES aggregate price index

$$P = \left[\int_0^1 p(j)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}} \tag{32}$$

All firms charge the same Dixit-Stiglitz markup $\frac{\sigma}{\sigma-1}$:

$$p(j) = \frac{\sigma}{\sigma - 1}\lambda(j) \tag{33}$$

where the marginal cost $\lambda(j)$ defined in (11) and (13).

C.1 Solution Algorithm for the CES Model

Out of iterations

1. Given the relative price of robots Q_a, the rental rate of robots r_a is determined by (6): $r_a = Q_a/\beta - Q_a(1 - \delta_a)$.
2. The distribution of firms is the stationary distribution of the productivity process because there is no entry or exit.

There are two loops to solve the problem. Y loop is outside W loop. And there is no q loop for the CES case because it does not have the demand shifter D.

Y loop: use bisection to determine the aggregate final goods and other aggregate variables

1. Guess a Y.
2. Compute W and firms' output $y(j)$ in the W loop as explained below.
3. Given the equilibrium wage rate, compute other aggregate variables by finding Y using the bisection method:
   (a) Given the known r_a and W, compute the marginal costs $\lambda(j)$ by eq. (11) and (13), and we can get $A(j)$ and $N(j)$ from eq. (9) and (10).
   (b) The aggregate labor and robot demand are determined by eq. (26) and eq. (27).

(c) Consumption C is determined by (5).

(d) The steady state I is from (4).

(e) Compute Y^{new} using the resource constraint (25). Stop if Y converges.

i. If $Y = Y^{\text{new}}$, Y and all other aggregate variables are found.

ii. If $Y > Y^{\text{new}}$, lower Y. Go back to Step 1.

iii. If $Y < Y^{\text{new}}$, increase Y. Go back to 1.

W loop: use bisection to determine the wage rate

1. Guess a wage W.

2. Given the factor prices r_{at} and W_t, the marginal cost of production is determined by eq. (11) with robots and (13) without robots. The prices with or without robots are from (33).

3. Compute $y(j)$ by the demand function (31) with and without robots.

4. Compute the automation decisions.

   (a) Compute the demand for $A(j)$ and $N(j)$ with and without robots from (9), (10), and (12).

   (b) Compute the profits with and without robots and thus get the automation cutoffs $\bar{f}_a$ according to (24) and thus the automation probabilities $F(\bar{f}_a)$.

5. Check whether the price of final goods (32) equals one.

   (a) If $P = 1$, the wage rate is found and jump out of W loop to Y loop.

   (b) If $P > 1$, lower the wage rate to lower P. Go back to Step 2.

   (c) If $P < 1$, increase the wage rate to raise P. Go back to Step 2.