3 Robots, Offshoring, and Welfare

Alessandra Bonfiglioli, Rosario Crinò, Gino Gancia, and Ioannis Papadakis

1 Introduction

The nature and the organization of production is undergoing a radical transformation. Advances in robotics technologies have led to the widespread use of automation in tasks previously performed by workers. At the same time, improvements in communication technologies have led companies to offshore stages of production to low-wage countries. These two phenomena are having a profound effect on advanced economies. Although they are believed to bring about higher productivity and lower costs, they are also often blamed for the decline in manufacturing employment and stagnation of real wages (see, for instance, Baldwin, 2019). More recently, a new hypothesis is gaining attention: that automation, which is much more prevalent in advanced economies, can increase competitiveness and bring back jobs that had been previously relocated to low-wage countries. Examples of this process of "reshoring" have started to populate the business literature. Yet, its scope, causes and consequences are still largely unknown.

In this chapter we study the interaction between automation and offshoring, from the perspective of advanced countries. From a theoretical viewpoint, we show that offshoring can change the welfare effects of automation. In particular, if robots replace foreign-sourced tasks, automation is always beneficial for domestic workers. However, if robots replace domestically-produced tasks, automation can be welfare-reducing for workers in the adopting country, even if it would have been welfare-improving in autarky. These results underscore the importance of identifying which workers are competing with robots more directly. We therefore turn to US data across industries, occupations and local labor markets to validate the predictions of the model and assess which scenario is empirically more plausible.[1]

To illustrate our theoretical result, we start from a simple task-based model of production that incorporates the standard effects of automation. In autarky, substituting labor with cheaper robots has a productivity effect, a capital deepening effect and a displacement effect. While the first two effects raise welfare, the latter one tends to lower real wages. But the negative effect is always dominated if the supply of robot capital is sufficiently elastic.[2] In the presence of offshoring,

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however, there is a new *terms-of-trade effect* that redistributes income across countries: automation lowers the relative wage of the workers that are displaced by robots the most. If automation substitutes foreign labor, domestic workers do not suffer any displacement, while they benefit from a higher productivity, capital deepening and cheaper foreign inputs. In this case, automation triggers reshoring and raises domestic welfare. However, if domestic workers are substituted by robots, they are harmed both by the displacement effect and by the increase in the cost of foreign inputs. In this case, automation can lower domestic welfare even if the higher productivity and capital deepening would compensate the displacement effect in autarky.

The model also illustrates that whether automation replaces domestic or foreign workers may depend not only on exogenous characteristics of the tasks they perform, but also on economic incentives, which depend on the wage gap between countries. This opens the possibility that, since offshoring increases foreign wages, the direction of automation may switch endogenously from domestically-produced to foreign-sourced tasks. Finally, from a normative perspective, the model implies that, since automation targeted at offshored tasks redistributes income from the foreign to the domestic country, policy makers may have an incentive to distort the use of robots strategically.

In the second part of the chapter, we move to the empirical analysis. Recent anecdotal evidence suggests that advanced countries across the world have started to shift away from foreign inputs. For instance, Walmart (2016), the biggest retailer in the world, launched the "Jobs in U.S. Manufacturing Portal" website as part of a broader "Investing in American Jobs" initiative which aims to bring manufacturing jobs back to the US. The COVID-19 pandemic has accelerated this trend by fostering automation and inducing governments to aim at increasing self-sufficiency in strategic sectors. However, systematic evidence about reshoring, defined as a reduction in the growth of offshoring which can even turn negative, is scant.

Motivated by our model, we study the effect of industrial automation between 1990 and 2015 on US local labor markets and how it relates to offshoring. To measure automation and offshoring, we use high-quality trade data on US imports of industrial robots and intermediate inputs, respectively, and assign them to industries using detailed Import Matrices. We then project these measures across 722 US commuting zones based on the industry composition of employment. We further instrument the change in US imports of industrial robots with similar changes observed in eleven European countries. With this data, we find that robot imports lower manufacturing employment. Since manufacturing is the sector where automation is concentrated, this evidence suggests that, on average, robots displace US workers. However, we also find positive effects on wages, though not always significant, consistent with the hypothesis that robots improve labor productivity.

Next, we ask how these effects depend on offshoring. To this end, we first show that occupations at risk of automation, denoted for short as "replaceable", and those classified as "offshorable", tend to have a relatively similar task content.[3] This suggests that automation and offshoring might indeed be substitutes, in that they may affect similar occupations. Consistent with this evidence, we find that robot imports tend to lower offshoring, both at the industry and at the commuting zone level. Building on these results, we further unpack the negative employment effect of robot imports across different occupations. This exercise reveals that the employment losses are especially concentrated in occupations performing non-offshorable and replaceable tasks. Finally, we look for heterogeneous effects across commuting zones specialized in industries with a different prevalence of offshoring. This exercise reveals that commuting zones that are more exposed to offshoring experience a relatively smaller negative effect on manufacturing employment as a consequence of automation. Overall, this evidence suggests that robot imports are associated with a reduction in offshoring, which is however not enough to fully compensate for the negative displacement effect on manufacturing employment.

This chapter makes several contributions to the literature. First, from a theoretical perspective, it shows that the welfare effects of automation may be very different in the presence of offshoring. To do so, it combines models of automation (such as Zeira, 1998, Acemoglu and Restrepo, 2019, Hemous and Olsen, 2020) with models of offshoring (such as Grossman and Rossi-Hansberg, 2008, Rodriguez-Clare, 2010, Acemoglu, Gancia and Zilibotti, 2015). The literature has shown that both phenomena can have ambiguous welfare effects due to the tension between a productivity effect, which tends to benefit everybody, and a displacement effect, which tends to have adverse effects on workers that compete with robots or imports. However, this chapter highlights two important differences between automation and offshoring: first, they may affect different workers; and, second, unlike foreign labor, robots can be reproduced. The combination of these two features generates the terms-of-trade effect that can change the welfare effect of automation. Artuc, Bastos and Rijkers (2018), Krenz, Prettner and Strulik (2018) and Furusawa and Sugita (2021) also develop models of automation and trade in intermediate inputs, but assume that robots replace domestic labor only.

Second, the chapter contributes to the empirical literature on the identification of automation. Earlier papers use data from the International Federation of Robotics, which are however available for nineteen aggregate sectors only. Recognizing the high concentration of this very specialized sector, in which Japan and Germany alone account for 50 percent of global revenues, some recent papers have turned to robot imports as a measure of automation. These include Acemoglu and Restrepo (2020) and Blanas, Gancia and Lee (2019), which use cross-country data; Acemoglu, Lelarge and Restrepo (2020) and Bonfiglioli et al. (2020), which use firm-level data for France; and Humlum (2019), which uses firm-level data for Denmark. In this chapter we show how to combine data on robot imports together with Import Matrices to obtain an indicator of industrial automation that varies across time and 66 industries. Following the literature on the measurement of offshoring started by Feenstra and Hanson (1999), we also construct time-varying offshoring indicators at the industry level using the information on imported intermediate inputs contained in the Import Matrices.

Third, in terms of empirical results, this chapter confirms the negative effect of industrial robots on manufacturing employment often found in the literature (see, for instance, Acemoglu and Restrepo, 2020, and Blanas, Gancia and Lee, 2019), but it also shows this effect to be weaker in occupations and commuting zones that are more exposed to offshoring and hence where reshoring is more likely. We obtain these findings following the shift-share approach across US local labor markets first applied to study the effect of Chinese import competition by Autor, Dorn and Hanson (2013) and automation by Acemoglu and Restrepo (2020). To unpack the effects across occupations, we use the classifications of replaceable tasks in Graetz and Michaels (2018) and of offshorable tasks in Autor and Dorn (2013).

Our results are also related to two recent papers. Using firm-level data from France, Aghion et al. (2020) find that machines have a positive effect on employment in sectors facing international competition. This is consistent with our view that automation may displace imports. On the other hand, Faia et al. (2021) show that automation can lower employment by making firms more selective and argue that offshoring may amplify this effect. Using data for a panel of 13 European countries, they document a positive correlation between measures of replaceability and offshorability and a fall over time in employment for occupations that are both replaceable and offshorable. Despite the use of different proxies, we confirm these patterns in our data. However, we also find that the employment losses in US commuting zones more exposed to robotization are concentrated in non-offshorable jobs. This evidence is consistent with the hypothesis that, while both automation and offshoring may displace workers, the effect of an increase in the former can be partially offset by a decline in the latter.

Finally, the chapter is related to the nascent literature on reshoring. The empirical evidence on this recent phenomenon is still inconclusive. For instance, Krenz, Prettner and Strulik (2018) and Carbonero, Ernst and Weber (2018) find evidence of robot-induced reshoring in a panel of countries and industries. Similarly, Faber (2020), Artuc, Christiaensen and Winkler (2019), Stemmler (2019), and Kugler et al. (2020) find evidence of reshoring in Mexico, Brazil and Colombia. On the other hand, Hallward-Driemeier and Nayyar (2019) and De Backer et al. (2016) argue that reshoring affects only a tiny minority of countries and industries, while Stapleton and Webb (2020) show that robots had a positive impact on imports and multinational activities of Spanish firms. Differently from us, these papers are mostly concerned with the impact of reshoring on developing countries, and none of them focuses on the US.

The remainder of the chapter is organized as follows. In Section 2, we build a simple model to illustrate the welfare effects of automation in the presence of offshoring. In Section 3, we construct the main variables used in the empirical analysis and describe the main patterns in the data. In Section 4, we present the results of the econometric analysis. Exploiting variation across occupations, industries and space, we study the relationship between automation and offshoring, and how the effect of automation on labor market outcomes depends on offshoring. Section 5 concludes.

2 A Simple Model of Industrial Robots and Offshoring

In this section, we build a simple two-country general-equilibrium model to illustrate the welfare effects of automation and offshoring.[4] The main lesson is that the effects of automation on real wages can be very different depending on whether robots displace tasks that are performed domestically or abroad. The theory will also suggest a simple way to identify this displacement effect in the data. Since the goal is to derive qualitative results that will guide the empirical analysis, the model is deliberately kept as simple as possible.

2.1 The Basic Set-Up

The world economy comprises two countries, North and South, populated by L_n and L_s units of workers, respectively. There is a single final good, which is the numeraire and is freely traded. Production requires a set of tasks, which can be performed by workers or robots. Robots differ from workers in that they are in perfectly elastic supply and can only perform a subset of the existing tasks. Specifically, there is a constant unit cost of producing robots, and we sometimes refer to the endogenous supply of this factor as “robot capital”. Workers in the two countries differ in their technological capabilities in that labor in South can only be employed in a subset of the tasks that North can perform. The production of tasks can be separated geographically at no costs. In this model, automation is the replacement of any worker with robots and offshoring is the replacement of a worker in North with one in South. We start with a one-sector model, but later consider a generalization in which workers displaced in one secotor may find employment in another. In both cases, however, we allow offshoring and automation to have general equilibrium effects.

Production of the final good Υ requires a measure one of tasks, which are aggregated according to a Cobb-Douglas function:

$$\ln \Upsilon = \int_0^1 \ln x_i \; di, \tag{1}$$

where x_i is the output of task i. We denote with p_i the cost of this task. Then, the demand for each task satisfies:

$$p_i x_i = \Upsilon. \tag{2}$$

With a symmetric Cobb-Douglas production function, each task gets the same share of expenditure.

Tasks can be performed by workers in North, with productivity a_n and wage w_n, workers in South, with productivity a_s and wage w_s, or robots, with a unit cost r (in terms of the numeraire Υ) and productivity a_r. We assume $r < a_r$ which, as we will see, guarantees that some robots are always used in equilibrium. Workers in North can potentially perform any task $i \in [0, 1]$. Workers in South, instead, can only perform a measure $\lambda < 1$ of tasks, and we refer to these tasks as “offshorable”. Finally, robots can only perform a measure $\kappa < 1$ of tasks, and we refer to these tasks as “replaceable”. Some tasks can be both offshorable and replaceable. Accordingly, we define ξ as the probability that a replaceable task is also offshorable.

