Automation and the Rise of Superstar Firms*

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November 7, 2022

Abstract

Using industry-level data, we present evidence that the rise in automation technology contributed to the rise of superstar firms in the past two decades. The empirical link between automation and industry concentration can be explained in a general equilibrium framework with heterogeneous firms and variable markups. A firm can operate a worker-only technology or, by paying a per-period fixed cost, an automation technology that uses both workers and robots as inputs. Given the fixed cost, larger and more productive firms are more likely to automate. Automation boosts labor productivity, enabling large, robot-using firms to expand further and raising industry concentration. Our calibrated model does well in matching the highly skewed usage of automation toward a few superstar firms observed in the Census data. Since robots substitute for labor, increased automation raises sales concentration more than employment concentration, also consistent with empirical evidence. Under our calibration, a modest subsidy for automating firms improves welfare since productivity gains more that offset increased markup distortions.

Keywords: Automation, industry concentration, markup, robots, reallocation, heterogeneous firms.

JEL Codes: E24, L11, O33.

*We are grateful to David Autor, Yan Bai, Martin Beraja, Narayana Kocherlakota, Sylvain Leduc, Huiyu Li, Yueran Ma, Christina Patterson, Mathieu Taschereau-Dumouchel, Ivan Werning, and seminar participants at the Federal Reserve Bank of San Francisco, Midwest Macroeconomics Meetings (Logan), and China International Conference in Macroeconomics 2022 for helpful comments. We also thank Mollie Pepper for excellent research assistance and Anita Todd for editorial assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

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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 industry concentration. We argue that the rapid growth of industrial robots and the rise of automation technology in general since the early 2000s have played an important role in explaining the increases in industry concentration, particularly in the manufacturing sector.

The link between automation and industry 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 manufacturing industries (Panel A).[1] The sales shares of the top 4 firms and the top 20 firms have increased steadily since the early 2000s. The employment shares of those top firms have also increased, but at a substantially 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 manufacturing employees has quadrupled.[2]

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 two-digit industry level. We also construct an industry-level measure of robot density, which is defined as the ratio of the operation stock of industrial robots from the International Federation of Robotics (IFR) to thousands of manufacturing employment from the Bureau of Labor Statistics.

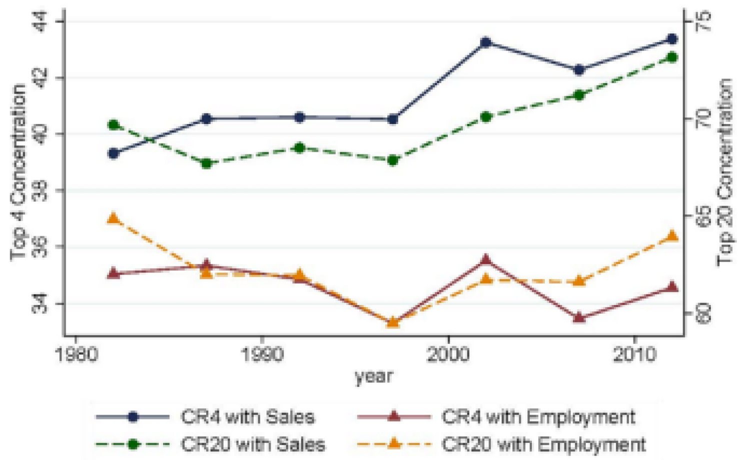
After controlling for industry and year fixed effects, we find that robot density is positively correlated with sales-based measure of industry concentration (i.e., the sales share of the top 1% firms) and the correlation is economically important and statistically significant. The correlation of robot density with employment-based concentration measures (the employment share of the top 1% firms) are also positive, although they are statistically insignificant and the magnitudes are much smaller than the correlations with sales-based measures.

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

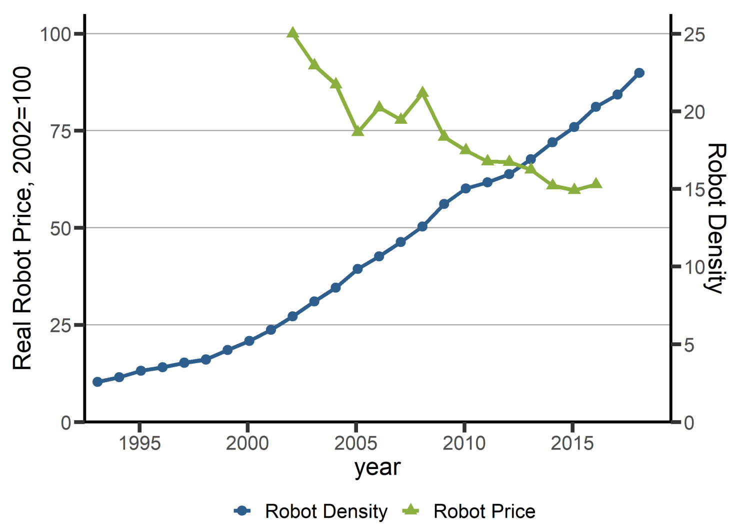
[2]An OECD study reports that sales concentration has increased in both Europe and North America (Bajgar et al., 2019). Furthermore, for the manufacturing sector, sales concentration in Europe started rising a few years ahead of that in North America (see Figure 9 of Bajgar et al. (2019)). This timing of the increases in industry concentration is consistent with the timing of automation adoptions: adoptions of automation technologies (in particular, industrial robots) started earlier in the European market than in the North American market (Acemoglu and Restrepo, 2020).

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 (left scale) or the top 20 firms (right scale) in a given industry. Panel B shows the unit value of newly shipped industrial robots deflated by the personal consumption expenditures 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).

Since both industry concentration and robot density are endogenous, the observed correlations do not necessarily reflect causal relations. To study the potential causal effects of automation on industry concentration, we estimate an instrumental variable (IV) panel specification. As documented by Acemoglu and Restrepo (2020), robot adoptions vary considerably across industries, and a common set of industries in both the

United States and Europe experienced rapid robot adoptions in the recent decades. More importantly, robot adoption trends in many European economies have been ahead of the United States. Thus, we use the lagged average robot density in five European economies as an instrumental variable for U.S. robot density in our industry-level panel regressions.[3] From the IV-regressions, we obtain robust evidence that automation has significantly contributed to the rise of sales concentration in the United States, but its effect on employment concentration is small and insignificant.

To understand the economic mechanism the links automation to industry concentration, we construct a general equilibrium model featuring heterogeneous firms, endogenous automation decisions, and variable markups (with Kimball (1995) preferences). 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 per-period 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, a larger firm is more likely to automate because it has higher productivity, higher market power, and thus higher profits. Automation improves a firm's labor productivity, allowing the robot-using large firms to expand their sales share further. This economy-of-scale effect leads to a positive connection between automation and industry concentration. Since robots substitute for workers, the expansion of those large firms relies more on robots than on workers. Thus, a rise in automation raises sales concentration more than it does employment concentration.

We calibrate our model parameters to match several moments in the data and in the empirical literature. Specifically, to calibrate the key non-standard parameters including 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).[4]

The calibrated model does well in predicting the cross-sectional distribution of automation 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

[3] The five European economies include Denmark, Finland, France, Italy, and Sweden, which all adopted robotics ahead of the United States.

[4] The ABS covers a large and nationally representative sample of over 850,000 firms in all private nonfarm business sectors.

in the relative price of robots for industry concentration. 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 industry concentration. At the same time, however, the extensive-margin effect implies that some smaller firms that initially operate the worker-only technology would switch to the automation technology when robot prices decline. This would reduce the sales share of the superstar firms and lower industry 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 industry concentration. This is because the calibrated model predicts that only a small fraction of firms automate and automation is highly skewed towards large firms, in line with the micro-level data (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 sales concentration.

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 our empirical evidence that robot adoptions raise the sales share of the top 1% firms significantly, but the effects on the employment share of the top firms are small and insignificant.

Under our calibration, the model predicts that a decline in the robot price of a magnitude similar to that observed during the past two decades can explain about 50% of the rise in sales concentration in U.S. manufacturing and about 25% of the diverging trends between sales concentration and employment concentration. 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), Acemoglu, Lelarge and Restrepo (2020), and Kehrig and Vincent (2021).

Our model implies that the relation between robot prices and industry 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 the top 1% firms. Thus, in an economy with widely spread automation technologies, a decline in automation costs may not increase (and even reduce) industry concentration.[5]

[5]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,

We use our calibrated model to study the implication of taxing (or subsidizing) robot-using firms for allocations and welfare. Because of monopolistic competition in the product markets, equilibrium allocations in the model are inefficient. Taxing automating firms reallocates production from large, robot-using firms to smaller firms, reducing industry concentration and the average markup. However, this reallocation also reduces aggregate productivity. Optimal tax policy faces a tradeoff between lowering average markup and reducing aggregate productivity. Under our calibration, a modest subsidy (of about 4%) on automating firms maximizes welfare, with a welfare gain equivalent to about 0.4% of steady-state consumption per year relative to the benchmark with no policy interventions.

2 Related literature

Our work is motivated by the empirical evidence on industry concentration documented by Autor et al. (2020). Their study highlights an important between-firm reallocation channel that connects the rise in industry 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 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 disproportionately benefits large and high-productivity firms, increasing industry 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, in line with both the time-series evidence in Autor et al. (2020) and our own cross-sectional evidence.

