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Taking over the World?

Automation and Market Power

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Abstract

This paper studies how automation technology affects market power in the global economy. We develop a theoretical model in which firms' markups are endogenous to factor input choices based on technology levels, but are also affected by technology adoption of other domestic and foreign firms. In an empirical analysis, we find that market power, measured as the markup of price over marginal cost, declines on average with higher levels of automation. However, there is substantial heterogeneity, with firms in the highest revenue and markup quintile gaining market power. Moreover, we find that exposure to foreign automation increases competition in the local market.

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1 Introduction

In recent years, there has been a surge of interest in three related phenomena in international economics: The declining share of labor, the accelerating concentration of market power, and the increasing use of automation technology. Although a link between these phenomena has been established ([Karabarbounis and Neiman, 2014](#); [Berg et al., 2021](#)), the exact interrelationships remain a matter of ongoing debate and are yet to be better understood ([Grossman and Oberfield, 2021](#)).

In this paper, we investigate whether automation technology contributes to the rise of market power in the form of markups. Specifically, we develop a theoretical model of oligopolistic competition in which firms' markups are endogenous to factor input choices, total factor productivity and the competitive environment created by other domestic and foreign firms. We test the model empirically, distinguishing between domestic robot adoption and exposure to robots in foreign economies. Our empirical analysis reveals considerable heterogeneity across firms. We find that firms in the highest markup quintile further increase their markups and market shares through sectoral robot adoption, while firms in lower quintiles suffer losses in terms of markups and market shares.

The recent literature on the evolution of global market power and hence market concentration has been largely influenced by [De Loecker and Warzynski \(2012\)](#), both methodologically and descriptively. In this paper the authors introduced an innovative method for estimating firms' markups based on a control function approach, which led to a large number of subsequent publications building on this methodology. For example [De Loecker and Eeckhout \(2018\)](#) and [Diez et al. \(2019\)](#) document a global rise in markups, which they mostly attribute to a reallocation of market shares from low to high markup firms. In this strand of literature, firms' markups are assumed to be proportional to firms' market shares, so that the documented rise in markups implies increasing market concentration.

Corroborating the notion that fewer firms are increasingly dominating markets, [Autor et al. \(2020\)](#) coined the term "superstar firms", to describe how high-tech firms excel in a "winner takes all" economy. In related work, [Autor and Salomons \(2018\)](#) and [Dorn et al. \(2017\)](#) link this to the labor share debate, arguing that the emergence of technology, and hence capital-intensive superstar firms has played a crucial role in the decline of the labor share. While most "superstar" firms have been documented in the digital, IT and service sectors, benefiting from platform economies ([Lashkari et al., 2018](#); [Autor et al., 2020](#)), similar but somewhat weaker trends have also been observed for technological leaders in manufacturing ([Andrews et al., 2016](#); [Stiebale et al., 2020](#)).

Advances in industrial robot technology and subsequent commercialization have led

to a steady increase in uptake over the past three decades ([International Federation of Robotics, 2018](#)). Several dimensions of robot adoption and its consequences have been studied in recent years. [Dinlersoz and Wolf \(2018\)](#) and [Koch et al. \(2019\)](#) show that the most affluent and technologically advanced manufacturers pioneer the adoption of industrial robots in manufacturing. A number of papers find that robot adoption at the firm level increases sales and employment, although it typically reduces the labor share ([Humlum, 2019](#); [Acemoglu et al., 2020](#); [Aghion et al., 2020](#); [Bonfiglioli et al., 2020](#)). At the more aggregate labor market level, [Acemoglu and Restrepo \(2020\)](#) argue that job displacement rather than job creation effects are the predominant consequence of robot adoption in the US economy. [Dauth et al. \(2021\)](#) document that more robot-exposed labor markets in Germany experience declines in manufacturing employment, but these are offset by increasing employment in services.

However, little research has been done on the impact of robot adoption on market power. In recent work closely related to this paper, [Stiebale et al. \(2020\)](#) investigate the existence of European superstar firms in manufacturing. In line with our results, they report within-sector heterogeneity across firms in the effect of robot adoption on markups. Our work adds to the literature by confirming the findings of [Stiebale et al. \(2020\)](#) using a different international firm dataset, providing a theoretical model, and extending the scope of the analysis to robot adoption by foreign firms.

Our theoretical framework builds on a model of oligopolistic competition from [Edmond et al. \(2015\)](#), which we adapt to the objective of our analysis. Specifically, we introduce a Cobb-Douglas production technology in which industrial robots serve as an input alongside labor to intermediate good producing firms. Moreover, we allow output elasticities to vary at the firm level, so that firms operate with different labor and robot intensities, similar to [Harrigan and Reshef \(2015\)](#). The model predicts that firms operating with above-average robot intensities benefit from a reduction in the robot rental rate in terms of market shares and markups at the cost of firms with below-average robot-intensity in the one-country economy. Furthermore, the model predicts that robot adoption by foreign competitors exerts downward pressure on the market shares and markups of all domestic firms in a two-country economy.

We combine publicly available firm-level balance sheet data, used to estimate average sectoral markups, with data on industry-level robot uptake from the [International Federation of Robotics \(2018\)](#) on 29 countries and 20 sectors between 1995 and 2015 for the empirical analysis. We employ an instrumental variable (IV) approach to account for endogenous uptake of robots within sectors. Our empirical results suggest that increased automation is associated with higher markups and larger market shares for the most productive quintile of firms in our sample. Analogously, we find that firms in the lower quintiles suffer losses in market shares and markups as a consequence of in-

creased automation. Taken together, these findings reconcile the notions that average markups in manufacturing have not increased much over the past years and that automation technologies increase profits for some firms. We take this as evidence for the hypothesis that the increasing use of industrial robots amplifies market concentration and makes only a few firms better off. Moreover, we find that the adoption of robots by foreign competitors exerts downward pressure on all local firms' markups and market shares.

The paper is structured as follows. In section 2, we develop the one-country and two-countries economy versions of the model, and derive the model's hypotheses about the effect of a change in the robot rental rate on markups and market shares. In section 3 we present our empirical strategy and in section ?? we present all the relevant results. We conclude the analysis in section ??.

2 Theory

In the following, we derive a theoretical model to motivate our analysis of the effects of increasing industrial robot adoption on the distribution of firm-level markups. In order to obtain a framework that allows the derivation of hypotheses about the interplay between robot adoption and markups, we combine a number of assumptions.

First, we assume that firms use industrial robots alongside labor as an input to production. We also assume that firms differ in the intensity with which they use factor inputs, i.e., we allow for firm-level heterogeneity in output elasticities. This assumption builds on the findings of previous work by, for example, Koch et al. (2019), who report firm-level heterogeneity in the adoption of industrial robots across but also within sectors.

Second, we assume that firms differ in terms of total factor productivity (TFP), as is common in the literature (see, for example, Melitz 2003). In sum, firms are thus subject to two sources of heterogeneity, which they obtain by drawing from probability distribution functions. A joint distribution function of the two technology parameters allows for correlation between the two, so that, for example, a high level of robot intensity is more likely to be drawn alongside a high level of TFP than a low level of TFP, as in Harrigan and Reshef (2015). While Koch et al. (2019) find a positive association between firm productivity and robot intensity, our data are insufficient to calibrate such a joint distribution function. Therefore, we refrain from calibrating the model and instead derive purely theoretical results allowing for different technology parameterizations.

Third, we assume that markups vary at the firm-level and are endogenous to a firm's competitiveness, which is determined by its technology relative to that of its competi-

tors. Thus, a firm's robot intensity, which depends on its technology draw, is one of the determinants of its markup. To provide a theoretical framework that allows for the combination of these assumptions, we adapt the model in [Edmond, Midrigan and Xu \(2015\)](#) (hereafter EMX model), which is a model of oligopolistic competition based on the [Atkeson and Burstein \(2008\)](#) model. Although it was originally designed as a trade model, we first simplify the model to a one-country economy version in order to derive the effect of decreasing robot prices on markups without interference from foreign competitors or trade effects. In this setting, we show how a reduction in the robot rental rate makes firms with above-average robot intensity better off in terms of market shares and markups.

We then extend the model to the two-country case and show how additional competition via trade aggravates this polarizing effect. Due to fixed costs of trade, only firms with high productivity and robot intensity choose to export. Thus, a reduction in the price of robots increases the average productivity and robot intensity in the export market. Firms that would have been on the margin of benefiting from the robot price reduction in the one-country economy are crowded out by foreign high-robot-intensity firms in the two-country case.

2.1 Small open economy: domestic competition

We model a two-stage economy, in which heterogeneous intermediate good producers provide inputs to homogeneous final good producers. While intermediate good producers operate under oligopolistic competition, final good producers operate under perfect competition. Consumers purchase the homogeneous final good and supply labor to the economy.

2.1.1 Final Good Producers

In the final good stage firms produce a homogeneous final good denoted Y under perfect competition

$$Y = \left(\int_0^1 y(s)^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}}, \quad (1)$$

where $\sigma > 1$ is the elasticity of substitution across a continuum of sectors $s \in [0, 1]$ from which inputs $y(s)$ are sourced. Consumers buy the final good at price P , which is the price index for the final good and given by

$$P = \left(\int_0^1 p(s)^{1-\sigma} ds \right)^{\frac{1}{1-\sigma}}, \quad (2)$$

where $p(s)$ is a sector specific price index defined below in Equation 5.

2.1.2 Intermediate Good Producers

The number of intermediate good producers is finite and assumed to be exogenous, as in the benchmark EMX model. Intermediate good producers use Cobb-Douglas production technology, where labor L and robots R are the only inputs. In addition, intermediate producers are subject to two sources of heterogeneity, which are imposed by draws from a joint distribution function. These two draws determine the total overall factor productivity of intermediate producers φ_i , as well as their output elasticity for labor in production θ_i , where the subscript i denotes the intermediate good producing firm. The joint distribution function is denoted as $g(\varphi_i, \theta_i)$ as in [Harrigan and Reshef \(2015\)](#). Assuming constant returns to scale, the draw of θ_i entails the output elasticity for robots, which follows as $1 - \theta_i$. This firm-level variation in output elasticities implies that producers of intermediate goods operate with different factor intensities, i.e., different factor input ratios. Their production technology for output in a given sector s takes the form

$$y_i(s) = \varphi_i(s)L_i(s)^{\theta_i}R_i(s)^{1-\theta_i}, \quad (3)$$

where firm-specific input of labor and robots in sector s are denoted $L_i(s)$ and $R_i(s)$ respectively.

