# Impact of Robots in Monopsonistic Labor Markets

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**Abstract**

Perhaps the two most important features of current labor markets in the US and other developed countries are the increasing importance of robots and the growing monopsony power of firms in labor markets. While each has been studied extensively in isolation, the interplay between them has been overlooked. This paper explores how monopsony power affects the impact of robot adoption on US labor markets. Theoretically, I show that robots have stronger effects (either positive or negative) on employment and wages in a perfectly competitive labor market than a perfectly monopsonistic labor market. Moreover, the sign of the effects depends on whether robots and labor are substitutes or complements. Empirically, I define a labor market as a commuting-zone-by-occupation cell, and measure robot exposure and labor market monpsony power for each cell. To alleviate endogeneity concerns, I instrument for both the US exposure to robots and labor market monopsony power. My empirical results show that, from 2006 to 2014, one more industrial robot per thousand workers significantly reduces the employment-to-population ratio by 2% and wages by 0.9% in near-perfectly competitive labor markets. But consistent with the theory, the employment and wage effects diminish as labor market monopsony power grows and they become statistically insignificant in near-monopsonistic labor markets.

**JEL:** J21, D43, O33
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# 1 Introduction

For decades, labor market power has been severely tilted toward employers. Labor's share of national income fell to a historical low after the millennium. Furthermore, the share of national income paid to the bottom 90 percent of the American workforce shrank radically from 58 percent in 1979 to 47 percent in 2015 (Bivens and Shierholz, 2018). Among other culprits, monopsony is undisputedly one of the most significant contributors to this inequality. It "decreases worker mobility, keeping wages lower than they would be in a competitive market" (Manning, 2020). And not merely in the low-income batch, the infamous 2010 secret agreement on hiring limitations for high-tech employees among many Silicon Valley companies, including Google and Apple, reminds us that monopsony exists everywhere in labor markets.[1] Hence, any causal analysis of labor market outcomes treating markets as perfectly competitive should be an exception rather than a rule.

As one of the biggest influences on labor markets outcomes, industrial robots in many developed or even some developing countries have been reshaping the labor market, especially on the demand side since Unimate, the first-ever industrial robot in the world, started working on an assembly line in 1961. As Figure 1 displays, the operational industrial robot stock quadrupled in Europe and quintupled in the US over the last three decades. However, when studying the relationship between robot adoption and labor market outcomes, empirical research typically aims to determine the average effect of robots at geographic levels, overlooking the effect heterogeneity caused by labor market monopsony power.

Global technological advances keep pushing down the price level of robots, making them affordable (relative to labor) to more firms, including small and mid-size enterprises. As a result, firms have incentives to adopt robots, leading to subsequent adjustments in employment.[2] However, in a highly monopsonistic market, firms are wage-setters rather than wage-takers as in perfectly competitive markets.[3] Therefore, in response to an employment change, a monopsonistic firm is assumed to adjust wages for all existing workers. Thus, a monopsonistic firm has less incentive to keep adjusting their employment relative to a perfectly competitive firm. The critical implication is that any robot-induced change in employment, either up or down, has a more muted effect on equilibrium employment and wages in a monopsonistic labor market.

I formalize this intuition by first presenting a static model to derive and compare the equilibrium impact of adopting robots on labor market outcomes in perfectly competitive and monopsonistic markets. To do

[1] In 2010, the Department of Justice alleged that Adobe, Apple, Google, Intel, Intuit, and Pixar had violated Section 1 of the Sherman Act by having a series of agreements between them to limit the hiring of each other's workers. The lawsuit ended up in 2014 with an agreement to settle for $324.5 million.

[2] Robots could potentially have either adverse effects, by substituting automatable workers, or positive effects, by creating new job positions, on employment.

[3] Their wage-setting power has been demonstrated by much empirical evidence that will be discussed later in this section.

this, I set up a profit maximization problem in which a monopsonistic firm faces an upward-sloping labor supply curve, but a competitive firm takes wages as given. The model predicts larger absolute effects of robots on employment and wages in a perfectly competitive labor market. Moreover, the sign of the effects on employment and wages depends on whether robots and labor are substitutes or complements, but not the concentration of the labor market.

