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ROBOTIZATION AND UNBALANCED CHANGES IN HIGH-SKILL EMPLOYMENT

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Robotization and Unbalanced Changes in High-Skill Employment *

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Abstract

This paper fills a gap in the literature by presenting new evidence of the negative impact of robotization on the change in high-skill employment in US labor markets between 2000 and 2014. I find that the adoption of one robot per thousand workers reduced the change in the high-skill employment-to-population ratio by 0.18 to 0.24 percentage points, which implies that each robot prevented the creation of 4 high-skill jobs. Though these findings are surprising with regard to the literature, which globally argues that technological change favors high-skill employment, they give new support to a range of theoretical studies. I show that these results can be explained by a model of tasks commonly used in the literature. In such models robotization generates reallocations of tasks between low-skill and high-skill workers, which can negatively impact the employment of high-skill workers. I calibrate the model and find that robotization reduced the magnitude of the effects that increase high-skill employment by almost half during this period.

Keywords: robotization, technological change, employment, skills, automation.
JEL Classification: J23.

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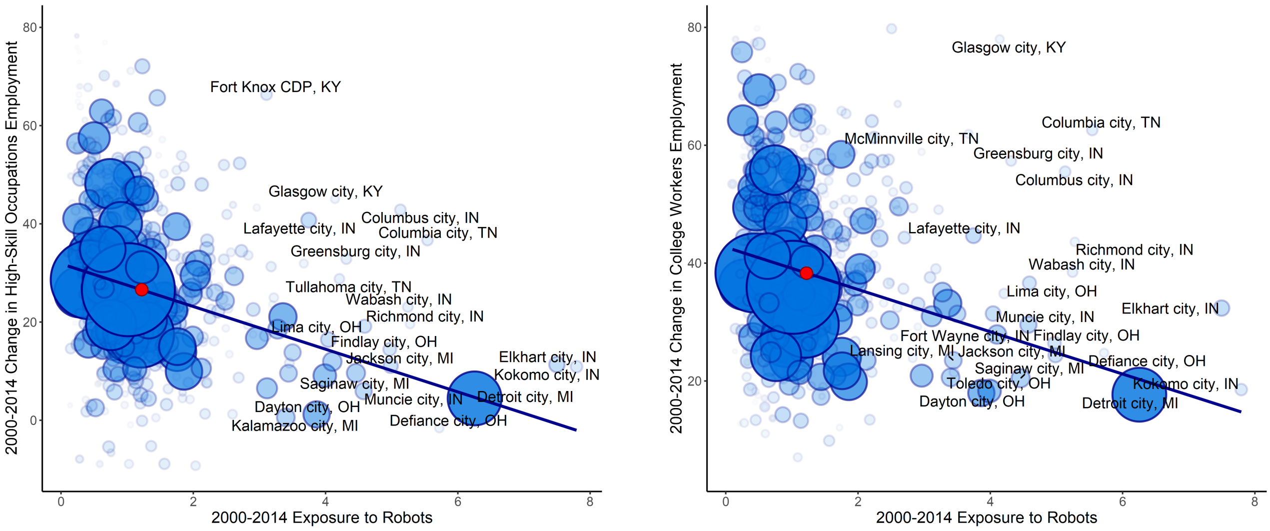
1 Introduction

The relationship between technological change and jobs is a leading issue in the literature. Although most of the studies argue that technological change increases employment, its potential negative effects have been discussed. In particular, different essays suggest that machines could eventually automate the whole range of production tasks and destroy the related jobs (Keynes 1931, Leontief 1952, Brynjolfsson and McAfee 2014). This concern notably gained importance recently next to the publication of empirical evidence that jobs are negatively affected by the adoption of particular smart machines: industrial robots (Chiacchio et al. 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, henceforth AR2020). The International Federation of Robotics (IFR) defines industrial robots as "automatically controlled, reprogrammable [and] multipurpose [machines] [...] for use in industrial automation applications" (IFR 2022), which implies that they exhibit a greater power of substitution for workers than the standard capital. "Robotization" refers to the adoption of cutting-edge robots that can automate complex tasks due to innovations in robotics, provided that robots are less costly than labor. The evidence that such a technology is able to destroy more jobs than it creates rekindled the debate around the impact of technological change on the labor market, and raised many issues. In particular different studies argue that automation caused the job polarization observed in many modern economies (Autor et al. 2003, Michaels et al. 2014), and therefore suggest that robotization favors high-skill employment. Meanwhile, to the best of my knowledge, no empirical study have assessed the impact of robotization on high-skill employment.

This paper fills this gap in three ways. First, I highlight novel facts about the relationship between robotization and the change in high-skill employment in US labor markets between 2000 and 2014. This is illustrated by Figure 1, where US labor markets are proxied by the commuting zones of Tolbert and Sizer (1996), and robotization is proxied by the exposure to robots (AR2020), namely the change in the stock of robots per thousand workers. Despite an average increase in high-skill employment, the changes were unbalanced across the commuting zones, so that the changes in high-skill employment were less than average in the commuting zones exposed to robots.

The second key contribution is new evidence of the negative and robust impact of robotization on the change in high-skill employment. I find that the adoption of one robot per thousand workers reduced the change in the high-skill employment-to-population ratio by 0.18 to 0.24 percentage points, which implies that each adoption of robot prevented the creation of 4 high-skill jobs. Additional estimates for hourly wages suggest that the adoption of one robot per thousand workers reduced the change in the hourly wage of high-skill workers by 1.73% to 2.82%. This indicates that robotization indeed impacted the demand side of the labor market, and not the supply side.



(a) (b)

Figure 1: US Exposure to Robots and Change in High-Skill Employment between 2000 and 2014

Source : Author's own calculations, AR2020, 2000 census, 2014 American Community Survey.
Notes : Residual plots of the relationship between robotization (proxied by the exposure to robots, a measure based on industrial changes in the stocks of robots per thousand workers) and the change in high-skill employment. High-skill employment is counted as the number of workers in high-skill occupations in Figure 1a (managers, professionals, and technicians), and the number of college-educated workers in Figure 1b. Each point corresponds to a commuting zone, with radius and opacity computed as increasing functions of the population. The solid lines are population-weighted regression lines. The red points indicate the centers of gravity.

Third, I show that these findings give new support to a range of theoretical discussions, even though they are surprising with regard to the literature. Indeed, the documented facts can be explained by a static model building on the model of tasks of Acemoglu and Autor (2011) and the extension of Acemoglu and Restrepo (2018). This class of models builds on the ricardian model so that the factor allocated on a task necessarily holds a comparative advantage, i.e. the highest productivity / cost ratio, for the production of this task. My main additional feature is a richer household side that enables the model to return endogenous employment levels. I lead a comparative statics analysis in which the equilibrium reacts to two types of processes: robotization and high-skill biased technological change. The model shows that both processes act as counter-balancing forces on high-skill employment. In particular robotization has a negative indirect impact on high-skill employment because it generates reallocations of tasks between both types of worker. This effect is known as the "ripple effect" in a few papers (Acemoglu and Restrepo 2018, 2022b). The overall employment of high-skill workers increased because high-skill workers were allocated on additional tasks initially performed by low-skill workers due to high-skill biased technological change. This is in line with the downskilling phenomenon documented by a range of studies (Beaudry et al. 2016; Modestino et al. 2016). However, in the exposed commuting zones robotization decreased the demand and the wage of low-skill workers, and maintained their comparative advantage for the tasks they were initially performing even though high-skill workers benefited from high-skill biased technological change. High-skill job creations were thus less than average. I calibrate the model and decompose the impact into different effects including, inter alia, the ripple effect. I find that the ripple effect reduced the magnitude of the effects that increase high-skill employment by almost half between 2000 and 2014.

This paper is most closely related to the literature studying the impact of automation on employment (Acemoglu and Restrepo 2018, 2022a, 2022b; Dauth et al. 2021; Graetz and Michaels 2018; Lankisch et al. 2019; Leduc and Liu 2020; Zhang 2019) and the demand for skills (Katz and Murphy 1992; Katz and Autor 1999; Acemoglu 1998, 2002; Autor et al. 1998; Autor et al. 2006; Goos and Manning 2007; Autor and Dorn 2013; Goos et al. 2014; Caines et al. 2017; Cortes et al. 2020). I contribute to the literature by showing that robotization does not favor high-skill employment, but rather acts as a counter-balancing force to high-skill biased technological change. I present new evidence of the negative impact of the adoption of industrial robots on the change in high-skill employment. These findings bolster the hypothesis of the overall negative impact of automation on jobs, which is supported by different papers. Moreover, they give new support to previous theoretical discussions around the ripple effect, and thus further the debate around the impact of technological change on employment. Finally, this is the first paper that assesses the magnitude of the isolated negative effect of robotization on the change in high-skill employment, namely the ripple effect.

The rest of the paper is organized as follows. Section 2 introduces the theoretical model and leads an exploration of the key mechanisms. Section 3 presents the data and provides different statistics of the main variables. Section 4 discusses the empirical results. Section 5 assesses the magnitude of the ripple effect, and Section 6 concludes.

2 A Model of Robots, Skills and Tasks

2.1 Environment and Equilibrium

I consider a static economy with two representative households characterized by different skills, denoted by s. Low-skill is denoted by L, high-skill is denoted by H. A household chooses its level of consumption and labor supply depending on the following quasi-linear preferences:

$$U_s(C_s, N_s) = C_s - B_s \tfrac{N_s^{1+\varepsilon}}{1+\varepsilon}, \quad s \in \{L, H\} \tag{1}$$

where C_s denotes the consumption of the household with skill s, N_s denotes employment, ε is the inverse of the wage elasticity of labor supply, and B_s is the parameter of the disutility of work. Each worker supplies one unit of labor. There is a unit mass of individuals so that employment levels are also employment-to-population ratios. In addition to labor, households hold robots and non-robot capital. The household with skill s owns a fixed quantity of non-robot capital K_s that is perfectly inelastically supplied to firms with a price R. I follow Guerreiro et al. (2022) and specify that each robot is produced with ϕ units of final good. They are traded on a perfectly competitive market, which implies that their supply is perfectly elastic with the quantity M and the price ϕ. The budget constraint of a household is thus:

$$C_s \leq W_s N_s + R K_s, \quad s \in \{L, H\} \tag{2}$$

where W_s denotes the wage rate of skill s.