Consistent with our empirical findings and model predictions, Hsieh and Rossi-Hansberg (2019) document evidence that employment concentration has stayed flat or

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* industry concentration because the extensive margin would dominate the intensive margin. Based on this finding, we conjecture that a decline in the relative price of capital equipment, which is more widely used than robots, could reduce industry concentration.

even declined in all but three broad sectors (services, wholesale, and retail) in the United States from 1977 to 2013, a period during which sales concentration in most sectors have steadily increased (Autor et al., 2020).

The rise in industry concentration is not limited to the United States. For example, concentration is also rising in other OECD countries (Sui, 2022; Bajgar et al., 2019). Neither is it a recent phenomenon. In an important study, Kwon, Ma and Zimmermann (2022) documents evidence that U.S. corporate concentration (measured by the asset share or sales share of the top 1% of firms) has been rising over the past century. They argue that the rising concentration in an industry is correlated with investment intensity in research and development and information technology, suggesting that economies of scale with high fixed costs and low marginal costs in production process might be an important driver of the secular increases in industry concentration.

Several other studies also highlight the importance of economies of scale for driving the increase in industry concentration. For example, Aghion et al. (2019) present a model showing that, following a decline in overhead costs, the most efficient firms (which are also large firms with high markups) spread into new product lines, raising industry concentration, leading to a short-run burst in growth. A similar mechanism is studied by Lashkari, Bauer and Boussard (2022), who use firm-level data from France and obtain a positive estimate of the output elasticity of information technology (IT) factor demand. They argue that this evidence suggests that a decline in IT prices that raises the relative demand for IT factors could enable large firms to expand through greater returns to scale. Tambe et al. (2020) document evidence that investment in digital capital, a complementary form of capital to other general-purpose technology such as information technology, has become increasingly concentrated in a small subset of superstar firms since the mid-1990s, contributing to the increases in industry concentration.

Our work complements these existing studies by focusing on the contribution of automation to the rise of superstar firms. We also provide a general equilibrium quantitative framework for understanding the theoretical mechanism that links automation to industry concentration. As our model illustrates, accessing automation technology requires a fixed cost of robot adoption, while the consequent improvement in productivity reduces the marginal cost of production. Thus, automation technology introduces a particular source of economies of scale, contributing to the rise in industry concentration in the past two decades.

Our work is related to Hubmer and Restrepo (2022), who present a model featuring heterogeneous firms with fixed costs of automating tasks in the spirit of Zeira (1998) and Acemoglu and Restrepo (2018). They focus on the role of automation in driving the observed declines in the labor share. A decline in capital prices reduces the aggregate labor share because large firms automate more tasks, while the median firm continues to operate a labor-intensive technology with a rising labor share. The uneven use of automation technologies also generates an endogenous rise in sales concentration, as in our model.

Our study is complementary to theirs: we focus on the relation between automation and industry concentration. We document evidence that the rise in automation in the past two decades has contributed to the rise of superstar firms in the United States, and it raises sales concentration more than it does employment concentration. We also present a calibrated quantitative model that corrects predicts the highly skewed usage of automation technology toward a few superstar firms, in line with the firm-level evidence documented by Zolas et al. (2020) using Census data. To our knowledge, no other studies in the literature have confronted their models to the observed cross-sectional distribution of the highly uneven usage of automation technology.

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; Prettner and Strulik, 2020). Empirical evidence suggests that, at the firm level, robot adoptions are associated with declines in the labor share (Autor and Salomons, 2018; Acemoglu, Lelarge and Restrepo, 2020). Our work suggests that automation has also important implications for the rise superstar firms, and the increased use of automation technology raises sales concentration more than employment concentration.

The increased usage of automation technology and its potential impact on income inequality have raised the important policy question: Should robots be taxed? Guerreiro, Rebelo and Teles (2022) present a quantitative model featuring technology progress in automation and endogenous skill accumulation. They show that, under the prevailing U.S. tax system, steady declines in robot prices can lead to persistent increases in income inequality by displacing routine workers. To the extent that the current generation of routine workers cannot move to non-routine occupations, optimal policy calls for taxing robots. Prettner and Strulik (2020) argue that a robot tax helps redistribute income from high-skilled workers to low-skilled workers, but it can also discourage RD investment and thus lower long-run growth. Our work contributes to this policy debate by highlighting a new source of policy tradeoff. Taxing automation reduces industry concentration and markup, improving allocation efficiency; however, by restraining automation investment, such a policy also reduces aggregate TFP. Under our calibration, the model implies an interior optimum of robot subsidy that would stimulate automation usage by a broader set of firms, not just a few superstar firms.

3 Industry-level Evidence

We now examine the empirical relation between automation and industry concentration for two-digit industries. We first present evidence that automation (measured by robot density) positively correlates with industry concentration. The correlations of robot density with sales concentration are statistically significant and economically important, whereas the correlations with employment concentration are small and insignificant. We then present evidence that automation has significant causal effects on sales concentration, but it has no such effects on employment concentration.

3.1 Data and measurement

We consider two measures of industry concentration, one based on the share of sales of the top 1% of firms in a given industry, and the other based on the share of employment of the top 1% of firms. We use firm-level data from Compustat to compute these two measures of industry concentration.

We construct a measure of robot density for each 2-digit industry using data on operation stocks of industrial robots from the International Federation of Robotics (IFR) and manufacturing employment. Specifically, our measure of robot density (denoted by $robot_{jt}$ for industry j in year t) is defined as

$$robot_{jt} = \frac{\text{robot stock}_{jt}}{\text{thousands of employees}_{jt}}. \tag{1}$$

For robustness, we consider an alternative measure of industry-level robot density, defined as the operation stock of robots per million labor hours. The data of industry-level employment (EMP) and labor hours (PRODH) are both obtained from the NBER-CES Manufacturing Industry Dataset.[6] We obtain an unbalanced panel with 13 industries covering the 12 years from 2007 to 2018.[7]

Table 1 reports the summary statistics of variables. First, it shows that robot density varies widely in our sample. For example, the inter-quartile range (IQR) of robots per thousand workers is about 10, which is 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

[6]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.

[7]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 in some industry-year cells.

Table 1. Summary Statistics

	#obs	mean	min	p25	p50	p75	max	s.d.
robots/thousand employees	156	30.42	0.00	0.24	2.26	10.90	419.92	87.96
robots/million hours	156	19.58	0.00	0.18	1.72	7.72	243.54	52.42
top 1% share of sales	121	0.30	0.08	0.22	0.30	0.36	0.77	0.13
top 1% share of employment	106	0.27	0.11	0.21	0.28	0.32	0.46	0.08

Note: This table shows the summary statistics of the data that we use in the regressions. The industry-level robot density is measured as the operation stock of industrial robots per thousand employees. We consider two measures of industry concentration: the sales and employment share of the top 1% of firms in the industry. For both measures of concentration, we restrict our sample to those industries with at least 10 firms.
Source: Authors' calculations using IFR, Compustat, and NBER-CES.

heterogeneity in robot adoption and the growth rates of robot use. Industry concentration in our sample also displays large variations. For example, the sales share of the top 1% of firms averages about 30%, with an IQR of about 14% and a standard deviation of 13%. The employment share of the top 1% of firms averages about 27% and varies less than the sales share, with an IQR of about 11% and a standard deviation of about 8%.

3.2 Correlations between automation and industry concentration

To examine the correlations of automation with industry concentration, we estimate the ordinary least squares (OLS) specification

$$log(Y_{jt}) = \beta \log(robot_{jt}) + \gamma_j + \delta_t + \varepsilon_{jt}. \tag{2}$$

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

The coefficient of interest is β, which measures the elasticity of industry concentration with respect to robot density. A positive value of β suggests that an industry with a higher robot density is associated with a higher concentration.

Table 2 shows the industry-level correlations of robot density with industry concentration, estimated from the OLS regressions, with industries weighted by their sales in the initial year (i.e., 2007) following the approach of Autor et al. (2020). Standard errors (the numbers in the parentheses) are clustered at the industry level.

Table 2. OLS Regressions for Robots and Industry Concentration

	ln(top 1% share of sales)		ln(top 1% share of emp)	
	(1)	(2)	(3)	(4)
ln(robot/thousand emp)	0.074***		0.013	
	(0.016)		(0.050)	
ln(robot/million hours)		0.073***		0.013
		(0.016)		(0.050)
Observations	117	117	104	104
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Note: This table shows the OLS regression results from the empirical specification (2) that projects the measures of industry concentration on robot density. The robot density is measured by the operation stock of industrial robots per thousand workers or million hours within the industry. All regressions weigh the industries by their sales share in the initial year (2007), and the regressions also control for industry and year-fixed effects. Standard errors in parentheses are clustered at the industry level. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 shows that robot density is positively correlated with sales concentration (i.e., the sales share of the top 1% of firms), with the correlation statistically significant at the 99 percent confidence level (Columns (1) and (2)).

The point estimate (in Column (1)) implies that, in an industry with robot density (in log units) that is one standard deviation above average, the sales share of the top 1% of firms would be about 20% above average, or equivalently, about 6 percentage points above the sample mean (the average sales share of the top 1% of firms in our sample is 30%).[8] The estimated correlation between the hours-based measure of robot density and sales concentration is similar in magnitude and statistical significance (Column (2)).

