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Robots, Reshoring, and the Lot of Low-Skilled Workers

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Robots, Reshoring, and the Lot of Low-Skilled Workers*

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Abstract. We propose a theoretical framework to analyze the offshoring and reshoring decisions of firms in the age of automation. Our theory suggests that increasing productivity in automation leads to a relocation of previously offshored production back to the home economy but without improving low-skilled wages and without creating jobs for low-skilled workers. Since it leads also to increasing wages for high-skilled workers, automation-induced reshoring is associated with an increasing skill premium and increasing inequality. We develop a measure for reshoring activity at the macro-level and, using data from the world input output table, we provide evidence for automation-driven reshoring. On average, within manufacturing sectors, an increase by one robot per 1000 workers is associated with a 3.5% increase of reshoring activity. Using robots in countries with similar sectoral structure as an instrument, we find that an increase by one robot per 1000 workers causes a 2.5% increase of reshoring activity. We also provide the first cross-country evidence that reshoring is positively associated with wages and employment for high-skilled labor but not for low-skilled labor and that tariffs increase the degree of reshoring.

Keywords: Automation, Reshoring, Employment, Wages, Inequality, Tariffs.

JEL: F13, F62, J31, O33.

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Trade reform and the negotiation of great trade deals is the quickest way to bring our jobs back to our country.[1]
(Donald Trump, 2016)

1. Introduction

The notion that jobs are lost because of the globalization-driven relocation of domestic firms to foreign countries and that jobs can be brought back by re-negotiating trade deals seems to be gaining ground in the political arena. Most prominently, it has been expressed by the U.S. president, as mentioned, for example, in the introductory quote. First enactments of these trade deals appeared in form of drastically increasing tariffs on U.S. imports from Germany, China, and other countries. From a theoretical perspective, however, there are reasons to doubt the bold claims that are often made. One of the reasons for being skeptical is that automation more and more replaces labor in the production of manufactured goods and that a re-location of manufacturing from low-wage countries back to high-wage countries might just go hand-in-hand with more automation and not with significant job creation.

An interesting example of re-location of manufacturing to high-wage countries is the case of Adidas, a German sportswear manufacturer. After years in which the production of sports shoes had been offshored mainly to China, Indonesia, and Vietnam, the firm built two new factories for trainers, one in Germany and one in the U.S. Most of the production in these newly established factories, however, is performed by automated computerized processes, industrial cutting robots, and 3D printers. Only about 160 workers are employed in such a factory for tasks that are still difficult to automate. This compares with at least 1000 workers in a comparable factory in Asia. Moreover, most of the tasks performed by humans in the automated firms are concerned with maintaining the robots and are performed by high-skilled workers (The Economist, 2017).

There exists plenty of further suggestive evidence on the robots-reshoring nexus from narratives and survey data samples. The Reshoring Initiative (2019), for example, collects data on reshoring announcements by U.S. headquartered companies. It mentions 961 companies that shifted production back to the U.S. between 2010 and 2017, about 75 percent of these companies are from China. Automation and additive manufacturing is one of the motivating factors

[1]See the transcript of the election campaign stop in Monessen, Pennsylvania on June 28, 2016: `http://time.com/4386335/donald-trump-trade-speech-transcript/` [accessed on July 5, 2017].

that increased significantly over this period. The European Reshoring Monitor (2019) lists 235 companies that reshored production to EU member states between 2014 and May 2019 of which about one third are reshored from China.

In this paper, we attempt to address the robots-reshoring nexus in a more general and systematic way, both theoretically and empirically. In the theory part, we develop a new economic model to analyze the effects of automation on reshoring, wages, employment, and inequality. Our framework is able to capture the most salient features of U.S. economic development since the 1970s: i) a sustained rise in per capita GDP (Jones, 2015), ii) a strong increase in the college wage premium (Acemoglu 2002; Goldin and Katz, 2008), iii) stagnating and even falling wages of low-skilled workers (Acemoglu and Autor, 2012; Autor, 2014) and, in combination with rising incomes of the better educated, an increase in wage inequality (Piketty, 2014), iv) offshoring of labor intensive production to low-wage countries (Grossman and Rossi-Hansberg, 2008), v) an uptick in reshoring to the extent that firms started to relocate production from abroad to the home country most recently (Chu et al., 2013; The Economist, 2013), vi) a rise in automation in terms of an increasing stock of industrial robots (Graetz and Michaels, 2015; Acemoglu and Restrepo, 2017), and vii) a reduction in average annual hours worked (Hazan, 2009; Jones, 2015).

Regarding the stylized facts iv) and v), the first academic study that explained the U-shaped relationship between offshoring and development over time is Chu et al. (2013). This study extends the offshoring framework of Grossman and Rossi-Hansberg (2008) to include the use of physical capital in the country to which production is offshored. Initially, the poorer country has a much lower capital stock such that it also exhibits much lower wages. This represents the main incentive for firms to offshore labor-intensive tasks to the poor country. Over time, physical capital accumulates in the poorer country. This leads to rising wages and thereby lowers the incentive for domestic firms to offshore production. At some point, the positive effect on offshoring due to the decrease in the capital rental rate in the destination country that comes with physical capital accumulation is overcompensated by the negative effect of the associated increase in wages. At that stage, reshoring starts and firms move back to the domestic economy. Overall, there appears a U-shaped relationship between economic development and offshoring over time.

Here, we present a complementary mechanism for the observed pattern of offshoring and reshoring, which is based on the effects of automation in the home country. In the 1970s, when the number of industrial robots used worldwide was negligible, the only way to save on the wage bill for labor-intensive manufacturing goods was to offshore part of the production to low-wage countries. In the 1990s, the number of industrial robots took off and it increased significantly over the last decade (see IFR, 2015). At the same time, robots, 3D printers, and devices based on machine learning have become better at performing the tasks of labor (see, for example, Acemoglu and Restrepo, 2019, 2020; Frey and Osborne, 2013, 2017; Brynjolfsson and McAfee, 2016). Improving productivity in automated processes provides an incentive for firms to reshore parts of their production in order to save tariffs and other costs of producing away from the home market. Because the tasks that are reshored are primarily carried out by automated processes such as industrial robots and 3D printers, reshoring does not generate new jobs or raise the wages of low-skilled workers. Low-skilled wages decline in response to increasing productivity from robots while wages of high-skilled workers, who perform mainly tasks that complement automated processes, benefit from increasing productivity. This implies a rise in the skill premium and in overall inequality. In conjunction with elastic labor supply, we furthermore expect reshoring to be associated with increasing employment of high-skilled labor and deteriorating employment of low-skilled labor.

In the empirical section we provide the first evidence in favor of these mechanisms. For that purpose we combine the World Input Output Database (WIOD) with data on the stock of robots from the International Federation of Robotics (IFR). We develop a measure for reshoring activity at the macro-level and find that, on average, within manufacturing sectors, an increase by one robot per 1000 workers is associated with a 3.5% increase of reshoring intensity. We corroborate these results using an instrumental variable regression framework. Using robots in countries with similar sectoral structure as an instrument, we find that an increase by one robot per 1000 workers causes a 2.5% increase of reshoring activity. We also provide the first cross-country evidence that reshoring improves wages and employment for high-skilled labor but not for low-skilled labor and that an increase in tariffs increases the degree of reshoring.

The rest of the paper is structured as follows. In Section 2, we design a model of production in the age of automation in which firms have the option to produce parts of an assembled final good at home or abroad. In Section 3, we solve the model and derive the mechanisms sketched above in a set of propositions. In Section 4, we illustrate these results with a numerical example. In section 5, we provide evidence for the suggested mechanisms, as outlined above. In Section 6, we conclude and draw some lessons for policymakers.

2. The Model

Consider a country endowed with a measure L_s of high-skilled workers and a measure L_u of low-skilled workers. At any time t, a representative firm assembles an aggregate consumption good Y_t by using high-skilled labor and a measure of size one of differentiated intermediate goods. Intermediates can be produced with low-skillled labor at home or abroad or with automated production (industrial robots, 3D printers) at home. In order to focus on the reshoring problem, we take the evolution of automation technology as exogenous.[2] For the basic model we consider a one sector economy. We later extend the model with a service sector and also briefly discuss a multi-sector economy.

Suppose there is a measure of size one of firms producing intermediate goods. Firms are ordered by the efficiency (productivity) of automated processes in production. Specifically, let q_t be the continuous firm-specific efficiency of automation in production and let $x(q_t)$ denote the quantity of an intermediate input in final goods production. Then, assuming a Cobb-Douglas technology, final goods production is given by:

$$Y_t = L_s^{1-\epsilon} \cdot \int_{Q_t}^{Q_t+1} x(q_t)^{\epsilon} \mathrm{d}q_t, \tag{1}$$

where $\epsilon \in (0,1)$ is the elasticity of output with respect to intermediate inputs. A straightforward interpretation is that Y_t refers to appliances, $x(q_t)$ to intermediate parts, and L_s to engineers who assemble the appliances by using the intermediate parts. The lower bound of the integral in equation (1) is denoted by Q_t, which refers to the efficiency in automation of the least productive firm. As a consequence of our setup, the upper bound of the integral is $Q_t + 1$, which refers to the efficiency in automation of the most productive firm. When Q_t rises, the efficiency of automated processes rises for all intermediate goods producers.

[2] In a companion paper (Prettner and Strulik, 2020), we analyze endogenous automation in an R&D-based growth model of a closed economy and show how innovation-driven growth leads to increasing automation, a higher skill premium, a larger population share of graduates, rising income and wealth inequality, and increasing unemployment.

Referring to the final good as the numéraire and normalizing its price to unity, profit maximization implies that the wage rate for high-skilled workers amounts to

$$w_{s,t} = (1-\epsilon)L_s^{-\epsilon} \cdot \int_{Q_t}^{Q_t+1} x_t(q_t)^{\epsilon} \mathrm{d}q_t = (1-\epsilon)\frac{Y_t}{L_s}. \tag{2}$$

The wage rate for high-skilled workers increases with aggregate output but decreases with the number of high-skilled workers employed at home. The inverse demand functions for intermediate parts $x_t(q_t)$ are given by

$$p_t = \epsilon L_s^{1-\epsilon} x_t^{\epsilon-1}, \tag{3}$$

where we omit the quality index of intermediates from now on to save notation.

Each intermediate variety is produced by one differentiated firm. Firms can choose to produce either at home – in which case we denote the output level of the corresponding intermediate part by $x_{H,t}$ – or abroad – in which case we denote the output level of the corresponding intermediate part by $x_{F,t}$. When producing at home, the firm has access to a production technology of the form

$$x_{H,t} = (l_{u,t} + q_t \cdot a_t)^{\alpha}, \tag{4}$$

where $l_{u,t}$ denotes the amount of low-skilled labor that is recruited from the domestic workforce, $\alpha \in (0,1)$ is the elasticity of output with respect to low-skilled labor input, and a_t denotes automation capital used by the particular firm. Automation capital is a perfect substitute for labor by its very definition (Merriam-Webster, 2017). A straightforward interpretation is that low-skilled labor refers to assembly line workers and automation capital to industrial robots. Depending on the productivity-adjusted wage of low-skilled workers and the productivity-adjusted price of industrial robots, the firm decides which of these two production factors it employs. If the productivity-adjusted wage of low-skilled workers is lower (higher) than the productivity-adjusted price of industrial robots, the firm only employs workers (robots).

In contrast to the production structure at home, firms that produce abroad have access to a production technology of the form

$$x_{F,t} = (l_{F,t})^{\alpha}, \tag{5}$$

where $l_{F,t}$ denotes the amount of low-skilled labor recruited from the foreign workforce. We assume that wages of low-skilled workers abroad are exogenously given and lower than at home because labor is abundant abroad. This assumption captures a central characteristic of low-income regions and it represents the main driving force behind offshoring (Grossman and Rossi-Hansberg, 2008; Chu et al., 2013). There are no robots employed abroad because of the abundance of labor and the associated low wages such that the incentive to automate production is limited (see Abeliansky and Prettner, 2017; Acemoglu and Restrepo, 2018). Firms producing in the poor area face tariffs τ and other trade costs σ if they ship their goods to the home market.[3] We model these costs as iceberg costs such that the amount $\tau\sigma$ of the specific intermediate good $x_{F,t}$ has to be shipped from abroad in order for one unit to arrive at home, $\sigma \geq 1$, $\tau \geq 1$.