The final good is produced by combining a unit continuum of tasks with non-robot capital using the following technology:

$$Y = A \exp\left(\int_0^1 \ln y(i) di\right)^{\alpha} K^{1-\alpha} \tag{3}$$

where A denotes the total factor productivity, $y(i)$ denotes the quantity of task $i \in [0, 1]$, and α is the share of tasks in the production process. It is traded on a perfectly competitive market with a price normalized to 1. Tasks are intermediate goods that can be produced with low-skill workers, high-skill workers or robots, using the technology:

$$y(i) = \begin{cases} A_L(i) n_L(i) + A_H(i) n_H(i) + A_M m(i) \ \forall \ i \in [0, \theta) \\ A_L(i) n_L(i) + A_H(i) n_H(i) \ \forall \ i \in [\theta, 1] \end{cases} \tag{4}$$

where $A_L(i)$, $A_H(i)$, and A_M are the productivities of low-skill workers, high-skill workers and robots; and $n_L(i)$, $n_H(i)$, $m(i)$ denote the masses of low-skill workers, high-skill workers and robots allocated on tasks. The production function of tasks is defined over a threshold θ that delimits the abilities of robots. Indeed, as it is admitted in the literature, I assume that robots cannot produce the tasks indexed above this threshold. Then, as it is usually done, I assume that robots hold a comparative advantage for all the tasks they are able to perform.

Assumption 1.

$$\frac{A_M}{\phi} > \frac{A_L(i)}{W_L}, \frac{A_H(i)}{W_H} \;\forall\; i \in [0, \theta] \tag{5}$$

The productivities of workers are functions of tasks, and their properties have important implications on the allocation of workers on tasks. Since I am not interested in the change in low-skill employment, I assume that the productivity of low-skill workers is constant over tasks, so that $A_L(i) = A_L$. To obtain realistic allocations of factors on tasks, namely those for which high-skill workers do not directly compete with robots, I follow Acemoglu and Zilibotti (2001) and assume that $A_H(i)$ is affine and increasing.

Assumption 2.

$$A_L(i) = A_L \tag{6}$$

$$A_H(i) = \gamma(1 + \delta i) \tag{7}$$

The economy is affected by two processes. The first one is robotization. It is modelized as any exogenous process that extends the set of tasks that can be robotized. More formally, robotization corresponds to an increase in θ. In response to this technological change producers choose to adopt additional robots because of Assumption 1. The second process is high-skill biased technological change, i.e. an exegeneous increase in γ.

An equilibrium is defined as an allocation of factors on tasks $\{m(i), n_L(i), n_H(i)\}_{i\in[0,1]}$, a tuple of quantities $\{C_L, C_H, N_L, N_H, M, Y, \{y(i)\}_{i\in[0,1]}\}$, and a tuple of prices $\{R, W_L, W_H\}$, such that households maximize their utility under budget constraint; producers minimize their production costs under production constraint; and markets clear:

$$M = \int_0^1 m(i)di, \quad N_L = \int_0^1 n_L(i)di, \quad N_H = \int_0^1 n_H(i)di \tag{8}$$

The next proposition characterizes the optimal allocation of factors on tasks.

Proposition 1. *Under Assumptions 1 and 2, for any optimal allocation of factors on tasks there exists a unique task index $I \in (\theta, 1)$ such that:*

$$m(i) = \begin{cases} \frac{y(i)}{A_M} \; \forall \; i \in [0,\theta) \\ 0 \; \forall \; i \in [\theta, 1] \end{cases} \qquad n_L(i) = \begin{cases} \frac{y(i)}{A_L} \; \forall \; i \in [\theta, I) \\ 0 \; \forall \; i \in [0,\theta) \cup [I, 1] \end{cases} \qquad n_H(i) = \begin{cases} \frac{y(i)}{A_H(i)} \; \forall \; i \in [I, 1] \\ 0 \; \forall \; i \in [0, I) \end{cases} \tag{9}$$

$$\frac{A_L}{W_L} = \frac{A_H(I)}{W_H} \tag{10}$$

Proof. See Appendix A1.1. □

Assumption 1 guarantees that robots are used at the equilibrium. Assumption 2 guarantees that there exists a unique task, indexed by I, for which the representative producer is indifferent between allocating low-skill and high-skill workers. Indeed due to the linearity of $A_H(i)$ there is a single task for which low-skill and high-skill workers return the same productivity / cost ratio. This indicated by Equation (10). High-skill workers are then allocated on the tasks with the greatest indexes, so that they do not diectly compete with robots. The equilibrium allocation is then as follows: robots are allocated on all the tasks indexed below θ; low-skill workers are allocated on all the tasks indexed between θ and I; and high-skill workers are allocated on all the tasks indexed above I. Figure 2 illustrates an equilibrium allocation of factors on tasks. Lines indicate the productivity / cost ratio of each factor as a function of the task index. Thick parts correspond to the sets of tasks allocated to factors.

2.2 Comparative Statics and Equilibrium Forces

The next proposition characterizes the equilibrium on both labor markets and highlights the forces shaping employments.

Proposition 2. *Under Assumptions 1 and 2:*

$$d \ln {N_L}^{Demand} = d \ln Y - d \ln W_L - \frac{d\theta}{I-\theta} + \frac{dI}{I-\theta} \tag{11}$$

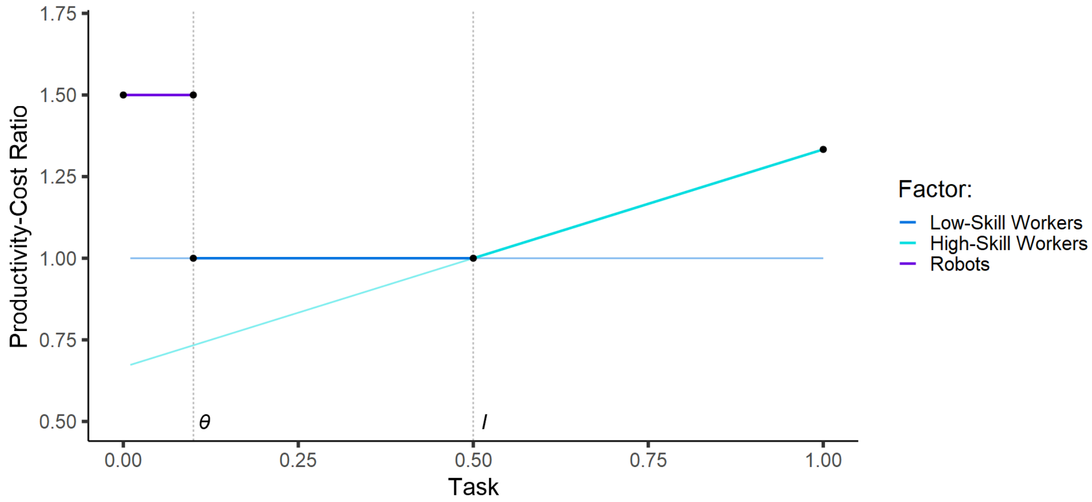


Figure 2: Equilibrium Allocation of Factors on Tasks

$$d \ln {N_H}^{Demand} = d \ln Y - d \ln W_H - \frac{dI}{1-I} \tag{12}$$

$$d \ln {N_L}^{Supply} = \frac{1}{\varepsilon} d \ln W_L \tag{13}$$

$$d \ln {N_H}^{Supply} = \frac{1}{\varepsilon} d \ln W_H \tag{14}$$

$$dI = \frac{1+\delta I}{\delta} \left(-d \ln \gamma + d \ln W_H - d \ln W_L\right) \tag{15}$$

Proof. Log-differentiating (A8), (A9), (A3), (A4) in Appendix A1.1 and (10) leads to (11), (12), (13), (14), and (15). □

Equations (11) and (12) give the changes in labor demands; Equations (13) and (14) give the changes in labor supplies; and Equation (15) characterizes the equilibrium variation of I. The impacts of the processes on labor markets can be decomposed into different effects. Each of these effects are described in the next paragraphs.

Productivity and Substitution Effects. The first and second terms in labor demands correspond respectively to the traditional productivity and substitution effects. The productivity effect arises when production costs decrease due to the processes, which gives incentives to producers to demand more workers. The productivity effect also affects the quantities of factors allocated on tasks. A decrease in production costs increases the production of tasks. As a result more workers are demanded on all tasks and wages increase. The substitution effect affects the tasks relative prices. When the price of a task increases relatively to the other tasks prices its relative demand decreases. These effects cannot be represented on the figure 2, since they do not shape the sets of tasks allocated to factors.

High-Skill Biased Technological Change Effect. High-skill biased technological change corresponds to an exogeneous increase in γ. Equation (15) shows that an increase in γ decreases I. When (15) is then inserted into (11) and (12), the set of tasks allocated to low-skill workers is reduced, whereas the set of tasks allocated to high-skill workers is extended. As a result, the demand of low-skill workers decreases and the demand of high-skill workers increases. Figure 3 illustrates this effect following the example presented in Figure 2.