I empirically test the predictions of the theoretical model using data on exposure to robots and concentration across US labor markets. Doing so requires one to confront three challenges: (i) defining a labor market, (ii) empirically measuring robot exposure and market concentration at the level of the labor market, and (iii) addressing the potential endogeneity of robot exposure and labor market concentration. To proceed, I define labor markets as location-by-occupation cells, measure exposure to robots using data from the International Federation of Robotics (IFR) following Acemoglu and Restrepo (2020). I capture labor market power using a well-constructed measure of concentration from Azar et al. (2020b).[4]

To address potential endogeneity issues, I follow Acemoglu and Restrepo (2020) to instrument the US exposure to robots using an analogous measure constructed from the robot adoption in the five European countries of Denmark, Finland, France, Switzerland, and Italy. These countries are slightly ahead of the US in automation, but their per worker industrial robot use trend is quite similar to the US trend, either at the aggregate level or the industry disaggregate level. Furthermore, based on the method from Lewbel (2012), I build heteroskedasticity-based instruments for labor market concentration. After controlling for various confounding factors (location-occupation-level demographics, location fixed effects, and occupation fixed effects), my instrumental variable (IV) estimation provides empirical evidence of whether the causal effect of robots varies across markets with different levels of labor market concentration. My regression results suggest that adopting one additional robot per thousand workers in a near-perfectly competitive labor market significantly reduces the employment-to-commuting-zone-population ratio by 2% and wages by 0.9%. However, my results also show that these significant impacts fade away as the labor market becomes more concentrated. Indeed, the effects on employment and wages become statistically indistinguishable from zero when monopsony power is sufficiently strong. Thus, the empirical results are consistent with the theoretical predictions.

My research makes three striking contributions: First, to my knowledge, this is the first paper to explore how the labor market effects of automation depend on labor market monopsony. Second, I develop a simple theory that shows robot adoption always has a more substantial impact on labor market outcomes in a perfectly competitive market than a monopsonistic one. Moreover, treating robot adoption as a labor demand shock, I show that the equilibrium employment and wage always move in the same direction in response to higher robot adoption, but the sign of the effects depends on whether robots and labor are

[4]The data can be found on Ioana Marinescu's website.

substitutes or complements. Third, consistent with the theory, my empirical results suggest that exposure to robots negatively affects employment and wages. However, these adverse effects become smaller as labor market concentration grows and eventually become statistically insignificant in highly concentrated markets. The empirical results are consistent with the theoretical predictions under the assumption of substitutability between robots and labor.

This study builds on two strands of literature: automation in labor markets and labor market monopsony. Many researchers have studied the effect of robot adoption on labor markets while abstracting from the effect of monopsony power. Graetz and Michaels (2018) find a positive impact of robot use on labor productivity but do not find any evidence that robots reduce overall employment, although it does affect the share of low-skilled employees. Acemoglu and Restrepo (2018) develop a task-based theoretical framework that shows automation reduces employment, the labor share, and wages as workers are displaced. However, automation also creates new tasks that may lead to positive labor market outcomes. Building on this model, Acemoglu and Restrepo (2020) theoretically examine the potential effects of robots on employment and wages. The authors then empirically estimate equilibrium impacts of industrial robots on local US labor markets. Measuring the variation of robot adoption using exposure to robots, their results present strong evidence that robots have robust adverse effects on employment and wages. I closely follow Acemoglu and Restrepo (2020) in terms of the basic research question and measuring and dealing with the endogeneity of robot exposure. However, my analysis differs from theirs in terms of the definition of a labor market and the allowance of heterogeneous effects of robot exposure by labor market concentration.