The correlation of robot density with employment concentration (i.e., the employment share of the top 1% of firms), although positive, is much smaller that that with sales concentration, and the estimated correlations are statistically insignificant (Columns (3) and (4)).

These regression results from cross-sectional data corroborate well with the time-series correlations between automation and industry concentration illustrated in Figure 1.

[8]The standard deviation of logged robot density is 2.71. The point estimate in Column (1) indicates that a one standard deviation increase in logged robot density implies that the sales share of the top 1% firms increases by $0.074 \times 2.71 \approx 0.20$ log points, or about 20% in the level of the sales share.

3.3 Effects of automation on industry concentration

The correlations between robot density and industry concentration do not necessarily reflect causal effects because both automation and industry concentration can be endogenous. Specifically, an omitted variable bias can arise when a time-varying industry-level factor affects both robot density and concentration.

To study potential causal effects of automation on industry concentration, we estimate an instrumental-variable (IV) panel specification. As documented by Acemoglu and Restrepo (2020), robot adoptions vary considerably across industries and the same industries are rapidly adopting robots in both the United States and Europe. More importantly, robot adoption trends in European economies are ahead of the United States. Inspired by the approach in Acemoglu and Restrepo (2020), we construct the average robot density of five European economies (EURO5) for each industry. The EURO5 economies include Denmark, Finland, France, Italy, and Sweden, which all adopted robotics ahead of the United States.[9] Similar to our measure of robot density for the U.S., we measure robot density in the EURO5 economies by the number of robots per thousand employees (or per million of worker hours) in each industry, with the employment (and hours) data taken from EUKLEMS. The average robot density of the five European economies is calculated by

$$robot_{jt}^{EURO5} = \frac{1}{5} \sum_{k \in EURO5} \frac{\text{robot stock}_{kjt}}{\text{thousands of employees}_{kjt}}, \tag{3}$$

where k is an index of economies in the EURO5 group. We use the one-year lagged EURO5 robot density as the instrumental variable for U.S. robot density in our industry-level panel regression.

Our two-stage least squares (2SLS) regressions are just identified, with one endogenous regressor and one instrumental variable. Specifically, in the first-stage, we regress robot density ($\ln robot_{jt}$) at the two-digit industry level in the United States on lagged average robot density ($\ln robot_{jt-1}^{EURO5}$) in the EURO5 group in the corresponding industries , controlling for industry and year fixed effects.

Table 3 displays the IV estimation results. The estimation shows that automation has significantly positive effects on industry concentration in terms of sales. By contrast, the effect of automation employment-based measures of concentration is not significantly different from zero. The p-values of Anderson-Rubin (AR) weak-instrument tests shown in the last row of the table suggest that the estimated effects of robot density on sales concentration are robust to weak instruments, whereas the effects on employment concentration are not.

[9]Following Acemoglu and Restrepo (2020), we exclude Germany from our sample because it is far ahead of the other countries in robot adoptions, making it less informative for the US adoption trends than those trends in the EURO5 economies.

Table 3. IV Regressions for Robots and Industry Concentration

	ln(top 1% share of sales)		ln(top 1% share of emp)	
	(1)	(2)	(3)	(4)
ln(robot/thousand emp)	0.113***		0.070	
	(0.024)		(0.069)	
ln(robot/million hours)		0.110***		0.080
		(0.026)		(0.071)
Observations	117	117	104	104
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Anderson-Rubin p-value	0.090	0.108	0.325	0.269

Note: This table shows the instrumental variable (IV) regression results from the empirical specification (2) that projects the measures of industry concentration on robot density. The robot density is measured by the operation stock of industrial robots per thousand workers or million hours within the industry. The instrumental variable for the U.S. robot density is the one-year lag of the robot density averaged over five European countries (EURO5). The last row shows the p-values of Anderson-Rubin weak instrument robust tests. All regressions weigh the industries by their sales share in the initial year (2007), and the regressions also control for industry and year-fixed effects. Standard errors in parentheses are clustered at the industry level. Stars denote the statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, the size of the estimate coefficients suggests that the effect of robot density on sales concentration is not only statistically significant but also economically important. Specifically, Column (1) shows that a one standard deviation increase in robot density raises the sales share of the top 1% firm by about 31 percent.[10] This number is higher than the 20% in the OLS estimation (Table 2), suggesting that omitted variables lead to a downward bias of the coefficient in the OLS regressions.

4 The Model

To understand the connection between automation and industry concentration, we construct a general equilibrium model featuring heterogeneous firms, variable markups, and endogenous automation decisions.

[10] The logged robot density in the US industries has a standard deviation of 2.71. Thus, the estimation shown in Table 3 implies that a one standard deviation increase in robot exposure raises the sales share of the top 1% firms by $2.71 \times 0.113 \approx 0.31$ log points, or 31 percent.

4.1 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

$$\sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \chi \frac{N_t^{1+\xi}}{1+\xi} \right], \tag{4}$$

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

$$C_t + v_t s_{t+1} \leq W_t N_t + (v_t + d_t) s_t, \tag{5}$$

where s_t denotes the equity share of firms held by the household, v_t denotes the equity price, d_t denotes the dividend flow, W_t denotes the real wage rate. The household takes W_t and v_t as given, and maximizes the utility function (4) subject to the budget constraints (5). The optimizing consumption-leisure choice implies the labor supply equation

$$W_t = \chi N_t^{\xi} C_t. \tag{6}$$

The optimizing decision for equity share holdings is given by

$$v_t = \rho_t (v_{t+1} + d_{t+1}), \tag{7}$$

where $\rho_t \equiv \beta \frac{C_t}{C_{t+1}}$ is the stochastic discount factor. We will be focusing on the steady state of the model and therefore $\rho_t = \beta$.

4.2 Final good producers

There is a large number of monopolistically competitive intermediate producers with a unit measure indexed by $j \in [0, 1]$. 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 goods price normalized to one. The final good Y is produced using a bundle of intermediate goods $y(j)$, according to the Kimball aggregator

$$\int_0^1 \Lambda\left(\frac{y_t(j)}{Y_t}\right) dj = 1, \tag{8}$$

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

4.3 Demand for intermediate goods

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

$$p(j) = \Lambda'(q(j))D, \tag{9}$$

where D is a demand shifter given by

$$D = \left(\int \Lambda'(q(j))q(j)dj \right)^{-1}. \tag{10}$$

We follow Klenow and Willis (2016) and assume that

$$\Lambda(q) = 1 + (\sigma - 1)\exp(\frac{1}{\varepsilon})\varepsilon^{\frac{\sigma}{\varepsilon}-1}[\Gamma(\frac{\sigma}{\varepsilon}, \frac{1}{\varepsilon}) - \Gamma(\frac{\sigma}{\varepsilon}, \frac{q^{\varepsilon/\sigma}}{\varepsilon})], \tag{11}$$

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

$$\Gamma(s, x) = \int_x^\infty v^{s-1}e^{-v}dv. \tag{12}$$

Under the specification (11) for Λ, we obtain

$$\Lambda'(q(j)) = \frac{\sigma - 1}{\sigma}\exp(\frac{1 - q(j)^{\frac{\varepsilon}{\sigma}}}{\varepsilon}), \tag{13}$$

which, using the demand schedule (9), implies that the demand elasticity (i.e., price elasticity of demand) faced by firm j is

$$\sigma(q(j)) = -\frac{\Lambda'(q(j))}{\Lambda''(q(j))q(j)} = \sigma q(j)^{-\frac{\varepsilon}{\sigma}}. \tag{14}$$

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

$$\mu(j) = \frac{\sigma(q(j))}{\sigma(q(j)) - 1}. \tag{15}$$

As a result, larger firms have more market power and charge higher markups.[11]

[11]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.

4.4 Intermediate goods producers

Intermediate producers, from now on indexed by their productivities ϕ, produce differentiated intermediate goods using two alternative technologies: one with labor as the only input, and the other with both labor and robots as input factors. If the firm uses robots in production, it faces a per-period fixed cost s drawn from the $i.i.d.$ distribution $F(\cdot)$, and the fixed cost is realized after observing the productivity ϕ. The production function takes the CES form

$$y = \phi \left[\alpha_a A'^{\frac{\eta-1}{\eta}} + (1-\alpha_a) N^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{16}$$

where y denotes the firm's output; N denotes the inputs of workers; and $A' \geq 0$ denotes the end-of-period robot stock. The labor-only technology corresponds to the special case with $A' = 0$. 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

$$\ln \phi' = \gamma \ln \phi + \varepsilon, \quad \varepsilon \sim N(0, \sigma_\phi^2), \tag{17}$$

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

A firm with the realized productivity ϕ and existing robot stock A that draws a fixed cost of operating robots s chooses the price p of its differentiated product, labor input N, and robot investment I_a to solve the dynamic programming problem

$$V(\phi, A; s) = \max_{p,N,I_a \geq (\delta_a - 1)A} \left[py - WN - Q_a I_a - s\mathbb{1}\{A' > 0\} + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right], \tag{18}$$

where $\mathbb{1}\{x\}$ equals one if x holds and zero otherwise. The firm hires workers in a competitive labor market with the wage rate W. The firm also chooses automation investment by purchasing I_a units of robots at the competitive price Q_a. Newly purchased robots add to the existing stock of robots, and robots depreciate at the constant rate $\delta_a \in (0,1)$. The firm's stock of robots evolves according to the law of motion

$$A' = (1-\delta_a)A + I_a. \tag{19}$$

Notice that we assume that the newly purchased robots can be used in the production process in the same period.