For simplicity, we assume that all goods face the same tariff τ and that other trade costs can assume two values, high and low; $\sigma \in \{\sigma_L, \sigma_H\}$, $\sigma_H > \sigma_L$. We assume that σ is independently distributed from automation efficiency q_t and constant over time. The share of firms with high trade costs is denoted by ϕ, $0 < \phi < 1$. This is a minimum setup to construct a world in which some goods are easier offshored than others and offshoring and home-production are observed simultaneously. In the Appendix we show that all main results are robust to the introduction of a continuous distribution of σ. In the Appendix we also briefly discuss the case were σ depends negatively on q, implying that products that are easier automated are also easier codifiable and thus easier offshored. The trade costs σ comprise shipping costs but they also proxy other aspects that make production near to the home market attractive. For example, important motives for reshoring are to increase quality and flexibility through proximity to the home market.

A unit of automation capital is produced from η units of raw capital. For simplicity, we assume that the price of raw capital, r, is exogenously given by the world interest rate. Putting all the information together, firms make the following profits, depending on whether they produce at home or abroad:

$$\pi_{H,t} = p_t \left(l_{u,t} + q_t a_t\right)^{\alpha} - w_{u,t} l_{u,t} - \eta r a_t = \epsilon L_s^{1-\epsilon} \left(l_{u,t} + q_t a_t\right)^{\alpha\epsilon} - w_{u,t} l_{u,t} - \eta r a_t, \tag{6}$$

$$\pi_{F,t} = \frac{p_t}{\tau\sigma} \left(l_{F,t}\right)^{\alpha} - w_F l_{F,t} = \frac{\epsilon L_s^{1-\epsilon}}{\tau\sigma} l_{F,t}^{\alpha\epsilon} - w_F l_{F,t}, \tag{7}$$

[3] We abstract from considering the demand for $x_{F,t}$ that originates in the poor area itself. Our results would not change qualitatively if we allowed for a positive demand within the poor area as long as demand within the poor area would be lower than demand within the rich area for each price level. This condition is generally fulfilled because it follows directly from the definition of the poor country. We also abstract from including a fixed cost of offshoring in order to obtain an analytically solvable problem.

where $w_{u,t}$ and w_F are the wages for low-skilled workers at home and abroad. The time index shows that the wage at home is an endogenous variable, whereas the wage abroad is exogenous and taken parametrically.[4]

Firms choose employment of workers and industrial robots to maximize profits. The first-order conditions for an interior solution at home are:

$$\frac{\partial \pi_{H,t}}{\partial l_{u,t}} = \alpha\epsilon^2 L_s^{1-\epsilon} \left(l_{u,t} + q_t a_t\right)^{\alpha\epsilon-1} - w_{u,t} = 0,$$
$$\frac{\partial \pi_{H,t}}{\partial a_t} = \alpha\epsilon^2 L_s^{1-\epsilon} q_t \left(l_{u,t} + q_t a_t\right)^{\alpha\epsilon-1} - \eta r = 0.$$

Both first-order conditions can hold simultaneously only for the special case in which

$$q_t = q_{L,t} \equiv \frac{\eta r}{w_{u,t}}. \tag{8}$$

This means that q_L is an automation threshold at which firms are indifferent between producing with industrial robots or with workers. If producing at home, firms facing a quality index below q_L prefer to employ low-skilled labor and firms facing a quality index above q_L prefer to employ robots.

Given that a firm produces at home with labor, we solve the first-order condition to obtain employment of low-skilled workers as given by equation (9) below. In case a firm produces at home with automated production, we obtain employment of robots as in equation (10). Analogously, given that a firm produces abroad, we obtain from the first-order condition associated with equation (7), employment abroad as given by equation (11):

$$l_{u,t} = \left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}, \tag{9}$$
$$a_t = \left(\frac{\eta r}{\alpha\epsilon^2 L_s^{1-\epsilon} q_t}\right)^{\frac{1}{\alpha\epsilon-1}} \cdot \frac{1}{q_t}, \tag{10}$$
$$l_{F,t} = \left(\frac{w_F \tau\sigma}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}. \tag{11}$$

Note that the exponent $1/(\alpha\epsilon - 1)$ is negative and larger than 1 in absolute terms because $\alpha \cdot \epsilon \in (0, 1)$. Equation (9) implies that, ceteris paribus, firms would employ fewer low-skilled

[4]By assuming that the world interest rate and the wage abroad are given, the model may be considered not to be general-equilibrium at the world level. If the world interest rate or the wage abroad were affected by the automation decision of domestic firms, we would obtain feedback effects (of second-order magnitude) on the domestic automation decision. These feedback effects could dampen but not overturn the results.

workers if their wages ($w_{u,t}$) were higher but they would employ more low-skilled workers if there were more high-skilled workers (L_s) in the final goods sector. The reason is that an increase in the number of high-skilled workers raises the demand for intermediate parts such that intermediate goods producers would want to raise their output. Equation (10) implies that firms would, ceteris paribus, want to raise their stock of automation capital if the productivity of automation (q_t) were higher and if the price of robots (ηr) were lower. Again, an increase in the number of high-skilled workers would raise demand for intermediates and, thus, induce firms to employ more industrial robots. Finally, equation (11) implies that, ceteris paribus, an increase in the foreign wage rate (w_F) and a rise in tariffs or other trade costs ($\tau\sigma$) would deter firms from offshoring production, while an increase in high-skilled workers would raise the demand for intermediates and hence reinforce the incentives to offshore.

3. Results

In making the production location decision, firms in the intermediate goods producing sector compare profits when producing at home with profits when producing abroad. In case that profits when producing at home are higher than when producing abroad ($\pi_{H,t} > \pi_{F,t}$), there is no incentive for offshoring and the corresponding firms stay at home. By contrast, in case that profits when producing at home are lower than when producing abroad ($\pi_{H,t} < \pi_{F,t}$), there is an incentive for offshoring and the corresponding firms move abroad. Finally, in case that firms have chosen to offshore in the past because the profits when producing at home were lower than the profits when producing abroad ($\pi_{H,t} < \pi_{F,t}$) at some point in time $t < \hat{t}$ and then the situation reversed ($\pi_{H,t} > \pi_{F,t}$) after automation has become economically feasible for $t > \hat{t}$, the corresponding firms have an incentive to reshore.

Inserting employment (9) - (11) into the expressions for profits as given by equations (6) and (7), we obtain

$$\pi_{H,L,t} = \epsilon(1-\alpha\epsilon)L_s^{1-\epsilon}\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{\alpha\epsilon}{\alpha\epsilon-1}}, \tag{12}$$

$$\pi_{H,A,t} = \epsilon(1-\alpha\epsilon)L_s^{1-\epsilon}\left(\frac{\eta r}{\alpha\epsilon^2 L_s^{1-\epsilon} q_t}\right)^{\frac{\alpha\epsilon}{\alpha\epsilon-1}}, \tag{13}$$

$$\pi_{F,t} = \frac{\epsilon(1-\alpha\epsilon)L_s^{1-\epsilon}}{\tau\sigma}\left(\frac{w_F(\tau\sigma)}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{\alpha\epsilon}{\alpha\epsilon-1}}, \tag{14}$$

where $\pi_{H,L,t}$ denotes profits when producing at home with labor and $\pi_{H,A,t}$ denotes profits when producing at home with robots. Comparing profits (12) and (14), we find that firms employing labor prefer to offshore if

$$w_{u,t} > w_F \cdot (\tau\sigma)^{1/(\alpha\epsilon)}. \tag{15}$$

This means that if the wage abroad is sufficiently lower than the wage at home, firms would choose to offshore to save on the wage bill. The amount by which the wage at home needs to exceed the wage abroad for offshoring to be a viable business strategy depends on tariffs and other trade costs: the higher these costs are, the larger the wage gap needs to be for firms to move abroad. Comparing profits (13) and (14), we find that firms are indifferent between offshoring and automated production at home for

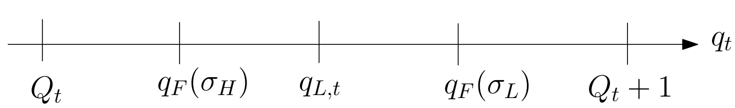
$$q_t = q_F(\sigma) \equiv \frac{\eta r}{w_F \cdot (\tau\sigma)^{1/(\alpha\epsilon)}}. \tag{16}$$

Firms endowed with productivity $q_t > q_F(\sigma)$ prefer automated production at home against offshoring. We write the threshold as a function of σ to indicate that goods with high transport costs face a lower threshold, $q_F(\sigma_H) < q_F(\sigma_L)$. Comparing the thresholds (8), (15), and (16), we observe the following.

Lemma 1. *A world in which all 3 modes of production, home production with low-skilled labor, offshoring, and automation are observed simultaneously requires the ordering* $q_F(\sigma_H) < q_{L,t} < q_F(\sigma_L)$.

For the proof, notice that $q_F(\sigma) < q_L \Leftrightarrow w_u < w_F(\tau\sigma)^{1/(\alpha\epsilon)}$. Thus, if both $q_F(\sigma_H)$ and $q_F(\sigma_L)$ were smaller than q_L, there would be no offshoring. If both were greater, there would be no production at home. In the following, we mainly focus on the intermediate case in which all modes of production are observed because this seems to approximate best the real world. Figure 1 displays the production choice of firms for different productivity levels in automation.

FIGURE 1. Home Production, Offshoring, and Automation



Since the measure of firms is one, we can read off the share of firms in the three production modes. Firms with $q_t > q_{L,t}$ prefer automation over home production with low-skilled labor. Of these firms, those with highest productivity in automation, i.e., those with $q_t > q_F(\sigma_L)$, prefer automation over offshoring regardless of trade costs while those with medium productivity, i.e., those with $q_F(\sigma_L) > q_t > q_{L,t}$, prefer automation only if they have high trade costs. This is a share $\phi[q_F(\sigma_L) - q_{L,t}]$ of firms. Altogether, the share of automated firms is then $\theta_{A,t} = Q_t + 1 - q_F(\sigma_L) + \phi[q_F(\sigma_L) - q_{L,t}]$.

Firms with $q_t < q_{L,t}$ do not automate and their decision on offshoring vs. home production is independent from automation efficiency q_t. A share ϕ of these firms faces high trade costs and produces at home such that the share of firms producing at home with low-skilled labor is given by $\theta_{L,t} = \phi(q_{L,t} - Q_t)$. Consequently, the share of offshored firms, which are all characterized by low trade costs, is given by the residual as

$$\theta_{F,t} = (1-\phi)[q_F(\sigma_L) - q_{L,t}] + (1-\phi)(q_{L,t} - Q_t) = (1-\phi)[q_F(\sigma_L) - Q_t]. \tag{17}$$

Aside from the discussed case, there exist also (uninteresting) border cases that are not shown in Figure 1: for $q_{L,t} > q_F(\sigma_L) > Q_t{+}1$, there is only production with low-skilled labor at home (a case capturing the far past of economic history); for $q_F(\sigma_L) < q_{L,t} < Q_{t+1}$, offshoring disappears (perhaps a case capturing the near future); and for $q_F(\sigma_L) < Q_t$ and $q_{L,t} < Q_t$, there is only automated production (perhaps a case for the distant future).