We denote with m_n, m_s and m_r the measure of tasks performed in equilibrium by workers in North, South and by robots, respectively, and assume for simplicity that workers in different locations and robots cannot be combined to produce the same task. This implies that $m_s + m_n + m_r = 1$. Then, the cost of task i is:

$$p_i = \begin{cases} p_n = \frac{w_n}{a_n}, & \text{if performed in North} \\ p_s = \frac{w_s}{a_s}, & \text{if performed in South} \\ p_r = \frac{r}{a_r}, & \text{if performed by robots.} \end{cases} \tag{3}$$

Imposing symmetry across tasks and labor-market clearing allows us to compute the quantity of each task produced by workers:

$$x_i = \begin{cases} x_n = \frac{a_n L_n}{m_n} & \text{if performed in North} \\ x_s = \frac{a_s L_s}{m_s} & \text{if performed in South.} \end{cases} \tag{4}$$

If task i is instead performed by robots, we can combine $p_r = r/a_r$ with $p_r x_r = \Upsilon$ to solve for its quantity:

$$x_r = \frac{\Upsilon a_r}{r}. \tag{5}$$

Substituting the quantities (4)-(5) into (1), we can solve for aggregate production as:

$$\Upsilon = \left(\frac{a_s L_s}{m_s}\right)^{\frac{m_s}{1-m_r}} \left(\frac{a_n L_n}{m_n}\right)^{\frac{m_n}{1-m_r}} \left(\frac{a_r}{r}\right)^{\frac{m_r}{1-m_r}}. \tag{6}$$

Next, substituting prices (3) and quantities (4) into the demand function (2), we obtain wages:

$$w_n = \frac{m_n}{L_n} \Upsilon, \tag{7}$$

with an analogous expression for w_s. Intuitively, the wage is increasing in the demand for labor, which is proportional to the measure of tasks performed and total production, and decreasing in the supply of labor.

Finally, we need to solve for m_s, m_n, and m_r. To this end, note that if $p_s < p_n$, then offshorable tasks are cheaper in South and hence will never be produced in North. This will be the case if wages per efficiency unit of labor in South are lower than in North, i.e., $w_s a_n < w_n a_s$. In turn, this requires the technological capabilities of South, as measured by λ, to be sufficiently low. A sufficient condition is

$$\frac{\lambda}{1-\lambda-\kappa(1-\xi)} < \frac{a_s}{a_n}\frac{L_s}{L_n}$$

and we assume it to be always satisfied. Next, we focus on equilibria in which robots are utilized. For this to be the case, automated tasks must be cheaper than those performed by workers in North, $p_r < p_n$, which requires the cost of robots, r, to be sufficiently low. As we will show later, this is guaranteed by the assumption $r < a_r$. Under these conditions, workers in North perform the set of tasks that are neither replaceable nor offshorable:

$$m_n = (1-\lambda) - \kappa(1-\xi).$$

Robots will also be used in offshorable tasks if $p_r < p_s$, which is equivalent to $r a_s < w_s a_r$. In this case, workers in South perform the set of tasks that are offshorable but not replaceable:

$$m_s = \lambda - \kappa\xi.$$

If instead $p_r > p_s$, then workers in South are cheaper than robots, which implies that they perform all offshorable tasks, $m_s = \lambda$. Finally, there is also an intermediate case in which $p_r = p_s$ and robots are used in a subset of the task that they can perform in South.

2.2 Robots, Offshoring, and Real Wages

We are now in the position to study the effect of robots on real wages which, in this model, coincide with welfare and also capture the demand for labor. We focus mostly on North, although it is straightforward to derive the results for South. Substituting (7) and (6) yields:

$$w_n = a_n \left(\frac{a_s}{a_n}\frac{w_n}{w_s}\right)^{\frac{m_s}{1-m_r}} \left(\frac{a_r}{r}\right)^{\frac{m_r}{1-m_r}} \tag{8}$$

with

$$\frac{w_n}{w_s} = \frac{L_s}{m_s}\frac{m_n}{L_n}. \tag{9}$$

Equation (8) says that workers in North benefit from their own productivity, a_n, but also from cheap labor in South, $\frac{a_s}{a_n}\frac{w_n}{w_s} > 1$, and cheap robots, $\frac{a_r}{r} > 1$. It also confirms that, under the assumptions $p_s < p_n$ and $r < a_r$, robots are cheaper than workers in North, i.e., $ra_n < w_n a_r$. Equation (9), instead, shows that the North-South wage gap, which we also refer to as the terms of trade, depends on the division of tasks between the two countries. These equations depend on the endogenous variables m_n, m_s and m_r, but are general in that they also apply to other models of offshoring and automation.[5] To better understand the effects of robots and offshoring, and how they interact, we start by considering them in isolation.

2.2.1 Offshoring Only

Suppose first that there is no automation, i.e., $\kappa = 0$. Then:

$$w_n = a_n \left(\frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\lambda} = a_n \left(\frac{1-\lambda}{\lambda} \frac{a_s L_s}{a_n L_n} \right)^{\lambda}.$$

Offshoring, i.e., an increase in λ, has two effects. First, as long as $a_s w_n > a_n w_s$, production costs are lower in South, and hence relocating tasks there lowers prices, which benefits all workers. Second, offshoring shifts the demand for labor in favor of workers in South, thereby lowering w_n/w_s. This fall in the terms of trade for workers in North tends to hurt them. Overall, the efficiency effect dominates for low values of λ, when the wage gap is large, but it vanishes for high values of λ, as the wage gap disappears for sufficiently high levels of offshoring. As a result, w_n is an inverted-U function of λ.

2.2.2 Automation Only

Consider now the case with no offshoring, i.e., $\lambda = 0$ and $\xi = 0$. Then:

$$w_n = \frac{m_n}{L_n} Y = a_n \left(\frac{a_r}{r} \right)^{\frac{\kappa}{1-\kappa}}. \tag{10}$$

Equation (10) shows that the real wage is always increasing in automation, κ. There are three effects at work here. First, as long as $a_r > r$, robots raise productivity. Second, as the measure of tasks performed by workers in North falls, there is also a displacement effect. However, the latter is offset by robot-capital deepening: the supply of robots increases so as to keep their price, r, constant. As a result, differently from offshoring, workers do not suffer any deterioration of their terms of trade from robots.[6]

2.2.3 Automation and Offshoring

We now study the effect of automation in the presence of offshoring. There are two cases to consider, depending on the relative wage in South. If the wage in South is sufficiently low, then offshoring is cheaper than using robots. We call this the "large wage gap" case. But if the wage in South is high enough, then offshorable tasks become at risk of automation. We call this the "small wage gap" case.

Large wage gap: $p_n > p_r > p_s$. In this case, robots replace North workers only. Without loss of generality, we can then set $\xi = 0$. Imposing $m_n = 1 - \lambda - \kappa$, $m_s = \lambda$ and $m_r = \kappa$ into (8) and (9) yields:

$$w_n = a_n \left[\left(\frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\lambda} \left(\frac{a_r}{r} \right)^{\kappa} \right]^{\frac{1}{1-\kappa}}$$

with

$$\frac{w_n}{w_s} = \frac{1 - \lambda - \kappa}{\lambda} \frac{L_s}{L_n}.$$

Compared to the case without offshoring, there are two differences. First, the productivity effect of robots is stronger, because they replace workers in North that are now more expensive: $\frac{a_s}{a_n} \frac{w_n}{w_s} > 1$. As a result of this, robots can raise real wages in North even if they would not be used in autarky ($a_r < r$). On the other hand, however, automation lowers the relative demand for North workers and hence increases the relative wage of workers in South, which are not competing with robots. Hence, workers in North now suffer from a negative terms-of-trade effect. Because of the latter, robots can now lower the real wage in North, even if they would have increased it in autarky ($a_r > r$). More precisely, w_n falls with κ if

$$\ln \left[\left(\frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\lambda} \frac{a_r}{r} \right] < \frac{\lambda(1 - \kappa)}{1 - \lambda - \kappa}.$$

This condition is more likely to be satisfied when r and w_s are high because in this case the productivity gains are small and the negative terms-of-trade effect may dominate.

Small wage gap: $p_n > p_s \geq p_r$. In this case, robots substitute workers in both countries. Consider first the case $p_s > p_r$, which implies $m_n = (1 - \lambda) - \kappa(1 - \xi)$, $m_s = \lambda - \kappa\xi$ and $m_r = \kappa$. Imposing these conditions into (8) and (9) yields:

$$w_n = a_n \left(\frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\frac{\lambda - \kappa\xi}{1-\kappa}} \left(\frac{a_r}{r} \right)^{\frac{\kappa}{1-\kappa}}$$

with

$$\frac{w_n}{w_s} = \frac{1 - \lambda - \kappa(1 - \xi)}{\lambda - \kappa\xi} \frac{L_s}{L_n}.$$

The novelty is that the effect of robots on the terms of trade depends on ξ. If $\xi > \lambda$, robots displace workers in South more than proportionally and hence improve the terms of trade of North. In this case, w_n necessarily increases with κ. If $\xi < \lambda$, robots lower the terms of trade of North. In this case, the effects are qualitatively similar to the large wage gap case discussed previously, and they become identical if $\xi \to 0$. Finally, we can also consider the case of a tie, $p_s = p_r$, in which robots and workers in South become perfect substitutes, and robots are used in an endogenous measure of tasks smaller than $\kappa\xi$. This intermediate equilibrium prevails when $p_s > p_r$ for $m_s = \lambda$, but $p_s < p_r$ for $m_s = \lambda - \kappa\xi$. In this range, the endogenous margin of robot utilization in South keeps all wages constant at $w_s = a_s r/a_r$ and $w_n = a_n a_r/r$.

We now briefly discuss some of the main implications of these results. The first lesson is that robots replacing North workers may hurt them by increasing the relative wage in South. Hence, in a world of global value chains, it is important to understand who is competing with robots. In turn, this may depend both on the technological characteristics of the tasks they perform and on the level of offshoring. The reason is that offshoring increases the relative wage in South, which makes automation of offshored tasks more profitable. More in general, the model suggests that both a decline in the cost of robots and technological catch-up in South can trigger a switch in automation from domestically sourced tasks only to offshored tasks too. These results also have important policy implications. In particular, since automation is likely to have terms-of-trade effects, which redistribute income between countries, policy makers may have an incentive to distort the use of robots strategically.

2.3 Extension: Two-Sector Model

Both automation and offshoring are more prevalent in the manufacturing sector. We now show how the displacement effect can be identified from the allocation of labor between sectors that are differentially exposed to automation. To this end, assume now that final output is produced combining manufacturing goods, X, and services, Z, as follows:

$$\Upsilon = X^{\alpha} Z^{1-\alpha}.$$

Labor is mobile between X and Z. As before, manufacturing workers in North earn a share of sector revenue, $\alpha\Upsilon$, equal to the fraction of tasks they perform, m_n^x:

$$w_n L_n^x = m_n^x \alpha \Upsilon,$$

where L_n^x is employment in manufacturing in North. The service sector is symmetric, hence $w_n L_n^z = m_n^z (1-\alpha)\Upsilon$. Combining these expressions yields the allocation of labor in North:

$$\frac{L_n^x}{L_n^z} = \frac{\alpha}{1-\alpha} \frac{m_n^x}{m_n^z}. \tag{11}$$

Equation (11) shows that this allocation depends exclusively on the tasks performed by domestic workers in the two sectors. The intuition is that the productivity effect affects both sectors equally and hence the allocation of labor only depends on the displacement effect. For our purposes, equation (11) also implies that the effect of automation on the tasks performed by workers in North can be read from changes in employment across sectors. In the remainder of the chapter, we build on this result to identify the displacement effect of industrial robots and test how it varies with offshoring. Given that industrial robots are used almost exclusively in manufacturing, their adoption should have no direct effect on m_n^z. Hence, if we find that an exogenous shock to automation shifts workers away from manufacturing, it must be that m_n^x is falling. Moreover, we will compare how the displacement effect differs across local labor markets and occupations depending on their exposure to offshoring. If we find a weaker or no displacement effect in areas or occupations where offshoring is more prevalent, it will be evidence consistent with the automation of foreign-sourced tasks.

3 Data and Stylized Facts

This section explains how we construct the main variables used in the empirical analysis and illustrates the main patterns in the data.

3.1 Data and Variables

Our empirical analysis relates automation, offshoring and labor market outcomes (employment and wages) across US local labor markets. Following Autor and Dorn (2013), Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2019), among others, we identify local labor markets using the concept of commuting zone (CZ) introduced by Tolbert and Sizer (1996). CZs are defined as clusters of counties characterized by strong commuting ties within them and weak commuting ties among them. Our sample includes 722 CZs covering the entire mainland United States.