The firm solves the recursive problem (18) subject to the production function (16), the robot law of motion (19), and the demand schedule (9). Since robot operation incurs a fixed cost s, a firm facing a sufficiently high s relative to its productivity would choose to sell its robots (i.e., by setting $A' = 0$) at the market price Q_a. In that case, we would have $I_a = (\delta_a - 1)A \leq 0$.

Appendix A shows that the recursive problem (18) can be simplified to

$$V(\phi, A; s) = Q_a(1-\delta_a)A + \max\{V^a(\phi) - s, V^n(\phi)\}, \tag{20}$$

where the continuation value of employing the automation technology this period (i.e., having $A' > 0$) is given by

$$V^a(\phi) = \max_{p,y,N,A'>0}\left[py - WN - Q_aA' + \beta E_{\phi'|\phi}\int_{s'} V(\phi', A'; s')dF(s')\right], \tag{21}$$

and the continuation value of employing the labor-only technology this period is given by

$$V^n(\phi) = \max_{p,y,N}\left[py - WN + \beta E_{\phi'|\phi}\int_{s'} V(\phi', 0; s')dF(s')\right]. \tag{22}$$

Firms with automation technology in (21) optimally choose their production inputs N and A' given their production y. As Appendix A shows, the first order conditions imply

$$\gamma_a = \alpha_a\lambda_a(\phi)\phi^{\frac{\eta-1}{\eta}}\left(\frac{y}{A'}\right)^{\frac{1}{\eta}}, \tag{23}$$

$$W = (1-\alpha_a)\lambda_a(\phi)\phi^{\frac{\eta-1}{\eta}}\left(\frac{y}{N}\right)^{\frac{1}{\eta}}, \tag{24}$$

where $\gamma_a \equiv Q_a[1-\beta(1-\delta_a)]$ denotes the effective marginal cost of robots, and $\lambda_a(\phi)$ denotes the marginal cost of production for a firm with productivity ϕ using the automation technology:

$$\lambda_a(\phi) = \frac{\left[\alpha_a^\eta\gamma_a^{1-\eta} + (1-\alpha_a)^\eta W^{1-\eta}\right]^{\frac{1}{1-\eta}}}{\phi}. \tag{25}$$

Moreover, firms employing the labor-only technology in (22) choose their labor input N given their production y:

$$N = \frac{y}{\phi}(1-\alpha_a)^{\frac{\eta}{1-\eta}}, \tag{26}$$

The marginal cost of production in this case would be

$$\lambda_n(\phi) = \frac{(1-\alpha_a)^{\frac{\eta}{1-\eta}}W}{\phi}. \tag{27}$$

Notice that given the productivity ϕ, the marginal cost of production using the labor-only technology is always larger than that using the automation technology, i.e., $\lambda_a(\phi) \leq \lambda_n(\phi)$.

The problem (20) implies that firms choose to operate the automation technology (i.e., to have $A' > 0$) if and only if their draw of the fixed automation cost is small enough:

$$s \leq s^*(\phi) \iff \mathbb{I}_a(\phi, s) = 1, \tag{28}$$

where $\mathbb{I}_a(\cdot)$ is an indicator of the automation decision, which is a function of the firm-level variables ϕ and s, and the cutoff fixed cost equals:

$$s^*(\phi) \equiv V^a(\phi) - V^n(\phi) \tag{29}$$

It follows that, for a firm with productivity ϕ, the ex ante (i.e., before drawing the automation fixed cost) automation probability equals $F(s^*(\phi))$, the cumulative density of the fixed costs evaluated at the indifference point.

As Appendix A shows, the automation cutoff can be written as the difference between the flow profit from operating the automation technology versus that from employing the labor-only technology. In other words,

$$s^*(\phi) = \pi^a(\phi) - \pi^n(\phi) \tag{30}$$

where

$$\pi^a(\phi) = \max_{p,y,N,A'} \Big[py - WN - Q_a[1 - \beta(1 - \delta_a)]A' \Big], \tag{31}$$

subject to the demand schedule (9) and production function (16), and

$$\pi^n(\phi) = \max_{p,y,N} \Big[py - WN \Big]. \tag{32}$$

subject to the same demand schedule and production function with $A' = 0$.

4.5 Stationary equilibrium

We focus on the stationary equilibrium and thus drop the time subscript for all variables. The world robot price Q_a is exogenously given. The equilibrium consists of aggregate allocations C, I_a, A, N, and Y, wage rate W, firm-level allocations $A'(\phi)$, $I_a(\phi)$, $N(\phi)$, and $y(\phi)$, and firm-level prices $p(\phi)$ for all $\phi \in G(\cdot)$, where $G(\cdot)$ denotes the ergodic distribution implied by the productivity process (17), such that (i) taking W as given, the aggregate allocations C and N solve the representative household's optimizing problem; (ii) taking W and Y as given, the firm-level allocations and prices solve each individual firm's optimizing problem; and (iii) the markets for the final good and labor clear.

The final goods market clearing condition is given by

$$C + Q_a I_a + \int_\phi \int_0^{s^*(\phi)} s \, dF(s) \, dG(\phi) = Y. \tag{33}$$

The labor market clearing condition is given by

$$N = \int_\phi N(\phi) dG(\phi). \tag{34}$$

The stock of robots is given by

$$A = A' = \int_\phi A'(\phi) F(s^*(\phi)) dG(\phi). \tag{35}$$

Total investment in robots equals

$$I_a = A' - (1 - \delta_a) A = \delta_a A = \delta_a \int_\phi A'(\phi) F(s^*(\phi)) dG(\phi). \tag{36}$$

Appendix B outlines the computational algorithm.

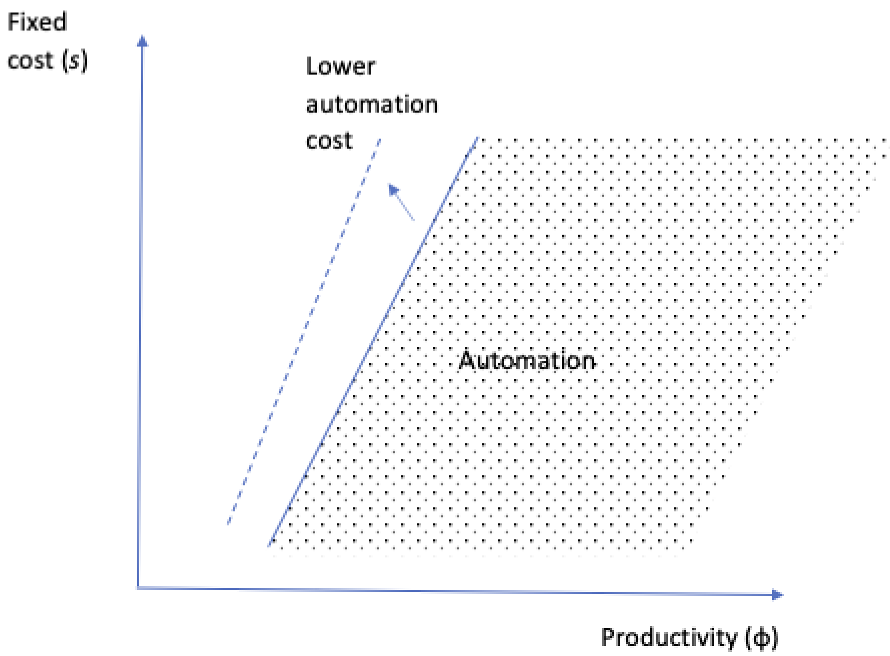
5 Model mechanism

Firms are heterogeneous along two dimensions: they face idiosyncratic shocks to both productivity (ϕ) and the fixed cost of operating the automation technology (s). The automation decision depends on the combination of the realizations of ϕ and s. Firms face a trade-off when deciding whether to automate. On the one hand, firms need to pay a fixed cost s to automate. On the other hand, however, the marginal cost of production using the automation technology (equation (25)) is always smaller than that using the labor-only technology (equation (27)). 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 s, a firm will automate if the realized productivity is sufficiently high. There is an upward-sloping line that separates the technology choices. To the right of the line (high ϕ or low s), firms use the automation technology and to the left of the line, they use the labor-only technology. Firms with combinations of ϕ and s 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 reduce the

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 (s). Firms with (ϕ, s) 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.

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 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.

Table 4. 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	50.6	Fraction of automating firms
Automation fixed cost	S_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.

A higher share of sales of the large firms does not directly translate into a higher share 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 industry concentration, but a negative correlation between automation and the labor share. The model mechanism also implies a larger correlation of automation with industry concentration measured by the share of sales of top firms than that measured by the share of employment.

Table 5. 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).

6 Calibration

Table 4 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). 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).[12] 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 IFR 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).[13] 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 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 $U(0, S_a)$, and we calibrate S_a, the upper bound of the uniform distribution. The calibrated values are shown in Panel B of Table 4.