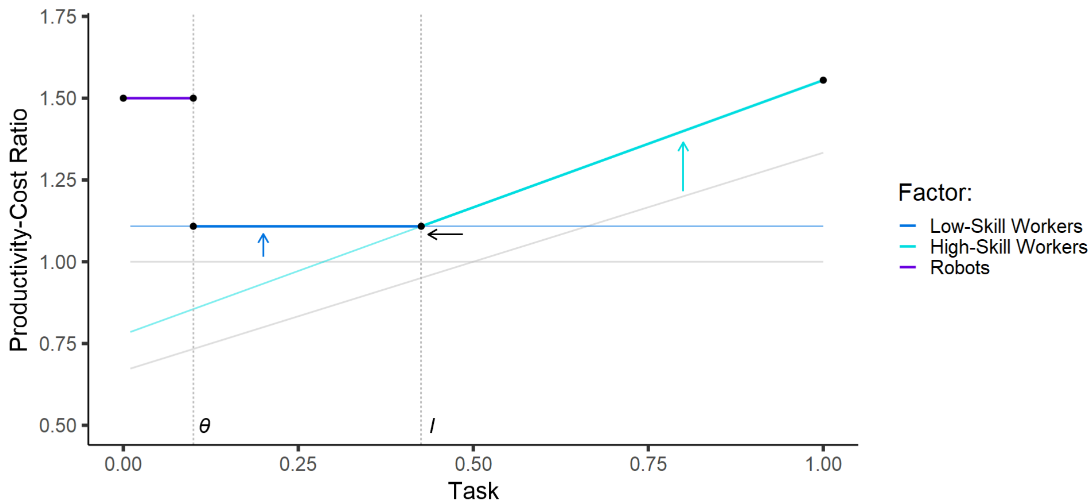


Figure 3: High-Skill Biased Technological Change Effect

Displacement Effect. Robotization extends the set of tasks produced by robots and reduces the set of tasks produced by low-skill workers. It affects labor markets by the importance of $d\theta$. Equation (11) shows that an increase in θ decreases the demand of low-skill workers. Figure 4 illustrates the displacement effect following the example presented in Figure 2.

Ripple Effect. Due to the displacement effect, the wage of low-skill workers decreases, and their productivity / cost ratios increase for all tasks. Indeed, Equation (15) shows that a decrease in W_L increases I. The set of tasks produced by low-skill workers is extended, whereas the set of tasks produced by high-skill workers

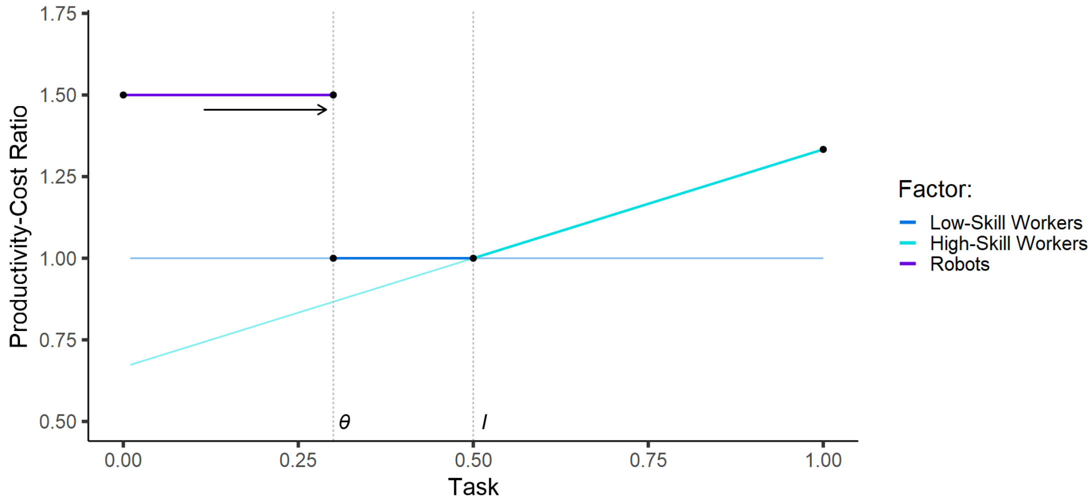


Figure 4: Displacement Effect

is reduced. This effect impacts labor markets by the importance of dI, similarly to the high-skill biased technological change effect. While high-skill biased technological change puts downward pressure on I, robotization puts upward pressure, so that the total effect of both processes is undetermined. This "ripple effect", already put forward in the literature (Acemoglu and Restrepo 2018, 2022b), thus acts as a counter-balancing force to high-skill biased technological change in the determination of the level of I. Figure 5 illustrates a ripple effect following the displacement effect presented in Figure 4.

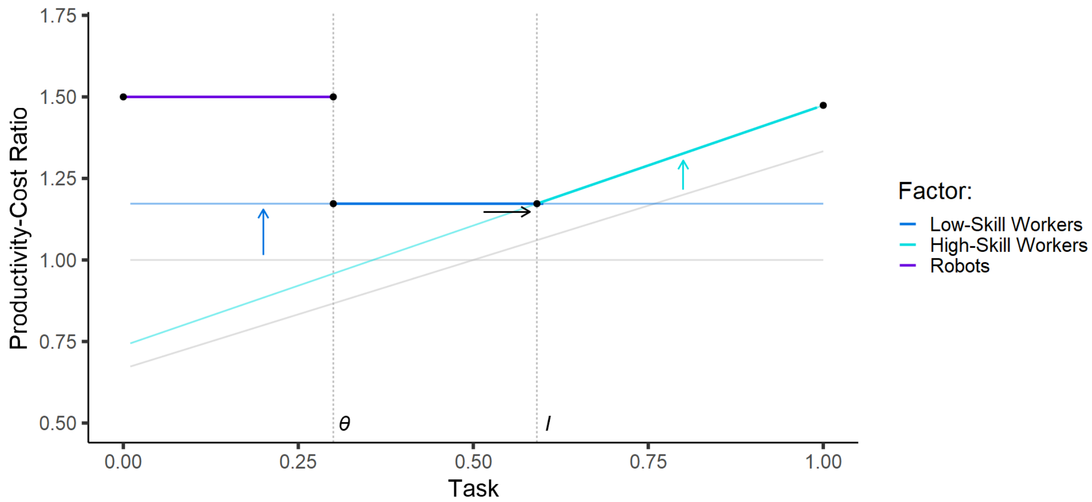


Figure 5: Ripple Effect

The next proposition characterizes the equilibrium change in high-skill employment.

Proposition 3. *Under Assumptions 1 and 2:*

$$d\ln N_H = \Lambda_\gamma d\ln\gamma - \Lambda_\theta d\theta \tag{16}$$

Proof. See Appendix A1.2. □

$\Lambda_\gamma \equiv \frac{\partial \ln N_H}{\partial \ln \gamma}$ is the elasticity of high-skill employment to the productivity of high-skill workers, and $-\Lambda_\theta \equiv \frac{\partial \ln N_H}{\partial \theta}$ is the semi-elasticity of high-skill employment to the threshold of robotization possibilities θ. Equation (16) is a tractable object that can be used for the explanation of the unbalanced changes in high-skill employment depicted by Figure 1. In the commuting zones that were not exposed to robots, i.e. the commuting zones with a low value of $d\theta$, high-skill workers were allocated on additional tasks initially performed by low-skill workers due to high-skill biased technological change, which had then no counter-balancing forces. In the exposed commuting zones, i.e. the commuting zones with a high value of $d\theta$, robotization decreased the wage of low-skill workers due to the displacement effect, and thus maintained their comparative advantage for the tasks they were initially performing. This cancelled out the effects of high-skill biased technological change, prevented the creation of high-skill jobs, and thus reduced the change in high-skill employment. The aim of the rest of the paper is to quantify these effects.

2.3 Empirical Specification

Equation (16) can be turned into a reduced-form model to estimate the relationship between robotization and high-skill employment. However it is unsuitable because $d\theta$ is not observable. In the literature the usual proxy of $d\theta$ is the exposure to robots, which is observable. It is defined as the change in the stock of robots per worker, adjusted to changes in output. It is obtained by dividing the differential of the demand for robots, given in Appendix A1.1 by Equation (A7), by the overall employment:

$$\mathcal{E} \equiv \frac{dM}{N} - \frac{M}{\alpha N} d\ln Y = \frac{m(\theta)}{N} d\theta \tag{17}$$

where N denotes the overall employment. Inserting (17) in (16) leads to:

$$d\ln N_H = \Lambda_\gamma d\ln\gamma - \Lambda_{\mathcal{E}}\mathcal{E} \tag{18}$$

where $-\Lambda_{\mathcal{E}}$ can be interpreted as the isolated impact of the exposure to robots on the change in high-skill employment. Finally, I follow the literature and choose to consider employment-to-population ratios instead of employment levels. Thus a reduced-form equivalent of (18) is:

$$dN_{Hc} = \beta_0 + \beta_1 \mathcal{E}_c + \beta_2 \Gamma_c + \epsilon_c \tag{19}$$

where dN_{Hc} denotes the 2000-2014 change in the high-skill employment-to-population ratio of the commuting zone $c \in \mathcal{C}$; $\mathcal{E}_c$ denotes the 2000-2014 exposure to robots; Γ_c is the vector of covariates; β_0 is the intercept, which captures the effect of high-skill biased technological change common to all commuting zones; β_1 is the average impact of the exposure to robots on the change in high-skill employment, which is expected to be negative; β_2 is the vector of coefficients associated to covariates; and ϵ_c is the error term specific to the commuting zone c.