In particular, Acemoglu and Restrepo (2020) neglect labor market monopsony, despite it being much more widespread in US labor markets than previously thought. "Monopsony" is not a new terminology in economics. It was first used in Robinson (1969), referring to a market situation of a single buyer confronted by many sellers, as analogous to monopoly where many buyers confront a single seller. The term is used more loosely to refer to a case where there are a few buyers of labor, or more broadly, to a case where individual buyers face an upward-slopping labor supply curve.

Steinbaum (2017) links monopsony to a wide range of market phenomena, including "wage stagnation, declining geographic and job-to-job mobility, deterioration of the job ladder, and the decline in entrepreneurship and business dynamism". These easily observable phenomena all imply that labor market monopsony is fairly pervasive in the US. A similar conclusion is reached in *Labor Market Monopsony: Trends, Consequences, and Policy Responses* from the Council of Economic Advisors Issue Brief. Although the pervasiveness of monopsony keeps climbing, few policies are made to deal with it. Naidu and Posner (2021) discuss the existing laws on monopsony and how limited they are when monopsony is extensive. To quantitatively examine the labor market monopsony power, most empirical researchers use labor market concentration levels, measured by the Herfindahl-Hirschman Index (HHI), to represent the extent of

market monopsony. Azar et al. (2020b) use a vacancy-share-based HHI to show that most labor markets in the US are highly concentrated according to the standards in the Horizontal Merger Guideline from the US Department of Justice & FTC.[5] By reason of the foregoing, taking monopsony into consideration when studying the effects of robots on labor markets is nontrivial and necessary. Therefore, I build on the literature of robots in labor markets by incorporating monopsony to provide a thorough assessment of whether the effects of robots on labor market outcomes are heterogeneous by labor market concentration.

In the literature of labor market monopsony, many recent papers find evidence that greater concentration causes lower wages. Using the Longitudinal Business Database (LBD) and focusing on manufacturing industries, Benmelech et al. (2020) find evidence that, at the county-by-industry level, higher concentration leads to slightly lower wages. However, this effect is smaller in industries with higher unionization rates. Rinz (2018) also finds negative effects of labor market concentration on wages at the location-by-industry level, but defines location as a commuting zone instead of a county. Furthermore, the author observes heterogeneous wage effects of concentration by demographic groups. Qiu and Sojourner (2019) define a labor market as the combination of an occupation, rather than industry, and a metropolitan area and build their measure of local concentration using data from Dun & Bradstreet. Their results reinforce the negative wage effects of concentration estimated by the prior literature.

The above three articles obtain their results using an employment-share-based HHI. Azar et al. (2020a, 2020b) leverage firm-level data from private companies to construct a vacancy-share-based concentration for each labor market, defined as a location-by-occupation cell. Similar to the previous findings, the authors present evidence that labor market concentration is negatively correlated with wages. Whereas Azar et al. (2020a) rely on only 17 occupations from one single job board, CareerBuilder.com, Azar et al. (2020b) use data on US online job vacancies in 2016 from Burning Glass Technology (BGT) to generate concentration levels for over 200,000 labor markets covering more than 800 occupations. Moreover, their HHI is the first economy-wide measure of labor market concentration made in many decades. Therefore, I use their data on HHI to capture the extent of labor market concentration in my empirical model.

The rest of the paper is organized as follows. Section 2 presents a static model of the labor market to motivate the analysis. Section 3 discusses the empirical method. Section 4 introduces the data and variables. Section 5 discusses the results. Section 6 concludes.

## 2 Theoretical Model

This section lays out a simple model to explain how the relationship between robot exposure and labor market outcomes differs depending on the market monopsony. To keep the analysis straightforward, I assume

[5] Horizontal Merger Guideline from U.S. Department of Justice & FTC considers markets in which the HHI is larger than 2500 to be highly concentrated.

there are only two types of labor markets: a perfectly competitive market and a perfectly monopsonistic market. Moreover, I assume that firms use only robots and labor as inputs in the production process.