The relative price of robots Q_a affects the fraction of firms that use the automation

[12] 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.

[13] Bloom et al. (2018) estimate a two-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%)).

technology (i.e., the automation probability), which is given by

$$\int_{\phi} F(s^*(\phi))\, dG(\phi).$$

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 S_a in the distribution of fixed costs of automation affects the relation between the firm size and automation decisions. Under a larger S_a, small firms would be 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 S_a, we target the employment share of firms that use the automation technology, which in our model equals

$$\frac{\int_{\phi} F(s^*(\phi))N(\phi)\, dG(\phi)}{\int_{\phi} N(\phi)\, dG(\phi)}. \tag{37}$$

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 $Q_a = 50.6$ and $S_a = 1.5$, as shown in Panel B of Table 4. The calibrated model matches the targeted moments closely, as shown in Table 5.

7 Model implications

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

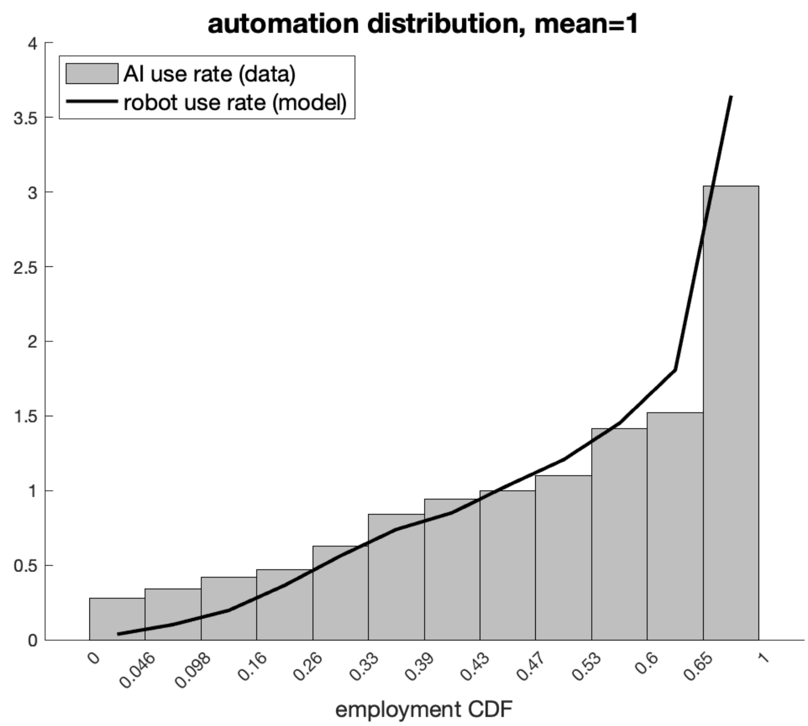
7.1 Model validation

The calibrated model does well in replicating the observed distribution of firm-level automation usage in the ABS data, which we do not target in the calibration procedure.

Figure 3 plots the distribution of AI use rate (i.e., fraction of firms that use AI in their production) in the ABS data documented by Zolas et al. (2020), along with the model-predicted share of firms that use the automation technology in each size bin (based on employment).[14] The model closely matches this non-targeted distribution. In

[14] In their Figure 8, Zolas et al. (2020) 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

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.

both the ABS data and our model, only a small fraction of firms use the automation technology and automation usage is highly skewed towards the few largest firms. In this sense, automation is quite different from general capital equipment, the usage of which is widespread.

The ability of the model to correctly predict this non-targeted distribution therefore lends credence to the model's mechanism. By matching the highly skewed distribution of automation usage, the model is capable of generating the observed sharper increases in sales concentration than in employment concentration when automation cost falls, as we show below.

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 means to one for ease of comparison.

7.2 Firm-level implications

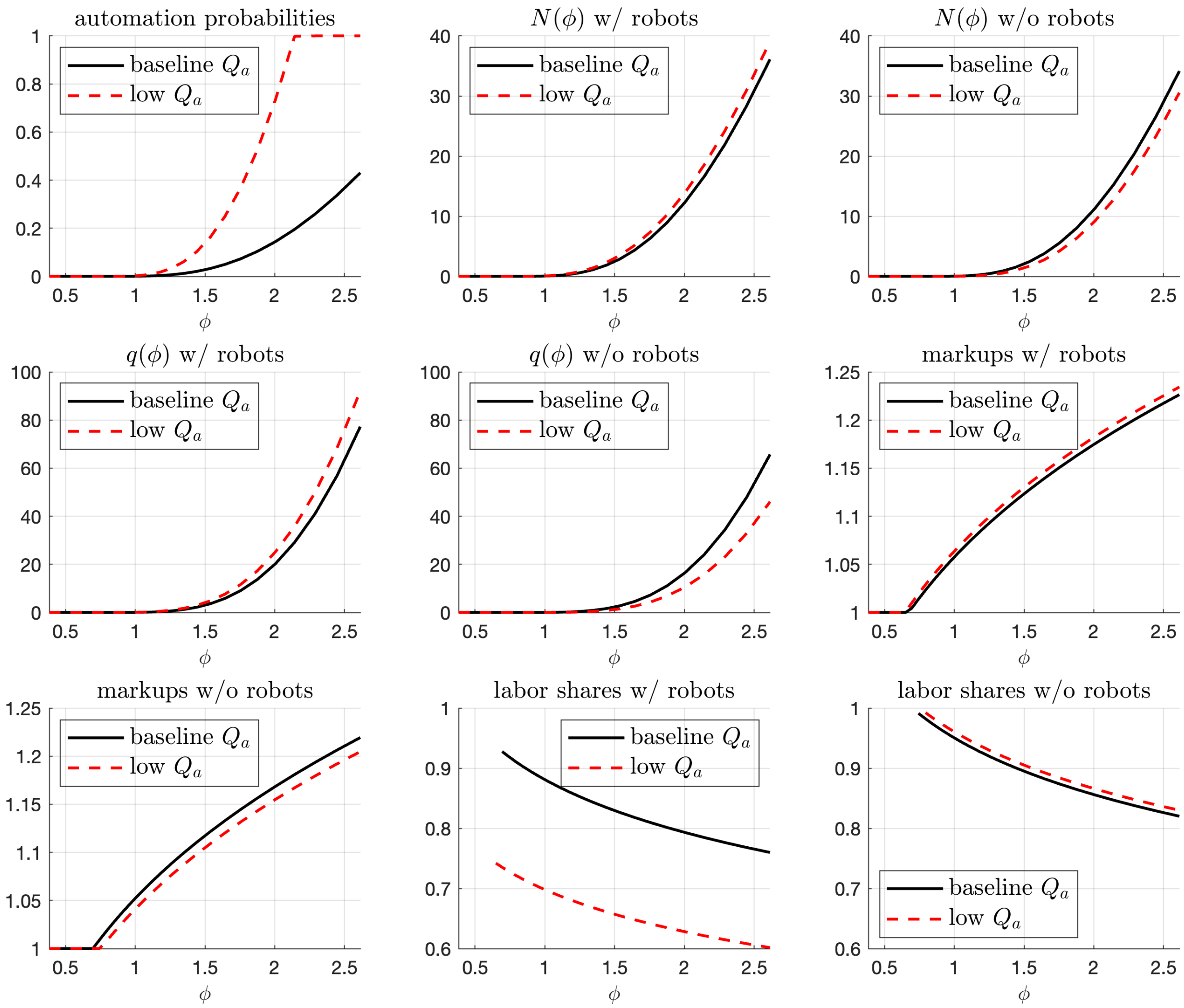
To further examine the automation mechanism, we plot in Figure 4 the firms' decision rules as a function of the idiosyncratic productivity level ϕ. In each panel, we show two lines, one in the baseline model with calibrated parameters (black solid line) and the other in a counterfactual scenario with a lower robot price (low Q_a, red dashed line). The figure shows that the automation probability increases with productivity, since more productive firms are more likely to be able to cover 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 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 that 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, with higher employment ($N(\phi)$), higher relative output ($q(\phi)$), have larger market power measured by markups, and have 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 works only for the firms that use robots.

Figure 4 further shows that the impacts of a decline in the robot price on the firms' decision 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, by adopting more robots, labor productivity at these firms rises, leading to an increase in labor demand, and to gain market share. As Figure 4 shows, the latter effect dominates and firms with robots employ more workers after the reduction in robot price. Interestingly, this is in line with what Zolas et al. (2020) report in the ABS data. 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 output increases.

For firms without robots, the decline in the robot price has the opposite effect 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.

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%.

7.3 Aggregate implications

The heterogeneous automation decisions and the consequent between-firm reallocation have important implications for the steady-state relations between aggregate variables and the robot price, as shown in Figure 5. To illustrate, we consider a wide range of the robot price, from 15 to 100 (this range covers the calibrated value of $Q_a = 50.6$, indicated by the vertical blue line in the figure).

At a lower robot price, more firms would find it profitable to automate, raising the fraction of automating firms. Given the fixed cost of operating the automation technology, larger firms are more likely to automate and thus they benefit more from the lower robot price. As a result, the product market becomes more concentrated and the share of top 1% of firms rises. Importantly, the sales share of the top firms rises more than their employment share as Q_a declines, because those top firms that use robots can expand production without proportional increases in their labor input, and also because they charge higher markups; while an increase in markups shows up in the sales share of top firms, it is not reflected in their employment share.