3 Data

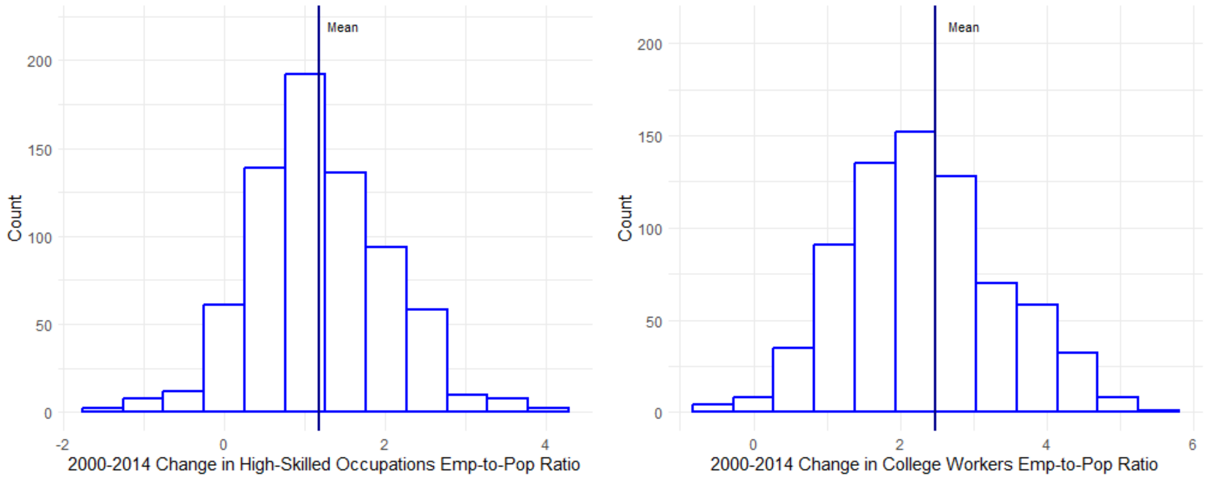
3.1 High-Skill Employment-to-Population Ratio

To measure high-skill employment, I use data from the 2000 census and the 2014 American Community Survey (ACS). I measure the high-skill employment-to-population ratio as 1) the number of non-self-employed workers in high-skill occupations per capita (1990 census occupation codes : 4-234); and 2) the number of non-self-employed college-educated workers per capita (henceforth college workers, census education detailed codes : 81-116). Figure 6 presents the distribution of the 2000-2014 change in high-skill employment-to-population ratio across the 722 continental commuting zones (excluding the states of Alaska and Hawaii). Figure 6a and Figure 6b give respectively results for high-skill occupations and college workers. The population-weighted means of the changes in the employment-to-population ratios of high-skill occupations and college workers are respectively 1.18 and 2.48. Both distributions exhibit large dispersions, coefficients of variation are 0.58 for high-skill occupations and 0.36 for college workers.

3.2 Exposure to Robots

I follow AR2020 and proxy robotization by the exposure to robots. The empirical expression of the exposure to robots is:

$$\mathcal{E}_c = \sum_{j \in \mathcal{J}} \ell_{c,j}^{2000} APR_j \tag{20}$$



(a) (b)

Figure 6: Distribution of the Change in High-Skill Employment-to-Population Ratio across US Commuting Zones
Source : Author's own calculations, 2000 census, 2014 American Community Survey.

with

$$APR_j = \frac{M_j^{2014} - M_j^{2004}}{N_j^{2000}} - \frac{M_j^{2004}}{N_j^{2000}} \frac{Y_j^{2014} - Y_j^{2000}}{Y_j^{2000}} \tag{21}$$

where $\ell_{c,j} \equiv \frac{N_{c,j}}{N_c}$ is the share of workers working in industry $j \in \mathcal{J}$ in the commuting zone c; and APR_j is the adjusted penetration of robots of the industry j, that is the change in the stock of robots per thousand workers of this industry adjusted to change in output. $\ell_{c,j}$ is computed with data from the 2000 census, and APRs come from AR2020. APRs are computed with data from the IFR, which contains data on US stocks of robots for 19 industries and for all years between 2004 and 2014 (see Figure A1 in Appendix A3 for further details about the IFR industries). The original measures are built on the US industrial employments of 1990. I divide them by N_j^{2000}/N_j^{1990} to obtain Equation (21). I follow the authors and rescale their measures into a 14-year equivalent change by multiplying (20) by a factor 1.4. The exposure to robots of a commuting zone is thus a weighted mean of the changes in the industrial stocks of robots per thousand workers, where the weights are its shares of employment in the different industries. Its expression is similar to Equation (17) but differs since the model makes simplifying assumptions by aggregating all industries into one representative industry. Figure 7 presents the distribution of the 2000-2014 exposure to robots across the commuting zones. The distribution is positively skewed, with a population-weighted mean of 1.22.

I assume that the exposure to robots is correlated with unobserved characteristics of commuting zones, captured by ϵ_c. For example wage pushes of unions

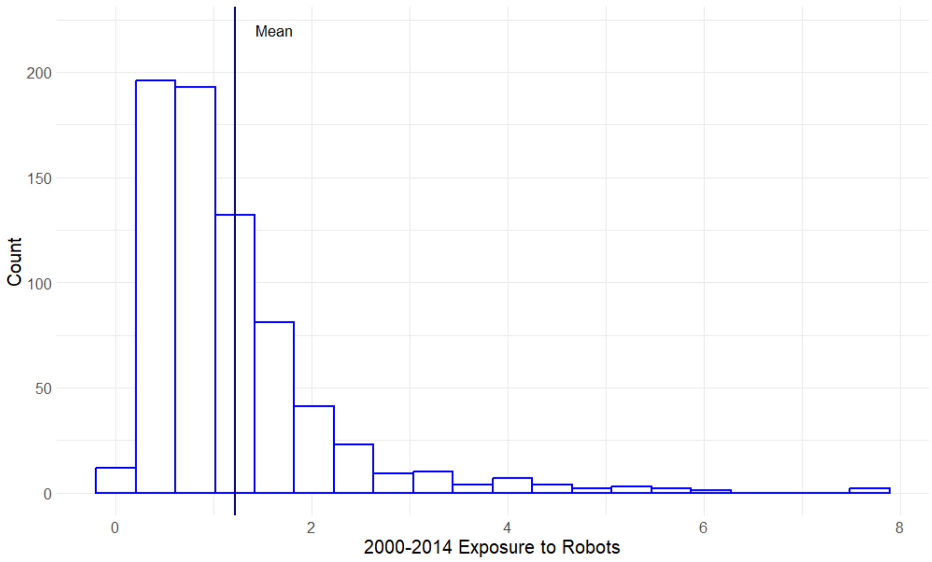


Figure 7: Distribution of the Exposure to Robots across US Commuting Zones
Source : Author's own calculations, AR2020, 2000 census.

enhance incentives for robots adoption and discourage employment. Under this assumption the exposure to robots has to be instrumented. AR2020 uses an instrument built as Equation (20) on a group of European countries. Indeed, between 2000 and 2014 the *APR*s of the US and European industries were significantly correlated. In particular the authors identify six European countries, namely Denmark; Finland; France; Germany; Italy and Sweden, that exhibit robotization trends similar to those of the US but with a greater intensity, which implies that these countries are the closest to the robotization possibilities frontier. For this reason I instrument the US exposure to robots by an EU exposure to robots built on these countries. The identifying assumption is thus that the robotization of the European countries impacts all commuting zones in a similar fashion. The instrument is:

$$\mathcal{E}_{EU\,c} = \sum_{j \in \mathcal{J}} \ell_{c,j}^{1990} APR_{EU\,j} \tag{22}$$

with

$$APR_{EU\,j} = \frac{1}{6} \sum_{q \in \mathcal{Q}} \left\{ \frac{M_{j,q}^{2014} - M_{j,q}^{2000}}{N_{j,q}^{2000}} - \frac{M_{j,q}^{2000}}{N_{j,q}^{2000}} \frac{Y_{j,q}^{2014} - Y_{j,q}^{2000}}{Y_{j,q}^{2000}} \right\} \tag{23}$$

where $\mathcal{Q} = \{Denmark, Finland, France, Germany, Italy, Sweden\}$. European APRs are means of the changes in the stocks of robots per thousand workers of the European countries. In order to avoid any mechanical correlation with the US exposure to robots, the weights used to compute the EU exposure to robots are the 1990 industrial shares of employment. The EU exposure to robots of a commuting zone is thus the one it would have in 2000 if it had followed the European trend, depending on its industrial specialization of 1990. Table 1 presents summary statistics of the exposure to robots and high-skill employment.

3.3 Covariates

I control for different effects that potentially impacted robots adoption or high-skill employment between 2000 and 2014. Firstly, I add a set of demographic covariates: the log of the population, the share of females, shares of race groups, shares of education groups and the share of individuals above 65 years old. Indeed Acemoglu and Restrepo (2022a) shows that the demographic profile of a commuting zone can affect its propensity to adopt robots. Secondly, I add covariates related to the manufacturing industry to disentangle the manufacturing-specific trends and the effects of robotization: the share of workers in manufacturing industries, the share of females in manufacturing industries, and the share of employment in light manufacturing industries, namely textile and paper-publishing-printing industries. Thirdly, I add the share of workers in routine-intensive occupations, namely production; transport; sales; administrative; and clerical occupations. The literature globally argues that automation technologies mainly displace routine-intensive workers, so that automation is globally observed in the commuting zones with the highest shares of routine-intensive occupations (Autor et al. 2003). The previously cited covariates are computed with data from the 2000 census. Fourthly, I control for the impacts of Chinese imports on labor markets, which were significant (Autor et al. 2013, 2021). I include the exposures to Chinese imports of Autor et al. (2021), which concludes the list of the baseline covariates. Finally a group of specifications, designed to check the robustness of the baseline results, assess whether the effects of robotization on the change in high-skill employment are different from the effects of the more intensive use of other types of capital. I include measures of exposures to capital, IT capital, softwares and value added that are built similarly to the exposure to robots. I use data from the EUKLEMS on the usage of the different types of capital by US industries.