### 2.1 A Perfectly Competitive Market

In a perfectly competitive labor market, a representative firm chooses labor and robots to maximize profits,

$$\max_{k,l} f(k,l) - rk - wl \quad ,$$

where $f$ is the production function and $r$ and $w$ are the per-unit market prices for robots, k, and labor, l, respectively. The output price is normalized to 1. Firms take all prices as given in the perfectly competitive labor market. A perfectly competitive firm's first order condition is given by

$$\begin{aligned} r: \quad & f_k(k,l) - r \equiv F^k(k,l,r,w) = 0 \\ l: \quad & f_l(k,l) - w \equiv F^l(k,l,r,w) = 0 \end{aligned}$$

where $f_k$ and $f_l$ denote first derivatives. The optimal level of $k$ and $l$ can be expressed implicitly as

$$\begin{aligned} k^{*,pc} &= \xi^k(w,r) \\ l^{*,pc} &= \xi^l(w,r). \end{aligned}$$

Using the Implicit Function Theorem, the following comparative static results can be derived[6]

$$\frac{\partial k^{*,pc}}{\partial r} = -\left[\frac{\partial F^k}{\partial r}\frac{\Delta_{1,1}}{\Delta} - \frac{\partial F^l}{\partial r}\frac{\Delta_{2,1}}{\Delta}\right] \tag{1}$$

$$\frac{\partial l^{*,pc}}{\partial r} = -\left[-\frac{\partial F^k}{\partial r}\frac{\Delta_{1,2}}{\Delta} + \frac{\partial F^l}{\partial r}\frac{\Delta_{2,2}}{\Delta}\right], \tag{2}$$

where $\Delta$ denotes the determinant of

$$\begin{bmatrix} \frac{\partial F^k}{\partial k} & \frac{\partial F^k}{\partial l} \\ \frac{\partial F^l}{\partial k} & \frac{\partial F^l}{\partial l} \end{bmatrix}$$

and $\Delta_{j,k}$ denotes the determinant of the matrix formed by deleting its $j^{th}$ row and $k^{th}$ column. Denoting second derivatives of the production function as $f_{ll}$, $f_{kk}$, and $f_{kl}$, Equations (1) and (2) can be rewritten

[6] Detailed algebra can be found in Border (2001).

as

$$\frac{\partial k^{*,pc}}{\partial r} = \frac{\Delta_{1,1}}{\Delta} = \frac{f_{ll}}{f_{kk}f_{ll} - (f_{kl})^2} \tag{3}$$

$$\frac{\partial l^{*,pc}}{\partial r} = -\frac{\Delta_{1,2}}{\Delta} = \frac{-f_{kl}}{f_{kk}f_{ll} - (f_{kl})^2}. \tag{4}$$

According to Equations (3) and (4), the effect of of a change in the price of robots on firm input choices in a perfectly competitive market only depends on second derivatives of production function.

## 2.2 A Perfectly Monopsonistic Market

In a perfectly monopsonistic labor market, a single firm exists and chooses labor and robots to maximize profits

$$\max_{k,l} f(k,l) - rk - w(l)l \quad ,$$

where $w(l)$ is the upward-sloping labor supply curve for the market. The first-order condition with respect to robots remains the same as in the perfectly competitive market. The first-order condition with respect to labor becomes

$$l : f_l(k,l) - w_l l - w(l) \equiv F^l(k,l,r,w) = 0 \quad .$$

This leads to new versions of Equations (3) and (4)

$$\frac{\partial k^{*,pm}}{\partial r} = \frac{\Delta_{1,1}}{\Delta} = \frac{f_{ll}}{f_{kk}f_{ll} - f_{kk}(w_{ll}l + 2w_l) - (f_{kl})^2} \tag{5}$$

$$\frac{\partial l^{*,pm}}{\partial r} = -\frac{\Delta_{1,2}}{\Delta} = \frac{-f_{kl}}{f_{kk}f_{ll} - f_{kk}(w_{ll}l + 2w_l) - (f_{kl})^2} \quad , \tag{6}$$

where $w_l$ and $w_{ll}$ are the first and second derivatives of the labor supply curve. According to Equations (5) and (6), in a perfectly monopsonistic labor market, the effect of a change in the price of robots on firm input choices depends on second derivatives of the production function, $f(k,l)$, and total wage function, $w(l)l$.