The automation mechanism in our model is important for explaining the observed rise in industry concentration. In the data, as documented by Autor et al. (2020), sales concentration in manufacturing measured by CR4 rose from about 40.5% in the mid-1990s to roughly 43.5% in 2012, an increase of about 7.4 percent. Sales concentration measured by CR20 rose from 68% to 73%, an increase of also 7.4 percent (see Figure 1). Our model implies that, if the robot price declines from 100 to 50.6, similar to the magnitude of changes in the relative price of industrial robots in the past two decades, the sales concentration (measured by the sales share of the top 1% of firms) would rise from 0.25 to 0.26, an increase of about 4 percent. Thus, the model can explain at least 50% of the observed increase in sales concentration (4 percent out of 7.4 percent).

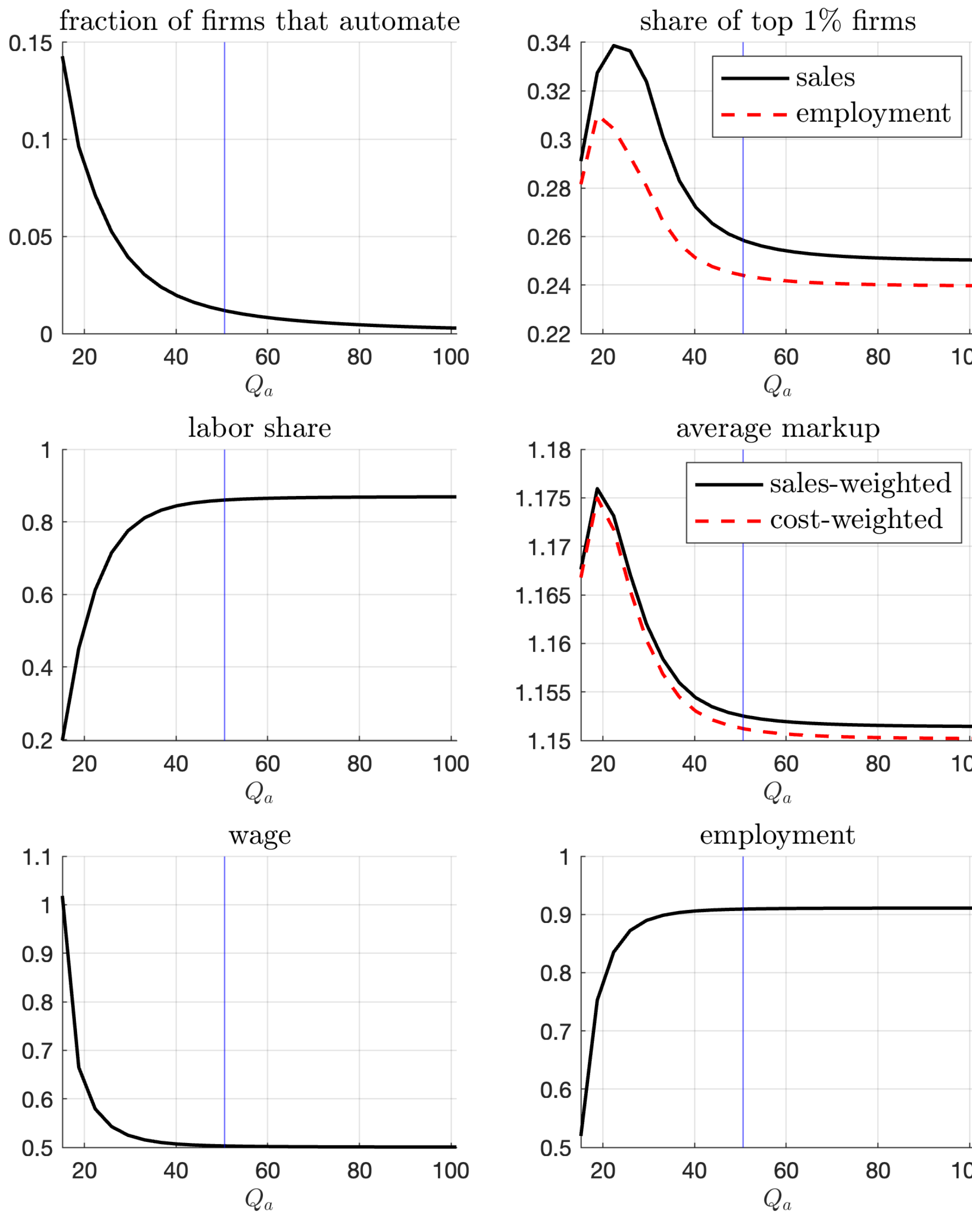
Our model can also explain about 25% of the divergence of sales concentration from employment concentration. In the data, sales concentration in manufacturing rose by 7.4 percent from the mid-1990s to 2012, while employment concentration stayed flat. In our model, as the robot price falls from 100 to 50.6, sales concentration rises by 4 percent while employment concentration rises by 2 percent (with the employment share of the top 1% of firms increasing from 0.24 to 0.245). Thus, the model accounts for 25% of the observed diverging trends between sales concentration and employment concentration (2 percent out of the 7.4 percent).

As Q_a falls, large firms become even larger, raising the average markup in the economy (both sales- and cost-weighted).[15] Moreover, as Figure 4 shows, a reduction in Q_a reallocates production and employment towards automating firms that have lower labor shares in the original steady state. Therefore, as Q_a falls, the labor share in the aggregate economy declines. Our model thus implies that declines in the aggregate labor share and increases in the average markup are mainly driven by the between-firm reallocation channel, in line with the empirical evidence in Autor et al. (2020) and Acemoglu, Lelarge and Restrepo (2020).

The relation between robot prices and industry 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 industry concentration. In an economy with relatively widespread automation, however, a reduction in the robot

[15] 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, the share of the top 1% of firms, the labor share, the average markup, the wage rate, and employment. We vary the robot price Q_a in the range 15 to 100.

price may not increase industry 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% of firms in both sales and employment. As the automation technology becomes accessible to smaller firms, the share of top firms in the economy falls. For similar reasons, the relation between average markup and the robot price is also non-monotonic, as shown in the figure.

These findings suggest that the rise in industry concentration and markups stem from automation that is highly skewed towards a small fraction of large firms, which is quite different from general capital equipment that is widely employed by many firms in the economy. Indeed, our model implies that a decline in the price of general equipment that is widely used in the economy would decrease, rather than increase, the share of superstar firms.

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 labor. The increased labor demand by the automating firms therefore drives up equilibrium wages for all firms. When the automating firms expand production, however, they gain market powers and their markups would rise, which would mitigate the increase in labor demand and dampen 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.[16]

7.4 Policy analysis

The rapid rise of the automation technology and the accompanying increase in industry concentration has stimulated ongoing policy debates on the efficacy of taxing automation. While it is argued that taxing robots might create jobs for workers, it might also reduce labor productivity and put a downward pressure on labor demand. Moreover, taxing robots in a variable-markup world might seem attractive since it would reduce the market power of large, automating firms. In this section, we explore the aggregate effects of taxing/subsidizing automation and whether it is welfare-improving.

We introduce a sales tax τ on firms that use the automation technology. The inter-

[16]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 industry 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.

mediate goods firms' problem in equation (18) therefore becomes:

$$V(\phi, A; s) = \max_{p,y,N,I_a} \left[(1 - \tau \mathbb{1}\{A' > 0\}) py - WN - Q_a I_a - s \mathbb{1}\{A' > 0\} + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right]. \tag{38}$$

We assume that the tax revenue is rebated to consumers in a lump-sum fashion.

To explore the welfare implications of this policy, we compute the consumption equivalent variation as follows. Denote by $W(\tau)$ the social welfare in the economy with the automation tax rate τ. We measure the welfare gains (or losses) under the automation tax by the increase in consumption in perpetuity that is required under the robot tax τ such that the household is indifferent between living in the economy with the tax and the benchmark economy without the tax. Specifically, the welfare in the economy with the tax rate τ is given by

$$W(\tau) = \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \chi \frac{N_t^{1+\xi}}{1+\xi} \right], \tag{39}$$

where C_t and N_t are equilibrium consumption and employment under the robot tax rate τ. The welfare gains associated with the tax rate τ is given by the consumption equivalent μ, which is defined by the relation

$$\sum_{t=0}^{\infty} \beta^t \left[\ln C_t(1+\mu) - \chi \frac{N_t^{1+\xi}}{1+\xi} \right] = W(0), \tag{40}$$

where $W(0)$ denotes the welfare in the benchmark model with $\tau = 0$.