In the interest of parsimony, we do not include conventional, non-automation-related capital, typically denoted K , in the production function. We assume that automation capital, here represented as robots R , differs from conventional capital conceptually in that it comprises capital directly linked to automation technology and no other forms of capital. Moreover, we hypothesize that it is also different from conventional capital in its degree of usage across firms. Strictly speaking, we assume that there is a difference in the underlying empirical distributions of the respective output elasticities, with the use of automation related capital being more heterogeneous across firms than the use of conventional capital. While we argue that a firm can be operational even with virtually no use of automation capital, we consider the use of conventional capital to be less variable. However, firm-level data would be required to estimate the corresponding output elasticities to verify these assumptions by interpreting the means and variances of the estimated underlying distributions. As data availability steadily increases, we expect such data to become available in the future so that we will then be able to calibrate the model we present here, including conventional capital. For the scope of this work, we argue that its inclusion in the production function would not alter the core predictions of our model regarding market concentration. We thus decide

to keep the production function as simple as possible for deriving our hypotheses of interest. Nevertheless, extending the model to include non-automation-related capital in the production function would be a natural extension and of interest for future calibration.

Following a similar reasoning, we make the simplifying assumption that the sum of the output elasticities equals one and that we are thus in the classical Cobb-Douglas scenario with constant returns to scale. Future empirical research must show whether this assumption should be relaxed in order for the derived hypotheses to match empirical observations as closely as possible. A deviation from the assumption of constant returns to scales at this point would add another layer of complexity not clearly being warranted by theoretical arguments nor the current body of evidence.

There is an ongoing debate in the literature as to whether automation has a positive or negative effect on labor demand. While the potential channels for both, job displacement and job creation effects, have been described in detail, evidence to which ultimately dominates is mixed. Moreover, apart from the labor demand effects observed at the level of the automating firm, the resulting industry-level changes may differ in a general equilibrium setting. In the context of modeling firm-level production, however, it has probably been more common to assume that technology-related capital and labor function as substitutes. We depart from this view building on the evidence from [Aghion et al. \(2020, 2022\)](#), and hence assume that robots and workers are complementary in the production of intermediate goods.

Demand for Intermediate Goods. Since the demand for intermediate goods in our one-country economy version is equivalent to the demand for intermediate goods on the home market in the EMX model, we keep the derivation thereof brief. It is derived from the final good producer's profit-maximization problem.¹

Demand for the intermediate good produced by firm i in sector s is given by

$$y_i(s) = \left(\frac{p_i(s)}{p(s)} \right)^{-\gamma} \left(\frac{p(s)}{P} \right)^{-\sigma} Y, \quad (4)$$

where $p(s)$ is the intermediate good price index for any given sector s and γ depicts the within-sector-elasticity of substitution, which is assumed to be larger than the cross-sector-elasticity of substitution, so that $\gamma > \sigma$. Equation 4 implies that the more competitive a firm is within its sector, the larger its share of aggregate demand Y will be. A firm's competitiveness is determined by its marginal cost advantage over its competitors, which results from its technology draws. The lower a firm's marginal cost, the more pricing power it has and the greater its potential to gain market share. Analo-

¹See eq. A1 in appendix A.1.2.

gously, the more competitive the sector in which the firm operates is relative to other sectors, the larger that firm's share of aggregate demand Y will be.

The sectoral price index is based on the prices of active firms in a given sector and the within-sector-elasticity γ and is defined as

$$p(s) = \left(\sum_{i=1}^{n(s)} p_i(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}}. \quad (5)$$

Market Structure. We impose Bertrand competition on the intermediate goods market. The choice between Cournot and Bertrand competition mainly affects the derivation of the demand elasticity that firms face. Since [Edmond et al. \(2015\)](#) show that Cournot and Bertrand lead to similar results in the EMX framework, we do not derive the results for Cournot competition.

Profit Maximization of Intermediate Good Producers. In the interest of parsimony, we do not introduce fixed operating costs. Intermediate good producers therefore maximize profits via

$$\pi_i(s) = \max_{p_i(s), L_i(s), R_i(s)} [p_i(s) y_i(s) - wL_i(s) - rR_i(s)], \quad (6)$$

where $p_i(s)$ is the price intermediate producer i charges, w denotes the wage rate, i.e. the cost of labor, and r denotes the robot rental rate. Indirect demand for goods produced by firm i follows from equation 4 and takes the form

$$p_i(s) = y_i(s)^{-\frac{1}{\gamma}} p(s) \left(\frac{p(s)}{P} \right)^{-\frac{\sigma}{\gamma}} Y^{\frac{1}{\gamma}}. \quad (7)$$

By plugging indirect demand into the intermediate producers' profit maximization problem (equation 6) we can derive the respective profit-maximizing factor demands using first order conditions. Profit-maximizing demand for labor, $L_i^*(s)$ and for robots $R_i^*(s)$ take the form

$$L_i^*(s) = \frac{y_i(s)}{\varphi_i(s)} \left(\frac{1 - \theta_i w}{\theta_i r} \right)^{-(1-\theta_i)}, \quad (8)$$

$$R_i^*(s) = \frac{y_i(s)}{\varphi_i(s)} \left(\frac{1 - \theta_i w}{\theta_i r} \right)^{\theta_i}. \quad (9)$$

An intermediate good producers' profit-maximizing price is obtained by plugging the profit-maximizing factor demands into the profit-maximization problem given by

equation 6 and deriving with respect to the price p_i , which gives

$$p_i(s) = \frac{\epsilon_i(s)}{\epsilon_i(s) - 1} \frac{V_i}{\varphi_i(s)}, \quad (10)$$

where an intermediate producing firm's marginal costs are defined as

$$V_i = w^{\theta_i} r^{1-\theta_i} \theta_i^{-\theta_i} (1 - \theta_i)^{\theta_i-1}. \quad (11)$$

We denote the demand elasticity intermediate producer i faces with ϵ_i . In line with the EMX Bertrand model, the demand elasticity depends on the underlying within-sector-elasticity of substitution γ and across-sector-elasticity of substitution σ in the form

$$\epsilon_i(s) = \gamma(1 - \omega_i(s)) + \sigma\omega_i(s), \quad (12)$$

where $\omega_i(s)$ denotes an intermediate producing firm's sectoral market share and is defined as

$$\omega_i(s) = \left(\frac{p_i(s)}{p(s)} \right)^{1-\gamma}. \quad (13)$$

An intermediate producer's market share is thus determined by its profit-maximizing price relative to the price index of its sector. Consequently, a reduction in the profit-maximizing price $p_i(s)$ is generally associated with an increase in market share $\omega_i(s)$.

Markups. An intermediate good producing firm's markup is a function of its demand elasticity and given by

$$\mu_i(s) = \frac{\epsilon_i(s)}{\epsilon_i(s) - 1}. \quad (14)$$

Hence, the lower the demand elasticity faced by an intermediate producer, the higher its markup. Accordingly, the higher a firm's market share, the lower the demand elasticity it faces and thus the higher its markup.

2.1.3 Market Clearing

Markets clear according to the factor shares in the economy. Aggregate demands for labor and robots take the form

$$L = \int_0^1 \left(\sum_{i=1}^{n(s)} L_i^*(s) \right) ds = \bar{\theta} Y, \quad (15)$$

$$R = \int_0^1 \left(\sum_{i=1}^{n(s)} R_i^*(s) \right) ds = (1 - \bar{\theta}) Y, \quad (16)$$

where $\bar{\theta}$ is the average draw of the output elasticity for labor. We assume that labor supply is perfectly elastic, so that changes in the demand for labor are reflected in changes in the wage w . In the case of robots, we assume that they are not produced domestically, but are imported from a foreign economy in exchange for the final good produced in the domestic economy. The production of robots is thus exogenous to the domestic economy and not modelled explicitly. We consider them to be inputs to production that fully depreciate each period, so that the robot rental rate equals the price of robots in exchange for final goods. Similarly to the classical setting of a small open economy, we assume that demand from the domestic economy does not affect the price for robots, but that it is determined on the world market. The assumption of inelastic robot supply implies that aggregate demand for robots as given by equation 16 is therefore met by foreign supply without affecting the world market price for robots. In related empirical work, [Duch-Brown and Haarburger \(2023\)](#) investigate the development of market concentration for the world market of industrial robots. They find that a few robot exporting countries provide the majority of world robot supply. The economy modelled here can be seen as a small economy sourcing robot supply from one of these large-scale exporters.

2.2 Reduction in the robot rental rate: only domestic competition

A reduction in the robot rental rate r , directly affects firms' marginal costs and profit-maximizing demands for labor and robots. In response, *both* firms' profit-maximizing prices and sectoral price indexes change, which affects market shares and markups. We are interested in identifying which firms gain market share and markups and which firms do not. To derive this result, we construct a set of robot price elasticities, that allow us to trace the effect of a change in the robot rental rate.

Effect on marginal costs. Due to the output elasticity of labor being constrained by $0 < \theta < 1$, all firms use both factor inputs in production. The direct effect of a reduction in

the price of robots r is therefore a reduction in the firm's marginal cost as defined in eq. (11). Using the differential of the marginal cost equation, we can solve for the elasticity of a firm's marginal costs with respect to the robot rental rate

$$\frac{d \ln V_i}{d \ln r} = \theta_i \frac{d \ln w}{d \ln r} + (1 - \theta_i). \quad (17)$$

We interpret the two terms on the right-hand side of equation 17 as the direct and indirect marginal cost effects induced by robot price changes. The higher a firm's robot intensity in production, i.e. the smaller θ_i , the larger is the direct effect $(1 - \theta_i)$ on a firm's marginal cost in response to changes in the robot rental rate. The indirect effect $(\theta_i \frac{d \ln w}{d \ln r})$ represents an adjustment of the wage in response to shifts in aggregate demand for both input factors in general equilibrium. Since robots and labor enter the production technology of intermediate firms as complements, a decline of the robot rental rate leading to increased robot uptake would entail a positive wage response, given that we model labor supply as perfectly inelastic. As indicated by θ_i , this affects firms proportionally to their labor-intensity of production.

Thus, a decrease in the robot rental rate implies a decrease in a firm's marginal costs V_i as long as the direct effect is larger than the indirect effect. We discuss the wage response effect in more detail in section 2.3 on the general equilibrium effects.