To close the model, we determine the endogenous low-skilled wage $w_{u,t}$ by the labor market equilibrium for low-skilled labor at home:

$$L_u = \phi(q_{L,t} - Q_t) l_{u,t}.$$

The left-hand side represents the aggregate supply of low-skilled workers at home and the right-hand side represents the aggregate low-skilled labor demand at home. Inserting $q_{L,t}$ and $l_{u,t}$, we obtain the wage rate of low-skilled workers, $w_{u,t}$, as implicitly given by:

$$G = \phi\left(\frac{\eta r}{w_{u,t}} - Q_t\right)\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}} - L_u = 0. \tag{18}$$

Once we found $w_{u,t}$, we can solve recursively for the rest of the model's variables. The production of intermediate parts is computed as

$$\int_{Q_t}^{Q_t+1} x(q)^{\epsilon}\mathrm{d}q = \theta_{L,t} l_{u,t}^{\alpha\epsilon} + \theta_{F,t} l_{F,t}^{\alpha\epsilon} + \int_{q_F(\sigma_L)}^{Q_t+1} (a_t q_t)^{\alpha\epsilon}\mathrm{d}q_t + \int_{q_L}^{q_F(\sigma_L)} (a_t q_t)^{\alpha\epsilon}\mathrm{d}q_t$$
$$= \theta_{L,t} l_{u,t}^{\alpha\epsilon} + \theta_{F,t} l_{F,t}^{\alpha\epsilon} \tag{19}$$
$$+ (1-\alpha\epsilon)\left(\frac{\eta r}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{\alpha\epsilon}{\alpha\epsilon-1}} \left[(Q_t+1)^{1/(1-\alpha\epsilon)} - (1-\phi)[q_F(\sigma_L)]^{1/(1-\alpha\epsilon)} - \phi q_L^{1/(1-\alpha\epsilon)}\right],$$

which can be used to back out GDP and high-skilled wages.

At this stage, we can state in Propositions 1 – 5 the central results of our theoretical considerations with respect to the effects of automation and of trade policies on wages and employment.

Proposition 1. *If the productivity of automation Q_t increases, the wage of low-skilled workers declines.*

The proposition is proved in the Appendix. The intuition for the result is straightforward. Automation competes with low-skilled workers at home because it is a substitute for low-skilled labor. An increase in the efficiency of automation implies that industrial robots become more productive such that more firms choose to switch from producing at home with labor to producing at home with industrial robots for a given wage rate of low-skilled workers. This reduces the demand for low-skilled workers and hence, via a general equilibrium effect, the wage for low-skilled workers.

Formally, productivity of automation Q_t increases the threshold $q_{L,t}$ but leaves the two q_F thresholds unaffected. As a result, we observe a clear positive effect of the productivity of automation on the share of firms that produce at home and hence on the output level that is produced within the home country. This is shown in the following proposition.

Proposition 2. *If the productivity of automation Q_t increases, the share of firms that offshore their production decreases, which implies reshoring of economic activity.*

Proof. From equation (17) the share of firms that are offshoring is given by $\theta_{F,t} = (1-\phi)(q_F(\sigma_L) - Q_t)$, which declines in Q_t. □

The reason for this finding is the following. If firms moved abroad in the past when the productivity of automation was still quite low and then the productivity of automation increases, there is another way to save on the wage bill apart from offshoring, namely automation at home. As a consequence, firms start to move production back to the home country and thereby avoid having to pay tariffs and transport costs that are associated with offshoring. Formally, there is a direct effect of improved efficiency of automation on reshoring, captured by increasing Q_t in equation (17). Additionally, improved automation has a dampening effect on low-skilled wages. Off equilibrium, the newly automated firms set free low skilled labor. In order for theses workers to be employed by the not-yet automated firms, w_u needs to decline. As a result, the threshold $q_{L,t}$ moves up. This means an additional positive effect on reshoring. Formally, the first term in square brackets in (17) declines. On the other hand, declining wages dampen the incentive to automate such that the reshoring of newly automated firms is smaller than it would be at constant wages. Formally, the second term in (17) declines by less than it would with rising Q and constant $q_{L,t}$. In equilibrium, these two labor market effects balance each other and only the direct effect through improving Q_t remains. Formally, the right-hand side of (17) is independent from q_L and declining in Q_t. The result is independent from ϕ, i.e., the share of firms facing high trade costs. The distribution of trade costs affects the magnitude but not the direction of the response of reshoring to increasing automation efficiency. In Appendix A.3 we show that these conclusions are robust against the introduction of a continuous distribution of trade costs.

Reshoring has a positive effect on production at home and by this channel also on the wages of high-skilled workers as we show in the next proposition.

Proposition 3. *If the productivity of automation Q_t increases, the share of automated firms, the stock of robots, GDP, and wages of high-skilled workers increase.*

The first part of the proposition is proven in the Appendix. It shows that $\partial q_{L,t}/\partial Q_t < 1$ such that the positive direct effect of increasing Q_t is always larger than the dampening labor market effect, which results from declining low skilled wages $w_{u,t}$. The remainder of the proposition is obvious. Since automated firms are more productive than firms producing with labor (at home and abroad) and the associated reshoring of economic activity as shown in Proposition 2 saves on transport costs, the overall effect is an increase in the production of intermediates $\int_{Q_t}^{Q_t+1} x(q)^{\epsilon}\mathrm{d}q$. This in turn raises GDP according to equation (1) and the wages of high-skilled workers according to equation (2).

Altogether, if the efficiency of automation rises, firms have an incentive to reshore their economic activity. The firms that are reshoring can produce more efficiently at home with robots than abroad with labor. In addition, they do not have to pay tariffs and transport costs anymore such that reshoring due to automation is definitely associated with a higher production level of intermediate parts. Since intermediate parts are to a certain degree complementary to high-skilled workers in the final goods sector, the wages of high-skilled workers increase. A direct corollary of the results in Propositions 1 and 3 is that the skill premium and inequality both rise when the efficiency of automation increases.

Corollary 1. *Since the wages of low-skilled workers decrease with an increase in the efficiency of automation, whereas the wages of high-skilled workers increase with the efficiency of automation, the skill premium as measured by the ratio of high-skilled to low-skilled wages, $w_{s,t}/w_{u,t}$, increases with the efficiency of automation. As a consequence, inequality rises.*

Until now we have only considered the situation of an inelastic labor supply. If we allow for an elastic labor supply with the standard property that labor supply decreases when the wage rate falls, we can also make a statement on employment.

Proposition 4. *In case that labor supply is elastic and falls with the wage rate, rising productivity of automation technology leads to less employment (fewer hours worked) of low-skilled workers and more employment of high-skilled workers.*

Proof. The proposition follows immediately from Propositions 1 and 3 and the definition of elastic labor supply. □

This result relates the stylized fact of declining hours worked to increasing automation and declining wages. If the trend continues, it may lead to a situation in which, among low-skilled workers, technological unemployment becomes an issue. One reason for why technological unemployment has not been a problem up to now might be that technological progress has been labor-augmenting in the past (Romer, 1990; Jones, 2005) and therefore it raised the productivity of low-skilled workers to the extent that their wages increased. This countervailing force dampened the downward pressure on wages from automation such that there were (yet) not too many workers discouraged and motivated to leave the labor force.[5]

[5] Notice that low-skilled workers would benefit from technological progress that augments high-skilled labor. From the perspective of low-skilled workers such progress operates like an exogenous increase of the high-skilled labor force, which induces more demand for intermediate goods and thus higher wages. This channel is omitted in the above analysis and dampens the downward trend of low-skilled wages. Moreover, we abstract here from a service sector. In reality, many workers who become unemployed in manufacturing will find jobs in a service sector (cf. Autor and Dorn, 2013).

With respect to the recent reshoring debate, the model predicts that even though trade policies in terms of increasing tariffs might bring production back home, they do not have the potential to raise the wages of low-skilled workers or their employability. This is summarized in the next proposition.

Proposition 5. *An increase in tariffs* τ

i) *leads to reshoring by reducing the share of firms that are offshoring in favor of firms that produce with industrial robots at home,*

ii) *does not change the share of firms producing with low-skilled labor at home.*

iii) *does not change the wage of low-skilled workers (and employment of the low skilled)*

iv) *reduces profits, GDP, and wages of high-skilled workers.*

Proof. For the proof of the first part of the proposition note that the threshold level of q_t between automation and producing with labor at home as represented by equation (8) does not depend on tariffs, while the threshold level of productivity q_t above which firms start to reshore and produce with industrial robots at home as represented by equation (16) decreases with tariffs. This shows that, for an increase in tariffs (τ), automated production of intermediate parts at home increases and offshoring declines. The proof of the second part of the proposition follows immediately from inspecting equation (18) and observing that it does not depend on τ.

□

The intuition behind this result is that the equilibrium wage for low-skilled labor is fixed by the trade-off between labor and robots as inputs, which is entirely determined by domestic parameters, cf. the labor market equilibrium (18). Changing tariffs have thus no influence on the low-skilled wage. In Figure 1, the threshold q_t^L does not move when tariffs change. A tariff increase raises production of intermediate parts at home. However, the tariff only affects the threshold (16) between offshoring and automated production at home but not the threshold (8) between automation and production with labor at home. As a consequence, the reshored firms produce with industrial robots such that there are no effects on the wages and on employment of low-skilled workers.

The result that the share of firms producing at home with labor is unaffected by trade policy is non-robust. In the Appendix, we extend the model by a continuous distribution of trade costs and show that then the share of firms producing at home with labor (θ_L) increases in response to increasing tariffs. The result that the low-skilled wage is independent from tariffs, however, is robust. The intuition provided above also applies in this case: the low-skilled wage is pinned down by the labor-automation trade-off in home production. The fact that the share of firms producing with labor increases although the low-skilled wage remains constant is thus an expression of inefficiency. The rising tariff reduces profits from offshored production. As an equilibrium response, profits in home production also need to decline. For that, firms employ less labor (and automated firms fewer robots) than before such that the number of firms increases while employment per firm declines. The tariff thus leads to inefficiently small firms. In the simple model this conclusion is made only for automated firms. In the extended model it holds for all domestic firms.

We next discuss how results change when there is a service sector in the economy that partly absorbs the effects of automation in manufacturing on the domestic labor market. In a mild abuse of notation we now consider Y_t in (1) as aggregate manufacturing output. The stylized service sector does not benefit from automation and produces with the linear homogenous production function $Y_t^S = AL_{u,t}^S$, in which $L_{u,t}^S$ is employment and A is productivity in services. Let p_t denote the relative price of services. GDP is then given by $Y_t + p_t Y_t^S$ and low-skilled wages are given by $p_t A$. Proceeding as for the basic model, we arrive at the labor market equilibrium condition (20), which replaces (18).

$$G = \phi \left(\frac{\eta r}{p_t A} - Q_t \right) \left(\frac{p_t A}{\alpha \epsilon^2 L_s^{1-\epsilon}} \right)^{\frac{1}{\alpha\epsilon - 1}} + L_{u,t}^S - L_u = 0. \tag{20}$$

An increase of Q_t now requires either (i) p_t to fall, or (ii) $L_{u,t}^S$ to rise, or (iii) both, such that labor market equilibrium prevails. Case (i) implies that the low-skilled wage declines and all results are isomorph to those of the basic model. Case (ii) implies that low-skilled wages remain unaffected by increasing productivity in automation. Inspection of (17) shows that the results for reshoring remain unaffected. We also see that $\partial\theta_L/\partial Q_t = -\phi$ and $\partial\theta_A/\partial Q_t = 1$. The response of θ_L is thus stronger and the response of θ_A weaker than for the basic model. This is so because employment effects are no longer cushioned by declining wages. Instead, increasing Q_t causes structural change, $\partial L_{u,t}^S/\partial Q_t > 0$. The manufacturing sector declines and labor shifts to the service sector. In the perhaps most plausible case (iii), wages decline less strongly than in the basic model and there is some induced structural change. This means that, qualitatively, all results from the basic model remain intact.