Table 1: Summary Statistics for the Main Variables

Variable	Mean	Standard Error	Min	1st Quartile	Median	3rd Quartile	Max
2000-2014 Exposure to Robots (US)	1.22	1.06	0.10	0.66	0.97	1.30	7.79
2000-2014 Exposure to Robots (EU)	0.91	0.79	0.17	0.48	0.69	1.01	4.93
2000 High-skill Occupations Emp-to-Pop Ratio	7.94	2.48	2.03	6.14	7.82	9.65	14.17
2000 College Workers Emp-to-Pop Ratio	8.78	2.98	1.79	6.60	8.54	10.57	16.47
2000-2014 Change in High-skill Occupations Emp-to-Pop Ratio	1.18	0.68	−1.33	0.75	1.17	1.60	4.21
2000-2014 Change in College Workers Emp-to-Pop Ratio	2.48	0.89	−0.60	1.95	2.40	3.05	5.48
2000 High-skill Occupations Employment (stats in log)	12.59	12.79	3.28	10.31	11.74	13.03	14.05
2000 College Workers Employment (stats in log)	12.71	12.92	3.63	10.28	11.89	13.16	14.12
2000-2014 Change in Log High-skill Occupations Employment	26.56	12.47	−39.18	18.66	26.10	33.82	87.13
2000-2014 Change in Log College Workers Employment	38.33	12.78	−1.34	29.58	36.15	45.12	111.00

Notes: All the statistics are computed over the 722 continental commuting zones (without Alaska and Hawaii) and weighted by population. Employment-to-population ratios and changes in log are given as percentage points.

4 Empirical Results

4.1 Baseline Results

Table 2 presents the baseline IV estimates of Equation (19). The relationship between the exposure to robots and the change in high-skill employment was negative and robust between 2000 and 2014. The estimates in Columns 3 and 6 indicate that the adoption of one robot per thousand workers reduced the change in the high-skill employment-to-population ratio by 0.18 to 0.24 percentage points in average. In 2000 there were nearly 210000 thousand people in the US. The average reduction of high-skill employment is thus $(0.0018 + 0.0024)/2 \times 210000 \approx 441$ thousand. There were approximately 120 thousand robots installed between 2000 and 2014, which implies that the number of prevented high-skill job creations per additional robot is $441/120 \approx 4$. AR2020 and Aghion et al. (2019) find respectively that each robot destroyed 6 jobs in the US between 1990 and 2007 and 11 jobs in France between 1994 and 2014. The magnitude of 4 is in line with these estimates but seems slightly overestimated with regard to the relative proportion of high-skill workers. The magnitudes are homogeneous within both groups of workers, and are not statistically different between them. This result is encouraging since the impact I aim to assess is expected to be constant whether skill is proxied by the occupation or the educational level.

The theoretical model indicates that the intercept captures the average high-skill biased technological change. In the most parsimonious specifications the intercept is positive as expected and significant at the 1% confidence level. However it becomes non-significant as more covariates are added. This suggests that a range of covariates exhibit high correlations with high-skill biased technological change. For example, the commuting zones with the highest shares of high-educated workers are probably the most likely to adopt high skill biased technologies. This would explain why the intercept becomes non-significant when demographic covariates are added. In the next paragraphs I present additional specifications that aim to capture other specific effects.

Table 2: Impact of the Exposure to Robots on the Change in the High-Skill Employment-to-Population Ratio

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.46***	−0.27	−0.24	2.85***	−3.14	−0.12
	(0.11)	(3.24)	(4.09)	(0.20)	(3.39)	(4.22)
Inst. US Exp. to Robots	−0.18***	−0.19***	−0.18***	−0.29***	−0.26***	−0.24***
	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)	(0.06)
First-Stage Coefficient	1.27***	1.27***	1.13***	1.27***	1.27***	1.13***
F-statistic	813	415	426	813	415	426
Adj. R^2	0.20	0.22	0.22	0.34	0.44	0.44
Num. obs.	722	722	722	722	722	722
			Covariates			
Division fixed-effects	✓	✓	✓	✓	✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports			✓			✓

Notes: Estimates of the impact of the exposure to robots on the high-skill employment-to-population ratio. Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. Regressions are weighted by the population of 2000. One observation is a commuting zone, so that I have 722 observations for all regressions. The specifications in Columns 1 and 4 only include census division fixed-effects. The specifications in Columns 2 and 5 add demographic covariates of 2000: the log of the population; the share of female; the shares of hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; and the share of the population that is more than 65 years old. The specifications in Columns 3 and 6 add the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing, and the exposure to Chinese imports. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

4.2 Robustness Checks

Table 3 presents the stacked-differences estimates. The specifications with stacked differences are designed to control for time-specific effects, in particular the effects of the Great Recession. I split the baseline period into three subperiods : 2000-2007 a period of slow recovery after the recession of 2000; 2007-2010, that covers the Great Recession; and 2010-2014 the recovery following the Great Recession. All the specifications contain time fixed effects, which give estimates relatively to the subperiod 2000-2007. Estimates are negative and remain robust when covariates are added. The magnitudes are not statistically different from the baseline magnitudes. This suggests that the impact of robotization on the change in high-skill employment was not significantly affected by the Great Recession. The coefficient associated with the dummy of the 2007-2010 period is negative, robust, and exhibit magnitudes much greater than the magnitudes of the impact of robotization. The estimates in Columns 3 and 6 indicate that the Great Recession reduced the change in high-skill employment by 0.49 to 1.28 percentage points compared to the pre-recession period. The coefficient associated with the dummy of the 2010-2014 period is positive and significant for high-skill occupations, but not significant for college workers. This result suggests that the employment of workers in high-skill occupations recovered faster than the employment of college workers.

Table 3: Impact of the Exposure to Robots on the Change in the High-Skill Employment-to-Population Ratio: Stacked-Differences

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Inst. US Exp. to Robots	-0.17^{***}	-0.19^{***}	-0.15^{***}	-0.22^{***}	-0.25^{***}	-0.24^{***}
	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)
Period: 2007-2010	-0.46^{***}	-0.44^{***}	-0.49^{***}	-1.21^{***}	-1.17^{***}	-1.28^{***}
	(0.07)	(0.07)	(0.09)	(0.08)	(0.08)	(0.09)
Period: 2010-2014	0.55^{***}	0.57^{***}	0.54^{***}	-0.01	-0.02	-0.09
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
First-Stage Coefficient	0.99^{***}	0.96^{***}	0.87^{***}	0.99^{***}	0.96^{***}	0.87^{***}
First-Stage F-statistic:	845	474	485	845	474	485
Adj. R^2	0.37	0.38	0.38	0.48	0.49	0.50
Num. obs.	2166	2166	2166	2166	2166	2166
			Covariates			
Division and time fixed-effects	✓	✓	✓	✓	✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports			✓			✓

Notes: Stacked-differences estimates of the impact of the exposure to robots on the high-skill employment-to-population ratio. Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. There are 3 subperiods : 2000-2007, 2007-2010, and 2010-2014. The reference subperiod is 2000-2007. Regressions are weighted by the population at the date opening the subperiod. One observation is a commuting zone / period combination, so that I have $722 \times 3 = 2166$ observations for all regressions. The specifications in Columns 1 and 4 include census division and time fixed effects. The specifications in Columns 2 and 5 add demographic covariates of starting-dates: the log of the population; the share of female; the shares of hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; and the share of the population that is more than 65 years old. The specifications in Columns 3 and 6 add the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing, and the exposure to Chinese imports. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 4 presents estimates analogous to those of Table 2 with four additional covariates : the exposures to capital, IT capital, softwares and value added. These specifications are designed to disentangle the effects of robotization and the effects of the more intensive use of capital. The estimates are similar to the baseline estimates, and I find no significant effect of the more intensive use of capital on the high-skill employment-to-population ratio. This indicates that the effects of robotization on the change in high-skill employment were not confounded with the effects of the more intensive use of non-robot capital.

Table 4: Impact of the Exposure to Robots on the Change in the High-Skill Employment-to-Population Ratio: Controlling for Exposures to Capital, IT Capital, Softwares and VA

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Inst. US Exp. to Robots	-0.16^{***}	-0.22^{***}	-0.24^{***}	-0.18^{***}	-0.27^{***}	-0.27^{***}
	(0.04)	(0.05)	(0.07)	(0.05)	(0.05)	(0.07)
Exp. to Capital	0.01	0.01	0.02	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Exp. to IT Capital	0.56	-4.34	-6.82	3.44	-3.88	-4.74
	(2.73)	(4.09)	(6.11)	(2.72)	(4.48)	(5.80)
Exp. to Softwares	-0.21	0.29	0.98	-0.14	0.66	1.04
	(0.58)	(0.90)	(1.58)	(0.60)	(0.91)	(1.48)
Exp. to Value Added	-0.00	0.03	0.04	-0.03^{**}	0.03	0.03
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
First-Stage Coefficient	1.23^{***}	1.25^{***}	1.11^{***}	1.23^{***}	1.25^{***}	1.11^{***}
First-Stage F-statistic:	706	417	435	706	417	435
Adj. R^2	0.22	0.24	0.23	0.40	0.44	0.44
Num. obs.	722	722	722	722	722	722
			Covariates			
Division fixed-effects	✓	✓	✓	✓	✓	✓
Exp. Capital, IT Capital, Soft., VA	✓	✓	✓	✓	✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports			✓			✓

Notes: Estimates of the impact of the exposure to robots on the high-skill employment-to-population ratio. Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. Regressions are weighted by the population of 2000. One observation is a commuting zone, so that I have 722 observations for all regressions. The specifications in Columns 1 and 4 include census division fixed-effects, and the exposures to capital, IT capital, softwares, and value added. The specifications in Columns 2 and 5 add demographic covariates of 2000: the log of the population; the share of female; the shares of hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; and the share of the population that is more than 65 years old. The specifications in Columns 3 and 6 add the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing, and the exposure to Chinese imports. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 5 presents the estimates when I exclude the outliers, namely the top 1% commuting zones with the highest exposures to robots. The aim of these specifications is to assess whether the outliers drive the baseline results. Estimates are negative and robust, but exhibit magnitudes greater than the baseline magnitudes. This indicates that the baseline qualitative results are not driven by the outliers, and the relationship between robotization and the change in high-skill employment is not linear. Indeed Figure 1 indicates that the relationship is rather inverse. Removing outliers thus increases the magnitudes of the slopes of the regression lines.