Effect on profit-maximizing price. To illustrate the effect of changes in the robot rental rate on an intermediate firm's profit-maximizing prices, we again construct the differential of our equation of interest, which in this case is the price equation (eq. 10). Based on the differential, we construct the elasticity of the profit-maximizing price with respect to the robot rental rate, which takes the form

$$\frac{d \ln p_i(s)}{d \ln r} = -\frac{1}{\epsilon_i(s) - 1} \frac{d \ln \epsilon_i(s)}{d \ln r} + \frac{d \ln V_i}{d \ln r}. \quad (18)$$

In addition to the effect on the marginal costs as depicted in equation 17, a firm's price is affected by a change in its demand elasticity, which, as shown above, is a function of its market share. We construct the differential of the demand elasticity to again rearrange for its elasticity with respect to the robot rental rate and obtain

$$\frac{d \ln \epsilon_i(s)}{d \ln r} = -(\gamma - \sigma) \frac{\varphi_i(s)}{\epsilon_i(s)} \frac{d \ln \omega_i(s)}{d \ln r}, \quad (19)$$

which is a function of the elasticity of the market share with respect to the robot rental rate.

Effect on market shares. A firm's market share is defined as a relative measure of its profit-maximizing price to the price index of the sector it is active in. Thus, how a firm's market share reacts to decreasing prices of robots depends on its factor intensity draw, i.e., its output elasticity of robots ($1 - \theta_i$). The higher a firm's output elasticity for robots, the larger the magnitude of the price reduction effect. The firm with the highest output elasticity for robots in a given sector will experience the largest increase in market share in a given sector. We find the elasticity of the market share with respect to the robot rental rate based on equation 13, it takes the form

$$\frac{d \ln \omega_i(s)}{d \ln r} = (1 - \gamma) \left(\frac{d \ln p_i(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r} \right). \quad (20)$$

Since $\gamma > 1$, a firm's market share will increase in response to a reduction in the robot rental rate, if its own price decreases by more than the price index.

Effect on sectoral price indexes. The elasticity of the sectoral price index with respect to the robot rental rate can be written as a market share weighted sum of the changes in individual firm prices.² We can write it as

$$\frac{d \ln p(s)}{d \ln r} = \sum_{i=1}^n (s) \omega_i(s) \frac{d \ln p_i(s)}{d \ln r}. \quad (21)$$

Markups. The final step to fully gauge the effect of a change in the robot rental rate on a firm's markup is to combine the above derived elasticities. We again refer to the appendix for details and present the fully expanded solution for equation 19

$$\frac{d \ln \epsilon_i(s)}{d \ln r} = \frac{(\gamma - \sigma)(\gamma - 1)}{1 + \Omega_i} \frac{\varphi_i(s)}{\epsilon_i(s)} \left(1 - \theta_i - \frac{\sum_{i=1}^{n(s)} \varphi_i(s) \frac{1 - \theta_i}{1 + \Omega_i}}{\sum_{i=1}^{n(s)} \frac{\Omega_i}{1 + \Omega_i}} \right), \quad (22)$$

where $\Omega_i = \frac{(\gamma - \sigma)(\gamma - 1)}{\epsilon_i(s) - 1} \frac{\varphi_i(s)}{\epsilon_i(s)}$. Whether the demand elasticity increases (decreases) and therefore the markup decreases (increases) in response to a reduction in the rental rate depends on a firm's robot intensity relative to the average robot intensity in the same sector. We can distinguish between two cases

- i) If $(1 - \theta_i) > \frac{\sum_{i=1}^{n(s)} \varphi_i(s) \frac{1 - \theta_i}{1 + \Omega_i}}{\sum_{i=1}^{n(s)} \frac{\Omega_i}{1 + \Omega_i}}$ then $\frac{d \ln \epsilon_i(s)}{d \ln r} > 0$ and $\mu_i(s)$ increases in response to reduction in r ,
- ii) If $(1 - \theta_i) < \frac{\sum_{i=1}^{n(s)} \varphi_i(s) \frac{1 - \theta_i}{1 + \Omega_i}}{\sum_{i=1}^{n(s)} \frac{\Omega_i}{1 + \Omega_i}}$ then $\frac{d \ln \epsilon_i(s)}{d \ln r} < 0$ and $\mu_i(s)$ decreases in response to reduction in r .

²See appendix A.1.8

2.3 General equilibrium

In the general equilibrium, firms will adjust their factor demands according to the changes in the robot rental rate. With robots and labor being complementary in the production technology we introduce, a decrease in the rental rate of robots will lead to increased labor demand, which implies upward pressure on wages with supply being perfectly inelastic. The feedback on wages following a decline in the robot rental rate will thus further exacerbate the effect of market concentration, since higher wages affect firms inversely to their robot intensity. High robot intensity firms are thus relatively better off compared to low robot intensity firms not only because they benefit more from the decreased robot rental rate, but also, because they are less affected by the increase in wages.

2.4 Small open economy: foreign competition

We extend the model to a simple two-country case, in which intermediate good producing firms can sell to the final stage in the country foreign to them, in addition to selling to the final stage in their home economy. We use this simplistic two-country economy model to illustrate, what we call, the international competition effect. As we have seen in the one-country model, the domestic effect of a reduction in the robot rental rate will make the high-robot-intensity firms better off, because they will be able to reduce their marginal costs the most, allowing them to achieve higher market shares and markups while setting lower prices. We introduce fixed costs, that a firm must pay in order to gain access to the respective foreign market. Firms therefore choose to export based on their technology draws. Increasing robot use by foreign exporters will thus exert downward pressure on domestic firms' markups across all technology levels. Firms that were on the verge of benefiting from decreasing robot prices in the one-country economy are displaced by more productive, more robot-intense foreign competitors in the two-country economy. Overall, firms operating with above-average robot intensity will benefit from a reduction in the robot rental rate in both countries, while labor-intensive firms, i.e. firms with below-average robot-intensity, will be crowded out in both markets. In the following, we derive the effect of increased foreign competition for firm's domestic outcomes.

2.4.1 Intermediate good producers

Due to constant returns, the markup a firm generates in its home and foreign markets are the result of separate firm problems. A firm therefore faces two separate demand functions, one representing demand from its home market and one from its foreign

market. Demand for intermediate goods from domestic producers in the home market takes the form

$$y_i^H(s) = \left(\frac{p_i^H(s)}{p(s)} \right)^{-\gamma} \left(\frac{p(s)}{P} \right)^{-\sigma} Y, \quad (23)$$

while demand for intermediate goods from foreign producers in the home market is

$$y_i^F(s) = \left(\frac{p_i^F(s)}{p(s)} \right)^{-\gamma} \left(\frac{p(s)}{P} \right)^{-\sigma} Y. \quad (24)$$

Conceptually, the aggregate price index P remains unchanged from the one-country economy model. The sectoral prices $p(s)$ now include the prices of not only domestic but also foreign firms. Thus, the aggregate price index P now reflects the prices of domestic and foreign firms operating in the home country. This is illustrated by the two-country sectoral price index equation

$$p(s) = \left(\sum_{i=1}^{n(s)} p_i^H(s)^{1-\gamma} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} p_i^F(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}}, \quad (25)$$

where $\tau \geq 1$ depicts iceberg trade costs. A firm's market share in its home market is therefore determined not only by its competitiveness vis-à-vis domestic competitors, but also vis-à-vis foreign competitors operating in its home market, whose revenue enters in the denominator

$$\omega_i^H(s) = \frac{p_i^H(s)y_i^H(s)}{\sum_{i=1}^{n(s)} p_i^H(s)y_i^H(s) + \tau \sum_{i=1}^{n(s)} p_i^F(s)y_i^F(s)} = \left(\frac{p_i^H(s)}{p(s)} \right)^{1-\gamma}. \quad (26)$$

We also introduce fixed costs of exporting denoted f_x . Due to profit-maximizing behavior some firms select into exporting. The exporting decision for foreign firms can be written as

$$\left(p_i^F(s) - \frac{V_i}{\varphi_i(s)} \right) y_i^F(s) \geq f_x. \quad (27)$$

2.5 Reduction in the robot rental rate with foreign competition

Using the equations adapted for the two-countries case laid out in the previous section, we pursue a similar strategy as in the one-country economy to examine the effect of foreign robot adoption on home market firm outcomes. We construct a set of elasticities, that, in combination illustrate the effect of foreign robot adoption on home firms'

market shares and markups.

Effect on the domestic market share. In contrast to the one-country economy model, in the two-countries economy a firm's domestic market share is additionally determined by the prices of foreign competitors, as formulated in equation 26. In order to capture the full effect on firms' domestic market shares in the two-countries economy, we construct the market share elasticity with respect to the robot rental rate. It takes the form

$$\frac{d \ln \omega_i^H(s)}{d \ln r} = (1 - \gamma) \left(\frac{d \ln p_i^H(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r} \right). \quad (28)$$

The presence of foreign firms implies downward pressure on domestic firms' markups, if it increases the elasticity of the sector price with respect to the robot rental rate. More specifically, the sign of equation 28 remains negative as long as the elasticity of the firm price is larger than the elasticity of the sector price.

A negative sign implies that a decrease in the robot rental rate leads to an increase in the domestic market share of firm i . If the sector price elasticity were larger than the firm price elasticity, the sign of equation 28 were positive, which would imply that a decrease in the robot rental rate led to a decrease in firm i 's domestic market share. Therefore, the next step is to derive the elasticity of the sectoral price with respect to the robot rental rate.

Elasticity of the sector price index. The elasticity of the sectoral price with respect to the robot rental rate in the two-countries case takes the form

$$\frac{d \ln p(s)}{d \ln r} = \sum_{i=1}^{n(s)} \omega_i^H(s) \frac{d p_i^H(s)}{d \ln r} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) \omega_i^F(s) \frac{d p_i^F(s)}{d \ln r}, \quad (29)$$

where ϕ_i^F is a binary variable indicating firm activity, based on a firm's exporting decision formulated in equation 27. The summand on the right-hand side represents the effect of foreign firms on the sectoral price index in the home country. Depending on their technology draws, some foreign firms will be able to lower their profit-maximizing prices in response to a reduction in the robot rental rate, while others will not. If the presence of foreign firms increases the sector price elasticity, or in other words, if the right-hand summand is positive, this puts downward pressure on the market shares of domestic firms. Due to exporting fixed costs the firms selecting into exporting are more competitive than firms not selecting into exporting. Assuming symmetric countries and thereby equal technology distributions, the average active foreign firm in the home market will be more competitive than the average domestic firm.

Effect on demand elasticity. Recall, that a firm’s demand elasticity determines its markup, as shown in equation 14. Deriving the results for changes in markups therefore requires deriving changes in firms’ demand elasticities in response to changes in the robot rental rate. We construct the corresponding elasticity

$$\frac{d \ln e_i^H(s)}{d \ln r} = -(\gamma - \sigma) \frac{\omega_i^H(s)}{e_i^H(s)} \frac{d \ln \omega_i^H(s)}{d \ln r}, \quad (30)$$

which again depends on the change in a firm’s market share. Thus, if the presence of foreign firms causes a firm’s market share elasticity to change from a negative sign to a positive sign as discussed above, the sign of the demand elasticity equation formulated in equation 30 changes from negative to positive in response. In this case, a firm that would have benefited from the decrease in the robot rental rate in the one-country economy would lose in terms of market share and markups due to the adoption robot by foreign competitors.