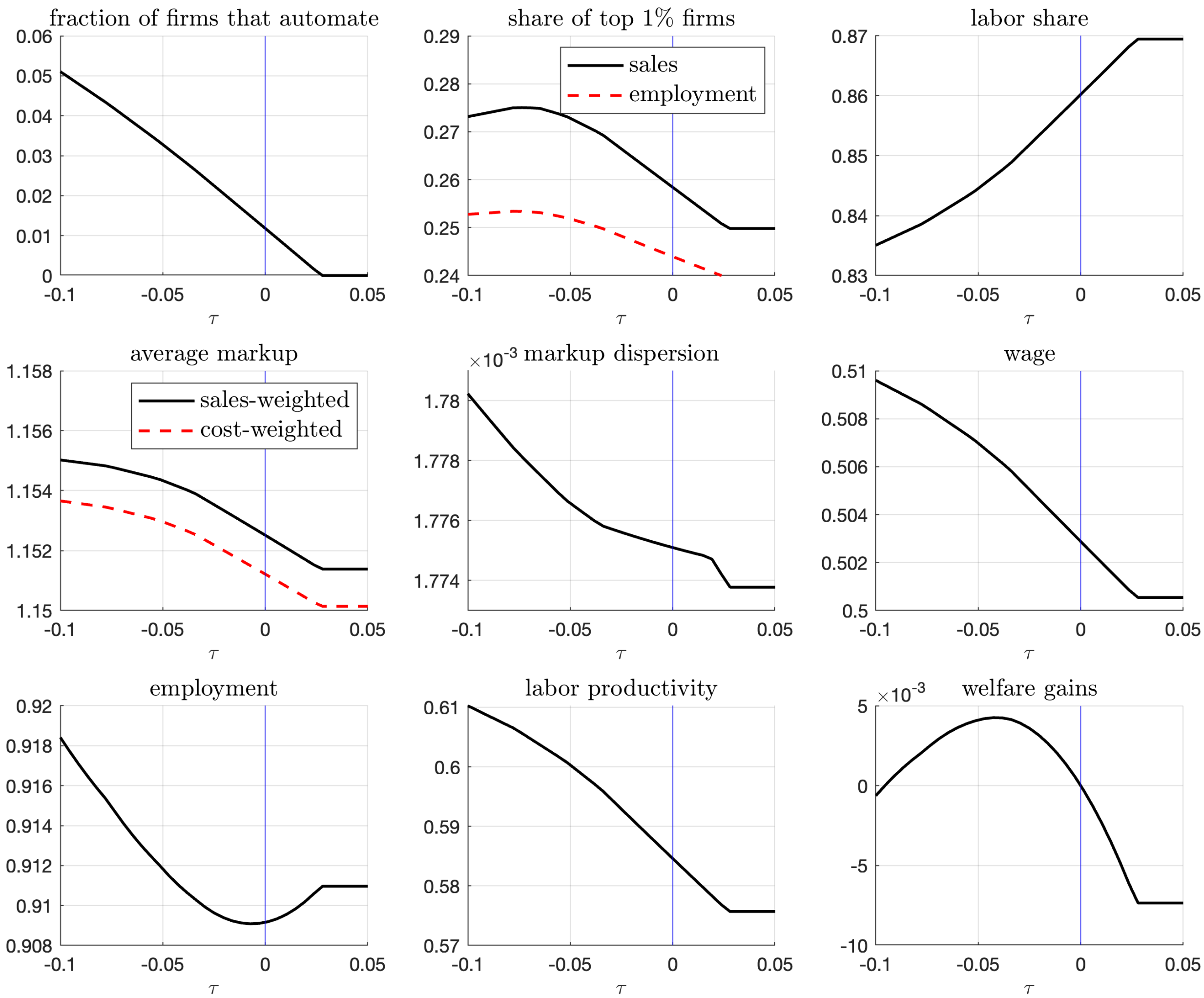
Solving for μ from Eq. (40), we obtain

$$\mu = \exp([(W(0) - W(\tau)(1-\beta)] - 1. \tag{41}$$

Figure 6 shows the aggregate effects of imposing a sales tax on firms that use the automation technology. First of all, notice that since only 1.3% of firms use the automation technology in the benchmark economy, even a small automation tax of around 2.5% would drive the mass of automating firms down to zero, after which increasing automation tax would have no effects. Since most of the actions are for the case of an automation subsidy, we will focus on $\tau < 0$ in what follows.

An automation subsidy (i.e., $\tau < 0$) reduces the marginal cost of using robots and therefore increases the fraction of automating firms. Automation subsidy has two competing effects on the market share of superstar (i.e., top 1%) firms. On the intensive margin, automation subsidy will increase automation intensity at large firms and make them even larger, leading to an increase in the share of superstar firms. On the extensive margin, however, an automation subsidy incentivizes some firms operating the labor-only technology to pay the fixed cost of automation and use the automation technology,

Figure 6. Effects of Taxing Automation



Note: This figure shows the aggregate effects of imposing a sales tax τ on firms that use the automation technology.

which would make these firms larger and in turn reduces the market share of superstar firms. As Figure 6 shows, an automation subsidy first increases and then decreases the share of superstar firms. Moreover, since larger firms are more likely to be able to cover the fixed cost of automation, an automation subsidy will favor larger firms and increase the average markup in the economy.

More robot usage in the economy that is induced by an automation subsidy increases labor productivity, while reduces the aggregate labor share mostly because a larger fraction of output in the economy will be produced using the automation technology.[17] Interestingly, an automation subsidy mostly increases aggregate employment in the economy. This is because while automation is a labor-substituting technology, an automation subsidy that leads to more robot usage in the economy increases labor productivity and labor demand, therefore pushing up both employment and wages.

An automation subsidy in our model influences welfare through two competing mechanisms. On the one hand, by increasing labor productivity, an automation subsidy tends to increase welfare. On the other hand, however, since an automation subsidy favors larger firms and increases both the average and dispersion of markups in the economy, it tends to put a downward pressure on welfare. The welfare-gains panel in Figure 6 plots the consumption equivalent μ. Our results imply that an automation subsidy of about 4% is optimal, which increases welfare by 0.43%.

8 Conclusion

We have presented empirical evidence suggesting that automation has contributed to the rise in industrial concentration since the early 2000s. The link between automation and industry concentration can be explained by an economy-of-scale effects stemming from fixed costs of operating the automation technology in a general equilibrium model. Our calibrated model predicts a highly skewed distribution of automation usage toward a small number of superstar firms, and this prediction aligns well with the firm-level data. Our model predicts that a decline in the robot price of a magnitude similar to that observed during the past two decades can explain about 50% of the rise in sales concentration in U.S. manufacturing and about 25% of the diverging trends between sales concentration and employment concentration. Thus, the rise of automation is quantitatively important for driving the rise of superstar firms.

References

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6): 2188–2244.

Acemoglu, Daron, and Pascual Restrepo. 2021. "Tasks, Automation, and the Rise in US Wage Inequality." National Bureau of Economic Research Working Paper 28920.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." *AEA Papers and Proceedings*, 110: 383–88.

[17] Notice that the rise in average markups also contributes to the fall in the labor share.

Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter J Klenow, and Huiyu Li. 2019. "A Theory of Falling Growth and Rising Rents." National Bureau of Economic Research Working Paper 26448.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2021. "What Are the Labor and Product Market Effects of Automation? New Evidence from France." Sciences Po.

Arnoud, Antoine. 2018. "Automation Threat and Wage Bargaining." Unpublished Manuscript, Yale University.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *The Quarterly Journal of Economics*, 135(2): 645–709.

Autor, David H., and Anna Salomons. 2018. "Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share." *Brookings Papers on Economic Activity*, 1: 1–87.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–2168.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics*, 118(4): 1279–1333.

Bajgar, Matej, Giuseppe Berlingieri, Sara Calligaris, Chiara Criscuolo, and Jonathan Timmis. 2019. "Industry Concentration in Europe and North America." OECD Productivity Working Papers.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry. 2018. "Really uncertain business cycles." *Econometrica*, 86(3): 1031–1065.

Cheng, Hong, Lukasz A Drozd, Rahul Giri, Mathieu Taschereau-Dumouchel, and Junjie Xia. 2021. "The Future of Labor: Automation and the Labor Share in the Second Machine Age." Federal Reserve Bank of Philadelphia Working Paper WP 21-11.

Eden, Maya, and Paul Gaggl. 2018. "On the welfare implications of automation." *Review of Economic Dynamics*, 29: 15–43.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu. 2021. "How costly are markups?" Unpublished Manuscript, New York University and Duke University.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics*, 107(5): 753–768.

Guerreiro, Joao, Sergio Rebelo, and Pedro Teles. 2022. "Should Robots be Taxed?" *Review of Economic Studies*, 89: 279–311.

Hsieh, Chang-Tai, and Esteban Rossi-Hansberg. 2019. "The Industrial Revolution in Services." National Bureau of Economic Research NBER Working Papers 25968.

Hubmer, Joachim, and Pascual Restrepo. 2022. "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital–Labor Substitution." National Bureau of Economic Research Working Paper 28579.

Jaimovich, Nir, and Henry E. Siu. 2020. "Job Polarization and Jobless Recoveries." *The Review of Economics and Statistics*, 102(1): 129–147.

Kehrig, Matthias, and Nicolas Vincent. 2021. "The Micro-Level Anatomy of the Labor Share Decline." *The Quarterly Journal of Economics*, 136(2): 1031–1087.

Khan, Aubhik, and Julia K Thomas. 2008. "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics." *Econometrica*, 76(2): 395–436.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit and Banking*, 27(4): 1241–1277.

Klenow, Peter J, and Jonathan L Willis. 2016. "Real rigidities and nominal price changes." *Economica*, 83(331): 443–472.