Table 5: 2000-2014 Impact of the Exposure to Robots on the Change in the High-Skill Employment-to-Population Ratio: Removing Outliers

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Inst. US Exp. to Robots	-0.25^{***}	-0.25^{***}	-0.25^{**}	-0.50^{***}	-0.40^{***}	-0.40^{***}
	(0.08)	(0.08)	(0.12)	(0.09)	(0.07)	(0.11)
First-Stage Coefficient	1.20^{***}	1.20^{***}	1.06^{***}	1.20^{***}	1.20^{***}	1.06^{***}
First-Stage F-statistic	446	264	268	446	264	268
Adj. R^2	0.20	0.22	0.21	0.35	0.44	0.44
Num. obs.	714	714	714	714	714	714
			Covariates			
Division fixed-effects	✓	✓	✓	✓	✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports			✓			✓

Notes: Estimates of the impact of the exposure to robots on the high-skill employment-to-population ratio when outliers are removed. Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. Regressions are weighted by the population of 2000. One observation is a commuting zone among the bottom 99% commuting zones with the lowest exposures to robots, so that I have 714 observations. The specifications in Columns 1 and 4 only include census division fixed-effects. The specifications in Columns 2 and 5 add Demographic covariates of 2000: the log of the population; the share of female; the shares of hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; and the share of the population that is more than 65 years old. The specifications in Columns 3 and 6 add the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing, and the exposure to Chinese imports. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 6 presents estimates of the impact of the exposure to robots on the change in the log of the hourly wage of high-skill workers. Hourly wages are computed with data from the 2000 census and the 2014 ACS. Both samples are trimmed so that the lowest nominal wages correspond to the federal minimum wages ($5.15 in 2000 and $7.25 in 2014), and the highest nominal labor incomes correspond to 1.5 times the census top codes ($175000 in 2000 and the 99.5th percentile in 2014). As in Acemoglu and Autor (2011) I split each commuting zone into 240 demographic cells. Demographic cells are defined over gender, six age groups (15-25, 26-35, 36-45, 46-55, 56-65, +65), four race groups (white, black, asian, other), and five education groups (less than high school, high school, some college, college or pro, master or PhD). The estimates in Columns 2 and 5 suggest that the adoption of one robot per thousand workers reduced the change in the hourly wage of high-skill workers by 1.73% to 2.82%. The negative relationships measured for both employment and wage suggest that robotization impacted the demand side of the labor market and not the supply side, as indicated by the theoretical analyses. Table A1 in Appendix A3 provides estimates of the impact of the exposure to robots on the change in additional labor market outcomes, which comfort the baseline results.

Table 6: Impact of the Exposure to Robots on the Change in the High-Skill Hourly Wage

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Inst. US Exp. to Robots	-2.36^{***}	-1.73^{***}	-1.30^{*}	-2.94^{***}	-2.82^{***}	-2.00^{**}
	(0.42)	(0.46)	(0.71)	(0.58)	(0.61)	(0.86)
First-Stage Coefficient	1.26^{***}	1.13^{***}	1.07^{***}	1.26^{***}	1.13^{***}	1.07^{***}
First-Stage F-statistic:	2209	3812	1950	2209	3812	1950
Adj. R^2	0.19	0.19	0.19	0.27	0.28	0.27
Num. obs.	40892	40892	40389	24064	24064	23781
	Covariates					
Fixed-Effects	✓	✓	✓	✓	✓	✓
Exp. Capital, IT Capital, Soft., VA		✓	✓		✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports		✓	✓		✓	✓

Notes: Estimates of the impact of the exposure to robots on the change in the log of the hourly wage of high-skill workers. Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. Regressions are weighted by the 2000 quantity of wage earners in each commuting zone / demographic cell combination. One observation is a commuting zone / demographic cell combination. Demographic cells are defined over gender, 6 age groups (15-25, 26-35, 36-45, 46-55, 56-65, +65), 4 race groups (white, black, asian, other), and 5 education groups (less than high school, high school, some college, college or pro, master or PhD). The specifications in Columns 1 and 4 include census division and demographic cell fixed-effects. The specifications in Columns 2 and 5 add the log of population, the shares of female, population that is more than 65 years old, hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; the shares of workers in routine-intensive occupations, workers in manufacturing, female workers in manufacturing, workers in light manufacturing; the exposures to Chinese imports, capital, IT capital, softwares and value added. The specifications in Columns 3 and 6 exclude the top 1% commuting zones with the highest exposures to robots. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

5 Magnitude of the Ripple Effect

The empirical results presented in the previous section provide magnitudes for the total impact of robotization on the change in high-skill employment. However they do not provide any information about the importance of the ripple effect among the five forces described in Section 2. This section presents a quantitative exercise that aims to decompose the total impact and assess the importance of the ripple effect.

I calibrate the model to fit the US economy of 2000 and the unbalanced changes in the employment of high-skill occupations of 2000-2014 (the calibration for college workers returns a similar decomposition). More precisely the model is calibrated for two fictive economies: an average commuting zone that exhibits the average exposure to robots; and a "deviating" commuting zone that exhibits the average exposure to robots plus one standard deviation. The model should then return 1) the average value of the change in the employment-to-population ratio of high-skill occupations for the average commuting zone, that is 1.18 percentage point (see Table 1); and 2) $1.18 - 0.18 \times 1.06 = 0.99$ percentage points for the deviating commuting zone, where -0.18 corresponds to the impact of the exposure to robots on the change in the employment-to-population ratio of high-skill occupations measured in Section 4 and 1.06 is the standard error of the exposure to robots. Both commuting zones have identical initial parameters so that the differences observed between the evolutions of their labor markets cannot be imputed to differences in their initial parameters.

The chosen parameters are as follows: $\alpha = 67\%$ which matches the usual share of capital; γ is set to 0.68 so that the productivity gap between skills is identical to the skill premium; $d\ln\gamma = 0.099$ which implies a change in the average high-skill employment-to-population ratio of 1.18 percentage point as indicated by the data (see Table 1); $\delta = 0.01$ which implies an initial high-skill employment-to-population ratio of 0.08; $\varepsilon = 0.43$ which implies a Frisch macro-elasticity of labor supply of 2.30 (Chetty et al. 2011); $\phi = 58$ which implies a productivity-cost ratio of robots 1.30 times greater than the productivity-cost ratio of low-skill workers (this target ensures that Assumption 1 holds with a magnitude in line with the estimates of BCG 2015); $\theta = 0.0625$ which implies a deviating change in the high-skill employment-to-population ratio of 0.99 percentage points; $d\theta_{Avg} = 0.108$ which implies an average exposure to robots of 1.22; $d\theta_{Dev} = 0.203$ which implies a deviating exposure to robots of $1.22 + 1.06 = 2.28$; A, K and B_L are normalized to 1 so that initial values of the output, the capital price and the low-skill wage are specified as references; $A_L = 0.405$ which implies an initial low-skill employment-to-population ratio of 0.21; $B_H = 2.56$ which implies a skill premium of 1.70; and $A_M = 59$ which implies an initial number of robots per thousand workers of 0.70 as indicated by the IFR data. Calibration choices are summarised in Table 7.

I compute the equilibrium and identify each effect according to the demand of

Table 7: Model Calibration

Parameter		Value	Target / Source
HOUSEHOLDS :			
ε	Inverse of the wage elasticity of labor supply	0.43	Chetty et al. (2011)
B_L	Desutility of work for low-skill workers	1	Normalization, W_L free
B_H	Desutility of work for high-skill workers	2.56	$W_H/W_L = 1.70$, Source : 2000 census
K	Stock of non-robot capital	1	Normalization, R free
TECHNOLOGY :			
α	Share of tasks in the production process	0.67	$RK/Y = 33\%$
δ	Slope of high-skill workers productivity	0.01	$N_H = 0.08$, Source : 2000 census
ϕ	Price of robots	58	$\frac{A_M/\phi}{A_L/W_L} = 1.30$, source : BCG (2015)
θ	Automation threshold	0.0625	$dN_{H\,Dev} = 0.99$ percentage points, see Table 1
A	TFP	1	Normalization, Y free
A_M	Robots productivity	59	$M/(N_L + N_H) = 7 \times 10^{-4}$, Source : IFR
A_L	Low-skill workers productivity	0.405	$N_L = 0.21$, Source : 2000 census
γ	High-skill workers productivity on the first task	0.68	$A_H/A_L = W_H/W_L$
EXOGENEOUS PROCESSES :			
$d\theta_{Avg}$	Robotization in the average commuting zone	0.108	$\mathcal{E}_{Avg} = 1.22$ (considering thousands of workers), see Table 1
$d\theta_{Dev}$	Robotization in the deviating commuting zone	0.203	$\mathcal{E}_{Dev} = 2.28$ (considering thousands of workers), see Table 1
$d\ln\gamma$	High-skill biased technological change	0.099	$dN_{H\,Avg} = 1.18$ percentage point, see Table 1

Notes: The values presented above are chosen to fit the US economy of 2000 and the unbalanced changes in high-skill employment of 2000-2014.

high-skill workers, given by Equation (12). Following the discussions of Section 2, the productivity effect henceforth includes the substitution effect since both effects affect the labor demands by the same channels, and the substitution effect cannot offset the productivity effect. Further details about the decomposition procedure are provided in Appendix A2. The baseline decomposition is illustrated by Figure 8a. In the average commuting zone, the sum of the "positive" effects, namely the productivity and high-skill biased technological change effects, was $0.49 + 1.6 = 2.09$, and the value of the ripple effect was -0.92. This indicates that the ripple effect reduced the positive effects by $0.92/2.09 \approx 44\%$. This decomposition enables a comparison between the high-skill biased technological change and the ripple effects to study the reallocation of tasks between workers. If the sum of both effects is positive, then tasks are reallocated from low-skill workers to high-skill workers. Conversely, when the sum is negative, tasks are reallocated from high-skill workers to low-skill workers. In the average commuting zone the sum of the high-skill biased technological change and the ripple effects was positive. This indicates that in average high-skill workers were allocated on additional tasks initially performed by low-skill workers, and thus gained jobs. In the deviating commuting zone the ripple effect totally cancelled out the high-skill biased technological change effect, so that high-skill job creations were less than average. One can also note that high-skill biased technological change effects were identical in both commuting zones as expected, while the productivity effect was greater in the deviating commuting zone due to the more intensive robotization.