In general, all domestic firms, regardless of their technology level, will experience downward pressure on market shares and markups as long as the foreign firms contribute to a decline in the sectoral price. For symmetric countries, this is the expected outcome, given the selection of above-average competitive firms into exporting.

3 Empirical Strategy

3.1 Markup Estimation

We estimate industry-level markups by slightly adapting the procedure developed by [De Loecker and Warzynski \(2012\)](#) to include robots in production. The firm-level data needed for the estimation comes from from [Worldscope](#). [Worldscope](#) contains financial statements for more than 80,000 companies worldwide. The sample consists mainly of publicly traded firms, with few privately held firms.³ Markups are the ratio of price (P) to marginal cost (MC) and are a direct measure of market power ([De Loecker et al., 2020](#)). The advantage of using markups instead of standard concentration indices such as the Herfindahl-Hirschman index is that the latter do not measure market power when there is product differentiation ([De Loecker et al., 2020](#)) and that one would require data on all firms in the market, which we do not have. The method builds on the observation that markups can be estimated using expenditure shares and output elasticities, which follows from standard cost minimization via a Lagrange function. Markups can thus be expressed as

³[De Loecker and Eeckhout \(2018\)](#) use the same data and perform some robustness tests to ensure that the selection of firms in the data does not lead to biased results.

$$\mu_{ist} = \frac{P_{ist}}{MC_{ist}} = \frac{\theta_{it}^V}{\alpha_{ist}^V},$$

where θ_{ist}^V is the output elasticity of variable input V and α_{ist}^V is the expenditure share on input V of firm i in sector s at year t . The expenditure shares are directly be observable in the data.

To obtain output elasticities, we estimate a Cobb-Douglas production function separately for each industry, following [De Loecker and Eeckhout \(2018\)](#). Unfortunately, since we do not have information about robots in the firm-level *Worldscope* data, but only at the sector level, it is not possible for us to directly estimate firm-level robot output elasticities. To adhere as much as possible to the established procedure for estimating markups on the one hand, and to incorporate robots in the markups estimation on the other hand, we alter the standard production function used for the markup estimation in [De Loecker and Eeckhout \(2018\)](#) by adding sector level robots. The result is a production function that extends the one introduced in the theoretical part of this paper including labor l and the stock of robots R , by variable inputs v , and capital k . We argue that omitting variable inputs v and capital k in the estimation equation could raise omitted variable bias concerns and thus include them in the estimation. The resulting Cobb-Douglas production function takes the form

$$q_{ist} = \beta_v v_{ist} + \beta_k k_{ist} + \beta_l l_{ist} + \beta_r R_{st} + \omega_{ist} + \epsilon_{ist}$$

with q denoting output and all variables being in logs and deflated.⁴ Unobserved productivity is given by ω . Estimating the production function yields output elasticities β . The estimation follows [Akerberg et al. \(2015\)](#), who use a control function approach to overcome simultaneity bias between input demand and unobserved productivity. In a first step, expected output (ϕ_{ist}) is estimated

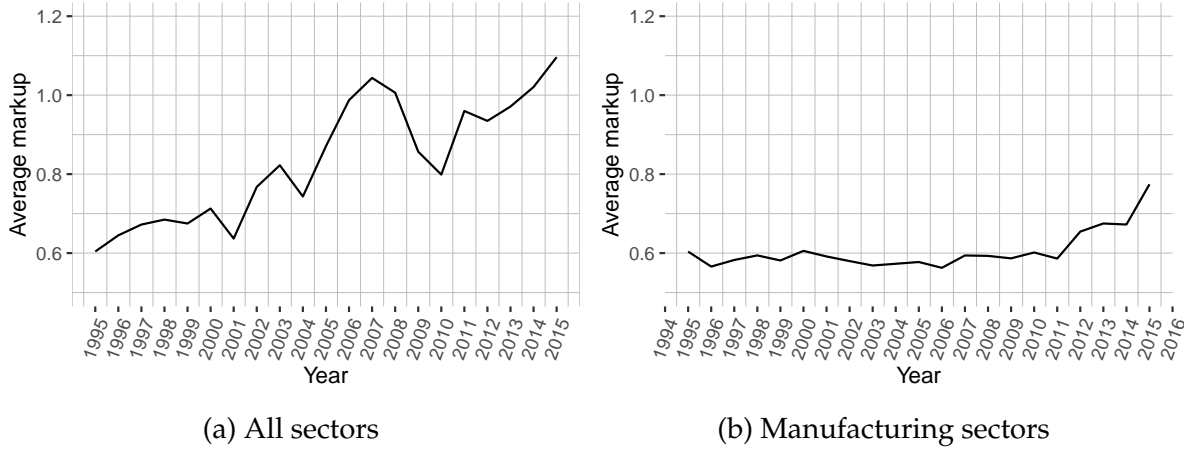
$$q_{ist} = \phi_t(v_{ist}, k_{ist}, l_{ist}, R_{st}, z_{ist}) + \epsilon_{ist},$$

where z are other variables that affect the demand for variable inputs (we use a set of fixed effects to control for other variables) and ϵ_{ist} is the residual of estimating expected output. Following the authors, we correct for variation in expenditure not correlated to variables impacting input demand using ϵ_{ist} : $\hat{\alpha}_{ist}^V = \frac{P_{ist}^V V_{ist}}{P_{ist} \hat{Q}_{ist} / \exp(\hat{\epsilon}_{ist})}$, where we use a set of fixed effects to control for other variables that affect the demand for variable inputs.

Next, the inverse demand of variable input $h_t(\cdot)$ is used to rewrite expected output as

⁴We obtain capital, price and GDP deflators from Worldbank's WDI and OECD's STAN database.

Figure 1: Estimated average markups over time for all sectors versus manufacturing sectors using Worldscope data.



$$\phi_{ist} = \beta_v v_{ist} + \beta_k k_{ist} + \beta_l l_{ist} + \beta_r R_{st} + h_t(v_{ist}, k_{ist}, l_{ist}, R_{st}, z_{ist}).$$

With the expected output, productivity can be computed as $\omega_{ist}(\beta) = \hat{\phi}_{ist} - \beta_v v_{ist} - \beta_k k_{ist} - \beta_l l_{ist} - \beta_r R_{st}$ (De Loecker and Warzynski, 2012). The productivity innovation ζ_{ist} is recovered by non-parametrically regressing $\omega_{ist}(\beta)$ on its lag. With this, all coefficients of the production function can be obtained through GMM with the moment conditions

$$E \left(\zeta_{ist}(\beta) \begin{pmatrix} v_{ist-1} \\ k_{ist} \\ l_{ist-1} \\ R_{st-1} \end{pmatrix} \right) = 0. \quad (31)$$

The output elasticity of variable input v is then given by $\theta_{st} = \hat{\beta}_v$.

After estimating markups at the firm level, we aggregate them to the sector level. In the main specification, we weight each markup by the firm's share of industry output. As a robustness test, we use the average markups as a measure. Figure 1 shows that markups have steadily increased over the past decades and, that our markup estimates are similar to those of De Loecker and Eeckhout (2018). In panel 1b, we plot the evolution of markups in the manufacturing sector only. While markups have increased after 2011, there is not as strong an overall upward trend as in panel . This suggests that the service sector was largely responsible for the strong markup increases between 1995 and 2015 (Lashkari et al., 2018; Autor et al., 2020).

3.2 Estimation Equation

To estimate the impact of automation on markups and other outcomes related to market power and concentration, we first employ a simple regression model

$$y_{cst} = \alpha_{cst} + \beta_R R_{cst} + \beta_\chi \chi_{cst} + \gamma_{cs} + \delta_{ct} + \eta_{st} + \epsilon_{cst}, \quad (\text{E.1})$$

where c denotes the country, s the sector, t the year and the outcome of interest is y_{cst} . R_{cst} is the stock of domestic robots per 1000 workers. In addition, χ_{cst} represents a vector of control variables, γ_{cs} country sector fixed effects, δ_{ct} country year fixed effects and η_{st} sector year fixed effects.⁵ Thus, we observe changes only within sectors of countries over time, while controlling for all other larger-scale developments and characteristics.

Data on the stock of robots by country, industry, and year are obtained from the International Federation of Robotics (IFR). The IFR provides the annual number of "multi-purpose industrial robots"⁶ installations at the country, industry and application levels ([International Federation of Robotics, 2018](#)). Industries are defined at the three-digit or two-digit level according to ISIC classifications.

Estimation equation E.1 already gives a first indication of the relationship between automation and markups. However, the choice to use robots in production is likely to be endogenous to markups. For instance industries with higher markups could have more resources to employ robots. Therefore, we use an IV approach to obtain exogenous variation in robot uptake. Following the current literature, we argue that the global stock of robots is likely to be exogenous to single industries, and represents the overall decline in robot prices ([Graetz and Michaels, 2018](#); [Artuc et al., 2019](#)). We construct a similar but novel IV,

$$R_{cst}^{IV} = R_t^G \frac{O_{cs}}{L_{cs}} I_c,$$

which interacts the global stock of robots R^G with country- and sector-level predictors of the degree of automation. The fraction O_{cs}/L_{cs} , output per worker of sector s in country c in 1995, reflects the *potential* of a sector to employ robots. The source of these data are the OECD's ICIO tables and the OECD's Annual Labor Force Statistics ([OECD, 2021, 2023](#)), respectively. I is a measure of technological *capacity* in 1990, developed by [Archibugi and Coco \(2004\)](#). Thus, our IV exploits exogenous variation over time and

⁵Our main controls are the number of patents and the capital stock, both of which we take from the Worldscope database, and net exports, which we take from the OECD ICIO.

⁶A robot is defined by ISO 8373:2012 as an automatically controlled, re-programmable, multi-purpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications ([International Federation of Robotics, 2018](#))

cross-sectional capabilities to install automation technologies.

In our main specification we estimate equation E.1 in a two-stage procedure, where R_{cst} is instrumented with R_{cst}^{IV} in the first stage. Given the data requirements, we are able to estimate the equation for 29 countries and 20 sectors, between 1995 and 2015. However, we do not have a complete panel for all combinations of countries and sectors.