Kwon, Spencer Y., Yueran Ma, and Kaspar Zimmermann. 2022. "100 Years of Rising Corporate Concentration." Unpublished Manuscript, University of Chicago Booth School of Business.

Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard. 2022. "Information Technology and Returns to Scale." Boston College.

Leduc, Sylvain, and Zheng Liu. 2019. "Robots or Workers? A Macro Analysis of Automation and Labor Markets." Federal Reserve Bank of San Francisco Working Paper No. 2019-17.

Prettner, Klaus, and Holger Strulik. 2020. "Innovation, automation, and inequality: Policy challenges in the race against the machine." *Journal of Monetary Economics*, 116: 249–265.

Rogerson, Richard, and Johanna Wallenius. 2009. "Micro and macro elasticities in a life cycle model with taxes." *Journal of Economic Theory*, 144(6): 2277–2292.

Sui, Xiamei. 2022. "Uneven Firm Growth in a Globalized World." *Working Paper*.

Tambe, Prasanna, Lorin Hitt, Daniel Rock, and Erik Brynjolfsson. 2020. "Digital Capital and Superstar Firms." National Bureau of Economic Research Working Paper 28285.

Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *Quarterly Journal of Economics*, 113(4): 1091–1117.

Zolas, Nikolas, Zachary Kroff, Erik Brynjolfsson, Kristina McElheran, David N Beede, Cathy Buffington, Nathan Goldschlag, Lucia Foster, and Emin Dinlersoz. 2020. "Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey." National Bureau of Economic Research Working Paper 28290.

Appendices

A Derivations

To simplify the intermediate producers' problem in equation (18), rewire the value function so that s is not a state variable:

$$
\begin{aligned}
V(\phi, A; s) &= \max_{p,y,N,A'} \left[py - WN - Q_a[A' - (1-\delta_a)A] - s\mathbb{1}\{A' > 0\} + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right] \\
&= Q_a(1-\delta_a)A + \max_{p,y,N,A'} \left[py - WN - Q_a A' - s\mathbb{1}\{A' > 0\} + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right] \\
&= Q_a(1-\delta_a)A + \max \Bigg\{ \underbrace{\max_{p,y,N,A'>0} \left[py - WN - Q_a A' + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right]}_{\equiv V^a(\phi)} - s, \\
&\qquad \underbrace{\max_{p,y,N} \left[py - WN + \beta E_{\phi'|\phi} \int_{s'} V(\phi', 0; s') dF(s') \right]}_{\equiv V^n(\phi)} \Bigg\} \\
&= Q_a(1-\delta_a)A + \max\{V^a(\phi) - s, V^n(\phi)\}
\end{aligned} \tag{42}
$$

The firm with productivity ϕ chooses $A' > 0$ if and only if $s \leq s^*(\phi) \equiv V^a(\phi) - V^n(\phi)$.

We solve for the optimal decisions in $V^a(\phi)$ and $V^n(\phi)$ using the first-order conditions. Notice that the capital stock A will not a state variable since there are no frictions on it. For automating firms, we have

$$
V^a(\phi) = \max_{p,y,N,A'>0} \left[py - WN - Q_a A' + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right] \tag{43}
$$

If s is paid, $A' > 0$ would always hold. Therefore, the value of an automating firm becomes:

$$
\begin{aligned}
V^a(\phi) &= \max_{p,y,N,A'} \left[py - WN - Q_a A' + \beta E_{\phi'|\phi} \int_{s'} V(\phi', A'; s') dF(s') \right] \\
&= \max_{p,y,N,A'} \left[py - WN - Q_a A' + \beta E_{\phi'|\phi} \int_{s'} \left[Q_a(1-\delta_a)A' + \max\{V^a(\phi') - s', V^n(\phi')\} \right] dF(s') \right] \\
&= \max_{p,y,N,A'} \left[py - WN - Q_a A' + \beta E_{\phi'|\phi} \left[Q_a(1-\delta_a)A' + \int_{s'} \max\{V^a(\phi') - s', V^n(\phi')\} dF(s') \right] \right] \\
&= \max_{p,y,N,A'} \Bigg[py - WN - Q_a A' + \beta E_{\phi'|\phi} \Bigg[Q_a(1-\delta_a)A' + \int_0^{s^*(\phi')} [V^a(\phi') - s'] dF(s')
\end{aligned}
$$

$$
\begin{aligned}
&+\int_{s^*(\phi')}^{\bar{s}} V^n(\phi')dF(s')\Big]\Big] \\
&= \max_{p,y,N,A'}\Big[py - WN - Q_aA' + \beta E_{\phi'|\phi}\Big[Q_a(1-\delta_a)A' + F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s'dF(s') \\
&+ [1 - F(s^*(\phi'))]V^n(\phi')\Big]\Big] \\
&= \max_{p,y,N,A'}\Big[py - WN - Q_aA' + \beta Q_a(1-\delta_a)A'\Big] + \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s'dF(s') \\
&+ [1 - F(s^*(\phi'))]V^n(\phi')\Big] \\
&= \max_{p,y,N,A'}\Big[py - WN - Q_a[1-\beta(1-\delta_a)]A'\Big] + \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s'dF(s') \\
&+ [1 - F(s^*(\phi'))]V^n(\phi')\Big] \qquad (44)
\end{aligned}
$$

Let $\gamma_a \equiv Q_a[1 - \beta(1 - \delta_a)]$ denote the effective marginal cost of robots. Then the optimal choices of A' and N are those reported in equations (23) and (24) in the main text.

The value of an automating firm can be written as:

$$
\begin{aligned}
V^n(\phi) &= \max_{p,y,N}\Big[py - WN + \beta E_{\phi'|\phi}\int_{s'} V(\phi', 0; s')dF(s')\Big] \\
&= \max_{p,y,N}\Big[py - WN + \beta E_{\phi'|\phi}\int_{s'}\big[\max\{V^a(\phi') - s', V^n(\phi')\}\big]dF(s')\Big] \\
&= \max_{p,y,N}\Big[py - WN + \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s'dF(s') + [1 - F(s^*(\phi'))]V^n(\phi')\Big]\Big] \\
&= \max_{p,y,N}\Big[py - WN\Big] + \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s'dF(s') + [1 - F(s^*(\phi'))]V^n(\phi')\Big] \qquad (45)
\end{aligned}
$$

To compute the automation cutoff $s^*(\phi)$, we can write:

$$
\begin{aligned}
s^*(\phi) =& V^a(\phi) - V^n(\phi) \\
=& \max_{p,y,N,A'}\Big[py - WN - Q_a[1-\beta(1-\delta_a)]A'\Big] + \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') \\
& - \int_0^{s^*(\phi')} s' dF(s') + [1 - F(s^*(\phi'))]V^n(\phi')\Big] \\
& - \max_{p,y,N}\Big[py - WN\Big] - \beta E_{\phi'|\phi}\Big[F(s^*(\phi'))V^a(\phi') - \int_0^{s^*(\phi')} s' dF(s') + [1 - F(s^*(\phi'))]V^n(\phi')\Big] \\
=& \max_{p,y,N,A'}\Big[py - WN - Q_a[1-\beta(1-\delta_a)]A'\Big] - \max_{p,y,N}\Big[py - WN\Big]. \qquad (46)
\end{aligned}
$$

B Solution Algorithm

There are three loops to solve the problem. The Y loop is outside of the W loop and the W loop is outside of the q loop.

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

1. Guess aggregate final goods 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 robot price Q_a and wage rate W, compute the marginal costs $\lambda(j)$ by eq. (25) and (27), and we can get $A'(j)$ and $N(j)$ from eq. (23), (24), and (26).
   (c) The aggregate employment and robot stock are determined by eq. (34) and eq. (35).
   (d) Consumption C is determined by eq. (6).
   (e) The steady state aggregate investment in robots I_a is from (36).
   (f) Compute Y^{new} using the resource constraint (33). Stop if Y converges.
      i. If $Y = Y^{\text{new}}$, Y and all other aggregate variables are found.
      ii. If $Y > Y^{\text{new}}$, reduce 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 (8) holds.
   (a) If LHS = RHS, the wage rate is found and jump out of W loop to Y loop.
   (b) If LHS > RHS, increase W to reduce $q(j)$ according to eq. (9). Go back to Step 2.
   (c) If LHS < RHS, reduce W to raise $q(j)$ according to eq. (9). Go back to Step 2.

q loop: find the relative production.

1. Given the factor prices Q_a and W, the marginal cost of production is determined by eq. (25) for the automation technology and by eq. (27) for the labor-only technology.

2. Guess a demand shifter D.

3. Use eq. (9) to solve for the relative output $q(\phi)$ for each ϕ, for firms with and without robots.

   (a) The right-hand side of (9) is a function of q by plugging in (13).

   (b) The price in the left-hand side is the marginal cost in (25) or (27) times the markup in (15), which is also a function of q.

   (c) Use the bisection method to solve for q in eq. (9).

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 eq. (23), (24), and (26).

   (c) For each productivity ϕ, compute the profits with and without robots and thus get the automation cutoffs $s^*(\phi)$ according to (30), and thus the automation probability $F(s^*(\phi))$.

5. Given the automation decisions, compute D^{new} by (10). 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 $D > D^{\text{new}}$, reduce D. Go back to Step 2.

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