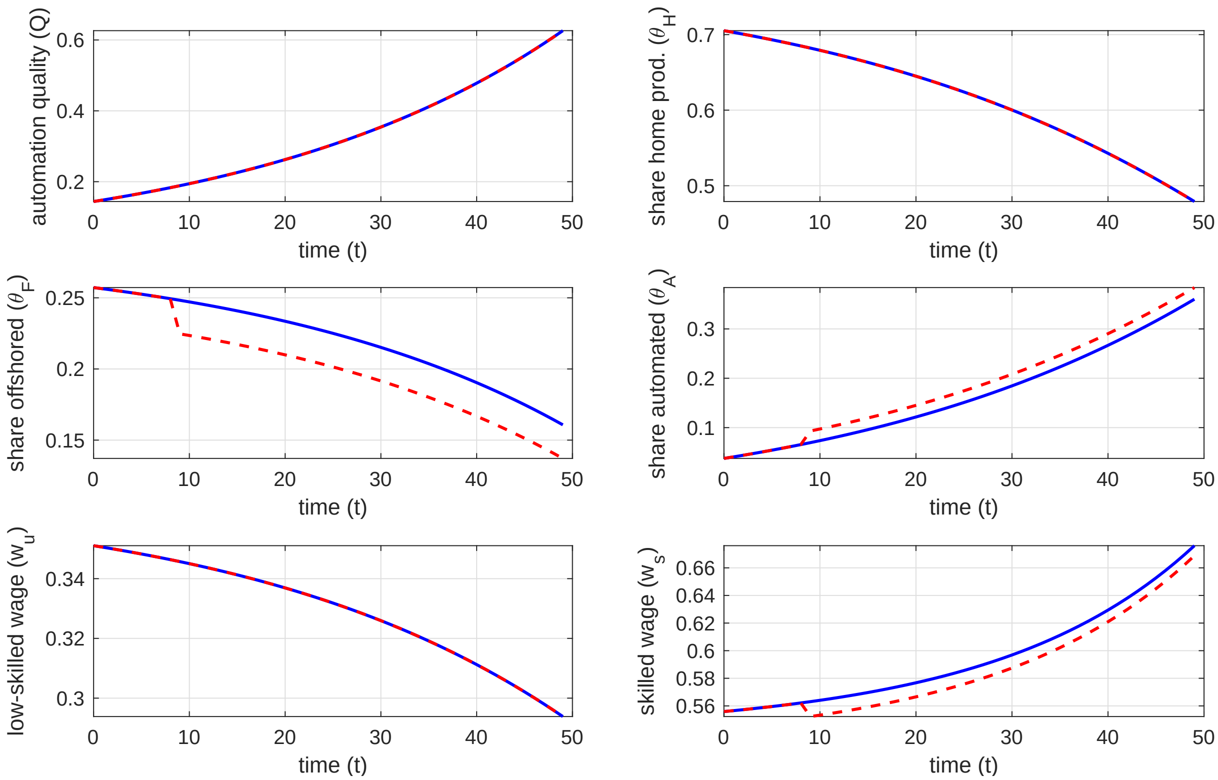
4. Numerical Illustration

In this section, we investigate numerically the impact of perpetual technological progress in automation. We assume that the productivity of robots is growing by 4 percent annually (approximating the estimate of yearly improvement of performance of robots by BCG, 2015), $\Delta Q_t/Q_t = 0.04$; that initially about 25 percent of all input production is offshored (approximating the foreign value added in German car production), and that 3% of production is initially automated. Parameter values for the numerical analysis are given below Figure 2. Solid (blue) lines in Figure 2 reflect the benchmark run. The evolution of Q is shown in the top left panel of Figure 2. As shown in the center right panel, the share of firms producing with robots increases with rising productivity of automation. Automation is fed by both declining production using low-skilled labor at home (top right panel) and declining off-shoring (center left panel). A declining share of firms producing offshore means that there is reshoring. Reshoring happens because increasing productivity of automation makes it attractive for an increasing share of firms to produce at home using robots.

The bottom panels of Figure 2 show the associated effects on wages. As the productivity of automation increases, the wage for low-skilled labor declines (bottom left panel). Intuitively, rising Q induces some firms to change the mode of production from low-skilled employment to automation. This sets free low-skilled workers and puts downward pressure on the low-skilled wage until the firms that are not yet automated are willing to employ the redundant workers. High-skilled labor, by contrast, benefits from automation because it complements automated products (bottom right panel). With increasing productivity Q and an increasing share of automated firms, the stock of intermediates in final goods production (19) increases, which induces GDP (1) and high-skill wages (2) to rise. As a result of the opposing trends of low and high-skill labor, inequality increases. The $w_{s,t}/w_{u,t}$–ratio increases from 1.7 at $t = 1$ to 2.5 at $t = 50$.

We next consider a rise in tariffs (from 5 to 10 percent) at time $t = 10$. Impulse responses are reflected by dashed (red) lines in Figure 2. We see that such a revisionist anti-globalization policy is effective in bringing firms home: the share of offshoring firms drops. However, this has no effect on home production employing low-skilled labor (top right panel). Instead, it raises the share of automated firms (center right panel). Formally, the reason is that trade policy does not affect the threshold q_{L_t} for lowskilled employment at home. It only affects the threshold for

FIGURE 2. Growing Automation Efficiency: Home Production, Offshoring and Automation

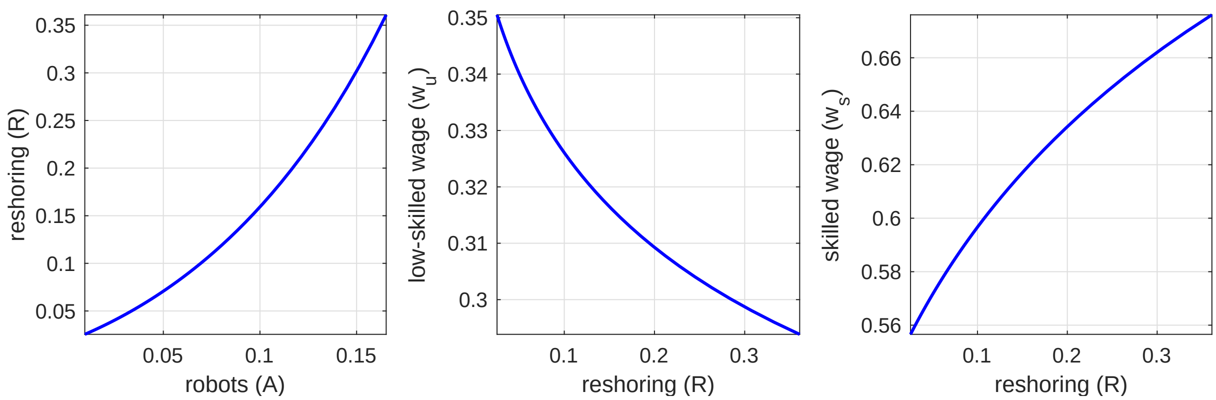


Parameters: Parameters: $\alpha = 0.6$, $\epsilon = 0.9$, $\eta = 6$, $r = 0.06$, $w_F = 0.23$, $Q(0) = 0.12$, $L_s = 0.1$, $L_u = 0.2$, $\sigma_L = 1$, $\sigma_H = 1.2$, $\phi = 0.8$. Solid lines: $\tau = 1.05$. Dashed lines: $\tau = 1.1$.

automation $q_F(\sigma_L)$. Intuitively, the reason is that trade policy does not affect the productivity of low-skilled workers at home and its relation to the productivity of robots. High-skilled labor, however, declines mildly after the tariff increase. Higher tariffs induce more reshoring of firms that produced more efficiently abroad before the policy change (q_F moves to the left in Figure 1). As a result, average productivity of firms declines and the aggregate stock of intermediate goods (19) declines, which has a (mildly) negative effect on the productivity of complementing high-skill labor.

Finally, in order to prepare for our econometric analysis, we consider an alternative representation of these results. For that purpose, we compute aggregate domestic inputs $DI = \theta_H w_u l_u^{\alpha\epsilon} + w_s L_s + \eta r \left[\int_{q_F(\sigma_L)}^{Q_t+1} a(q)dq + \phi \int_{q_L}^{q_F(\sigma_L)} a(q)dq\right]$ as well as aggregate foreign inputs $FI = \theta_F w_F l_F^{\alpha\epsilon}$. We then define reshoring as the increase of domestic relative to foreign inputs, $R_t = (DI_t/FI_t) - (DI_{t-1}/FI_{t-1})$. We compute the stock of robots used in production as $A = \left[\int_{q_F(\sigma_L)}^{Q_t+1} a(q)dq + \phi \int_{q_L}^{q_F(\sigma_L)} a(q)dq\right]$. The left panel in Figure 3 shows, for the example from above, the implied positive association between the stock of robots and the reshoring measure.

Figure 3. Robots, Reshoring, and Wages



Parameters as for Figure 2.

The center panel shows the implied negative association between reshoring and low-skilled wages and the right panel shows the implied positive association between reshoring and high-skilled wages. Notice that both automation and reshoring are endogenous and driven by technological progress in automation technology (rising Q). According to the model we would thus expect, with ongoing technological progress, a positive association between robots and reshoring, a negative association between reshoring and low-skilled wages, and a positive association between reshoring and high-skilled wages

5. Evidence

5.1. **Methodology and Data.** In this section we examine whether and to what extent our theory on robots and reshoring is supported by empirical evidence. Using panel data, we first look at the association between robot density and reshoring activity within countries and within manufacturing sectors. We then investigate the association between reshoring and labor market outcomes of low- and high-skilled workers. In contrast to previous analyses on reshoring, which largely focussed on surveys or small samples of specific industries, countries, and years, we consider a large data set for a panel of countries, subdivided in 9 manufacturing industries, over the years 2000–2014.

Decreasing offshoring can be a misleading indicator of reshoring since it takes not into account that foreign input shares in value added decline due to a decline in production without a move of production activities back home. Moreover, firms engage both in offshoring and reshoring activities (see Krenz and Strulik, 2019), such that offshoring can exist in parallel to reshoring activities, a situation that is not properly taken into account when negative offshoring is used to measure reshoring.

We use data from three main sources: the World Input Output Database (Timmer et al., 2015), the International Federation of Robotics (IFR, 2016), and Eurostat (2018). The World Input Output Database (WIOD) provides annual time series of world input output tables. We use the 2016 release, which covers 43 countries, among which all EU member countries are present. A "Rest of the World" region is constructed to close the model. The WIOD provides information on industries at the ISIC Rev.4 level. We use data on domestic and foreign inputs measured in million USD for the manufacturing industries with codes 10 to 30.

The database from the International Federation of Robotics (IFR) provides information on industrial robots. We collect data on the stock of robots of all available countries and industries. We meet the problem that the classification of sectors differs between the IFR and the WIOD database by harmonizing and aggregating the variables at a common sectoral level. Details on the harmonization procedure and the list of harmonized sectors can be found in the Appendix (Table A.1 and A.2). For the years before 2010, the IFR reports robot stocks only for an aggregated 'North America'. We thus use robots data for Canada, Mexico, and the U.S. only from 2011 onwards. The robot stock is measured in numbers of robots.

In the regression we use two alternative measures of robot density; robots per 1000 workers and robots per 1000 hours worked. We take the number of persons engaged (measured in thousands) and hours worked (measured in thousands) at the country level from EU KLEMS, (2017; Jaeger, 2017). Disaggregated by skill level, however, there seems to exist no perfect solution to match reshoring with labor market outcomes. The last EU KLEMS release containing information disaggregated by skill-levels and sectors provides only data until the year 2005 and the WIOD socioeconomic database, which contains data until 2009, does not provide sufficient variation in the skill dimension across sectors and time. We circumvent these problems by using data on hours worked, employment, and earnings from Eurostat's labor market statistics. The advantage of the Eurostat (2018) data is that they provide information on occupations according to the International Standard Classification of Occupations ISCO-08 until the year 2014. We extract data on elementary occupations – to cover low-skilled employees – and on professional occupations to cover high-skilled employees.[6] These data are available at the country-year level.

[6] The professional occupation group is defined as major group 2 according to ISCO-08. Included are occupations that demand a high level of professional knowledge and experience in the fields of physical and life sciences or

The earnings data from Eurostat is not available at annual levels but comes in four surveys for the years 2002, 2006, 2010, and 2014.

The Eurostat employment variable is measured for males and females in thousand workers. Hours worked are measured as average number of weekly hours of work in the main job for both male and female employees in full time employment. Earnings are measured as mean earnings per hour for males and females who work full-time, for all ages, within the industry and construction sectors. In order to make the earnings data comparable, we extract further data from Eurostat for bilateral exchange rates and for the harmonized consumer price index which is used to convert values (earnings) into constant 2015 euro prices. The drawback of using the high-quality Eurostat data is that, naturally, they are available only for European countries. We thus focus, like Graetz and Michaels (2018), on a set of developed countries. Table A.2 in the Appendix presents the lists of these countries.