In a second step, we test the theoretical predictions made in section 2.5 and include a measure of foreign robot competition in our model. Following De Benedictis and Tajoli (2007a,b), we construct a similarity index for the correlation between sectoral exports between two countries of the following form:

$$m_{cdst} = 1 - \frac{\sum_{ps} |x_{cst} - x_{dst}|}{\sum_{ps} x_{cst} + x_{dst}}.$$

Within each sector s , the index compares the exports of two countries c and d over a range of products p in each year t .⁷ The resulting index is bounded between 0 and 1, where the closer it is to 1, the more similar the exports of two countries are in that sector.

We expect that the more similar the domestic and foreign economies are, the greater the competition from foreign robots. Therefore, to construct a measure of foreign automation, we weight the stock of foreign robots per worker R_{dst} by the similarity index, which yields a competition-weighted measure of foreign robots F_{cst} :

$$F_{cst} = \sum_d m_{cds} R_{dst}.$$

We can therefore test for the differential effects of domestic and foreign automation by including F_{cst} in the estimation equation E.1.

3.3 Automation and Markups

In this section, we test the theoretical predictions of the model, by estimating how an increase in automation has affected markups. As laid out in section 2, automation is likely to affect firms differently depending on their level of productivity. We start with estimating how increasing usage of robots affects markups and other measures of market power domestically, before moving to the effects of foreign automation. We thereby establish a complete picture of the effects of automation on market power.

Table 1 presents the results of estimating equation E.1 with an OLS model. In all specifications, the standard errors are two-way clustered at the country and sector level.

⁷We use exports at the 4-digit level from Comtrade, over our 18 sectors.

The outcome is the logarithm of markups, where industry-level markups are obtained by weighting each firm's markup by its share of sales in the industry total. In the first two columns, the regressions are run over all sectors, while in the latter two only manufacturing sectors are examined. Columns 2 and 3 add industry-level production and net exports in logarithms as controls. The coefficient on the stock of robots per worker is statistically significant in all specifications and indicates a negative relationship between the stock of robots and average markups on average. The effect is stronger for manufacturing sectors.

As laid out above, a firm's market power reflects idiosyncratic characteristics of firms that are associated with the likelihood of robot adoption. The results are thus likely to be biased by reverse causality and we therefore use an IV approach to obtain unbiased estimates. As outlined in section 3.2, we address the endogeneity in the decision to automate by using an instrumental variable. The results of the first-stage regression are presented in Table 2. While the instrumental variable is not significant for all sectors, it is highly significant and has a positive coefficient for the manufacturing sectors. This is not surprising, as industrial robots are almost exclusively used in manufacturing production. The inclusion of the control variable does not change the coefficient or the precision of the instrument. The instrument is therefore a valid predictor of robot adoption.

Table 3 shows the results of the second-stage. The first thing to note is that the Kleibergen-Paap F-statistic is low with all sectors, but is above the usual thresholds in the manufacturing sectors, indicating that the instrument is not valid in the service and agricultural sectors, as found in Table 2.

As in the OLS setting, the stock of domestic robots has a negative and statistically significant coefficient. Since the coefficient is free of endogeneity concerns, we can now interpret the coefficient as a causal effect. The coefficient on the stock of robots is statistically significant and negative throughout. In columns 3 and 6, we add the logarithm of the number of patents at the industry-level as well as the logarithmized industry-level capital stock. The number of patents controls for the industry's innovation capacity and the capital stock for the overall capital intensity, both of which are correlated with the adoption of robots. The inclusion of the additional control variables reduces the sample size because the variables are not available for all observations, but the coefficient in column 6 remains statistically significant at the 1% level. Thus, a larger stock of robots appears to reduce industry markups, on average. This finding points to a distribution of technology across firms which according to our model (section 2) suggests that: New technology benefits only a few firms at the expense of others, leading to an average negative effect on markups. The effect of automation on markups is substantial: A one standard deviation increase in the stock of robots per worker reduces

average markups by 17%.

To examine whether it is only high-productivity and high-sales firms which benefit from automation, we split the firms in our sample into quintiles within each sector, based on their sales and markups in the previous year, to obtain a fuller picture of the distributional effects of automation.⁸ Autor et al. (2016) show that the rise of markups is driven by "superstar" firms. Furthermore, in another recent study using a similar setting, Stiebale et al. (2020) find no effect of automation on markups for manufacturing firms on average, but an increase for the highest quintile of firms.

In Table 4, the level of observation is now sector-quintiles. The first column reproduces the previous results at the alternative level of observation. In columns 2 and 3, we interact the sales quintile with the domestic stock of robots and the corresponding instrument. The same procedure is repeated in columns 4 and 5, using firms' markups to construct quintiles. In both settings, and in line with the current literature (Stiebale et al., 2020), we also find that the decline in average markups is driven by firms in the lowest 3 quintiles. Conversely, firms in the top quintile experience an increase in markups.⁹

This suggests interesting within-industry heterogeneity. The largest and most productive firms are able to reap disproportional benefits from automation. At the same time, less productive firms face greater competition due to the lower production costs of automating firms. As a consequence, markups of these firms decrease.

To see whether this pattern is driven by individual industries, we disaggregate the manufacturing sector in Table A3. We run the quintile-level analysis for each individual industry. The Table shows that most sectors have a similar pattern. Although the estimation power is limited due to the smaller number of observations, the coefficient of the interaction between the stock of robots and the highest quintile is positive in almost all industries. Similarly, the coefficients of the first and second quintile are almost entirely negative. Notably, there are negative and statistically significant coefficients in the computer electronics industry.

3.4 Alternative Outcomes

Having provided evidence above that domestic automation reduces average markups, we now turn to alternative outcomes related to output and market concentration.

First, in Table 5, we examine how automation affects production and exports. Produc-

⁸For observations without information on the previous year, we use sales and markups of the same year.

⁹We find the same pattern when estimating markups using a translogirathmized instead of a Cobb-Douglas function. Table A2 shows that robots have, on average, a negative effect on markups estimated in this way, and that the negative effect is driven by lower quantiles.

tion increases with a larger stock of robots (columns 1 and 2), as might be expected and as has been found, for example, by [Graetz and Michaels \(2018\)](#) and [Koch et al. \(2019\)](#). Net exports, on the other hand, are not affected by automation.¹⁰ Table A1 in the appendix displays firms' sales as an outcome, based on quintiles by their sales and markups in the previous year. The results show that the average decline is again driven by the firms in the lowest quintile, which are less likely to install robots in production and thus face more competition. As with markups, more productive firms benefit from automation.

Next, we turn to alternative measures of market concentration. First, in columns 1 and 2 of Table 6, we find no changes in the total number of firms in a sector associated with an increased robot adoption. It should be noted, however, that the sample size here is relatively small, as data on the number of firms are not available for all countries.

In columns 3 and 4, we examine how prices are affected by automation. We find a negative association between the stock of robots and prices in the baseline setting and with additional controls, which supports the previous results. Robotization reduces sectoral prices and only the most productive firms benefit due to lower marginal costs. Lastly, we use firms' operating margin as an alternative measure of markups. Firms report their operating margin directly in the *Worldscope* data, which eliminates the possibility of estimation error.¹¹ The coefficient on the stock of robots per worker is again statistically significant and even larger in size, both in the baseline setting and with additional controls. Our results are thus robust to alternative measures of markups.

3.5 Foreign Automation

Having established that domestic automation reduces average industry level markups, driven by low-sales, and low-markup firms, we now turn to the question of how foreign automation affects domestic markups. Our theoretical model predicts that foreign automation will depress domestic markups, due to increased competition through lower production costs abroad.

Table 7 presents the results of including the foreign weighted robot measure F_{cst} (see section 3.2) into our estimation equation E.1. We focus on the manufacturing sectors, as these were found to drive our previously found results. The coefficient of foreign-weighted robots is statistically significant and negative throughout. Adding controls in column 2 doesn't change the coefficient. While including the domestic stock of robots in column 3 reduces the size of the coefficient, it remains statistically significant at the

¹⁰The same holds true for the log of exports, rather than the log of net exports.

¹¹The operating margin is defined as the operating income divided by net sales.

5% level. Moreover, The finding is robust to the inclusion of additional controls.

Compared to domestic automation, we expect that increasing competition from foreign automating firms will not only affect lower productivity and smaller firms. Indeed, in the fully specified model with sales quintiles we find a decrease in markups along the entire distribution of firms, as shown in column 2 of Table 8. With quintiles based on markups, we find a statistically significant effect only for the fourth quintile. In contrast to the previous results, it is rather the firms in the middle quintiles that experience a larger reduction in markups. These firms seem to face the strongest competition from foreign firms.

Foreign automation thus seems to put additional strain on domestic firms, but not only on the smallest ones. Competition from foreign producers, which can reduce their production costs, reduces the market power and market share of domestic firms. Table 8 provides further evidence of this pattern. While domestic automation leads to larger industry-level production, competition to foreign automation is associated with lower production levels. No effect is found for net exports.

While exporting firms face greater competition from foreign firms that can produce at lower costs, increased production by the latter could increase demand for inputs. Therefore, foreign automation may have countervailing effects. Increased demand for inputs may spur prices and output of input-providing firms. We therefore add an additional measure of exposure to foreign robots in Table A4, which captures input-output linkages. We weight each foreign sector's stock of robots per worker by the share of input exports (imports) from a domestic sector to the respective foreign sector.¹² In columns 1 and 2, we weight foreign robots with imports and in columns 3 and 4 with exports. Contrary to domestic robots and similarity-weighted foreign robots, the coefficient of input-trade-weighted foreign robots is positive. However, the coefficients are only statistically significant when not including additional control variables and thereby losing observations. Moreover, the coefficient of export-weighted foreign robots is larger in both magnitude and statistical significance than the the coefficient of import-weighted robots. Therefore, input-providing firms appear to profit from automation abroad.

On the one hand, finding a positive coefficient for trade-weighted foreign robots reinforces confidence that we are indeed capturing increasing competition with our similarity-weighted robot measure. It also shows that automation affects different types of firms differently. Those which compete with automating firms are crowded out, while firms that provide inputs to these firms are may benefit from their increased production.

¹²Data on input exports and imports are taken from the OECD's ICIO database.

Table 1: Automation and markups - OLS

	All sectors		Only manufacturing	
	(1)	(2)	(3)	(4)
Stock of robots p.w.	-0.049*** (0.01)	-0.047*** (0.01)	-0.052*** (0.02)	-0.050*** (0.02)
Observations	4580	4185	3354	3354
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls		✓		✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The stock of robots per worker is mean standardized to a standard deviation of one. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Markups are aggregated on the industry level by each firm's share of sales. Regressions run from 1995 to 2016.

Table 2: Automation IV - First stage

	All sectors		Only manufacturing	
	(1)	(2)	(3)	(4)
Robot IV	0.716 (0.43)	0.688 (0.42)	1.170*** (0.21)	1.123*** (0.20)
Observations	4530	4155	3354	3354
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls		✓		✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The stock of robots per worker is mean standardized to a standard deviation of one. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Regressions run from 1995 to 2016.