Labor Market Outcomes. For each CZ, we measure employment and wages, both on aggregate and for different sectors (manufacturing and non manufacturing) or skill groups of workers (college and non-college educated), using micro-level data from two sources: the decennial Censuses, for the years 1990 and 2000; and the American Community Survey (ACS), for the years 2005, 2010 and 2015. Both data sources are extracted from IPUMS (Ruggles et al., 2020).[7]

Following Autor and Dorn (2013), we restrict the estimation sample to working-age individuals (aged 16 to 64) who are not unpaid family workers, do not reside in institutional group quarters and have reported being employed over the previous year. We construct CZ-level employment using sample weights. To construct wages, we further exclude individuals who are self-employed or farm workers, lack information on working hours, weeks or wages, and report working less than 40 weeks per year and 35 hours per week. We compute average wages as annual wages and salary income divided by total hours worked. Wages are expressed at constant 2005 prices using the Personal Consumption Expenditure Index. We also construct CZ-level population figures using data from the Censuses and the ACS. In the regressions, we use ten-year equivalent changes of employment-to-population ratios and log average wages, computed as 10 times the annualized change in each variable over a given period (1990-2000, 2000-2005, 2005-2010 and 2010-2015).

Robot Exposure. To construct our proxy for automation at the CZ level, we use high-quality data on US imports of industrial robots and project these imports across local labor markets using information on the industrial structure of employment in each CZ. We start by extracting the value of robot imports from detailed product-level import data collected by the US Customs and available for the 1989–2018 period (Schott, 2008); robot imports are classified into specific 10-digit product codes of the Harmonized Tariff Schedule (HTS) classification.[8] We apportion the overall value of US robot imports to 66 industries (defined according to the classification of the Bureau of Economic Analysis, henceforth BEA industries) using information on the cross-industry distribution of machinery (including robot) imports in each year extracted from the US Import Matrices.[9] Finally, we apportion the industry-level robot imports to individual CZs based on the industrial structure of employment in each CZ. In particular, our final measure of CZ-level robot exposure is constructed as follows:

$$\Delta Robots_{ct} = \sum_{j} \lambda_{cjt} \cdot \Delta \ln Rob\_M_{jt}, \tag{12}$$

where c denotes CZs; $\Delta \ln Rob\_M_{jt}$ is the ten-year equivalent log change in US robot imports in industry j over period t; and λ_{cjt} is the share of industry j in total employment of CZ c at the beginning of period t.[10]

The choice of using imports to measure automation in the US is motivated by the high concentration of the robot-producing sector. The vast majority of robot production worldwide takes place in a handful of non-US countries (especially Japan and Germany), while the US is not yet a major robot producer. Most of the production of robots occurring in the US is made by local affiliates of foreign multinationals and is aimed at serving manufacturing firms operating in neighboring countries, mostly Canada and Mexico (see, e.g., Casanova, 2019). On the contrary, the US is the second largest importer of robots worldwide, and also the second country in the world in terms of net robot imports (see, e.g., Furusawa and Sugita, 2021). Consistent with this, robot imports into the US are highly correlated with the overall stock of robots installed in the country, as recorded by the International Federation of Robotics (IFR): a regression of the log change in robot imports, $\Delta \ln Rob\_M_{jt}$, on the log change in the IFR stock of robots across industries and time periods yields a coefficient of 0.998 (s.e. 0.058). While the IFR data have important limitations—most notably, they only contain counts of robots (not values) and, by encompassing domestically-sourced robots, they could reflect technological shocks affecting the domestic labor market—such a high correlation suggests that robot imports are likely to capture the bulk of the variation in the use of robots in the US.[11] In Section

4.1, we will further show that, if we use net robot imports (i.e., imports minus exports) to construct robot exposure, our main evidence is unchanged, in line with the limited size of domestic production and exports of robots in the US.

As previously mentioned, to apportion nationwide robot imports to individual industries, we use the cross-industry distribution of machinery imports obtained from the US Import Matrices. This choice is made for consistency with the use of import data but turns out to be inconsequential for the results. First, the distribution of machinery imports across industries is very similar to the distribution of total (domestic plus foreign) machinery purchases, as obtained from the US Input-Output Tables: a regression of industry shares in total machinery purchases on the corresponding shares in machinery imports yields a coefficient of 1.069 (s.e. 0.021). Consistent with this, our results are unchanged if we reconstruct $\Delta Robots_{ct}$ using industry shares in total machinery purchases to apportion robot imports to individual industries (see Section 4.1). More generally, the cross-industry distribution of machinery imports is also highly correlated with the overall stock of installed robots in the US: a regression of the log IFR robot stock on the log industry shares in machinery imports across the nineteen aggregate sectors covered by the IFR data over 1993–2016 yields a coefficient of 0.541 (s.e. 0.123). This suggests that the cross-industry distribution of machinery imports closely reflects the actual usage of robots across US industries.

Variation in $\Delta Robots_{ct}$ across CZs could be driven by CZ-specific factors that also influence labor market outcomes. For instance, positive demand shocks may induce firms to automate and simultaneously raise employment and wages. Similarly, firms may adopt robots to increase productivity after some negative labor market shock. This implies that the OLS estimates of the effects of automation on labor market outcomes could be biased, either upward or downward. To account for the potential endogeneity of $\Delta Robots_{ct}$, we build on Autor, Dorn and Hanson (2013) and construct an instrument that is meant to isolate the variation in $\Delta Robots_{ct}$ induced by supply shocks in robot exporting countries, rather than by shocks occurring in individual CZs. To construct the instrument, we source (from UN Comtrade) data on robot exports from non-US countries to eleven European economies over 1989–2018.[12] To apportion the country-level robot imports to individual industries, we use the share of each industry in total machinery imports into a given country, as extracted from country-specific Import Matrices available in the World Input-Output Database (Timmer et al., 2015). Finally, we construct the instrument as follows:

$$\Delta Robots\_Oth_{ct} = \sum_j \lambda_{cjt} \cdot \Delta \ln Rob\_M\_Oth_{jt}, \tag{13}$$

where $\Delta \ln Rob\_M\_Oth_{jt}$ is the ten-year equivalent log change in robot exports from non-US countries to the eleven European countries in industry j over period t.

Identification requires that supply shocks boosting robot exports from non-US countries are uncorrelated with US-specific technology shocks affecting labor market outcomes in individual CZs. Similarly, demand shocks in the eleven European importing countries must be uncorrelated with demand shocks in US local labor markets. To assuage identification concerns, we will use a highly demanding specification (presented in Section 4.1) that controls for a host of fixed effects, both at the state and at the year level. These fixed effects absorb any US-specific shock that is common to all CZs, as well as differential trends across US states. The specification also controls for several proxies for other types of shocks to trade, technology and demand conditions at the CZ level. Overall, the wealth of controls and fixed effects included in the specification should largely reassure that the IV results are not obviously driven by US-specific shocks potentially correlated with the instrument.

Offshoring Intensity. Following Feenstra and Hanson (1999), we measure offshoring as the share of imported intermediate inputs in total input purchases. A higher value of this ratio corresponds to a greater usage of foreign inputs in production, reflecting a more intensive relocation of production stages to foreign countries. We construct offshoring intensities for the BEA industries using US Input-Output Tables and Import Matrices over 1997–2018. We use two complementary indicators of offshoring. The first, called *broad* offshoring, considers imports of all types of inputs. The second, called *narrow* offshoring, considers only imports of inputs that are closely related to the production process of an industry and could thus be performed in house by firms.

The two indicators are constructed as follows:

$$B\_Offsh_{jt} = \frac{\sum_h I\_M_{jht}}{\sum_h \left(I\_M_{jht} + I\_D_{jht} \right)} \quad \text{and} \quad N\_Offsh_{jt} = \frac{I\_M_{jjt}}{\sum_h \left(I\_M_{jht} + I\_D_{jht} \right)},$$

where I_M_{jht} and I_D_{jht} denote imports and domestic purchases, respectively, of intermediates made by industry j from industry h in period t; and I_M_{jjt} indicates imports of intermediates made by industry j from within itself at time t. Then, we construct the intensity of offshoring in each CZ similarly to eq. (12), using the industry-specific offshoring indicators, B_Offsh_{jt} and N_Offsh_{jt}, in place of the log change in robot imports. Namely,

$$B\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot B\_Offsh_{jt} \quad \text{and} \quad N\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot N\_Offsh_{jt}. \tag{14}$$

Since we are not interested in identifying the effects of offshoring, we do not build an instrument for it.[13]

Occupational Characteristics. Finally, we use information on occupational characteristics to unpack the overall employment effects of automation across different groups of workers. Following Graetz and Michaels (2018), we classify each occupation according to whether workers perform tasks that can or cannot be replaced by robots. Graetz and Michaels (2018) define an occupation as “replaceable” if its title corresponds to at least one of the robot application categories (e.g., welding, painting and assembling) identified by the IFR. We source replaceability data by occupation from Graetz and Michaels (2018).

We also classify occupations depending on how easy it is to relocate their tasks to foreign countries. Our main index of occupational offshorability is sourced from Autor and Dorn (2013). The authors use the simple average of two variables constructed by Firpo, Fortin and Lemieux (2011), who employ data from the O*Net database to measure the degree to which workers require face-to-face interaction and physical presence on the job. The index is reversed, so higher levels indicate higher offshorability. We standardize the index to have mean 0 and standard deviation 1 across occupations, and define as offshorable all occupations whose index is above the median. The two occupational characteristics are available for 331 US Census occupations. We match these characteristics to the US Censuses and the ACS using information on each worker's occupation of employment provided in the two data sources.[14]

3.2 Stylized Facts

We now present a number of facts about labor market outcomes, robot imports and offshoring in the US over the period of analysis. Figure 3.1 shows the evolution of employment from 1990 to 2015, based on the whole sample of

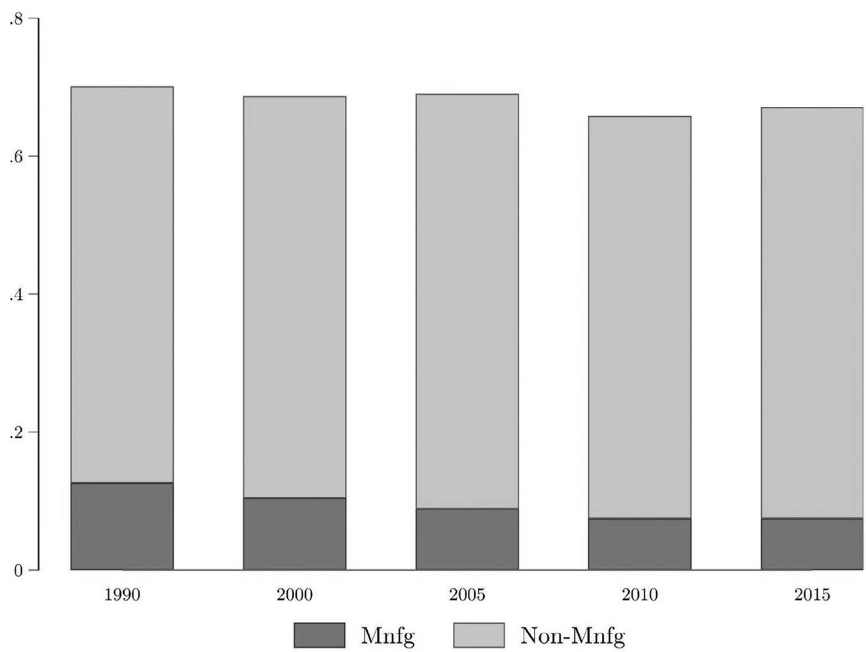

Figure 3.1 Employment-to-Population Ratio by Sector
Source: US Censuses (1990, 2000) and American Community Survey (2005–2015).

individuals contained in the Censuses and the ACS. As a percentage of total population, overall employment has gone down from 70% in 1990 to 67% in 2015. This aggregate trend masks heterogeneity between manufacturing and non-manufacturing sectors. The employment-to-population ratio has steadily fallen in manufacturing, moving from 13% in 1990 to 7% in 2015. At the same time, employment has significantly risen relative to population in non-manufacturing sectors, passing from 57% in 1990 to 60% in 2015. The existence of a shrinking industrial sector and an expanding service sector are common trends to most industrialized countries and reflect the structural change occurring in these economies over recent decades. As we show later on, automation has contributed to these trends by inducing a reallocation of labor outside of manufacturing.