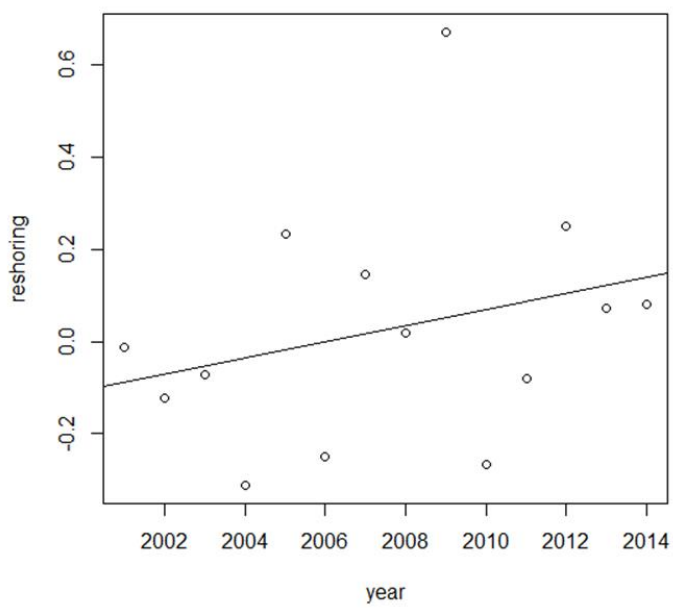
So far, the literature has not developed a measure for reshoring at the macro-level. In our companion paper (Krenz and Strulik, 2019) we explain in detail how we exploit the relation between domestic and foreign inputs in production to derive a novel measure of reshoring intensity. The basic idea is as follows. Let DI_t denote domestic inputs and FI_t foreign inputs for a specific sector and country in year t. Our broad measure of reshoring is then given by $R_t \equiv (DI_t/FI_t) - (DI_{t-1}/FI_{t-1})$ with the restriction that $R_t > 0$. The reshoring measure shows by how much domestic inputs increased relative to foreign inputs compared to the previous year. In contrast to our theoretical analysis, where all developments were monotonic, the broad measure of reshoring may in practice indicate reshoring when there is none. This could happen, for example, when both domestic and foreign inputs decline but foreign inputs decline by more. In order to exclude these "degenerate cases" we derive a narrow measure of reshoring by explicitly controlling for production declines and increases over time. For our narrow measure, we require that the changes $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are neither both positive nor both negative or equal to zero. While the broad measure is likely to overestimate actual reshoring somewhat, the narrow measure is likely to underestimate it somewhat, given that cases where $DI_t - DI_{t-1}$ and

social sciences and humanities. Most occupations in this group require skills at the fourth ISCO-08 skill level, usually obtained as a result of tertiary education, ISCED 97 level 5 or 6, ISCED 2011 level 5 to 8. The elementary occupation group is defined as major group 9 according to the ISCO-08. Included are occupations that demand the performance of simple and routine tasks which may require the use of hand-held tools and considerable physical effort. Most occupations in this group require skills at the first ISCO skill level; see Eurostat Statistics Explained (OECD, 2018) and ILO documentation, ISCO-08 Part 3: Group definitions (ILO, 2018).

$FI_t - FI_{t-1}$ are both positive, both negative or equal to zero are not measured. The descriptive statistics of our data are summarized in Table A.3 in the Appendix.

To get a first impression of recent reshoring trends, Figure 4 shows R_t, without positivity restriction, aggregated over all sectors and countries. Positive values are taken as our broad measure of reshoring. We observe an increasing trend of reshoring intensity. According to the estimated trendline, R_t breaks even in 2006 and increases to about 0.15 in 2014, indicating that the ratio of domestic relative to foreign inputs increased by 15 percent (compared to the previous year). There is a large variation of reshoring over time and (hidden in the aggregates) over countries and sectors.[7].

Figure 4: Reshoring at the World Level: All Sectors



The figure shows $R_t \equiv (DI_t/FI_t) - (DI_{t-1}/FI_{t-1})$ aggregated over all sectors and countries.

5.2. **Robots and Reshoring.** To scrutinize the association between automation and reshoring within countries and within sectors, we set up the following estimation model:

$$\log(\text{Reshoring})_{ict} = \beta_0 + \beta_1 \text{Robots}_{ict} + \gamma_i + \delta_c + \varphi_t + \epsilon_{ict},$$

[7]The spike of reshoring intensity in the year 2009 can be attributed to particularly large increases in R_t for some countries and sectors. Specifically, reshoring intensity increased by 57 percent for the UK, mainly in the sectors 'computers and electronics' and 'textiles apparel' and it increased by 54 percent in the Netherlands, mainly in the sectors 'basic metal products', 'chemicals' and 'motor vehicles'.

where c denotes the country, i denotes the sector, t the time period, and ϵ is an idiosyncratic error term. We also conduct regressions that contain the interactions of fixed effects, that is κ_{ic}, λ_{ct}, and ν_{it}. Table 1 shows the results. We use clustered standard errors at the country-industry level. This way of clustering provides conservative and perhaps unnecessarily large estimates of standard errors. The associated p-values are shown in parentheses. Columns (1) and (3) consider the association between automation measured as the stock of robots per 1000 workers with our broad and narrow measure of reshoring activity. Columns (2) and (4) show results when automation is measured as the stock of robots per thousand hours worked. Using the country-, sector-, and year-fixed effects, we find that an increase of robots (per 1000 workers) by one unit is associated with an increase of the reshoring activity by 1.6 percent. When we focus on the impact of robots per hours worked, the estimated effect rises up to 2.7 percent. The F-tests reject the null hypothesis of a negative coefficient for the automation variable at around the 5 percent level. The point estimates increase to about 3.5 and 5.7 percent, respectively, when country-year, sector-year, and country-sector fixed effects are included, which control, among other things, for institutional and price effects. The estimated size of the coefficients does not depend significantly on the narrowness of the applied reshoring measure.

Table 1. Automation and Reshoring

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Log(Reshoring)				
	broad	broad	narrow	narrow	broad	broad	narrow	narrow
Robots per 1000 workers	0.0161		0.0168		0.0358		0.0341	
	(0.109)		(0.096)		(0.060)		(0.041)	
Robots per 1000 hours worked		0.0262		0.0270		0.0551		0.0508
		(0.089)		(0.080)		(0.059)		(0.055)
Country FE	√	√	√	√				
Sector FE	√	√	√	√				
Year FE	√	√	√	√				
Country-year FE					√	√	√	√
Sector-year FE					√	√	√	√
Country-sector FE					√	√	√	√
F-test $\beta \leq 0$ (p-value)	0.055	0.044	0.048	0.040	0.03	0.029	0.021	0.028
Obs.	992	942	992	942	897	845	897	845
R^2	0.322	0.322	0.359	0.357	0.814	0.813	0.826	0.824

Notes: p-values are given in parentheses. Cluster-robust standard errors at the industry-country level. Sources: IFR (2016), WIOD (2016), EU KLEMS (2017).

The IFR database does not always provide detailed information on the number of robots for all sectors in all countries. In several cases the robots stock is not attributed to a sector but rather mentioned as unspecified "rest stock" of robots. As a robustness check we thus focussed on countries with comparatively low shares of the unspecified robot stock, which on average is less than five percent. These countries are Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the UK. The results are reported in Table A.4 in the Appendix. The results show that reshoring remains positively associated with automation and that the coefficients increase slightly in size.

Table 2. Sensitivity Analyses

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Reshoring)							
	broad	broad	narrow	narrow	broad	broad	narrow	narrow
Robots per 1000 workers$_{t-1}$	0.0561		0.0545		0.0559		0.0545	
	(0.002)		(0.001)		(0.002)		(0.001)	
Robots per 1000 hours worked$_{t-1}$		0.0939		0.0906		0.0939		0.0906
		(0.002)		(0.001)		(0.002)		(0.001)
Tariff$_{t-1}$					0.0827	0.0837	0.0306	0.0339
					(0.021)	(0.022)	(0.360)	(0.316)
Country-year FE	√	√	√	√	√	√	√	√
Sector-year FE	√	√	√	√	√	√	√	√
Country-sector FE	√	√	√	√	√	√	√	√
F-test $\beta \leq 0$ (p-value)	0.001	0.001	0.001	0.001	0.0009	0.0010	0.0006	0.0007
Obs.	843	799	843	799	843	799	843	799
R^2	0.819	0.820	0.829	0.83	0.82	0.821	0.83	0.83

Notes: p-values are given in parentheses. Cluster-robust standard errors at the industry-country level. Sources: IFR (2016), WIOD (2016), EU KLEMS (2017), WTO IDB (2019).

We next check the robustness of the results with further sensitivity analyses. First, we address potential reverse causality by running a regression of reshoring on the lagged value of the stock of robots. As can be seen in Table 2, columns (1) to (4), the effect of robots on reshoring remains positive and the p-values become smaller than before. Moreover, the effect of robots on reshoring increases in size.

We next account for a potential influence of tariffs on reshoring. For the analyses we used tariff data from the WTO Integrated Database (WTO IDB, 2019). MFN tariff rates were used which are equal to the effectively applied rates. The tariff data had to be harmonized with the IFR and WIOT industry sector classification. The commodity level tariff data were averaged at the sectoral aggregation level that we chose for the IFR and WIOT data (see Table A.1 in the Appendix). Further, EU-wide tariffs were applied to the national level, intra-country tariffs were set to zero and tariffs between EU countries were set to zero, as well. From these bilateral tariff data, which are based on the imports by partner country (exporters) and by sector, we performed a final aggregation by averaging the import tariff across all exporters (EU countries plus USA). This procedure provides tariffs that vary across country, sector and year.

The regression results shown in columns (5)–(8) of Table 2 document a weakly positive association of tariffs on reshoring, which is significant at conventional levels for the specifications using the broad measure of reshoring (columns 5 and 6). F-tests indicate that the effect of tariffs on reshoring is non-negative. More importantly, the coefficients for the robots stock remain positive and significant and hardly change in terms of magnitude.

TABLE 3. Automation and Reshoring: Instrumental Variable Regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Reshoring)							
	broad	broad	narrow	narrow	broad	broad	narrow	narrow
Robots per 1000 workers	0.0117		0.0249		0.0111		0.0248	
	(0.235)		(0.043)		(0.253)		(0.040)	
Tariffs					0.0437		0.0089	
					(0.319)		(0.848)	
First stage	0.1743		0.1745		0.1739		0.174	
	(0.000)		(0.000)		(0.000)		(0.000)	
F-statistic	14.03		14.37		13.99		14.31	
Robots per 1000 hours worked		0.013		0.0247		0.0124		0.0245
		(0.110)		(0.025)		(0.129)		(0.023)
Tariffs						0.0432		0.0107
						(0.326)		(0.818)
First stage		271.011		271.04		270.169		270.09
		(0.000)		(0.000)		(0.000)		(0.000)
F-statistic		13.65		13.84		13.58		13.75
Country-year FE	√	√	√	√	√	√	√	√
Sector-year FE	√	√	√	√	√	√	√	√
Country-sector FE	√	√	√	√	√	√	√	√
Obs.	992	942	992	942	992	942	992	942
R^2	0.743	0.741	0.759	0.756	0.743	0.741	0.759	0.756

Notes: p-values are given in parentheses. Standard errors are clustered at industry-country level. A country's robots stock is instrumented by the aggregated robots stock of the two countries that have the closest output share across sectors and time. Sources: IFR (2016), WIOD (2016), EU KLEMS (2017).