Table 3: Automation and markups - IV

	All sectors			Only manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
Stock of robots p.w.	-0.246** (0.11)	-0.245** (0.10)	-0.237** (0.10)	-0.176*** (0.02)	-0.183*** (0.02)	-0.172*** (0.02)
Observations	4530	4155	3628	3354	3354	2843
Country × Sector Dummies	✓	✓	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓	✓	✓
Controls		✓	✓		✓	✓
Additional Controls			✓			✓
KP F-Statistic	2.77	2.65	2.9	31.8	30.8	57.5

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The stock of robots per worker is mean standardized to a standard deviation of one. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Markups are aggregated on the industry level by each firm's share of sales. Regressions run from 1995 to 2016.

Table 4: Automation and markups - Quintile regressions

	(1)	Sales-quintiles		Markup-quintiles	
		(2)	(3)	(4)	(5)
Stock of robots p.w.	-0.004** (0.00)				
1. Quintile × Stock of robots p.w.		-0.016*** (0.01)	-0.013** (0.00)	-0.035** (0.01)	-0.037** (0.01)
2. Quintile × Stock of robots p.w.		-0.011*** (0.00)	-0.009*** (0.00)	-0.018** (0.01)	-0.018** (0.01)
3. Quintile × Stock of robots p.w.		-0.006*** (0.00)	-0.005** (0.00)	-0.004** (0.00)	-0.003 (0.00)
4. Quintile × Stock of robots p.w.		0.003 (0.00)	0.005 (0.00)	0.012* (0.01)	0.015** (0.01)
5. Quintile × Stock of robots p.w.		0.014* (0.01)	0.015** (0.01)	0.033* (0.02)	0.039** (0.01)
Observations	11654	11641	10389	11618	10365
Country × Sector Dummies	✓	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Additional Controls			✓		✓
KP F-Statistic	29	.835	1	.858	.998

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. Quintiles are based on firms' sales in the previous year in columns 2 and 3 and on firms' markups in the previous year in columns 4 and 5. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table 5: Automation, production and exports

	log Production		log Exports	
	(1)	(2)	(3)	(4)
Stock of robots p.w.	0.199*** (0.02)	0.156*** (0.02)	1.845 (1.89)	1.239 (1.45)
Observations	3353	2842	3353	2842
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Additional Controls		✓		✓
KP F-Statistic	31.2	59.7	31.3	58.3

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The stock of robots per worker is mean standardized to a standard deviation of one. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the log industry production in columns 1 and 2 and the log net exports in columns 3 and 4. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table 6: Automation and alternative outcomes

	log Number of Firms		log Output Prices		log Operating Margin	
	(1)	(2)	(3)	(4)	(5)	(6)
Stock of robots p.w.	-0.032 (0.35)	0.423 (0.28)	-0.137* (0.07)	-0.140* (0.07)	-0.622*** (0.21)	-0.838*** (0.17)
Observations	1565	1282	2637	2216	2365	1932
Country × Sector Dummies	✓	✓	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Additional Controls		✓		✓		✓
KP F-Statistic	9.63	10.3	21.5	31.6	13.7	26.5

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The stock of robots per worker is mean standardized to a standard deviation of one. The sample consists of manufacturing sectors only. All outcome variables are measured in logs. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Markups are aggregated on the industry level by each firm's share of sales. Regressions run from 1995 to 2016.

Table 7: Foreign automation and markups

	Only manufacturing sectors			
	(1)	(2)	(3)	(4)
Foreign weighted robots	-0.033*** (0.01)	-0.035*** (0.01)	-0.015** (0.01)	-0.022** (0.01)
Stock of robots p.w.			-0.046** (0.02)	-0.047** (0.02)
Observations	3354	3354	3354	2843
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls		✓	✓	✓
Additional Contols				✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. The weighted foreign robot stock and the stock of domestic robots per worker are mean standardized to a standard deviation of one. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Markups are aggregated on the industry level by each firm's share of sales. Regressions run from 1995 to 2016.

Table 8: Foreign automation and markups - Quintile regressions

	Sales-quintiles		Markup-quintiles	
	(1)	(2)	(3)	(4)
1. Quintile \times Stock of robots p.w.	-0.004*** (0.00)	-0.003** (0.00)	-0.007*** (0.00)	-0.008*** (0.00)
2. Quintile \times Stock of robots p.w.	-0.002** (0.00)	-0.002 (0.00)	-0.003*** (0.00)	-0.004*** (0.00)
3. Quintile \times Stock of robots p.w.	-0.001 (.)	-0.001 (0.00)	-0.001 (0.00)	-0.002* (0.00)
4. Quintile \times Stock of robots p.w.	0.003*** (0.00)	0.003** (0.00)	0.003*** (0.00)	0.004** (0.00)
5. Quintile \times Stock of robots p.w.	0.004** (0.00)	0.006** (0.00)	0.007*** (0.00)	0.010** (0.00)
1. Quintile \times Foreign weighted robots	-0.002 (.)	-0.011** (0.01)	0.003 (0.02)	-0.004 (0.02)
2. Quintile \times Foreign weighted robots	-0.013 (0.01)	-0.025** (0.01)	0.003 (0.02)	-0.007 (0.01)
3. Quintile \times Foreign weighted robots	-0.013 (0.01)	-0.022** (0.01)	-0.002 (0.01)	-0.011 (0.01)
4. Quintile \times Foreign weighted robots	-0.019** (0.01)	-0.038*** (0.01)	-0.010 (0.01)	-0.031* (0.02)
5. Quintile \times Foreign weighted robots	0.006 (0.01)	-0.023** (0.01)	-0.007 (0.02)	-0.042 (0.03)
Observations	11641	10389	11618	10365
Country \times Sector Dummies	✓	✓	✓	✓
Country \times Year Dummies	✓	✓	✓	✓
Sector \times Year Dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Additional Controls		✓		✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. Quintiles are based on firms' sales in the previous year in columns 2 and 3 and on firms' markups in the previous year in columns 4 and 5. The sample consists of only manufacturing sectors. The coefficients of foreign robot exposure are displayed in 1000s, to ensure visibility. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table 9: Foreign automation, production and exports

	log Production		log Exports	
	(1)	(2)	(3)	(4)
Stock of robots p.w.	0.106*** (0.03)	0.087*** (0.03)	1.127 (0.78)	1.059 (0.84)
Foreign weighted robots	-0.094*** (0.03)	-0.081*** (0.02)	-0.132 (1.04)	0.553 (0.77)
Observations	3353	2842	3353	2842
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Additional Controls		✓		✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. Coefficients of foreign robot exposure are displayed in 1000s, to ensure visibility. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the log industry production in columns 1 and 2 and the log net exports in columns 3 and 4. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

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Appendices

A Appendix

A.1 Theory

A.1.1 One-country economy

A.1.2 Intermediate goods producers

Profit-maximization-problem of the final good producer.

$$PY - \int_0^1 \left(\sum_{i=1}^{n(s)} p_i(s) y_i(s) \right) ds. \quad (\text{A1})$$

Demand for intermediate goods. The relative demand for two varieties i and j within the same sector s is given by:

$$\frac{y_i(s)}{y_j(s)} = \left(\frac{p_i(s)}{p_j(s)} \right)^{-\gamma}. \quad (\text{A2})$$

We multiply with the price of one variety and aggregate over $n(s)$ varieties within a sector:

$$\begin{aligned} p_i(s) y_i(s) &= p_j(s)^\gamma y_j(s) p_i(s)^{1-\gamma}, \\ \sum_{i=1}^{n(s)} p_i(s) y_i(s) &= p(s) y(s) = p_j(s)^\gamma y_j(s) \sum_{i=1}^{n(s)} p_i(s)^{1-\gamma}. \end{aligned}$$

By taking into account the definition of the price index (5), we obtain the demand for one variety:

$$\begin{aligned} p(s) y(s) &= p_j(s)^\gamma y_j(s) p(s)^{1-\gamma}, \\ y_j(s) &= \left(\frac{p_j(s)}{p(s)} \right)^{-\gamma} y(s). \end{aligned} \quad (\text{A3})$$

Combining equation A3 with the demand function for one sector leads to:

$$y_j(s) = \left(\frac{p_j(s)}{p(s)} \right)^{-\gamma} \left(\frac{p(s)}{P} \right)^{-\sigma} Y. \quad (\text{A4})$$

A.1.3 One country economy - reduction in the robot rental rate

A.1.4 Effect on marginal costs

Marginal costs of a firm i :

$$V_i = w^{\theta_i} r^{1-\theta_i} \theta_i^{-\theta_i} (1 - \theta_i)^{\theta_i-1} \quad (\text{A5})$$

The total differential of marginal costs V_i with respect to changes of endogenous variables can be derived as follows:

$$dV_i = \theta_i w^{\theta_i-1} dw r^{1-\theta_i} \theta_i^{-\theta_i} (1 - \theta_i)^{\theta_i-1} + w^{\theta_i} (1 - \theta_i) r^{-\theta_i} dr \theta_i^{-\theta_i} (1 - \theta_i)^{\theta_i-1}$$

The change of θ_i can be neglected, as this is an exogenous firm-specific draw. We can simplify the total differential by using the definition of marginal costs V_i :

$$dV_i = \theta_i w^{-1} dw V_i + V_i^{-1} (1 - \theta_i) dr$$

$$\frac{d \ln V_i}{d \ln r} = \frac{dV_i}{dr} \frac{r}{V_i} = \theta_i \frac{d \ln w}{d \ln r} + (1 - \theta_i)$$

A.1.5 Effect on price

The optimal price of a firm is given by

$$\begin{aligned} p_i(s) &= \frac{\epsilon_i(s)}{\epsilon_i(s) - 1} \frac{V_i}{\varphi_i} \\ \frac{dp_i(s)}{dr} &= \frac{\frac{d\epsilon_i(s)}{dr} (\epsilon_i(s) - 1) - \epsilon_i \frac{d\epsilon_i(s)}{dr}}{(\epsilon_i(s) - 1)^2} \frac{V_i}{\varphi_i} + \frac{\epsilon_i(s)}{\epsilon_i(s) - 1} \frac{dV_i}{dr} \frac{1}{\varphi_i} \\ \frac{dp_i(s)}{dr} &= - \frac{1}{\epsilon_i(s) - 1} \frac{p_i(s)}{\epsilon_i(s)} \frac{d\epsilon_i(s)}{dr} + p_i(s) \frac{dV_i}{dr} \frac{1}{V_i} \\ \frac{d \ln p_i(s)}{d \ln r} &= - \frac{1}{\epsilon_i(s) - 1} \frac{d \ln \epsilon_i(s)}{d \ln r} + \frac{d \ln V_i}{d \ln r} \end{aligned}$$