Figure 3.2 unpacks the overall trend in employment across occupations with different characteristics. The figure shows average employment-to-population ratios across CZs in a given year, separately for offshorable and replaceable occupations. The difference between the overall employment-to-population ratio and the ratio corresponding to either group is equal to the employment-to-population ratio in the complement group of (non-offshorable or non-replaceable) occupations. Employment has increased in offshorable occupations, especially after the year 2000. At the same time, after reaching a plateau in 2000, the employment share of replaceable jobs has significantly declined in subsequent years, with a rapid acceleration in 2010. These trends reveal a marked change in the occupational structure of US employment over recent decades: employment has shifted from non-offshorable to offshorable jobs and from occupations that can be replaced by robots to those that cannot.

These adjustments in the US labor market have been concurrent with significant changes in the importance of automation and offshoring. Figure 3.3 shows the evolution of US robot imports over the period of analysis. To highlight the main trends in this variable, the graph reports overall imports in each five-year interval starting in 1989. The graph also displays the evolution of the two offshoring indicators, averaged across industries in each five-year period. Two main facts emerge from Figure 3.3. First, robot imports have remained at very low levels over the 1990s and the first half of the 2000s but have rapidly risen thereafter with a marked acceleration after 2010. This confirms that automation and adoption of industrial robots have significantly gained momentum in the US over recent years.[15] Second, the growth in offshoring has decelerated in the second half of the 2000s and become negative after 2010. While the reduced incidence of offshoring could have resulted from various factors, including the shrinkage of the manufacturing sector, it could also reflect the tendency by firms to bring back foreign activites to the US. From now on, we will accordingly refer to a reduction in the offshoring indicators as "reshoring", for brevity. In this sense, the concomitant increase in robot imports and reduction in offshoring is consistent with anecdotal evidence, according to which automation is leading firms to reshore an increasing number of production stages.

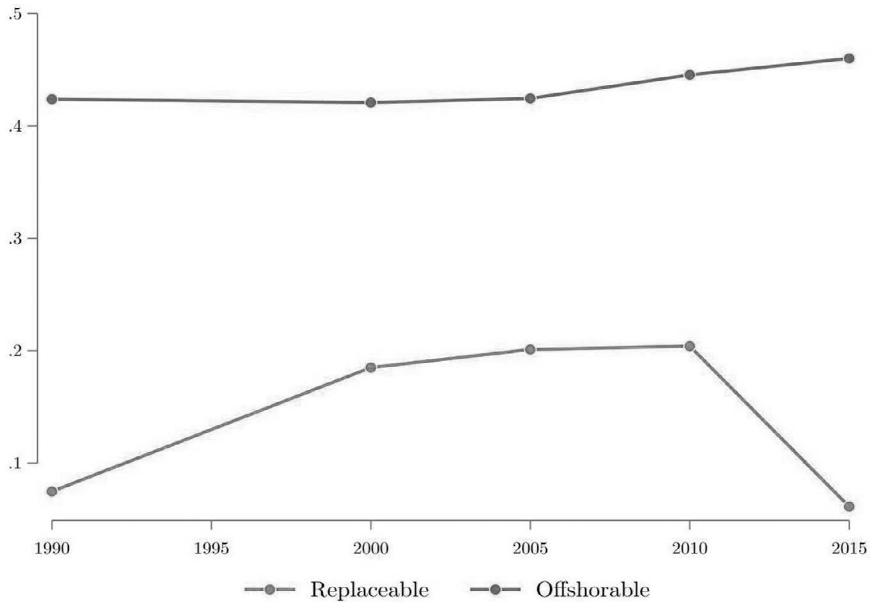

Figure 3.2 Employment-to-Population Ratio by Occupation Group

Source: US Censuses (1990, 2000) and American Community Survey (2005-2015).

Notes: Replaceable occupations are those whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics (Graetz and Michaels, 2018). Offshorability is measured by an index capturing the degree to which workers require face-to-face interaction and physical presence on the job (Autor and Dorn, 2013). The index is rescaled so that higher values indicate higher offshorability. Offshorable occupations are those for which the index is above the sample median. All figures are arithmetic averages across CZs.

The aggregate trends in robot imports and offshoring hide heterogeneity across sectors, as shown in Figure 3.4. The latter reports the average values of robot imports per worker (panel a) and of the two offshoring indicators (panel b) over the sample period, separately for manufacturing and non-manufacturing sectors. Robot imports are almost entirely concentrated in manufacturing and still almost inexistent in services. In particular, average robot imports per worker amount to roughly 575,000$ in manufacturing and 63,000$ in non-manufacturing industries. Similarly, despite the growth of service offshoring in recent years (see, e.g., Crinò, 2010), offshoring is still higher in manufacturing than in other sectors. According to both indicators, offshoring in manufacturing exceeds offshoring in non-manufacturing industries by about three times over the period of analysis.

Since different economic activities are not equally distributed in space, the heterogeneous incidence of automation and offshoring across industries is likely to give rise to differences in the extent to which each CZ is exposed to these

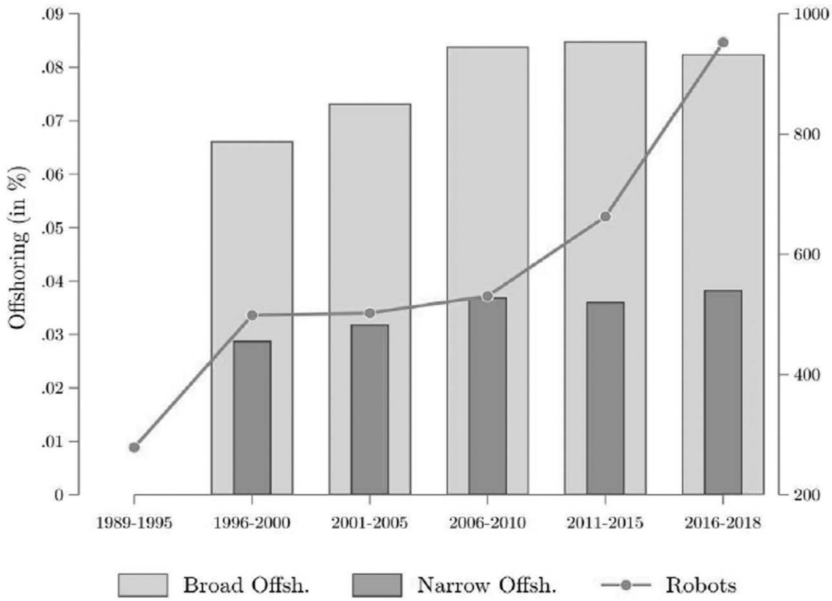

Figure 3.3 Robot Imports and Offshoring over Time

Source: US Customs data (Schott, 2008), Import Matrices and Input-Output Tables.

Notes: *Robots* are the overall value of US robot imports in each time period. *Broad Offsh.* and *Narrow Offsh.* are averages of the two offshoring indicators across industries and years in each time period.

phenomena. To document the geographical distribution of automation and offshoring in the US, Figure 3.5 reports two maps showing the mean of $\Delta Robots_{ct}$ (map a) and the average change in offshoring (maps b) in each CZ over the sample period.[16] Two facts are worth highlighting. First, both variables vary substantially in space. Interestingly, variation is high not only across but also within states. This reflects the heterogeneous industrial structure of CZs and will be crucial for our econometric analysis. Second, the correlation between automation and offshoring is negative also across CZs. While automation has especially risen in the Great Lakes region and in coastal states, offshoring intensity has especially increased in South-Central United States. We will systematically document this negative correlation in Section 4.2. For the time being, the descriptive evidence in Figure 3.5 further corroborates the view that automation could have induced a reshoring of activities in the US.

Finally, Table 3.1 reports summary statistics on the main variables used in the regressions. All statistics are computed across CZs and time periods. The employment-to-population ratio has increased on average by 2.6 percentage points (p. p.) per decade, as the combination of a 4.6 p.p. average decadal increase in non-manufacturing industries and a 2 p.p. average decadal reduction in the

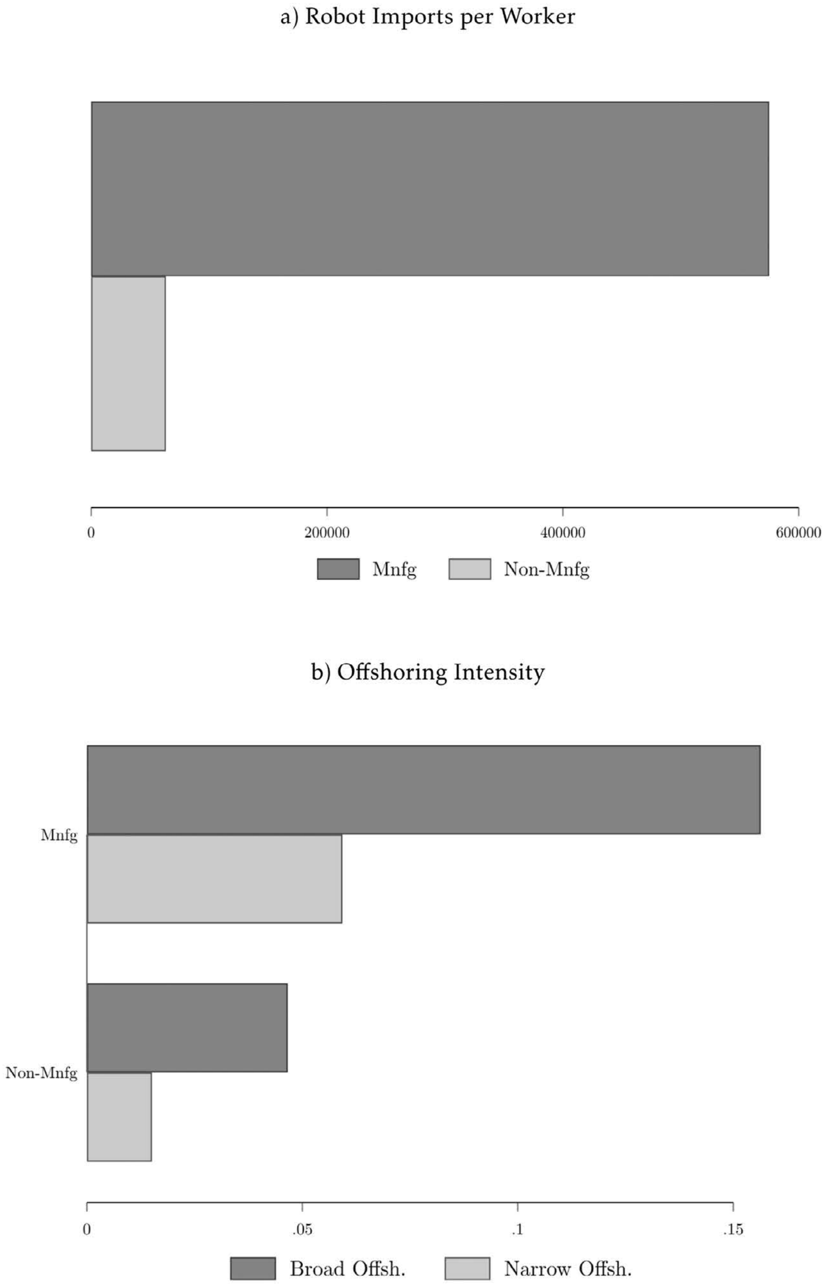

Figure 3.4 Robot Imports and Offshoring by Sector

Source: US Customs data (Schott, 2008), Import matrices and Input-Output Tables.

Notes: All figures are averages across year and industries within a sector.