Finally, we perform an instrumental variable regression to account for potential reverse causality, measurement error and omitted variables. A country's robots stock is instrumented by the aggregated robots stock of the two countries that have the closest output share – based on the WIOD – across sectors and time. The idea is that these countries have a similar sectoral structure and would benefit to similar degrees from sector-specific technological progress in automation, which is the common (exogenous) driving force of automation. Results are shown in Table 3. The coefficients from the first-stage regressions as well as the respective F-statistics indicate a strong instrument. The estimated coefficients at the second state are somewhat smaller than in the respective OLS regressions. Focussing on the narrow measure, an increase of 1 robot per thousand workers is predicted to cause an increase in reshoring intensity of 2.5 percent. An increase of 1 robot per thousand hours worked is predicted to cause a similar increase in reshoring intensity. These results are hardly affected by the inclusion of tariffs in the regression.

5.3. **Reshoring and Labor Market Outcomes.** In order to investigate the nexus between reshoring and labor market outcomes for low- and high-skilled workers, we set up the following estimation model:

$$\mathrm{Y}_{ct} = \beta_0 + \beta_1 \mathrm{Reshoring}_{ct} + \delta_c + \varphi_t + \epsilon_{ct}$$

where Y denotes a labor market variable, i.e., either the annual change in employment, hours worked or in earnings per hour worked, c denotes the country, t the time period, and ϵ is an idiosyncratic error term. The regression is estimated at the country-year level given the availability of required data.[8]

Table 4. Reshoring and Change in Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Professional Occupations				Elementary Occupations			
Log(reshore) broad measure	7.795		5.3435		-1.897		-1.1928	
	(0.0651)		(0.1622)		(0.4635)		(0.6306)	
Log(reshore) narrow measure		11.50		7.7324		-2.284		-1.6923
		(0.036)		(0.0741)		(0.3994)		(0.5485)
Country FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Level of employment			√	√			√	√
F-test $\beta \geq 0$ (p-value)	0.958	0.974	0.905	0.956	0.255	0.224	0.328	0.275
F-test $\beta \leq 0$ (p-value)	0.042	0.026	0.095	0.044	0.745	0.776	0.672	0.725
Obs.	130	130	130	130	130	130	130	130
R^2	0.129	0.139	0.349	0.3609	0.118	0.118	0.267	0.267

Notes: p-values in parentheses. Wild bootstrapped cluster-robust standard errors with Rademacher weights and 999 replications were computed at the country level. Sources: WIOD (2016), Eurostat (2018).

Table 4 presents the results for the change in employment. The point estimates suggest that a ten percent increase of reshoring is associated with a yearly increase of employment in professional occupations by between 780 to 1150 workers, depending on the narrowness of the reshoring measure. The size of the coefficient declines somewhat (to between 534 and 773 workers) when we control for the level of employment. For low-skill employment, the point estimates indicate a negative association, which is, however, insignificantly different from zero. Summarizing, these observations suggest that reshoring is associated with better employment opportunities for high-skilled labor but not for low-skilled labor.

[8]Given that the reshoring measure varies only across countries and time but not across occupations, our estimation strategy is to run separate regressions for different occupational groups, which will allow us to infer the effects of reshoring on labor market outcomes according to occupational group.

Table 5. Reshoring and Change in Hours worked

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Professional Occupations				Elementary Occupations			
Log(reshore) broad measure	16.405		18.182		-3.106		-5.419	
	(0.0771)		(0.0571)		(0.5435)		(0.3774)	
Log(reshore) narrow measure		25.346		26.192		-3.7997		-6.355
		(0.0310)		(0.038)		(0.4454)		(0.327)
Country FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Level of hours worked			√	√			√	√
F-test $\beta \geq 0$ (p-value)	0.955	0.978	0.966	0.98	0.295	0.263	0.2104	0.173
F-test $\beta \leq 0$ (p-value)	0.045	0.022	0.034	0.02	0.705	0.737	0.7896	0.827
Obs.	129	129	129	129	129	129	129	129
R^2	0.122	0.134	0.022	0.036	0.094	0.093	0.299	0.299

Notes: p-values in parentheses. Wild bootstrapped cluster-robust standard errors with Rademacher weights and 999 replications were computed at the country level. Sources: WIOD (2016), Eurostat (2018).

In Table 5 we show the impact of reshoring on the total number of hours worked in the economy (in millions). To this end, the weekly hours worked per employee from Eurostat were multiplied by 52 and by the aggregate number of employees. Due to this upscaling we obtain a higher degree of variation in the data. The results show that a 1 percent increase in reshoring is associated with an increase in hours worked for employees in professional occupations of between 164 to 253 thousand hours, depending on the narrowness of the reshoring measure. For hours worked in elementary occupations, the association is negative but not significantly different from zero at conventional levels.

Table 6 presents results on the reshoring–earnings nexus. They indicate a positive association between reshoring and earnings per hour in professional occupations. According to the point estimate, a 1 unit increase in the reshoring measure is associated with an increase of about 25 Euros per hour in earnings. In other words, a one standard deviation increase in reshoring is associated with an increase in professional earnings by 13.8 Euros (i.e., by slightly more than one standard deviation). The association between reshoring and earnings in elementary occupations appears to be negative though not statistically significant from zero. Finally, we report results for the skill premium, measured as the ratio between professional and elementary earnings. As shown in column (5) and (6), the F-tests indicate a positive association of reshoring and the skill premium at about the 10 percent level. The size of the coefficient is economically significant, suggesting that a one standard deviation increase in reshoring is associated with an increase of the skill premium by 1.2 units and thus with increasing inequality, as predicted by the model.

Table 6. Reshoring and Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Earnings				Skill Premium	
	Professional Occupations	Professional Occupations	Elementary Occupations	Elementary Occupations		
Reshoring broad measure	25.21		-1.942		2.3638	
	(0.013)		(0.477)		(0.329)	
Reshoring narrow measure		25.406		-1.850		2.3721
		(0.011)		(0.521)		(0.331)
Country FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
F-test $\beta \geq 0$ (p-value)	0.928	0.929	0.238	0.246	0.891	0.891
F-test $\beta \leq 0$ (p-value)	0.072	0.071	0.762	0.754	0.109	0.109
Obs.	115	115	115	115	115	115
R^2	0.0170	0.0211	0.0003	0.0028	0.0273	0.0267

Notes: p-values in parentheses. Wild bootstrapped cluster-robust standard errors with Rademacher weights and 999 replications were computed at country level. Sources: WIOD (2016), Eurostat Earnings Surveys (2002, 2006, 2010, 2014), Eurostat (2018).

6. Conclusion

We propose a simple theory of offshoring and reshoring in the age of automation. The theory suggests that initially, when industrial robots are not very productive, firms facing low trade costs save on the wage bill by offshoring production to low-wage countries. As the productivity of industrial robots increases, the incentive to reshore increases because firms with high productivity in automation produce more efficiently at home with robots than abroad. The relocation of firms, however, is not associated with an increase in the number of low-skilled jobs at home and therefore does not help to raise the wages of low-skilled workers. Instead, high-skilled labor, which complements automated processes, benefits from reshoring such that altogether reshoring is associated with increasing inequality.

In order to clearly elaborate on the mechanism, we assume that robots at once take over all low-skill jobs (or tasks) in a manufacturing firm when productivity of automation in the specific industry becomes sufficiently large. This stylized result, of course, overstates the real process of automation that appears to be more gradual. In the Adidas shoe factory mentioned in the Introduction, for example, robots are engaged in knitting, cutting, and additive manufacturing (3D-printing) but they are (yet) unable to put the lace into the shoe, implying that of the 120 tasks involved in producing a sneaker, some are left for manual labor (Bain, 2017). In this sense, reshoring is likely to bring back a few low-skilled jobs. Most of the tasks in shoe production, however, are taken over by robots, the winners of the race for jobs in manufacturing (Acemoglu and Restrepo, 2017).

Using the world input-output database and a new measure of reshoring activity at the macro-level, we find evidence for an economically strong association between reshoring and automation (density of robots) within countries and within manufacturing sectors. We find support for these results within an Instrumental Variable regression framework. We also confirm a positive association between reshoring and labor market conditions (employment, hours worked, earnings) of high-skilled labor but find no significant association between reshoring and labor market outcomes for low-skilled labor. Summarizing, we thus conclude that reshoring is positively associated with labor market conditions for high-skilled labor but not for low-skilled labor, which means that it is associated with increasing inequality. Moreover, we provide evidence that an increase in tariffs is increasing the degree of reshoring.

As far as the policy conclusion is concerned, our model suggests that re-negotiating "trade deals" will not be a highly effective tool if the goal is to raise wages and employment of industrial workers at home. The most promising alternative policy measure would be to ensure that people acquire skills that are complementary to automation technologies such that they can benefit from the rise in demand for these types of workers that goes hand in hand with automation. Additional funds should therefore be provided for education and particularly for re-training schemes that benefit workers who lose their jobs due to automation. Concerning recent developments along the lines of education policies and trade policies, however, does not seem to be very likely to occur.

Appendix

A.1 Proof of Lemma 1.

Proof. We implicitly differentiate equation (18) to compute

$$\frac{\mathrm{d}w_{u,t}}{\mathrm{d}L_u} = -\frac{\partial G/\partial L_u}{\partial G/\partial w_{u,t}} =$$

$$= -\frac{-1}{\frac{1}{\alpha\epsilon-1}\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}-1}\frac{1}{\alpha\epsilon^2 L_s^{1-\epsilon}}\left(\frac{\eta r}{w_{u,t}} - Q_t\right) - \left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}\frac{\eta r}{w_{u,t}}} < 0.$$

Note that the denominator is negative because $\alpha\epsilon < 1$. Since the numerator is also negative, we know that the whole expression is negative. This proofs that the low-skilled wage decreases with the number of low-skilled workers.

Next, we implicitly differentiate equation (18) to compute

$$\frac{\mathrm{d}w_{u,t}}{\mathrm{d}L_s} = -\frac{\partial G/\partial L_s}{\partial G/\partial w_{u,t}} =$$

$$= -\frac{\frac{1}{\alpha\epsilon-1}\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}-1}\left[-\frac{w_{u,t}\alpha\epsilon^2(1-\epsilon)L_s^{-\epsilon}}{(\alpha\epsilon^2 L_s^{1-\epsilon})^2}\right]\left(\frac{\eta r}{w_{u,t}} - Q_t\right)}{\frac{1}{\alpha\epsilon-1}\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}-1}\frac{1}{\alpha\epsilon^2 L_s^{1-\epsilon}}\left(\frac{\eta r}{w_{u,t}} - Q_t\right) - \left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}\frac{\eta r}{w_{u,t}}} > 0.$$

Again, the denominator is negative because $\alpha\epsilon < 1$. However, the numerator is positive such that the whole derivative is positive. This proofs that the low-skilled wage increases with the number of high-skilled workers. □

A.2 Proof of Proposition 1.

Proof. For the proof, we implicitly differentiate equation (18) and compute

$$\frac{\mathrm{d}w_{u,t}}{\mathrm{d}Q_t} = -\frac{\partial G/\partial Q_t}{\partial G/\partial w_{u,t}} =$$

$$= -\frac{-\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}}{\frac{1}{\alpha\epsilon-1}\left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}-1}\frac{1}{\alpha\epsilon^2 L_s^{1-\epsilon}}\left(\frac{\eta r}{w_{u,t}} - Q_t\right) - \left(\frac{w_{u,t}}{\alpha\epsilon^2 L_s^{1-\epsilon}}\right)^{\frac{1}{\alpha\epsilon-1}}\frac{\eta r}{w_{u,t}}} < 0.$$

Note that the denominator is negative because $\alpha\epsilon < 1$. Since the numerator is also negative, the whole expression is negative, which proofs that the low-skilled wage decreases with the state of technology in automation. □

A.3 Proof of Proposition 3.