A.1.6 Effect on demand elasticity

In the Bertrand version of the model, the demand elasticity is defined as

$$\begin{aligned} \epsilon_i(s) &= \gamma(1 - \omega_i(s)) + \sigma \omega_i(s) \\ \frac{d\epsilon_i(s)}{dr} &= -(\gamma - \sigma) \frac{d\omega_i(s)}{dr} \\ \frac{d \ln \epsilon_i(s)}{d \ln r} &= -(\gamma - \theta) \frac{\omega_i(s)}{\epsilon_i(s)} \frac{d \ln \omega_i(s)}{d \ln r} \end{aligned}$$

We now use the expression of the market share

$$\begin{aligned}\omega_i(s) &= \left(\frac{p_i(s)}{p(s)}\right)^{1-\gamma} \\ \frac{d\omega_i}{dr} &= (1-\gamma) \left(\frac{p_i(s)}{p(s)}\right)^{-\gamma} \frac{\frac{dp_i(s)}{dr} p(s) - p_i(s) \frac{dp(s)}{dr}}{p(s)^2} \\ \frac{d\omega_i(s)}{dr} &= (1-\gamma) \left(\frac{p_i(s)}{p(s)}\right)^{1-\gamma} \left(\frac{d \ln p_i(s)}{dr} - \frac{d \ln p(s)}{dr}\right) \\ \frac{d \ln \omega_i(s)}{d \ln r} &= (1-\gamma) \left(\frac{d \ln p_i(s)}{dr} - \frac{d \ln p(s)}{dr}\right)\end{aligned}$$

A.1.7 Summary of effects

$$\frac{d \ln p_i(s)}{d \ln r} = -\frac{1}{\epsilon_i(s) - 1} \frac{d \ln \epsilon_i(s)}{d \ln r} + \frac{d \ln V_i}{d \ln r} \quad (\text{A6})$$

$$\frac{d \ln V_i}{d \ln r} = (1 - \theta_i) > 0 \quad (\text{A7})$$

$$\frac{d \ln \epsilon_i(s)}{d \ln r} = -\gamma(\gamma - \sigma) \frac{\omega_i(s)}{\epsilon_i(s)} \frac{d \ln \omega_i(s)}{d \ln r} \quad (\text{A8})$$

$$\frac{d \ln \omega_i(s)}{d \ln r} = (1 - \gamma) \left(\frac{d \ln p_i(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r}\right) \quad (\text{A9})$$

Combining eqs. A6 and A7 leads to:

$$\frac{d \ln p_i(s)}{d \ln r} = -\frac{1}{\epsilon_i(s) - 1} \frac{d \ln \epsilon_i(s)}{d \ln r} + (1 - \theta_i) \quad (\text{A10})$$

Combining eqs. A8 and A9 leads to:

$$\frac{d \ln \epsilon_i(s)}{d \ln r} = (\gamma - \sigma)(\gamma - 1) \frac{\omega_i(s)}{\epsilon_i(s)} \left(\frac{d \ln p_i(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r}\right) \quad (\text{A11})$$

Inserting eq. A11 into eq. A10 leads to:

$$\frac{d \ln p_i(s)}{d \ln r} = -\frac{1}{\epsilon_i(s) - 1} (\gamma - \sigma)(\gamma - 1) \frac{\omega_i(s)}{\epsilon_i(s)} \left(\frac{d \ln p_i(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r}\right) + (1 - \theta_i)$$

$$\frac{d \ln p_i(s)}{d \ln r} \left(1 + \frac{(\gamma - \sigma)(\gamma - 1) \omega_i(s)}{\epsilon_i(s) - 1} \frac{\omega_i(s)}{\epsilon_i(s)}\right) = \frac{(\gamma - \sigma)(\gamma - 1) \omega_i(s)}{\epsilon_i(s) - 1} \frac{d \ln p(s)}{d \ln r} + (1 - \alpha_i)$$

Define $\Omega = \frac{(\gamma - \sigma)(\gamma - 1) \omega_i(s)}{\epsilon_i(s) - 1} \frac{\omega_i(s)}{\epsilon_i(s)}$, so that

$$\begin{aligned}\frac{d \ln p_i(s)}{d \ln r} &= \frac{1 - \theta_i}{1 + \Omega_i} + \frac{\Omega_i}{1 + \Omega_i} \frac{d \ln p(s)}{d \ln r} \\ \frac{d \ln \epsilon_i}{d \ln r} &= (\gamma - \sigma)(\gamma - 1) \frac{\omega_i(s)}{\epsilon_i(s)} \left(\frac{1 - \theta_i}{1 + \Omega_i} + \frac{\Omega_i}{1 + \Omega_i} \frac{d \ln p(s)}{d \ln r} - \frac{d \ln p(s)}{d \ln r} \right) \\ \frac{d \ln \epsilon_i(s)}{d \ln r} &= \frac{(\gamma - \sigma)(\gamma - 1)}{1 + \Omega_i} \frac{\omega_i(s)}{\epsilon_i(s)} \left(1 - \theta_i - \frac{d \ln p(s)}{d \ln r} \right)\end{aligned}$$

A.1.8 Sector price

The sector price is defined as

$$\begin{aligned}p(s) &= \frac{1}{1 - \gamma} \left(\sum_{i=1}^{n(s)} p_i(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \\ \frac{dp(s)}{dr} &= \left(\sum_{i=1}^{n(s)} p_i(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}-1} (-1) \sum_{i=1}^{n(s)} p_i(s)^{-\gamma} \frac{dp_i(s)}{dr}\end{aligned}$$

The derivative takes into account that all prices adjust to a change in the rental rate.

$$\begin{aligned}\frac{dp(s)}{dr} &= p(s) \left(\sum_{i=1}^{n(s)} p_i(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma}-1} \sum_{i=1}^{n(s)} p_i(s)^{-\gamma} \frac{dp_i(s)}{dr} \\ \frac{d \ln p(s)}{d \ln r} &= \sum_{i=1}^{n(s)} \left(\frac{p_i(s)}{p(s)} \right)^{1-\gamma} \frac{d \ln p_i(s)}{d \ln r}\end{aligned}$$

Note, that $\left(\frac{p_i(s)}{p(s)} \right)^{1-\gamma} = \omega_i(s)$, so

$$\frac{d \ln p(s)}{d \ln r} = \sum_{i=1}^{n(s)} \omega_i(s) \frac{d \ln p_i(s)}{d \ln r}$$

Thus, the change in the sector price is a weighted sum of changes in firm prices, where the weights are the respective market shares of goods. We now insert the reaction of a firm's price into the response of the sector price:

$$\begin{aligned}
\frac{d \ln p_i(s)}{d \ln r} &= \frac{1 - \theta_i}{1 + \Omega_i} + \frac{\Omega_i}{1 + \Omega_i} \frac{d \ln p(s)}{d \ln r} \\
\frac{d \ln p(s)}{d \ln r} &= \sum_{i=1}^{n(s)} \omega_i(s) \left(\frac{1 - \theta_i}{1 + \Omega_i} + \frac{\Omega_i}{1 + \Omega_i} \frac{d \ln p(s)}{d \ln r} \right) \\
\frac{d \ln p(s)}{d \ln r} - \sum_{i=1}^{n(s)} \omega_i(s) \frac{\Omega_i}{1 + \Omega_i} \frac{d \ln p(s)}{d \ln r} &= \sum_{i=1}^{n(s)} \omega_i(s) \frac{1 - \theta_i}{1 + \Omega_i} \\
\frac{d \ln p(s)}{d \ln r} &= \frac{\sum_{i=1}^{n(s)} \omega_i(s) \frac{(1 - \theta_i)}{1 + \Omega_i}}{1 - \sum_{i=1}^{n(s)} \omega_i(s) \frac{\Omega_i}{1 + \Omega_i}}
\end{aligned}$$

Next, we insert the reaction of the sectoral price into the response of a firm's price:

$$\begin{aligned}
\frac{d \ln p_i(s)}{d \ln r} &= \frac{1 - \theta_i}{1 + \Omega_i} \frac{\Omega_i}{1 + \Omega_i} \frac{\sum_{i=1}^{n(s)} \omega_i(s) \frac{(1 - \theta_i)}{1 + \Omega_i}}{1 - \sum_{i=1}^{n(s)} \omega_i(s) \frac{\Omega_i}{1 + \Omega_i}} \\
\frac{d \ln p_i(s)}{d \ln r} &= \frac{1}{1 + \Omega_i} \left(1 - \theta_i + \Omega_i \frac{\sum_{i=1}^{n(s)} \omega_i(s) \frac{(1 - \theta_i)}{1 + \Omega_i}}{1 - \sum_{i=1}^{n(s)} \omega_i(s) \frac{\Omega_i}{1 + \Omega_i}} \right)
\end{aligned}$$

We then insert the reaction of the sectoral price into the response of a firm's markup:

$$\begin{aligned}
\frac{d \ln \epsilon_i(s)}{d \ln r} &= \frac{(\gamma - \sigma)(\gamma - 1)}{1 + \Omega_i} \frac{\omega_i(s)}{\epsilon_i(s)} \left(1 - \theta_i - \frac{d \ln p(s)}{d \ln r} \right) \\
\frac{d \ln \epsilon_i(s)}{d \ln r} &= \frac{(\gamma - \sigma)(\gamma - 1)}{1 + \Omega_i} \frac{\omega_i(s)}{\epsilon_i(s)} \left(1 - \theta_i - \frac{\sum_{i=1}^{n(s)} \omega_i(s) \frac{(1 - \theta_i)}{1 + \Omega_i}}{1 - \sum_{i=1}^{n(s)} \omega_i(s) \frac{\Omega_i}{1 + \Omega_i}} \right)
\end{aligned}$$

The markup effect depends on the size of $1 - \theta_i$ relative to the weighted average of $1 - \theta_i$ across all firms in sector s .