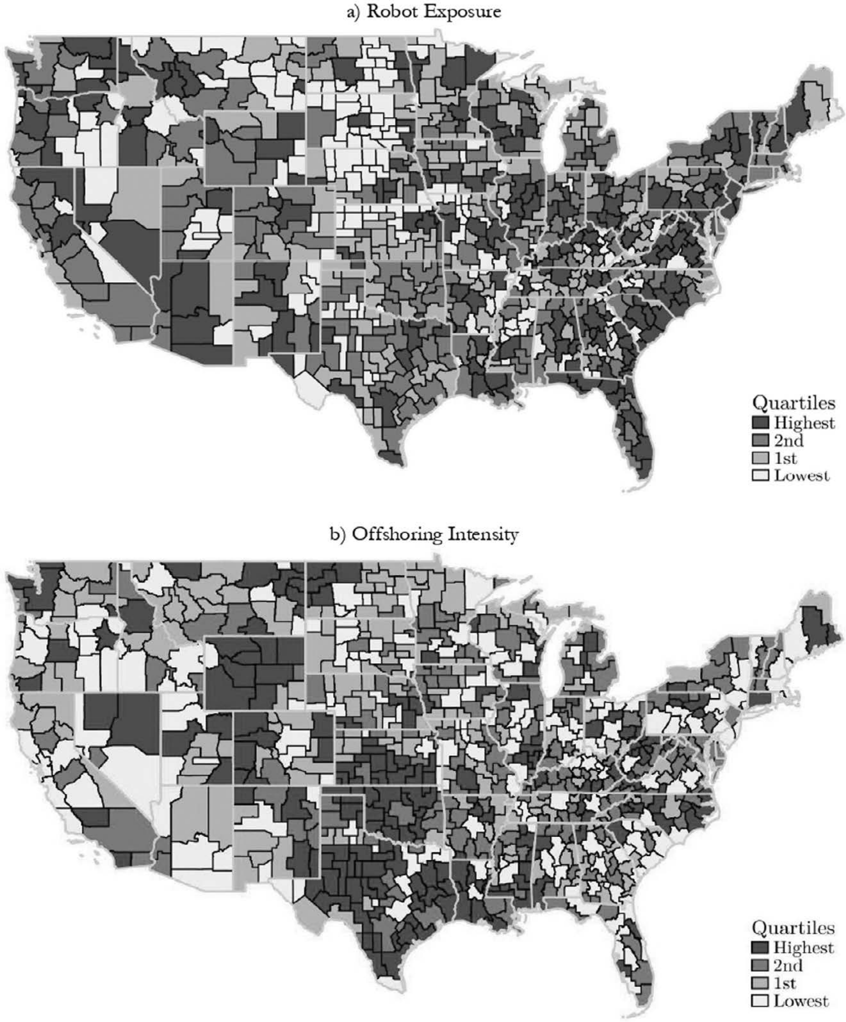

Figure 3.5 Robot Exposure and Offshoring across Commuting Zones

Notes: The first map shows the mean of Δ *Robots* in each CZ over the sample period. The second map shows the average change in the broad offshoring indicator by CZ over time.

manufacturing sector. Average wages have risen by 0.1 log points per decade in both sectors. Table 3.1 also confirms the significant increase in automation documented before, with $\Delta Robots_{ct}$ being equal to 0.41 log points per decade on average. The high standard deviation of $\Delta Robots_{ct}$ points to significant variation in robot exposure both in space and over time, consistent with the evidence emerging from Figure 3.5. Finally, offshoring intensity is equal to 4.8 p.p. on average according to the broad indicator and to 1 p.p. according to the narrow indicator. Also in this case, there is significant variation across CZs and time periods as suggested by the high standard deviations reported in the table.

4 Empirical Analysis

In this section, we present the results of the econometric analysis. We start by discussing the average effects of robot exposure on labor market outcomes across CZs. We then provide novel evidence on the relationship between automation and offshoring, exploiting variation across occupations, industries and space. Building on this evidence, we finally revisit the average employment effects of robot exposure and unpack them across occupations and CZs with different exposure to offshoring.

4.1 Average Effects

To study how robot exposure affects labor market outcomes across CZs, we build on Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2019), and estimate specifications of the following form:

$$\Delta \Upsilon_{ct} = \alpha_s + \alpha_t + \beta \cdot \Delta Robots_{ct} + \mathbf{X}_{ct}^{'} \cdot \gamma + \varepsilon_{ct}, \tag{15}$$

where $\Delta \Upsilon_{ct}$ is the change in outcome Υ in CZ c over period t; α_s and α_t are fixed effects for US states and time periods, respectively; $\Delta Robots_{ct}$ is our measure of

Table 3.1 Summary Statistics

	Mean	*Std. Dev.*	*Obs.*
Δ Total Emp./Pop.	0.026	0.043	2888
Δ Mnfg Emp./Pop.	–0.020	0.041	2888
Δ Non Mnfg Emp./Pop.	0.046	0.053	2888
Δ ln Avg Wages	0.100	0.115	2888
Δ ln Mnfg Wages	0.105	0.255	2888
Δ ln Non Mnfg Wages	0.103	0.125	2888
Δ Robots	0.411	0.699	2888
B_Offsh	0.048	0.033	2888
N_Offsh	0.007	0.017	2888

Notes: Statistics for variables in changes are computed across 722 CZs and four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. Statistics for variables in levels *(B_Offsh* and *N_Offsh)* are computed across 722 CZs and four years: 2000, 2005, 2010 and 2015. Changes in employment-to-population ratios and in log average wages over a given time period are expressed in decadal terms. *Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *B_Offsh* and *N_Offsh* are weighted averages of the broad and narrow offshoring indicators across industries, with weights given by the industrial structure of employment in each CZ and year.

CZ-level exposure to imported robots; $\mathbf{X}_{ct}$ is a vector of controls for other observable characteristics of the CZ (details follow); and ε_{ct} is an error term.

We estimate eq. (15) by stacking ten-year equivalent first differences for four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. The state fixed effects control for heterogeneous trends in labor market outcomes across states, while the year fixed effects absorb shocks hitting outcomes uniformly in all CZs. The control variables $\mathbf{X}_{ct}$ include start-of-period proxies for the following CZ-level characteristics: size (log employment), demographic composition of the labor force (employment shares of female, foreign born and college-educated workers), and composition of economic activities (employment share of workers in routine-intensive occupations and offshoring intensity). These variables account for heterogeneous trends across CZs characterized by different initial conditions. $\mathbf{X}_{ct}$ also includes proxies for other shocks potentially occurring in CZ c over period t, namely, export shocks and shocks to import competition from China and other countries. These variables control for changes in trade, technology and demand conditions concurrent with the import of robots.[17] We weight the observations by the initial-period share of each CZ in total population and correct the standard errors for clustering at the state level to account for residual correlation across CZs within the same state. We first estimate eq. (15) using OLS. Then, to account for possible endogeneity of $\Delta Robots_{ct}$, we turn to 2SLS regressions, instrumenting $\Delta Robots_{ct}$ with $\Delta Robots\_Oth_{ct}$. Because eq. (15) restricts coefficients to be the same across CZs, the parameter β measures the average effect of robot exposure on a given outcome across US local labor markets.

Table 3.2 contains results for employment. OLS estimates are reported in panel a and 2SLS estimates in panel b. To study how the effect of robot exposure is influenced by the covariates, we first present results from a parsimonious specification including only state and year fixed effects (columns 1–3) and then add control variables (columns 4–6). We estimate eq. (15) for three different outcomes. The first, used in columns (1) and (4), is the change in total employment over population. The other two outcomes, used in columns (2) and (5) and in columns (3) and (6), respectively, are the changes in manufacturing and non-manufacturing employment over population. Because total employment is the sum of manufacturing and non-manufacturing employment, the properties of linear estimators like OLS and 2SLS imply that the estimates of β reported in columns (2) and (3) add up to the estimate reported in column (1); similarly, the estimates of β shown in columns (5) and (6) add up to the estimate shown in column (4). This provides us with an immediate way of decomposing the employment effects of robot exposure across manufacturing and other sectors.

The OLS estimates show a negative and statistically significant correlation between robot exposure and manufacturing employment. The correlation with non-manufacturing employment is instead positive and becomes statistically significant when adding control variables. The two effects partly offset each other, so the correlation of robot exposure with overall employment is weak and not always statistically significant. In Appendix Table B1, we dig deeper into the

Table 3.2 Robot Exposure and Employment

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Total Emp./Pop.	*Δ Mnfg Emp./Pop.*	*Δ Non Mnfg Emp./Pop.*	*Δ Total Emp./Pop.*	*Δ Mnfg Emp./Pop.*	*Δ Non Mnfg Emp./Pop.*
	a) OLS					
ΔRobots	−0.012**	−0.016***	0.004	−0.006	−0.016***	0.010*
	[0.005]	[0.004]	[0.005]	[0.004]	[0.004]	[0.006]
Obs.	2879	2879	2879	2157	2157	2157
R2	0.43	0.29	0.36	0.53	0.36	0.36
	b) 2SLS					
	2nd Stage					
ΔRobots	0.016	−0.056***	0.072***	0.006	−0.049***	0.055***
	[0.016]	[0.014]	[0.018]	[0.010]	[0.010]	[0.014]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.23	0.20	0.01	0.52	0.30	0.29
	1st Stage (Dep. Var.: ΔRobots)					
ΔRobots_Oth	2.708***	2.708***	2.708***	4.085***	4.085***	4.085***
	[0.450]	[0.450]	[0.450]	[0.411]	[0.411]	[0.411]
Kleibergen-Paap *F-stat.*	36.2	36.2	36.2	99.0	99.0	99.0
State FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Control variables	no	no	no	yes	yes	yes

Notes: The sample consists of 722 CZs and four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. The dependent variables, indicated in the columns' headings except for the first-stage regressions, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). Δ*Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. The instrument Δ*Robots_Oth* is constructed analougously to Δ*Robots* using industry-level data on robot exports from non-US countries to eleven European countries. *Control variables* are start-of-period log employment, offshoring intensity (broad indicator), the employment shares of female workers, foreign-born workers, college graduates and routine-intensive occupations, and the ten-year equivalent changes in exports, imports from China and imports from other countries over total employment. The first period with available data on offshoring is 2000–2005. Regressions are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are correted for clustering within states. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

timing of these relationships. Using the parsimonious specification, we find that the correlations are stronger when estimated on later periods (2005–2010 and 2010–2015) than on earlier periods (1990–2000 and 2000–2005). This is consistent with the acceleration of robot imports occurring in the second part of the sample, as documented in Figure 3.3. Moreover, we perform a falsification test by regressing current employment changes on the first lead of $\Delta Robots_{ct}$. The coefficients are always close to zero, which further suggests that the relationship between robot exposure and employment is not driven by secular trends in outcomes that antedate an increase in automation.

Appendix Table B1 also contains an extensive set of robustness checks on the baseline specification. We show, in particular, that the main results are not driven by outliers, as they remain unchanged when excluding CZs in the top percentile of the distribution by $\Delta Robots_{ct}$ in each period. We also control for exposure to other types of capital and find that the correlations are not contaminated by other forms of investment.[18] Moreover, we find similar results when considering alternative ways of constructing robot exposure, namely, by using (i) changes in the stock of robot imports, (ii) changes in net robot imports, and (iii) the cross-industry distribution of total machinery purchases to apportion nationwide robot imports to individual industries.[19]

Finally, in Appendix Figure B1, we use alternative ways of correcting the standard errors for clustering. In particular, we account for residual correlation within CZs over time (clustering by CZ); across CZs in the same state and year (clustering by state-year); within CZs over time and across CZs in the same state and year (two-way clustering by CZ and state-year); across CZs in the same geographical neighborhood (spatial clustering); and across CZs with similar industrial structure (clustering by industry similarity).[20] The confidence intervals around β are similar to, and frequently narrower than, the baseline confidence intervals, suggesting that correcting the standard errors for clustering within states provides a conservative inference.

We now turn to the 2SLS estimates. The bottom part of panel b shows that the first-stage coefficient on $\Delta Robots\_Oth_{ct}$ is positive, large and very precisely estimated, which underscores the strong predictive power of the instrument at explaining differences in robot exposure across CZs.[21] The second-stage coefficients, reported at the top of panel b, are larger than their OLS counterparts in absolute value, suggesting OLS estimates to be biased towards zero. Qualitatively, however, the 2SLS estimates confirm the evidence emerged from the OLS regressions. In particular, robot exposure reduces employment in manufacturing. This is consistent with robot adoption currently being larger in manufacturing than in other sectors. At the same time, robot exposure raises employment outside of manufacturing. This is consistent with the model in Section 2.3 where displaced workers in manufacturing find employment in the service sector. Overall, the two effects almost exactly cancel out, so robot exposure has no significant impact on overall employment.