Figure 8b presents the analogous decomposition obtained with an extension that does not include the ripple effect (I becomes exogeneous and takes the value obtained in the presence of ripple effects; and dI is set to 0). In the absence of the ripple effect the change in high-skill employment of the deviating commuting zone is greater than average. Indeed, in such a model the demand of high-skill workers contains no negative effect, except for the substitution effect which cannot offset the productivity effect. The ripple effect is thus definitively an interesting mechanism to understand the facts presented in introduction.

6 Concluding Remarks

This paper contributes to the literature by presenting new evidence that the adoption of robots reduced the change in high-skill employment in US labor markets between 2000 and 2014. Though these findings are puzzling with regard to the literature, I show that the results can be explained by a model of tasks, and thus

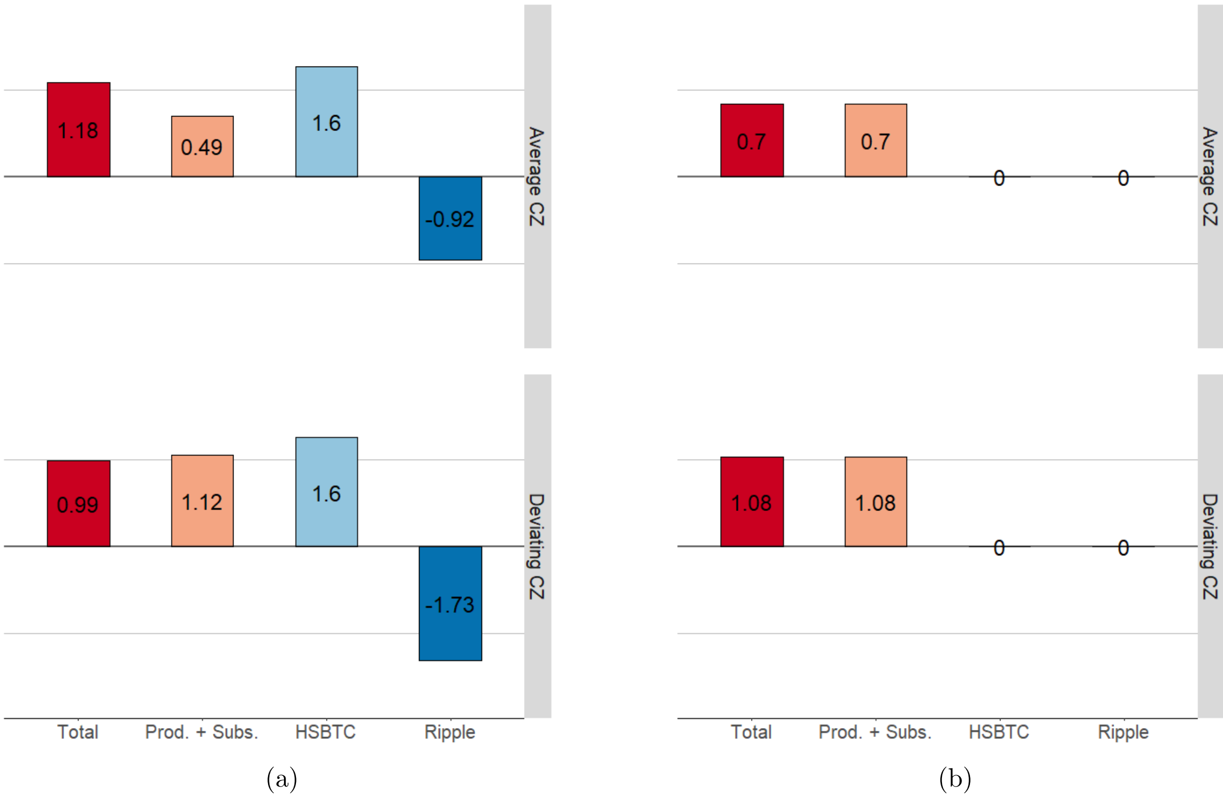


Figure 8: Impact Decomposition

Source : Author's own calculations.

Notes : Bar plots of the decomposition of the impact of robotization on the change in high-skill employment. Figure 8a presents the decomposition obtained with the baseline model. Each bar corresponds to a particular effect described in Section 2. The displacement effect is omitted since it does not impact the demand of high-skill workers directly. The value of an effect is indicated within the corresponding bar, so that the sum of all values is the total effect. The top panel presents the decomposition for the average commuting zone. The bottom panel presents the decomposition for the deviating commuting zone. Figure 8b presents the analogous decomposition obtained with an extension that does not contain the ripple effect. Its structure is similar to the structure of Figure 8b.

give new support to such models. Indeed, robotization generates reallocations of tasks between low-skill and high-skill workers, which can negatively impact the employment of high-skill workers. These effects are quantified for the first time, there are two magnitudes to remember: 1) the adoption of one robot per thousand workers reduced the change in the high-skill employment-to-population ratio by $0.18 - 0.24$ percentage points in average, and 2) the negative effect of the reallocation of tasks induced by robotization, namely the ripple effect, reduced the magnitude of the effects that increase high-skill employment by about 44%.

The model can be extended to explore other potential mechanisms. Indeed, the ripple effect is probably not the only force that reduces the change in high-skill employment. In particular, Acemoglu et al. (2020) shows that robots adopters are among the superstar firms, which have large market shares but small labor shares (Autor et al. 2020). This suggests that robotization can increase the concentration of the labor market, which is in line with recent evidence that the adoption of robots in a firm increases its employment and reduces those of its competitors (Acemoglu et al. 2020; Acemoglu et al. 2023). This is certainly a topic for future research.

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Appendices

A1 Appendix of Theoretical Analyses

A1.1 Proof of Proposition 1

I start by characterizing the optimal choices of households. The program of a household is:

$$\begin{gathered}\max_{C_s,N_s} U_s(C_s,N_s) = C_s - B_s\tfrac{N_s^{1+\varepsilon}}{1+\varepsilon} \\ \textit{subject to} \\ \begin{cases} C_s \leq W_s N_s + RK_s \\ K_s \ \textit{given} \end{cases}\end{gathered} \tag{A1}$$

Since the budget constraint must bind, the problem can be written as:

$$\max_{C_s,N_s} U_s(C_s,N_s) = W_s N_s + RK_s - B_s\frac{N_s^{1+\varepsilon}}{1+\varepsilon} \tag{A2}$$

The first-order conditions of (A2) give the following labor supplies:

$$N_L^{Supply} = \left(\frac{W_L}{B_L}\right)^{\frac{1}{\varepsilon}} \tag{A3}$$

$$N_H^{Supply} = \left(\frac{W_H}{B_H}\right)^{\frac{1}{\varepsilon}} \tag{A4}$$

Consumption levels are then obtained from binding budget constraints: $C_s = W_s N_s + RK_s$. Now I turn to the choices of producers. Let $X = \exp\int_0^1 \ln y(i)di$ be the quantity of a task-based intermediate good traded on a perfectly competitive market with a price P_X. Then due to the unit elasticity of substitution between factors the share of non-robot capital in the value added is equal to $1-\alpha$. Consequently the demands of factors are $P_X X = \alpha Y$ and $RK = (1-\alpha)Y$. Applying the same reasoning for the choices of the task-based intermediate good producer I obtain the following demands of tasks : $p(i)y(i) = P_X X = \alpha Y \ \forall\ i \in [0,1]$, where $p(i)$ denotes the price of the task i. Due to Assumption 1 robots are allocated on all the tasks below θ. Due to Assumption 2 there exists a unique task index I such that $\frac{A_H(i)}{W_H} \geq \frac{A_L}{W_L} \ \forall\ i \geq I$, thus high-skill workers are allocated on all the tasks above I, what leads to (9). Since tasks are traded on a perfectly competitive market, their prices are equal to their marginal cost. Therefore:

$$p(i) = \begin{cases} \phi A_M^{-1} \text{ if } i \in [0, \theta) \\ W_L A_L^{-1} \text{ if } i \in [\theta, I) \\ W_H A_H(i)^{-1} \text{ if } i \in [I, 1] \end{cases} \tag{A5}$$

Hence, inserting (9) and (A5) into the demands of tasks leads to:

$$m(i) = \begin{cases} \alpha Y \phi^{-1} \text{ if } i \in [0, \theta) \\ 0 \ \text{ else} \end{cases} \qquad n_L(i) = \begin{cases} \alpha Y W_L^{-1} \text{ if } i \in [\theta, I) \\ 0 \ \text{ else} \end{cases} \qquad n_H(i) = \begin{cases} \alpha Y W_H^{-1} \text{ if } i \in [I, 1] \\ 0 \ \text{ else} \end{cases} \tag{A6}$$