Proof. The share of automated firms is $\theta_{A,t} = Q_t + 1 - q_F(\sigma_L) + \phi[q_F(\sigma_L) - q_{L,t}]$ such that

$$\frac{\partial\theta_{A,t}}{\partial Q_t} = 1 - \phi\frac{\partial q_{L,t}}{\partial Q_t} = 1 - \phi\left(\frac{\partial q_{L,t}}{\partial w_{u,t}}\frac{\partial w_{u,t}}{\partial Q_t}\right).$$

Since $\phi < 1$, it is sufficient for a positive the response of $\theta_{A,t}$ to show that $\partial q_{L,t}/\partial Q_t < 1$. From (8) and (18) we obtain

$$\frac{\partial q_{L,t}}{\partial w_{u,t}} \frac{\partial w_{u,t}}{\partial Q_t} = \frac{c_1}{c_1 + c_2}$$

with

$$c_1 \equiv \phi \left(\frac{\eta r}{\alpha \epsilon^2 L_s^{1-\epsilon}} \right)^{\frac{1}{\alpha\epsilon - 1}} \frac{\eta r}{w_{u,t}^2} > 0$$

$$c_2 \equiv \frac{1}{1 - \alpha\epsilon} \left(\frac{\eta r}{\alpha \epsilon^2 L_s^{1-\epsilon}} \right)^{\frac{1}{\alpha\epsilon - 1} - 1} (q_{L,t} - Q_t) \geq 0$$

and thus $\partial q_{L,t}/\partial Q_t < 1$. □

A.3 Two-Dimensional Firm Space. Suppose that trade costs are continuously distributed in $\sigma \in (1, \sigma_{max})$. For simplicity we focus on a uniform distribution and for now consider the basic case in which the distribution is independent. The threshold (16) from the basic model is now two-dimensional. Firms are indifferent between automation and offshoring for $q_t = \eta r / [w_F (\tau\sigma)^{1/(\alpha\epsilon)}]$. Solving for trade costs we obtain that firms prefer automation over offshoring if

$$\sigma > \bar{\sigma}(q) = \frac{\Psi}{\tau} \cdot q^{-\alpha\epsilon}, \qquad \Psi \equiv \left(\frac{\eta r}{w_F} \right)^{\alpha\epsilon}. \tag{A.1}$$

The threshold is a falling line (a hyperbola) in q–σ–space, as shown in Figure A.1. All other elements are kept from the basic model in the main text. In particular, the threshold at which firms prefer automation over home production is still given by (8), which is, for convenience, stated again as (A.2):

$$q_{L,t} = \frac{\eta r}{w_{u,t}}. \tag{A.2}$$

In two-dimensional firm space, the threshold is represented by a vertical line through $q_{L,t}$. The new feature of the two-dimensional model is that we can now identify the non-automated firms that prefer offshoring over home production. These are the firms with productivity below q_t^L and trade costs below $\sigma(q_t^L)$. At time t, the productivity in automation runs from Q_t to $Q_t + 1$. The measure of all firms is thus given in Figure 1 by the rectangle of size $(\sigma_{max} - 1)$. Analogously to the bivariate σ_H and σ_L values from the basic model, we obtain two cutoff points. Firms with productivity below q^{low} never prefer automation over offshoring irrespective of their trade costs σ. Firms with productivity above q^{high} always prefer automation over offshoring irrespective of their trade costs. These cutoffs can be read off from Figure A.1 as:

$$q^{low} = \left(\frac{\Psi}{\tau \sigma_{max}} \right)^{\frac{1}{\alpha\epsilon}}, \qquad q^{high} = \left(\frac{\Psi}{\tau} \right)^{\frac{1}{\alpha\epsilon}}. \tag{A.3}$$

Inspection of Figure A.1 shows that, analogously to the basic model, there is no offshoring if $q^{high} < q_t^L$ and there is no automation if $q^{low} > Q_{t+1}$. In any case the measure of firms producing at home can be simply read off from Figure A.1. It consists of all firms to the left of the threshold q_t^L and above $\tilde{\sigma}(q_L^t)$, i.e. in Figure A.1 by the area

$$\tilde{\theta}_L = \left[\sigma_{max} - \tilde{\sigma}(q_t^L) \right] \left(q_t^L - Q_t \right) = \left[\sigma_{max} - \frac{\psi}{\tau} \left(q_t^L \right)^{-\alpha\epsilon} \right] \left(q_t^L - Q_t \right). \tag{A.4}$$

The share of firms that prefer home production is obtained by dividing $\tilde{\theta}_H$ by the measure of all firms. A larger q_t^L moves the threshold to the right and increases the measure of firms that produce at home:

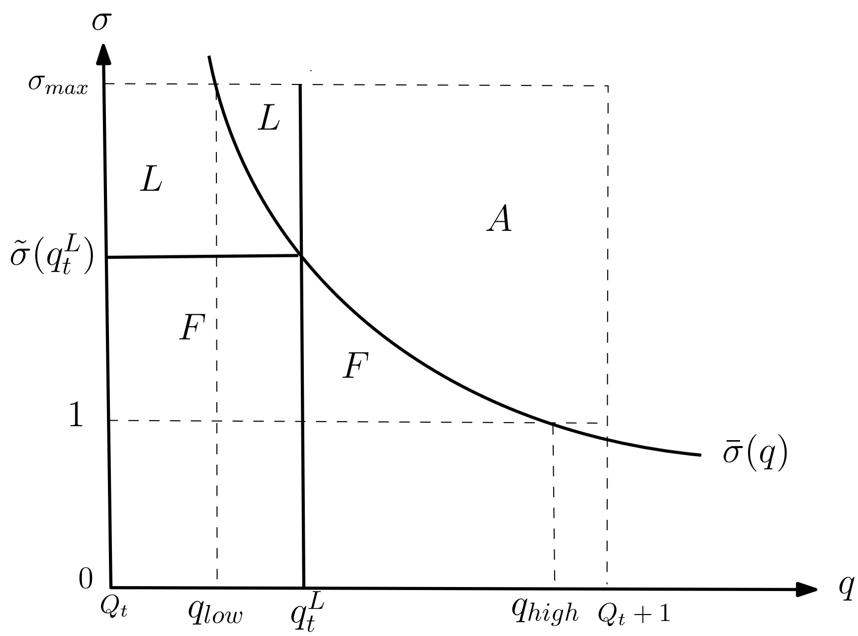
$$\frac{\partial\theta_L}{\partial q_t^L} = \alpha\epsilon\frac{\psi}{\tau}\left(q_t^L\right)^{-\alpha\epsilon-1}\left(q_t^L - Q_t\right) + \left[\sigma_{max} - \frac{\psi}{\tau}\left(q_t^L\right)^{-\alpha\epsilon}\right] > 0. \tag{A.5}$$

Proceeding as in the main text we arrive at the labor market equilibrium condition:

$$G = \tilde{\theta}_L(q_t^L)l_{u,t} - L_u = 0. \tag{A.6}$$

The difference to (18) from the main text is that the measure of firms with "low trade costs" is now endogenous.

Figure A.1 Two-Dimensional Firm Space



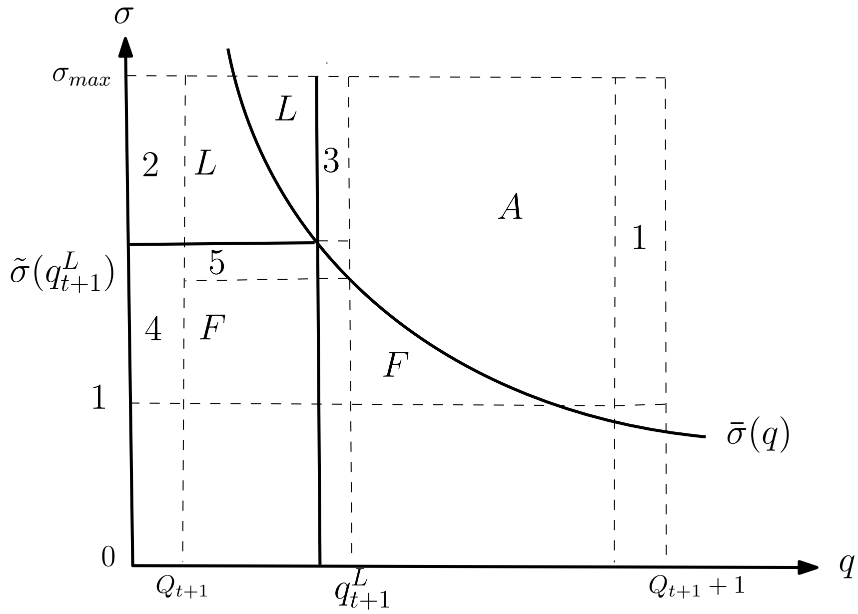
Mode of production by region in σ–q-space: home (H), abroad (F), automated (A).

Inspection (A.6) in conjunction with (A.5) and (9) shows that $\partial G/\partial Q_t < 0$ and

$$\frac{\partial G}{\partial w_u} = \frac{\partial\tilde{\theta}_L}{\partial q_t^L}\frac{\partial q_t^L}{w_u\partial}l_{u,t} + \tilde{\theta}_L\frac{\partial l_{u,t}}{\partial w_u} < 0. \tag{A.7}$$

We thus conclude that $\mathrm{d}w_{u,t}/\mathrm{d}Q_t = -(\partial G/\partial Q_t)/(\partial G/\partial w_{u,t}) < 0$. Thus, Proposition 2 is confirmed for the 2-dimensional model. Increasing productivity in automation leads to lower low-skilled wages. Since lower wages imply greater labor input by firms that produce with low-skill labor, it implies that the measure of low-skill labor firms declines. The productivity increase in automation is shown in the Figure A.2. From period t to $t+1$, the lower and upper boundaries of firm productivity move to the right to the new values Q_{t+1} and $Q_{t+1}+1$. The implied wage decline of low-skilled wages moves the vertical threshold to the right to q_{t+1}^L. Thus firms using low-skill labor lose area 2 due to productivity advances and gain area 3 and 5 due to lower wages. As shown above, the size of area 2 is larger than the combined size of area 3 and 5.

Figure A.2 Advancing Productivity of Automation



Automated firms gain area 1 and lose 3; offshored firms lose 4 and 6 (reshoring); home production looses 2 and gains 3 and 5.

Analogously to the basic model, we focus on the case $q^{high} < Q_t + 1$ in order to limit case differentiations. This means that there exists at least one firm where production is automated irrespective of trade costs. In this case the measure of offshored firms is obtained as:

$$\tilde{\theta}_F = \left(\tilde{\sigma}(q_t^L) - 1\right) + \frac{\psi}{\tau}\int_{q_t^L}^{q^{high}} q^{-\alpha\epsilon}\mathrm{d}q + \left(q^{high} - q_t^L\right). \tag{A.8}$$

The first term in (A.8) corresponds to the area below $\tilde{\sigma}(q_t^L)$ and to the left of q_t^L in Figure A.1, i.e. the area where non-automated firms prefer offshoring over home production with labor. The remainder of (A.8) corresponds to the area to the right of q_t^L, below the $\tilde{\sigma}(q)$–threshold, and above the horizontal line at minimum trade costs, i.e. the area where firms prefer offshoring over automation. Offshoring declines when the productivity of automation increases:

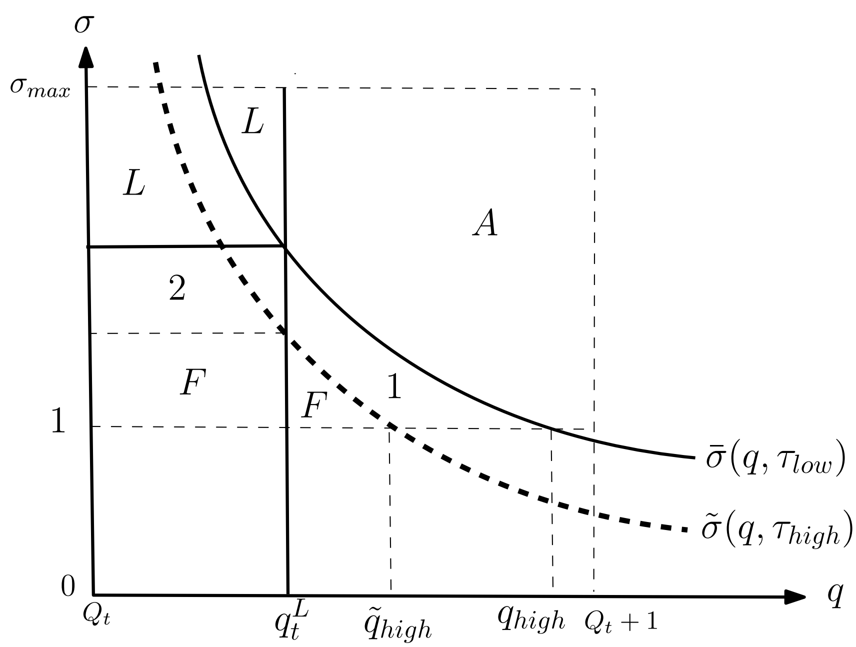
$$\frac{\partial\tilde{\theta}_F}{\partial Q_t} = \frac{\partial\sigma(q_t^L)}{\partial Q_t} + \left[1 - \frac{\psi}{\tau}\left(q_t^L\right)^{-\alpha\epsilon}\right]\frac{\partial q_t^L}{\partial w_{u,t}}\frac{\partial w_{u,t}}{\partial Q_t} < 0. \tag{A.9}$$