To have a sense of the magnitude of these effects, we multiply the average value of $\Delta Robots_{ct}$ reported in Table 3.1 by the 2SLS coefficients shown in columns (5) and (6) of Table 3.1. This yields –0.02 for manufacturing employment and 0.022 for non-manufacturing employment. Accordingly, in a CZ with average robot exposure, manufacturing employment would fall by 2 p.p. per decade relative to population, roughly the average change documented in Table 3.1. At the same time, non-manufacturing employment relative to population would increase by 2.2 p.p. per decade, approximately half the size of the average change reported in Table 3.1. These figures suggest that automation has significantly contributed to the reallocation of employment from manufacturing to non-manufacturing sectors occurring in the US over the sample period.

Finally, in Table 3.3, we complement the employment results by studying the implications of robot exposure for wages. The estimates show that automation increases average wages. The effect is driven by non-manufacturing sectors. Together with our previous evidence on employment, this further suggests that robot exposure increases labor demand outside of manufacturing. When separately considering college-educated and non college-educated workers, we find positive wage effects for both groups, although the point estimate is larger and precisely estimated for high-skill individuals. In manufacturing, the effect of automation on average wages is negative, albeit imprecisely estimated, consistent with automation reducing labor demand in this sector. When separately considering workers with and without a college degree, we find a small positive estimate of β for the former group and a larger negative estimate for the latter. While none of these coefficients is precisely estimated, these results suggest that robots tend to reduce labor demand in manufacturing especially for low-skill individuals.

Overall, these results are broadly consistent with Acemoglu and Restrepo (2019), who study the effect of automation across US CZs over the 1990–2007 period using data on the stock of robots in nineteen industries from the IFR. Similarly to us, they find evidence of negative employment effects, which are more pronounced in manufacturing. However, they also find stronger negative effects on wages.

4.2 Robots and Offshoring

Having documented the average effects of robot exposure on labor market outcomes, we turn to the main part of the analysis. Our interest lies in understanding how automation interacts with offshoring and what consequences such an interaction could have for the US labor market. In this section, we analyze the relationship between robot exposure and offshoring using different sources of variation in the data. In the next section, we turn to investigating the implications for US employment.

As a starting point, we study the nature of tasks that can be performed by robots. Specifically, we ask whether robots are suited for tasks with a high degree of offshorability or for relatively hard-to-offshore activities. To this purpose, we take advantage of the occupation-level measures of offshorability and replaceability introduced in Section 3. We regress the offshorability index of Autor and Dorn (2013) on the replaceability dummy of Graetz and Michaels

Table 3.3 Robot Exposure and Wages

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	Δ ln Avg Wages	*Δ ln Mnfg Wages*	*Δ ln Mnfg Wages (College)*	*Δ ln Mnfg Wages (Non-College)*	*Δ ln Non Mnfg Wages*	*Δ ln Non Mnfg Wages (College)*	*Δ ln Non Mnfg Wages (Non-College)*
				a) OLS			
$\Delta Robots$	0.031**	0.003	0.017	0.004	0.039***	0.044***	0.032
	[0.012]	[0.023]	[0.030]	[0.027]	[0.013]	[0.014]	[0.022]
Obs.	2157	2157	2151	2154	2157	2157	2157
R2	0.52	0.20	0.18	0.08	0.49	0.51	0.24
				b) 2SLS, 2nd Stage			
$\Delta Robots$	0.064*	–0.075	0.013	–0.102	0.097***	0.114***	0.055
	[0.033]	[0.097]	[0.099]	[0.105]	[0.030]	[0.032]	[0.034]
Obs.	2157	2157	2151	2154	2157	2157	2157
R2	0.51	0.19	0.18	0.06	0.48	0.50	0.23

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables, indicated in the columns' headings, are ten-year equivalent log changes in average wages (column 1), manufacturing wages (column 2), manufacturing wages of college graduates (column 3), manufacturing wages of non-college graduates (column 4), non-manufacturing wages (column 5), non-manufacturing wages of college graduates (column 6) and non-manufacturing wages of non-college graduates (column 7). $\Delta Robots$ is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period The instrument is $\Delta Robots\_Oth$, constructed analogously to $\Delta Robots$ using industry-level data on robot exports from non-US countries to eleven European countries All regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors reported in square brackets are correted for clustering within states ***,** and * denote significance at the 1%, 5% 10% level, respectively.

Table 3.4 Robots Exposure and Offshoring Across Occupations, Industries and Commuting Zones

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	Offshorability (AD, 2013)	*Offshoring (Broad)*	*Offshoring (Narrow)*	*Offshoring (Broad)*	*Offshoring (Narrow)*	*Offshoring (Broad)*	*Offshoring (Narrow)*
Replaceability	0.277** [0.130]						
Δ ln Rob_M		–0.076*** [0.006]	–0.080*** [0.005]				
Δ*Robots*				–0.019*** [0.004]	–0.024*** [0.003]	–0.014*** [0.005]	–0.017*** [0.004]
Obs.	331	535	408	2157	2157	2157	2157
R2	0.01	1.00	1.00	0.69	0.71	0.68	0.68
Sample	Occupations	Industries Panel		CZs Panel			
Estimator	OLS	OLS	OLS	OLS	OLS	2SLS	2SLS

Notes: The regression in column (1) is estimated on a cross-section of occupations. The dependent variable is an indicator of offshorability, which measures the degree to which workers in a given occupation require face-to-face interaction and physical presence on the job (Autor and Dorn, 2013). *Replaceability* is a dummy equal to 1 for occupations whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics, and equal to 0 otherwise (Graetz and Michaels, 2018). The regressions in columns (2) and (3) are estimated on a panel of 66 industries. The dependent variables are changes in the broad and narrow offshoring indicators, respectively, over five-year periods. Δ *ln Rob_M* is the log change in US robot imports in each industry. The regressions include fixed effects for industries and sector-year pairs, and are weigthted by start-of-period industry employment. The repressions in columns (4)-(7) are estimated on a panel of CZs. The dependent variables are weighted averages of ten-year equivalent changes in the industry-level offshoring indicators, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. Δ*Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. In columns (6) and (7), the instrument is Δ*Robots_Oth*, constructed analougously to Δ*Robots* using industry-level data on robot exports from non-US countries to eleven European countries. The regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are robust to heteroskedasticity in column (1), corrected for clustering within industries in columns (2) and (3), and corrected for clustering within states in columns (4)–(7). ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

(2018) across 331 US Census occupations. The results are reported in column (1) of Table 3.4. The coefficient on the replaceability dummy is positive and statistically significant, implying that replaceable occupations are more offshorable than non-replaceable occupations, on average. Given that the offshorability index is standardized with mean 0 and standard deviation 1, the coefficient implies a sizable difference of 28% of a standard deviation between the average offshorability of replaceable and non-replaceable occupations.

In untabulated regressions, we have assessed the robustness of this result using two alternative offshorability indices, developed by Blinder (2009) and Blinder and Krueger (2013), respectively. The Blinder (2009) indicator assigns each occupation an offshorability degree based on the author's subjective assessment of how amenable tasks are to electronic delivery. The Blinder and Krueger (2013) indicator quantifies the offshorability of an occupation based on information from household surveys and professional coders' assessment of the ease with which tasks can be relocated abroad. Also in these cases, we found positive and precisely estimated coefficients on the replaceability dummy, suggesting that the positive correlation between replaceability and offshorability does not depend on how we measure the latter characteristic.

These results imply that automation and offshoring affect similar occupations. Accordingly, automation may act as a substitute for offshoring, allowing firms to use robots in tasks that were previously performed abroad. We now provide more direct evidence of this substitutability by studying the relationship between robot imports and the two offshoring indicators across industries. To this purpose, we regress changes in the offshoring indicators on changes in log robot imports over five-year periods across industries. We control for industry fixed effects to absorb industry-specific trends and for sector × year fixed effects to soak up common shocks across sectors; the regressions are weighted by industry employment at the beginning of each period. The results are reported in columns (2) and (3) of Table 3.4. Regardless of the offshoring indicator, the coefficient on robot imports is always negative and very precisely estimated: industries experiencing a more rapid growth in robot imports also exhibit a relatively larger reduction in offshoring. This finding is consistent with robots substituting tasks that used to be performed abroad and suggests that the rise of automation over the sample period has been associated with a reshoring of activities to the US.

In the remaining columns of Table 3.4, we complement the previous results with evidence across CZs. To this purpose, we estimate eq. (15) using changes in the two offshoring indicators as the dependent variables.[22] We run these regressions using both OLS (columns 4 and 5) and 2SLS (columns 6 and 7), to mitigate concerns with reverse causality and omitted variables; in the latter case, we use $\Delta Robots\_Oth_{ct}$ as an instrument for $\Delta Robots_{ct}$. The coefficient on $\Delta Robots_{ct}$ is always negative and highly statistically significant. Consistent with the descriptive evidence emerging from Figure 3.5, firms have more intensively resorted to reshoring in CZs characterized by stronger robot exposure.

4.3 Robot Exposure, Offshoring and Employment

That robots and offshoring are substitutes for one another has potentially important implications for the employment effects of automation. If robots induce reshoring, their effects are likely to be heterogeneous both across occupations and across CZs. First, automation may induce a relatively larger reduction in domestic employment in occupations that are harder to offshore. The reason is that, in offshorable occupations, automation should partly affect foreign employment and foster reshoring to the US. Second, automation may lead to a relatively smaller reduction in domestic employment in CZs characterized by a higher offshoring intensity, as the scope for reshoring is relatively larger in these CZs. We now revisit the average effects of robot exposure on employment in the light of these considerations. In particular, we allow the effects to vary across jobs and in space, and study whether this heterogeneity is consistent with the substitutability between robots and offshoring documented before.

Our first exercise consists of unpacking the effects of robot exposure across occupations with different characteristics. To this purpose, we decompose the overall change in the employment-to-population ratio across mutually exclusive groups of occupations, and then re-estimate eq. (15) using changes in group-specific employment over population as the dependent variables. The results are reported in Table 3.5. To begin with, in panel a, we divide occupations into two groups and use OLS regressions to describe the central tendencies in the data. Columns (1) and (2) show, as expected, that robot exposure is associated with a significant fall in employment in replaceable occupations but no change in non-replaceable occupations. More interestingly, columns (3) and (4) show that robot exposure is uncorrelated with employment in offshorable jobs, but strongly negatively correlated with employment in non-offshorable tasks.

In panel b, we examine this heterogeneity in greater detail by dividing occupations into four mutually exclusive groups, which are obtained by combining replaceability and offshorability. For instance, offshorable-replaceable occupations are those for which the replaceability dummy is equal to 1 and the offshorability indicator is above the sample median; the other groups are defined accordingly. The results show that the employment changes in non-replaceable occupations are uncorrelated with robot exposure regardless of offshorability. On the contrary, for replaceable occupations, employment changes are uncorrelated with robot exposure if these occupations are also offshorable but strongly negatively correlated if they are non offshorable. The 2SLS regressions reported at the bottom of the table confirm the qualitative pattern of results. Hence, automation has heterogeneous effects across occupations depending on offshorability: while offshorable occupations are largely sheltered from automation, non-offshorable occupations whose tasks can be replaced by robots bear the burden of the negative effects of automation.

Next, we turn to the second exercise and study whether the employment effects of robot exposure vary across CZs depending on offshoring intensity.