A.1.9 Two-countries economy

Derivation of the sector price elasticity with respect to the robot rental rate.

$$\begin{aligned}
\frac{dp(s)}{dr} &= \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{1-\gamma} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{1-\gamma} \right)^{\frac{1}{1-\gamma} - 1} \\
&\quad \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{-\gamma} \frac{dp_i^H(s)}{dr} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{-\gamma} \frac{dp_i^F(s)}{dr} \right)
\end{aligned}$$

$$\frac{dp(s)}{dr} = p(s) \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{1-\gamma} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{1-\gamma} \right)^{-1} \\ \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{-\gamma} \frac{dp_i^H(s)}{dr} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{-\gamma} \frac{dp_i^F(s)}{dr} \right)$$

$$\frac{d \ln p(s)}{d \ln r} = \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{1-\gamma} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{1-\gamma} \right)^{-1} \\ \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{-\gamma} \frac{dp_i^H(s)}{d \ln r} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{-\gamma} \frac{dp_i^F(s)}{d \ln r} \right)$$

$$\frac{d \ln p(s)}{d \ln r} = \frac{1}{p(s)^{1-\gamma}} \left(\sum_{i=1}^{n(s)} \phi_i^H(s) p_i^H(s)^{-\gamma} \frac{dp_i^H(s)}{d \ln r} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) p_i^F(s)^{-\gamma} \frac{dp_i^F(s)}{d \ln r} \right)$$

$$\frac{d \ln p(s)}{d \ln r} = \sum_{i=1}^{n(s)} \phi_i^H(s) \frac{p_i^H(s)^{1-\gamma}}{p(s)^{1-\gamma}} \frac{dp_i^H(s)}{d \ln r} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) \frac{p_i^F(s)^{1-\gamma}}{p(s)^{1-\gamma}} \frac{dp_i^F(s)}{d \ln r}$$

$$\frac{d \ln p(s)}{d \ln r} = \sum_{i=1}^{n(s)} \phi_i^H(s) \omega_i^H(s) \frac{dp_i^H(s)}{d \ln r} + \tau^{1-\gamma} \sum_{i=1}^{n(s)} \phi_i^F(s) \omega_i^F(s) \frac{dp_i^F(s)}{d \ln r}$$

A.2 Empirical Analysis

Table A1: Automation and sales - Quintile regressions

	Sales-quintiles		Markup-quintiles	
	(1)	(2)	(3)	(4)
1. Quintile \times Stock of robots p.w.	-0.337** (0.15)	-0.336** (0.14)	-0.092** (0.04)	-0.056 (0.03)
2. Quintile \times Stock of robots p.w.	-0.125** (0.06)	-0.117* (0.06)	-0.053* (0.03)	-0.026 (0.02)
3. Quintile \times Stock of robots p.w.	0.038** (0.01)	0.052*** (0.02)	0.027 (0.02)	0.053*** (0.01)
4. Quintile \times Stock of robots p.w.	0.186** (0.07)	0.225*** (0.07)	0.086** (0.03)	0.103*** (0.03)
5. Quintile \times Stock of robots p.w.	0.369** (0.15)	0.408*** (0.13)	0.115** (0.05)	0.123* (0.06)
Observations	11641	10389	11618	10365
Country \times Sector Dummies	✓	✓	✓	✓
Country \times Year Dummies	✓	✓	✓	✓
Sector \times Year Dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Additional Controls		✓		✓
KP F-Statistic	.832	1	.843	.998

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. Quintiles are based on firms' sales in the previous year in columns 2 and 3 and on firms' markups in the previous year in columns 4 and 5. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table A2: Automation and Markups - Translog function

	(1)	(2)
Stock of robots p.w.	-0.149*** (0.02)	
1. Quintile \times Stock of robots p.w.		-0.009** (0.00)
2. Quintile \times Stock of robots p.w.		-0.005** (0.00)
3. Quintile \times Stock of robots p.w.		-0.002 (0.00)
4. Quintile \times Stock of robots p.w.		0.003 (0.00)
5. Quintile \times Stock of robots p.w.		0.007* (0.00)
Observations	2842	10389
Country \times Sector Dummies	✓	✓
Country \times Year Dummies	✓	✓
Sector \times Year Dummies	✓	✓
Controls	✓	✓
Additional Controls	✓	✓
KP F-Statistic	57.5	1

Notes: In this table, markups are estimated with a translog function. Standard errors, in parentheses, are two-way clustered on the country and sector level. Quintiles are based on firms' sales in the previous year. The sample consists of manufacturing sectors only. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table A3: Automation and markups - industry-level quintile regressions

	Food, beverages and tobacco	Textiles and leather products	Other manufacturing	Paper and printing	Chemicals and pharmaceuticals	Rubber and plastic	Mineral products
1. Quintile × Stock of robots p.w.	0.063 (0.17)	-0.616 (1.78)	-0.012 (0.06)	0.191 (0.48)	-0.016 (0.01)	-0.015 (0.01)	-0.084 (0.13)
2. Quintile × Stock of robots p.w.	0.058 (0.17)	-0.707 (2.02)	-0.007 (0.05)	0.201 (0.50)	-0.009 (0.01)	-0.013 (0.01)	-0.049 (0.14)
3. Quintile × Stock of robots p.w.	0.076 (0.16)	-0.388 (2.02)	0.024 (0.05)	0.315 (0.51)	-0.009 (0.01)	-0.010 (0.01)	-0.035 (0.13)
4. Quintile × Stock of robots p.w.	0.122 (0.17)	0.065 (1.89)	0.038 (0.05)	0.422 (0.51)	-0.003 (0.01)	-0.001 (0.01)	0.027 (0.15)
5. Quintile × Stock of robots p.w.	0.152 (0.17)	0.439 (1.75)	0.090 (0.06)	0.518 (0.50)	0.002 (0.01)	0.008 (0.02)	0.084 (0.15)
Observations	1152	732	792	756	1196	416	527
	Basic metals	Fabricated metals	Computer electronics	Electrical equipment	Machinery and equipment	Automotive	Other vehicles
1. Quintile × Stock of robots p.w.	-0.073 (0.04)	0.089 (0.09)	-0.055** (0.02)	-0.034 (0.09)	-0.062 (0.06)	-0.000 (0.01)	-0.998 (1.19)
2. Quintile × Stock of robots p.w.	-0.063 (0.04)	0.099 (0.10)	-0.041** (0.01)	-0.030 (0.09)	-0.052 (0.06)	-0.001 (0.01)	-0.926 (1.14)
3. Quintile × Stock of robots p.w.	-0.054 (0.04)	0.096 (0.09)	-0.046** (0.02)	-0.023 (0.09)	-0.043 (0.06)	0.000 (0.01)	-0.991 (1.22)
4. Quintile × Stock of robots p.w.	-0.027 (0.05)	0.103 (0.09)	-0.023 (0.02)	-0.014 (0.09)	-0.027 (0.06)	0.002 (0.01)	-0.894 (1.13)
5. Quintile × Stock of robots p.w.	-0.020 (0.05)	0.113 (0.09)	0.004 (0.03)	0.005 (0.09)	0.007 (0.06)	0.007 (0.01)	-0.401 (1.02)
Observations	675	545	875	982	1048	413	295
Country Dummies	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors, in parentheses, are clustered on the country level. Quintiles are based on firms' sales in the previous year. All specifications include country dummies and year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table A4: Trade-weighted foreign automation and markups

	Import weighted		Export weighted	
	(1)	(2)	(3)	(4)
Stock of robots p.w.	-0.052*** (0.01)	-0.053*** (0.02)	-0.054*** (0.02)	-0.052** (0.02)
Foreign weighted robots	-0.035*** (0.00)	-0.039*** (0.01)	-0.021*** (0.00)	-0.025*** (0.01)
Export weighted foreign robots	0.032** (0.01)	0.025 (0.02)		
Import weighted foreign robots			0.018* (0.01)	0.011 (0.01)
Observations	3354	2843	3354	2843
Country × Sector Dummies	✓	✓	✓	✓
Country × Year Dummies	✓	✓	✓	✓
Sector × Year Dummies	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Additional Controls		✓		✓

Notes: Standard errors, in parentheses, are two-way clustered on the country and sector level. All variables are mean standardized to a standard deviation of one. All specifications include country sector dummies, country year dummies and sector year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.

Table A5: Foreign automation and markups - industry-level quintile regressions

	Food, beverages and tobacco	Textiles and leather products	Other manufacturing	Paper and printing	Chemicals and pharmaceuticals	Rubber and plastic	Mineral products
1. Quintile × Foreign weighted robots	-0.629 (0.48)	-15.527*** (3.70)	-0.121 (0.35)	-3.494 (4.00)	0.064 (0.59)	-0.066 (0.09)	-2.618** (0.79)
2. Quintile × Foreign weighted robots	-0.514 (0.47)	-24.368*** (6.10)	0.367 (0.27)	-6.541* (3.42)	-0.513 (0.58)	0.006 (0.09)	-2.752** (0.92)
3. Quintile × Foreign weighted robots	-0.580 (0.44)	-9.853*** (2.97)	0.226 (0.34)	-4.912 (2.85)	-0.336 (0.57)	0.103 (0.09)	-3.403*** (0.71)
4. Quintile × Foreign weighted robots	-0.658 (0.41)	2.157 (13.34)	0.273 (0.23)	-0.463 (3.00)	-0.120 (0.55)	0.103 (0.10)	-2.290* (1.06)
5. Quintile × Foreign weighted robots	-0.245 (0.38)	26.492** (10.51)	0.005 (0.48)	0.777 (2.55)	0.153 (0.51)	0.288** (0.10)	2.153 (3.95)
Observations	1152	732	792	756	1196	416	527
	Basic metals	Fabricated metals	Computer electronics	Electrical equipment	Machinery and equipment	Automotive	Other vehicles
1. Quintile × Foreign weighted robots	0.249 (0.20)	0.167 (0.12)	-0.118 (0.09)	0.101 (0.07)	0.268 (0.58)	-0.001 (0.02)	-1.884* (0.96)
2. Quintile × Foreign weighted robots	0.082 (0.15)	0.253* (0.14)	-0.141* (0.07)	0.091 (0.06)	0.016 (0.64)	0.001 (0.01)	-2.217 (1.27)
3. Quintile × Foreign weighted robots	0.134 (0.16)	0.243 (0.14)	-0.034 (0.05)	0.104* (0.05)	0.098 (0.54)	-0.007 (0.01)	-0.917 (1.22)
4. Quintile × Foreign weighted robots	0.190 (0.23)	0.265 (0.16)	0.003 (0.04)	0.048 (0.07)	0.408 (0.63)	-0.007 (0.01)	-0.244 (0.93)
5. Quintile × Foreign weighted robots	0.068 (0.31)	0.367** (0.16)	0.044 (0.06)	0.014 (0.10)	1.704*** (0.49)	0.010 (0.01)	1.699** (0.60)
Observations	675	545	875	982	1048	413	295
Country Dummies	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors, in parentheses, are clustered on the country level. Quintiles are based on firms' sales in the previous year. All specifications include country dummies and year dummies. Controls are the logs of net exports and industry production. Additional controls are the log number of patents and the log capital stock. Regressions run from 1995 to 2016.