The first term in (A.9) is negative since $\partial\sigma(q_t^L)/\partial Q_t = \partial\sigma(q_t^L)/\partial q_t^L \cdot \partial q_t^L/\partial w_{u,t} \cdot \partial w_{u,t}/\partial Q_t$ of which all three derivatives have been signed as negative. The second term is negative because $\partial q_t^L/\partial w_{u,t}$ and $\partial w_{u,t}/\partial Q_t$ have been signed as negative and

$$q_t^L < q^{high} = \left(\frac{\psi}{\tau}\right)^{\frac{1}{\alpha\epsilon}} \quad\Leftrightarrow\quad \left(q_t^L\right)^{\alpha\epsilon} < \frac{\psi}{\tau}. \tag{A.10}$$

In Figure A.2, offshored firms lose area 4 when the productivity of automation increases. Due to the implied wage decline (movement of the q_t^L threshold to the right), offhored firms lose furthermore area 5 to home production with labor. Summarizing, since increasing productivity of automation reduces the measure of offshored firms and the measure of firms producing with low-skilled labor, it increases the measure of automated firms. This confirms Proposition 3 for the two-dimensional case since the remainder of the model coincides with basic model.

Figure A.3 Increasing Tariff



Automated firms gain area 1; home production gains area 2; offshoring loses area 1 and 2 (reshoring).

Results deviate from the basic model with respect to the comparative statics of a tariff change. To see this compute from (A.1)

$$\frac{\partial \tilde{\theta}_L}{\partial \tau} = \frac{\psi}{\tau} \left(q_t^L\right)^{-\alpha\epsilon} \left(q_t^L - Q_t\right) > 0. \tag{A.11}$$

A tariff increase leads to a larger measure (and thus share) of firms producing at home with labor. In Figure A.3, the tariff increase shifts the $\tilde{\sigma}(q)$ threshold downwards and offshored firms loose area 1 to automation and area 2 to home production with low-skilled labor. The gain for low-skilled-labor production, however, is short-lived if productivity Q_t rises over time. More importantly, the gain in production share does not benefit the low-skilled workers. As for the basic model, the low-skilled wage is determined by the trade-off between automation and low-skilled employment and does not change with changing tariffs. In the diagram, the threshold q_t^L does not move. The fact that there are more firms producing with labor with unchanged low-skill wage is thus an expression of increasing inefficiency in the economy. The economy could produce more with lower tariffs. Notice that this result would not change if labor supply were endogenous since the equilibrium wage is fixed by the trade-off between automation and low-skilled employment and does not change with changing tariffs.

Finally, we consider a dependent distribution of σ. Specifically, suppose that $\sigma = \hat{\sigma} q^{\kappa}$, $\hat{\sigma} \in (1, \sigma_{max}$, and $Q_t > 0$. For $\kappa < 0$ this captures the notion that more codifiable products are both more easily offshored and automated. Proceeding as for the independent distribution, we obtain the threshold between automation and offshoring

$$\sigma > \bar{\sigma}(q) = \frac{\Psi}{\tau} \cdot q^{-\alpha\epsilon-\kappa}, \qquad \Psi \equiv \left(\frac{\eta r}{w_F}\right)^{\alpha\epsilon}, \tag{A.12}$$

which is isomorph to (A.1) since the rest of the model does not change, the analysis proceeds as above. Ceteris paribus, the threshold $\bar{\sigma}(q)$ is flatter than in Figure A.1 if $\kappa < 0$. This implies that a large measure of firms prefer home-production over offshoring and a larger measure of firms prefers offshoring over automation without change in the results of the comparative static analysis.

A.3. Harmonization of Industry Sectors. The classification of industry sectors across the data sets from IFR, WIOD and EU KLEMS required a harmonization procedure. For example, the IFR applies a classification of industries that deviates from ISIC Rev.4 for the sectors 19 to 22. Sector 19 in the IFR (2016) data denotes the pharmaceutical sector, whereas in the WIOD database, sector 19 denotes the manufacture of coke and refined petroleum and sector 21 denotes pharmaceuticals. Moreover, in the IFR data set, the values listed for subsector 229 are not a subset to sector 22 (rubber and plastics). We added the values to the biggest sector among them, which is sector 22. The values listed for subsector 299, by contrast, are an actual subset of the values in sector 29 (automobiles). The details of the harmonization process and the availability of information across the different data sets is shown in Tables A.1 and A.2.

A.4. Robots data from IFR. The IFR provides data on industry robots for a panel of countries. There are some particularities about this data set. On the one hand robots stock is listed for North America, consisting of Canada, Mexico, USA together up until 2010. We decided to work with the single country data which are available from 2011 for Canada, Mexico and the USA.

On the other hand, the robot stock information is not classified for different sectors for a couple of countries for several years. We decided to work with the data at sectoral level when the robot stock information is first allocated to the manufacturing sector and across different sub-sectors. This is the case for (first year in parenthesis): Austria (2004), Belgium (2004), Bulgaria (2006), Croatia (2005), Czech Republic (2004), Estonia (2005), Greece (2006), Hungary (2004), Ireland (2006), Latvia (2006), Lithuania (2006), Malta (2006), Netherlands (2004), Poland (2004), Portugal (2004), Roumania (2004), Slovakia (2004), Slovenia (2005), and for the other countries we can use robots data that start from 2000.

Table A.1: Industry Sectors, Information on Aggregation, and Availability across Data Sets

Code	Description	WIOD (2016)	IFR(2016)	EU KLEMS (2017)	Our aggregation
10t12	Food products, beverages and tobacco products	$\surd$	$\surd$	$\surd$	10-12
13t15	Textiles, wearing apparel and leather products	$\surd$	$\surd$	$\surd$	13-15
16	Wood, products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials	$\surd$	$\surd$	together with sector 17 and 18	16-18
17	Paper and paper products	$\surd$	together with sector 18	together with sector 16 and 18	
18	Printing of reproduction of recorded media	$\surd$	together with sector 17	together with sector 16 and 17	
19	Coke and refined petroleum products	$\surd$	Sector 20 and 21 listed together	$\surd$	19-21
20	Chemicals and chemical products	$\surd$	Sector 20 and 21 listed together	together with sector 21	
21	Basic pharmaceutical products and pharmaceutical preparations	$\surd$	Named sector 19	together with sector 20	
22	Rubber and plastics products	$\surd$	consists of sector 22; sector 229 added	together with sector 23	22-23
23	Other non-metallic mineral products	$\surd$	$\surd$	together with sector 22	
24	Basic metals	$\surd$	$\surd$	together with sector 25	24-25
25	Fabricated metal products, except machinery and equipment	$\surd$	$\surd$	together with sector 24	
26	Computer, electronic and optical products	$\surd$	together with sector 27	together with sector 27	26-27
27	Electrical equipment	$\surd$	together with sector 26	together with sector 26	
28	Machinery and equipment, nec	$\surd$	consists of sector 28; sector 289 added	$\surd$	28
29	Motor vehicles, trailers and semi-trailers	$\surd$	together with sector 30	together with sector 30	29-30
30	Other transport equipment	$\surd$	together with sector 29	together with sector 29	

Table A.2: List of countries used in the estimations and availability across data sets

	WIOD (2016)	IFR (2016)	EU KLEMS (2017)	Eurostat (2018)	Country-Sector-Year Sample	Country-Year Sample
Australia	√	√				
Austria	√	√	√	√	√	√
Belgium	√	√	√	√	√	√
Bulgaria	√	√	√	√	√	√
Brazil	√	√				
Canada	√	√ from 2011				
Chile		√				
China	√	√				
Croatia	√	√	√	√	√	√
Cyprus	√		√	√		√
Czech Republic	√	√	√	√	√	√
Denmark	√	√	√	√	√	√
Estonia	√	√	√	√	√	√
Finland	√	√	√	√	√	√
France	√	√	√	√	√	√
Germany	√	√	√	√	√	√
Greece	√	√	√	√	√	√
Hungary	√	√	√	√	√	√
Iceland		√		√		
India	√	√				
Indonesia	√	√				
Ireland	√	√	√	√	√	√
Israel		√				
Italy	√	√	√	√	√	√
Japan	√	√				
Korea	√	√				
Latvia	√	√	√	√	√	√
Lithuania	√	√	√	√	√	√
Luxembourg	√		√	√		√
Malta	√	√	√	√	√	√
Mexico	√	√ from 2011				
Netherlands	√	√	√	√	√	√
New Zealand		√				
Norway	√	√		√		√
Poland	√	√	√	√	√	√
Portugal	√	√	√	√	√	√
Roumania	√	√	√	√	√	√
Russia	√	√				
Slovakia	√	√	√	√	√	√
Slovenia	√	√	√	√	√	√
South Africa		√				
Spain	√	√	√	√	√	√
Sweden	√	√	√	√	√	√
Switzerland	√	√		√		√
Taiwan	√	√				
Turkey	√	√		√		√
UK	√	√	√	√	√	√
USA	√	√ from 2011	√		√	

Table A.3: Descriptive Statistics

Country-Sector-Year Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Stock of robots	4014	2614.10	11886.75	0.00	142286.00
No of persons engaged (in 1000)	3798	177.01	337.68	0.00	2794.00
Hours worked (in thousands)	3517	327031	601567.70	0.00	4958000
Robots (per 1000 persons engaged)	2715	5.85	13.02	0.00	99.32
Robots (per thousand hours worked)	2574	3.78	8.45	0.00	65.77
DI/FI	5805	5.08	16.82	0	376.85
$DI/FI_t - DI/FI_{t-1}$	5418	-0.19	5.11	-126.37	160.61
Log(reshore)	2136	-2.19	2.42	-40.63	5.08
Tariffs	3645	1.4743	3.4327	0	64.4241
Robots stock (IV)	4014	5019.29	19124.72	0	221160

Country-Year Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Earnings elementary occupations (deflated and converted)	115	7.54	6.41	0.009	26.87
Earnings professional occupations (deflated and converted)	115	15.50	12.61	0.03	54.94
Change employment elementary occupations	388	7.80	69.63	-367.55	796.23
Change employment professional occupations	388	41.29	161.52	-616.13	2603.25
Change hours elementary occupations	386	15759	159783	-900893	1895535
Change hours professional occupations	386	88892	348001	-1288290	5718997
Log(reshore)	218	-2.61	1.48	-6.90	1.67

Table A.4: Automation and Reshoring - Reduced Sample of 8 countries

Variables	(1) Log(Reshore) broad	(2) Log(Reshore) narrow	(3) Log(Reshore) broad	(4) Log(Reshore) narrow
Robots per 1000 workers	0.0504	0.0404		
	(0.111)	(0.148)		
Robots per 1000 hours worked			0.0684	0.0500
			(0.098)	(0.124)
Country-year FE	$\surd$	$\surd$	$\surd$	$\surd$
Sector-year FE	$\surd$	$\surd$	$\surd$	$\surd$
Country-sector FE	$\surd$	$\surd$	$\surd$	$\surd$
F-test $\beta <= 0$ (p-value)	0.0556	0.0491	0.0740	0.0618
Obs.	276	276	276	276
R^2	0.839	0.839	0.845	0.845

Notes: p-values in parentheses. Cluster-robust standard errors at industry-country level. Sources: IFR (2016), WIOD (2016), EU KLEMS (2017).

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