Table 3.5 Robot Exposure and Employment Across Occupation Groups

	(1) *Replaceable (GM, 2018)*	*(2)* *Non-Replaceable (GM, 2018)*	*(3)* *Offshorable (AD, 2013)*	*(4)* *Non-Offshorable (AD, 2013)*
		a) OLS		
ΔRobots	−0.010*	0.003	0.006	−0.013***
	[0.005]	[0.005]	[0.005]	[0.005]
Obs.	2157	2157	2157	2157
R2	0.19	0.17	0.30	0.46
	Offshorable & Replaceable	Offshorable & Non-Replaceable	Non-Offshorable & Replaceable	Non-Offshorable & Non-Replaceable
		b) OLS		
ΔRobots	0.001	0.005	−0.011**	−0.002
	[0.003]	[0.005]	[0.005]	[0.004]
Obs.	2157	2157	2157	2157
R2	0.09	0.28	0.23	0.21
		c) 2SLS, 2nd Stage		
ΔRobots	0.018	−0.001	−0.033**	0.019
	[0.012]	[0.021]	[0.014]	[0.015]
Obs.	2157	2157	2157	2157
R2	0.06	0.28	0.21	0.19

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables are ten-year equivalent changes in employment (relative to population) in mutually exclusive groups of occupations, as defined in the columns' headings. Offshorable occupations are those for which the offshorability index developed by Autor and Dorn (2013) is above the sample median. Replaceable occupations are those whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics (Graetz and Michaels, 2018). Non-offshorable and non-replaceable occupations are defined accordingly. $\Delta Robots$ is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. The instrument is $\Delta Robots\_Oth$, constructed analogously to $\Delta Robots$ using industry-level data on robot exports from non-US countries to eleven European countries. All regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are correted for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

Table 3.6 Robot Exposure, Offshoring and Employment, Broad Offshoring Indicator

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	Δ Total Emp./ Pop.	*Δ Mnfg Emp. /Pop.*	*Δ Non Mnfg Emp./ Pop.*	*Δ Total Emp./ Pop.*	*Δ Mnfg Emp./ Pop.*	*Δ Non Mnfg Emp./ Pop.*
	a) Baseline			**b) No Machinery in Offshoring Indicator**		
ΔRobots	–0.002	–0.037***	0.035***	–0.003	–0.041***	0.037***
	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
ΔRobots × B_Offsh	–0.057	0.330**	–0.387**	–0.032	0.377**	–0.409**
	[0.133]	[0.157]	[0.168]	[0.141]	[0.145]	[0.158]
B_Offsh	0.067	–0 279***	0.346***	0.062	–0 245***	0.307***
	[0.067]	[0.057]	[0.072]	[0.064]	[0.049]	[0.068]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.53	0.36	0.36	0.53	0.37	0.36
	c) Additional Interactions of Robot Exposure			**d) Exposure to Other Types of Capital**		
ΔRobots	–0.259	–0.035	–0.224	0.000	_0.047***	0.047***
	[0.160]	[0.130]	[0.150]	[0.009]	[0.012]	[0.015]
ΔRobots × B_Offsh	–0.061	0 427***	_0.488***	–0.176	0.553***	–0.730***
	[0.125]	[0.114]	[0.173]	[0.145]	[0.179]	[0.227]
B_Offsh	0.019	–0 321***	0 339***	–0.143	–0.400*	0.257
	[0.061]	[0.062]	[0.081]	[0.222]	[0.218]	[0.262]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.53	0.38	0.36	0.54	0.37	0.38

Notes: All regressions are estimated on a panel of 722 *CZ*s. The dependent variables, indicated in the columns' headings, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). Δ*Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *B_Offsh* is the weighted average of the start-of-period broad offshoring indicator across industries, with weights given by the initial industrial structure of employment in each CZ. In panel b, the offshoring indicator excludes imports of machinery made by each industry. All regressions are estimated with OLS; include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. The regressions in panel c also include interactions of Δ*Robots* with log employment and the employment shares of female workers, foreign-born workers, college graduates and routine-intensive occupations at the beginning of each period. The regressions in panel d also include four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. These variables, which enter both linearly and interacted with *B_Offsh*, are constructed analogoulsy to Δ*Robots* using ten-year equivalent log changes in expenditure on each type of capital across industries in place of log changes in US robot imports. Standard errors, reported in square brackets, are correted for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

Table 3.7 Robot Exposure, Offshoring and Employment, Narrow Offshoring Indicator

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Total Emp./ Pop.	*Δ Mnfg Emp. /Pop.*	*Δ Non Mnfg Emp./ Pop.*	*Δ Total Emp./ Pop.*	*Δ Mnfg Emp./ Pop.*	*Δ Non Mnfg Emp./ Pop.*
	a) Baseline			**b) No Machinery in Offshoring Indicator**		
ΔRobots	–0.002	–0.023***	0.021***	–0.002	–0.024***	0.022***
	[0.006]	[0.007]	[0.008]	[0.007]	[0.006]	[0.008]
ΔRobots ×	–0.162	0.322*	–0.484**	–0.139	0.349**	–0.488**
N_Offsh	[0.129]	[0.167]	[0.203]	[0.134]	[0.153]	[0.192]
N_Offsh	0.099	–0 319***	0.418***	0.088	–0.335***	0 423***
	[0.079]	[0.070]	[0.090]	[0.081]	[0.064]	[0.087]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.53	0.36	0.36	0.53	0.36	0.36
	c) Additional Interactions of Robot Exposure			**d) Exposure to Other Types of Capital**		
ΔRobots	–0.266*	–0.038	–0.228	–0.007	–0.022***	0.015*
	[0.158]	[0.122]	[0.150]	[0.005]	[0.007]	[0.008]
ΔRobots ×	–0.169	0.389**	–0.558**	–0.303**	0.802***	–1.106***
N_Offsh	[0.143]	[0.146]	[0.210]	[0.134]	[0.154]	[0.192]
N_Offsh	0.040	–0.387***	0.428***	–0.267	–0.535*	0.268
	[0.081]	[0.085]	[0.106]	[0.404]	[0.272]	[0.343]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.54	0.38	0.36	0.55	0.37	0.39

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables, indicated in the columns' headings, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). *Δ Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *N_Offsh* is the weighted average of the start-of-period narrow offshoring indicator across industries, with weights given by the initial industrial structure of employment in each CZ. In panel b, the offshoring indicator excludes imports of machinery made by each industry. All regressions are estimated with OLS; include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. The regressions in panel c also include interactions of *ΔRobots* with log employment and the employment shares of female workers, foreign-born workers, college graduates and routine intensive occupations at the beginning of each period. The regressions in panel d also include four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. These variables, which enter both linearly and interacted with *N_Offsh,* are constructed analogoulsy to *ΔRobots* using ten-year equivalent log changes in expenditure on each type of capital across industries in place of log changes in US robot imports. Standard errors, reported in square brackets, are corrected for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

To do so, we augment eq. (15) with an interaction between $\Delta Robots_{ct}$ and the start-of-period level of either offshoring indicator, B_Offsh_{ct} or N_Offsh_{ct}.[23] We report results for the overall employment-to-population ratio and for its manufacturing and non-manufacturing components. Given the well-known difficulty in instrumenting interaction terms, we focus on OLS regressions.

The results are reported in Table 3.6 for the broad offshoring indicator and in Table 3.7 for the narrow measure. Strikingly, in the regression for manufacturing employment, the coefficient on the interaction between robot exposure and offshoring is always positive and very precisely estimated. This confirms that automation reduces manufacturing employment relatively less in CZs that are initially more reliant on offshoring. To quantify the extent of heterogeneity, we use the estimated (linear and interaction) coefficients on $\Delta Robots_{ct}$ along with the observed distribution of offshoring across CZs in our data. This exercise reveals that the employment effect of robot exposure is negative in the majority of CZs; yet, for a small fraction of high offshoring-intensive CZs (the top 5% by B_Offsh_{ct} and the top 1% by N_Offsh_{ct}), automation actually leads to an increase in manufacturing employment. In the regression for non-manufacturing employment, the coefficient on the interaction between robot exposure and offshoring is always negative and precisely estimated, consistent with the view that displaced workers reallocate, at least partially, outside of the manufacturing sector.

In the remaining panels, we submit the baseline results to various robustness checks. In panel b, we re-compute the offshoring indicators by excluding imports of machinery made by each industry. This avoids the offshoring measures to be contaminated by robot imports. In panel c, we augment the specification by adding interactions of $\Delta Robots_{ct}$ with all other start-of-period controls included in $\mathbf{X}_{ct}$. This prevents our coefficients of interest from being influenced by differences in other CZ-level characteristics that could interact with automation. Finally, in panel d, we extend the specification by including the four variables measuring exposure to other types of capital, both linearly and interacted with offshoring. This allays the concern that the baseline results could be driven by the correlation between robot adoption and other forms of investment. In all cases, the results confirm that offshoring plays an important role at mediating the employment effects of automation across US local labor markets.

5 Conclusions

In this chapter, we have studied the effects of automation, measured by the adoption of industrial robots, in the presence of offshoring. The literature has mostly studied these phenomena in isolation. This is unfortunate, because what we have shown is that offshoring can change the impact of automation in important ways. In particular, when robots affect differentially domestically-produced and foreign-sourced tasks, automation has terms-of-trade effects that redistribute income across countries. This has important implications. While automation replacing foreign workers is necessarily welfare-improving for the domestic economy, automation replacing domestically-produced tasks can lower the real wage of domestic workers through a deterioration of the terms of trade.

These results underscore the importance of identifying which workers are in more direct competition with robots and motivate the empirical analysis conducted in the chapter. Using US data across industries, occupations and local labor markets, we have studied the interaction between automation and offshoring over the 1990–2015 period. Our results suggest that industrial robots displace US workers from manufacturing industries, but that the effect is weaker in CZs that are more exposed to offshoring. We also found that industrial robots lower the incidence of offshoring and that their negative employment effects are concentrated in occupations performing tasks that are classified as non-offshorable. These results are consistent with the view that automation contributes to the reshoring of economic activity, which in turn tends to mitigate any adverse labor market effects for US workers.

We conclude by discussing some limitations and possible extensions of our analysis. The empirical findings in this chapter are based entirely on US data. However, we consider equally important to study the effect of US automation on low-wage countries. Consistent with our results, some papers tend to find negative effects on labor market outcomes in the developing world (see, for instance, Faber, 2020, Artuc, Christiaensen and Winkler, 2019, Stemmler, 2019, Kugler et al. 2020). Yet, it would be desirable to combine data across countries to directly identify the terms-of-trade effect of automation. We view this as an interesting direction for future research.

From a normative perspective, the result that automation is likely to redistribute income across countries implies that policy makers may have an incentive to promote the adoption of technologies that lower the dependence on foreign inputs. Such an effort can, however, lead to an inefficient equilibrium with excessive automation and too little trade. In fact, we speculate that foreign competition may even be the trigger for the adoption of policies aiming at self-sufficiency. Exploring this scenario and possible remedies goes beyond the scope of this paper but seems another important and interesting avenue for future research.

Notes

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1 We define automation as the replacement of human labor with robots. Robots are programmable machines that have the capability to move on at least three axes. Unlike other pieces of equipment, robots are designed to replicate human actions.
2 Although we study a static model, we follow the literature in referring to the endogenous increase in the supply of robot as “capital deepening”. See, for instance, Acemoglu and Restrepo (2021).

3 To measure replaceability, we use the classification of occupations developed by Graetz and Michaels (2018). To measure offshorability, we use the index employed by Autor and Dorn (2013). The two indexes capture different dimensions. For instance, replaceable occupations tend to perform manual and repetitive works, while offshorable occupations do not require face-to-face interaction and physical presence on the job.

4 The model builds on earlier formalizations of automation, such as Zeira (1998), Acemoglu and Restrepo (2019) and Hemous and Olsen (2020); and offshoring, such as Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010) and Acemoglu, Gancia and Zilibotti (2015).

5 For instance, they would still apply in a model where automation and offshoring opportuinities are endogenous as in Acemoglu, Gancia and Zilibotti (2015), Grossman and Rossi-Hansberg (2008) or Acemoglu and Restrepo (2018). See Appendix A for more details on the relationship between the model in the text and the task-based approach.

6 This result would change if the supply of robots were not perfectly elastic. In this case, r would also increase with κ.

7 The Censuses and the ACS are 5% and 1% samples, respectively, of the US population and are representative at the level of micro-regions known as Public Use Microdata Areas (PUMAs). We map PUMAs to CZs using a crosswalk developed by Autor and Dorn (2013). We have also experimented with an extended sample including ACS data for the year 2020. In this case, because the automation data illustrated in the following are available up to the year 2018, we have used data for 2018 to construct automation variables referring to the year 2020. Our main results hold also in this extended sample (available upon request).

8 In particular, imports of industrial robots for multiple uses, lifting, handling, loading or unloading and industrial robot parts are classified in the following HTS codes: 8479899540, 8479500000, 8428900100, 8428908015, 8428900120, 8428900220, 8479909740 and 8479909540.

9 Specifically, we compute US robot imports in industry j and year t as $Rob\_M_{jt} = \omega_{jt} \cdot Rob\_M_t$, where Rob_M_t is the total value of US robot imports and ω_{jt} is the share of industry j in total US imports of machinery in year t, constructed from the US Import Matrices.