Using market clearing conditions leads to:

$$M^{Demand} = \alpha \theta Y \phi^{-1} \tag{A7}$$

$$N_L^{Demand} = \alpha (I - \theta) Y W_L^{-1} \tag{A8}$$

$$N_H^{Demand} = \alpha (1 - I) Y W_H^{-1} \tag{A9}$$

Dividing (A6) by the aggregate quantities leads to:

$$m(i) = \begin{cases} \frac{M}{\theta} \text{ if } i \in [0, \theta) \\ 0 \ \text{ else} \end{cases} \qquad n_L(i) = \begin{cases} \frac{N_L}{I-\theta} \text{ if } i \in [\theta, I) \\ 0 \ \text{ else} \end{cases} \qquad n_H(i) = \begin{cases} \frac{N_H}{1-I} \text{ if } i \in [I, 1] \\ 0 \ \text{ else} \end{cases} \tag{A10}$$

Inserting (A10) into (3) leads to:

$$Y = e^{\alpha \int_I^1 \ln A_H(i) di} A \left(\frac{A_M M}{\theta} \right)^{\alpha \theta} \left(\frac{A_L N_L}{I - \theta} \right)^{\alpha (I - \theta)} \left(\frac{N_H}{1 - I} \right)^{\alpha (1 - I)} K^{1 - \alpha} \tag{A11}$$

The cost function of the final good producer is thus:

$$Cost = \alpha^{-\alpha} (1 - \alpha)^{-(1-\alpha)} e^{-\alpha \int_I^1 \ln A_H(i) di} \frac{Y}{A} \left(\frac{\phi}{A_M} \right)^{\alpha \theta} \left(\frac{W_L}{A_L} \right)^{\alpha (I - \theta)} W_H^{\alpha (1 - I)} R^{1 - \alpha} \tag{A12}$$

The final good producer chooses the value of I that minimizes its cost. (10) is the first-order condition of this cost-minimization problem. The equilibrium allocation of factors on tasks $\{m(i), n_L(i), n_H(i)\}_{i \in [0,1]}$ is thus given by (A10); equilibrium quantities $\{C_L, C_H, N_L, N_H, M, Y, \{y(i)\}_{i \in [0,1]}\}$ are given by binding budget constraints, (A3), (A4), (A7), (3) and (4); equilibrium prices $\{R, W_L, W_H\}$ are given by the demand of non-robot capital $RK = (1 - \alpha) Y$, (A8), and (A9); and I is given by (10).

A1.2 Proof of Proposition 3

Log-differentiating (A11) and (A7) leads to:

$$\frac{1}{\alpha}d\ln Y = \theta d\ln M + (I-\theta)d\ln N_L + (1-I)(d\ln N_H + d\ln\gamma) + \ln\frac{A_M/\phi}{A_L/W_L}d\theta \tag{A13}$$

$$d\ln M = d\ln Y + \frac{d\theta}{\theta} \tag{A14}$$

Therefore the changes $\{d\ln Y, d\ln M, d\ln N_L, d\ln N_H, d\ln W_L, d\ln W_H, dI\}$ are obtained by solving the linear system consisting of Equations (A13), (A14), (11), (12), (13), (14), (15) with $d\ln\gamma$ a constant and $d\theta$ a free variable. Therefore the equilibrium changes in the variables are affine functions of $d\theta$, which implies that $d\ln N_H$ takes the form of (16).

A2 Impact Decomposition

The decomposition procedure consists in computing each element of the high-skill labor demand, given by Equation (12), using the results obtained with the calibrated model. The values of $d\ln Y$, the productivity effect, and $d\ln W_H$, the substitution effect are directly given by the model. However the high-skill biased technological change effect and the ripple effect still have to be disentangled since they are confounded in dI. I define the high-skill biased technological change effect as $d\ln N_{H|d\ln Y = d\ln W_H = d\theta = 0}$, i.e. the change in high-skill employment when γ changes and Y, W_H and θ are held constant. Similarly I define the ripple effect as $d\ln N_{H|d\ln Y = d\ln W_H = d\ln\gamma = 0}$, which isolates the impact of robotization on high-skill employment. Their expressions are then obtained by solving the system consisting of (11), (12), (13), (14) and (15). The resulting decomposition is:

Total	Productivity - Substitution + HSBTC - Ripple
Productivity	$d\ln Y$
Substitution	$d\ln W_H$
HSBTC	$(I-\theta)\frac{1+\varepsilon}{\omega}d\ln\gamma$
Ripple	$\frac{\varepsilon}{\omega}d\theta$

where $\omega = \varepsilon(1-\theta) + (1+\varepsilon)(I-\theta)(1-I)\frac{\delta}{1+\delta I} > 0$. The high-skill biased technological change and ripple effects are null in the absence of ripple effect.

A3 Additional Tables and Figures

Table A1: Impact of the Exposure to Robots on the Change in Additional Labor Market Outcomes

	High-skill Occupations			College Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A : Log of Employment Level					
Inst. US Exp. to Robots	-3.83^{***}	-3.75^{***}	-2.61^{***}	-3.51^{***}	-4.09^{***}	-2.59^{***}
	(0.72)	(0.80)	(0.87)	(0.73)	(0.88)	(0.86)
First-Stage Coefficient	1.27^{***}	1.27^{***}	1.13^{***}	1.27^{***}	1.27^{***}	1.13^{***}
F-statistic	813	415	426	813	415	426
Adj. R^2	0.29	0.39	0.41	0.30	0.45	0.48
Num. obs.	722	722	722	722	722	722
	Panel B : Employment Rate					
Inst. US Exp. to Robots	-0.25^{***}	-0.26^{***}	-0.25^{***}	-0.39^{***}	-0.36^{***}	-0.33^{***}
	(0.07)	(0.07)	(0.08)	(0.10)	(0.08)	(0.10)
First-Stage Coefficient	1.27^{***}	1.27^{***}	1.13^{***}	1.27^{***}	1.27^{***}	1.13^{***}
F-statistic	813	415	426	813	415	426
Adj. R^2	0.15	0.17	0.17	0.31	0.37	0.38
Num. obs.	722	722	722	722	722	722
	Panel C : Emp-to-Pop Ratio including Self-Employed Workers					
Inst. US Exp. to Robots	-0.19^{***}	-0.18^{***}	-0.20^{***}	-0.33^{***}	-0.29^{***}	-0.29^{***}
	(0.06)	(0.05)	(0.06)	(0.10)	(0.05)	(0.08)
First-Stage Coefficient	1.27^{***}	1.27^{***}	1.13^{***}	1.27^{***}	1.27^{***}	1.13^{***}
F-statistic	813	415	426	813	415	426
Adj. R^2	0.23	0.31	0.31	0.38	0.50	0.51
Num. obs.	722	722	722	722	722	722
	Covariates					
Division fixed-effects	✓	✓	✓	✓	✓	✓
Demographic		✓	✓		✓	✓
Manuf., Routine, Chinese Imports			✓			✓

Notes: Estimates of the impact of the exposure to robots on additional labor market outcomes : the log of the high-skill employment level (Panel A); the high-skill employment rate, defined as high-skill employment over working-age population (Panel B); and the high-skill employment-to-population ratio including self-employed workers (Panel C). Columns 1-3 give results for high-skill occupations and Columns 4-6 give results for college workers. Regressions are weighted by the population of 2000. One observation is a commuting zone, so that I have 722 observations for all regressions. The specifications in Columns 1 and 4 only include census division fixed-effects. The specifications in Columns 2 and 5 add demographic covariates of 2000: the log of the population; the share of female; the shares of hispanics, whites, blacks, and asians; the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree; and the share of the population that is more than 65 years old. The specifications in Columns 3 and 6 add the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing, and the exposure to Chinese imports. Standard errors that are robust against heteroskedasticity and clustered by state are given in parenthesis. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

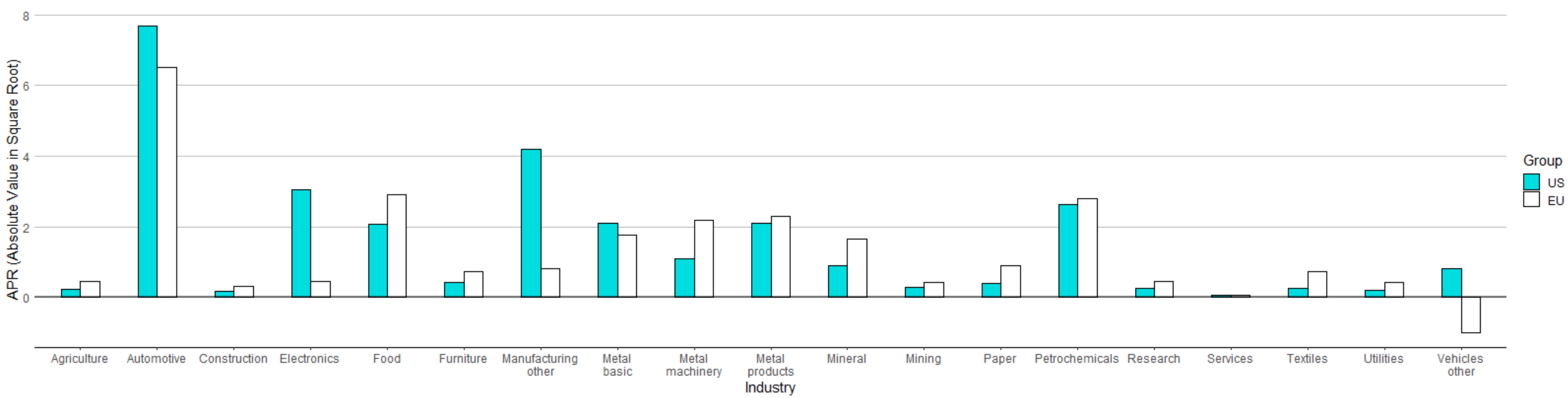

Figure A1: Adjusted Penetration of Robots (APR) by Industry in the US and Europe

Source : AR2020.

Notes : APRs by industry in the US and Europe (mean on six countries : Denmark; Finland; France; Germany; Italy and Sweden). Absolute values are given in square root for convenience.

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