10 We construct λ_{cjt} using data from the County Business Patterns (CBP). In the CBP, industries are defined according to the 6-digit level of the 2012 NAICS classification. We map BEA industries into 6-digit NAICS industries using a crosswalk provided with the US Input–Output Tables. In case of missing data on robot imports for some years, we use data for the closest available year. Robot imports are expressed at constant 2005 prices using the US Consumer Price Index.

11 Consistent with this, our main results would continue to hold if robot exposure was constructed using the log change in the IFR stock of robots in place of the log change in robot imports in eq. (12).

12 The eleven European countries are Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland and the UK. In the UN Comtrade database, trade in industrial robots is recorded under code 847950 of the Harmonized System classification.

13 Wright (2014) proposes a plausibly exogenous measure of offshoring, derived using variation in US offshoring to China.

14 In case an index is missing for an occupation, we use information for the corresponding broader occupational group.

15 See, among others, Acemoglu and Restrepo (2019) for additional evidence on the growth in the usage of industrial robots in the US based on data from the IFR.

16 The change in offshoring in a CZ is constructed as $\Delta B\_Offsh_{ct} = \Sigma_j \lambda_{cjt} \cdot \Delta B\_Offsh_{jt}$, where ΔB_Offsh_{jt} is the change in offshoring in industry j over period t. For each CZ, Figure 3.5 shows the mean of $\Delta Robots_{ct}$ (map a) and the mean of ΔB_Offsh_{ct} (map b) across all available time periods.

17 The proxies for the demographic composition of employment and the share of routine-intensive occupations are constructed following Autor, Dorn and Hanson (2013). Unless otherwise indicated, we control for offshoring intensity using the broad offshoring indicator; the first period with available data on offshoring is 2000–2005. The proxies for export shocks and for shocks to import competition from China and other countries are defined as changes in a given variable divided by start-of-period employment in the CZ, and are constructed as in Autor, Dorn and Hanson (2013) using trade data from Schott (2008).

18 These variables are constructed analogously to $\Delta Robots_{ct}$, by replacing $\Delta \ln Rob\_M_{jt}$ in eq. (12) with ten-year equivalent log changes in expenditure on software and databases, ICT, machinery and other types of capital and machinery.

19 The proxy for robot exposure based on changes in the stock of robot imports over a given period is constructed as $\Delta Robots\_Stk_{ct} = \Sigma_j \lambda_{cjt} \Sigma_{\tau \in t} \ln(1+ Rob\_M_{j\tau})$, where τ denotes individual years within time period t. The other two proxies are constructed analogously to eq. (12).

20 We implement the correction for spatial clustering using the approach presented in Conley (1999). We define the spatial cluster of a CZ as including all other CZs within a range of 660 km or 768 km. These distances ensure that the spatial cluster of the most remote CZ consists of at least 5 or 10 CZs, respectively. The resulting clusters can overlap with each other and can span different states. To define industry similarity, we instead use cluster analysis and group CZs into 25, 50 or 100 groups characterized by a similar industrial structure, as proxied by the industry shares in total CZ employment, λ_{cjt}. The standard errors are then corrected for clustering within each group of CZs.

21 The Kleibergen-Paap *F*-statistic for excluded instruments easily exceeds the value of 10, which is normally considered as the rule-of-thumb threshold for instrument relevance.

22 In particular, the dependent variables are constructed as follows: $\Delta B\_Offsh_{ct} = \Sigma_j \lambda_{cjt} \cdot \Delta B\_Offsh_{jt}$ and $\Delta N\_Offsh_{ct} = \Sigma_j \lambda_{cjt} \cdot \Delta N\_Offsh_{jt}$, where ΔB_Offsh_{jt} and ΔN_Offsh_{jt} are changes in a given offshoring indicator in industry j over period t.

23 The control variables $\mathbf{X}_{ct}$ already include the linear term of B_Offsh_{ct}. When interacting $\Delta Robots_{ct}$ with N_Offsh_{ct}, we use a linear term in N_Offsh_{ct} in place of the linear term in B_Offsh_{ct}.

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Appendix A

A More General Model of Automation and Offshoring

We consider now a more general case in which productivity varies across tasks and factors, as in the models of offshoring and automation in Grossman and Rossi-Hansberg (2008) and Acemoglu and Restrepo (2018). Tasks are allocated to factors so as to minimize costs:

$$p_i = \min\left\{\frac{w_s}{a_{s,i}}, \frac{w_n}{a_{n,i}}, \frac{r}{a_{r,i}}\right\}.$$

Using p_i, we can then solve for output of each task:

$$\begin{aligned} x_{s,i} &= \frac{a_{s,i} L_s}{m_s} \\ x_{n,i} &= \frac{a_{n,i} L_n}{m_n} \\ x_{r,i} &= \frac{a_{r,i} Y}{r}. \end{aligned}$$

Using these quantities into (1), we obtain (6) where

$$a_x \equiv \exp\left(\int_{i \in N_x} \frac{\ln a_{x,i}}{m_x} \mathrm{d}i\right)$$

is now endogenous and is equal to the average productivity over the tasks N_x performed by factor $x \in \{s, n, r\}$. Equations (7) (8) and (9) are still valid.

In this model, a shock to automation is an increase in some $a_{r,i}$. This can raise m_r (the extensive margin of automation), a_r (the intensive margin of automation), or both. In turn, the change in m_r and/or a_r can affect the allocation of tasks to the other factors too. Holding constant m_r, an increase in a_r benefits all factors. This is the most benign form of automation, corresponding to factor-augmenting technical change without any displacement. Holding constant a_r, the effects of an increase in m_r are those discussed Section 2.2. This is the case in which automation displaces workers. The general model shows that m_r and a_r may change simultaneously. The result that automation can lower both the relative and the real wage of displaced workers still holds. This is because the effect of displacement on wages is unchanged. However, the productivity effect may be weaker or stronger in the more general model.

Appenidx B

Additional Results

Table 3.B1 Robot Exposure and Employment, Additional Results and Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Total Emp./Pop.	*Δ Mnfg Emp./Pop.*	*Δ Non-Mnfg Emp./Pop.*	*Δ Total Emp./Pop.*	*Δ Mnfg Emp./Pop.*	*Δ Non-Mnfg Emp./Pop.*
	a) Sample: 1990–2005			**b) Sample: 2005–2015**		
ΔRobots	–0.010	–0.012**	0.003	–0.013***	–0.019***	0.006
	[0.009]	[0.005]	[0.007]	[0.005]	[0.005]	[0.006]
Obs.	1441	1441	1441	1438	1438	1438
R2	0.50	0.28	0.59	0.30	0.32	0.08
	c) Placebo, Future Rob_Exp			**d) Excl. CZs in Top 1% of Rob_Exp**		
ΔRobots	0.001	–0.001	0.001	–0.004	–0.018***	0.014**
	[0.001]	[0.001]	[0.002]	[0.005]	[0.004]	[0.006]
Obs.	3600	3600	3600	1937	1937	1937
R2	0.41	0.30	0.33	0.54	0.37	0.37
	e) Exposure to Other Types of Capital			**f) Cumulative Stock of Robot Imports**		
ΔRobots	–0.004	–0.016***	0.012**	–0.0002***	–0.0003***	0.0001
	[0.005]	[0.005]	[0.006]	[0.0001]	[0.0001]	[0.0001]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.54	0.37	0.37	0.53	0.36	0.35
	g) Net Robot Imports			**h) Industry Shares of Machinery Purchases**		
ΔRobots	–0.005*	–0.013***	0.008**	–0.005*	–0.013***	0.008**
	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.004]
Obs.	2157	2157	2157	2157	2157	2157
R2	0.53	0.37	0.36	0.53	0.37	0.36

Notes: The table contains additional results and robustness checks on the OLS regressions reported in Table 3.2. All regressions are estimated on a panel of 722 CZs. The samples used in panels a and b cover two time periods: 1990–2000 and 2000-2005 in panel a; 2005–2010 and 2010–2015 in panel b. In panel c, *Δ Robots* enters with a one-year lead. Panel d excludes CZs in the top percentile of the distribution of *ΔRobots* in each year. Panel e includes four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. In panel f, *ΔRobots* is constructed as the weighted average of cumulative sums of log US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each period. In panel g, *ΔRobots* is constructed using US net robot imports (imports minus export) rather than US robot imports. In panel h, *ΔRobots* is constructed by apportioning US robot imports to individual industries using industry shares in total (domestic plus foreign) machinery purchases from the US Input-Output Tables, rather than industry shares in machinery imports from the US Import Matrices. The specifications in panels a include state and year fixed effects; the specifications in panels d-h also include the same control variables as in Table 3.2. All regressions are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are corrected for clustering within states. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

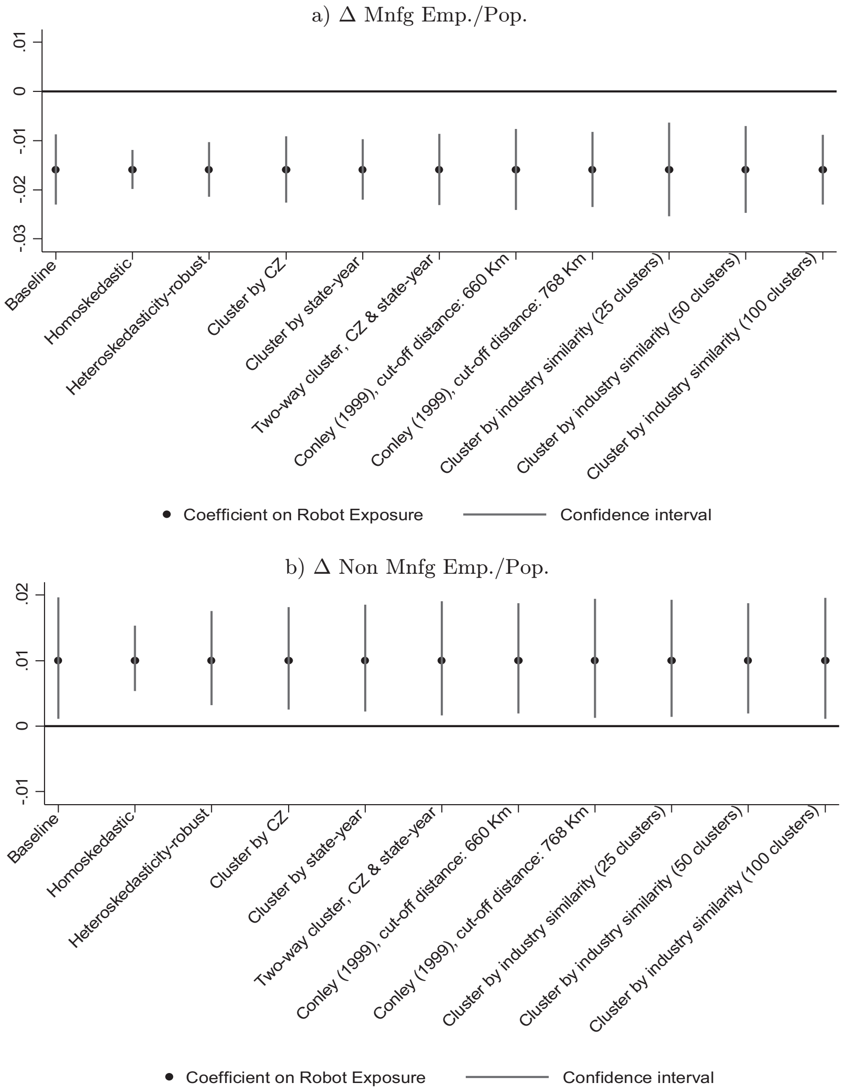

Figure 3.B1 Robot Exposure and Employment: Alternative Corrections of Standard Errors

Notes: The figure plots the OLS coefficients on $\Delta Robots$ obtained with the baseline specifications reported in columns (5) and (6) of Table 3.2 (top and bottom graph, respectively), together with 90% confidence intervals corresponding to alternative ways of correcting the standard errors, as indicated on the horizontal axis. The baseline confidence intervals refer to standard errors corrected for clustering within states. The Conley (1999) confidence intervals refer to standard errors corrected for residual correlation among CZs belonging to the same spatial cluster, as defined by the reported cutoff distance. The last three confidence intervals are obtained by first using cluster analysis to create 25, 50 or 100 groups of CZs with a similar industrial structure of employment and then correcting the standard errors for clustering within each group.