## 2.3 Equilibrium Analysis

The objectives here are to sign and compare (4) and (6) under minimal and transparent assumptions. To do this, I first sign and compare the denominators. Throughout, I impose the following three weak assumptions.

**Assumption 1.** *$f_{kk} < 0$ and $f_{ll} < 0$*

Assumption 1 is the standard assumption that the marginal revenue product of each input is decreasing in that input.

**Assumption 2.** $f_{kk}f_{ll} - f_{kl}^2 > 0$

In perfectly competitive markets, one expects a firm to use less of an input when its price increases. Assumption 2 ensures this is true given Assumption 1 (see Equations (3) and (4)).

**Assumption 3.** $\frac{d^2[w(l)l]}{dl^2} = w_{ll}l + 2w_l > 0$

With an upward sloping labor supply curve, the firm's total wage bill must be increasing in labor, i.e., $\frac{d[w(l)l]}{dl} > 0$. Moreover, the monopsonist has to pay higher wages for both the marginal workers and existing workers when adjusting employment. As the number of workers needed to be compensated due to the hiring of an additional worker increases, the total compensation paid by the firm is likely to increase at an increasing rate. Therefore, the pressure an additional labor unit puts on the monopsonistic firm's total wage bill is likely to be increasing in labor.[7]

These assumptions appear reasonable and are fairly unrestrictive, yet still imply

$$f_{kk}f_{ll} - f_{kk}(w_{ll}l + 2w_l) - (f_{kl})^2 > f_{kk}f_{ll} - (f_{kl})^2 > 0. \tag{7}$$

Importantly, Equation (7) implies that not only is the denominator of $\frac{\partial l^{*,pc}}{\partial r}$ and $\frac{\partial l^{*,pm}}{\partial r}$ positive, but the denominator is larger for the monopsonistic firm (i.e., in Equation (4) versus Equation (6)). Thus, the response of the monopsonistic firm to a change in the price of robots is muted relative to perfectly competitive firms. I now investigate three special cases.

**Case 1.** $f_{kl} = 0$

Suppose the cross-derivative is zero, implying that robot adoption has no impact on the marginal revenue product of labor. This implies

$$\frac{\partial l^{*,pc}}{\partial r} = \frac{\partial l^{*,pm}}{\partial r} = 0.$$

That is, higher exposure to robots has no impact on the optimal level of workers firms would hire in either a perfectly competitive market or a perfectly monopsonistic market.

**Case 2.** $f_{kl} > 0$

Suppose the cross-derivative is positive, implying that robots help workers be more productive. If this

[7] A sufficient but not necessary condition for Assumption 3 to be true is an increasing marginal wage with respect to labor, i.e., $w_{ll} > 0$.

is the case, then $f_{kl}$ is positive. This is consistent with the conventional view that capital and labor are complements. This implies Equations (4) and (6) are both negative, and

$$\frac{\partial l^{*,pc}}{\partial r} < \frac{\partial l^{*,pm}}{\partial r} < 0.$$

This says that higher exposure to robots (through lower price) results in higher employment. Additionally, employment growth (in percentage) caused by the higher exposure is greater, ceteris paribus, in a perfectly competitive labor market than in a perfectly monopsonistic labor market.

**Case 3.** $f_{kl} < 0$

Suppose the cross-derivative is positive, implying that robots compromise the productivity of labor. If this is the case, then $f_{kl}$ is negative. Since robots are capable of performing routine tasks, robot adoption is usually treated as a routine-biased technological change (Katz et al. (1999); Acemoglu and Autor (2011); Goos et al. (2014)). Greater use of robots may displace the vast labor force used intensively in routine tasks. The remaining workers have to learn how to co-work (e.g., collaborate, program, and fix) with robots. Robots could severely compromise the productivity of labor (i.e., $f_{kl} < 0$) in this scenario. This implies Equations (4) and (6) are both positive, and

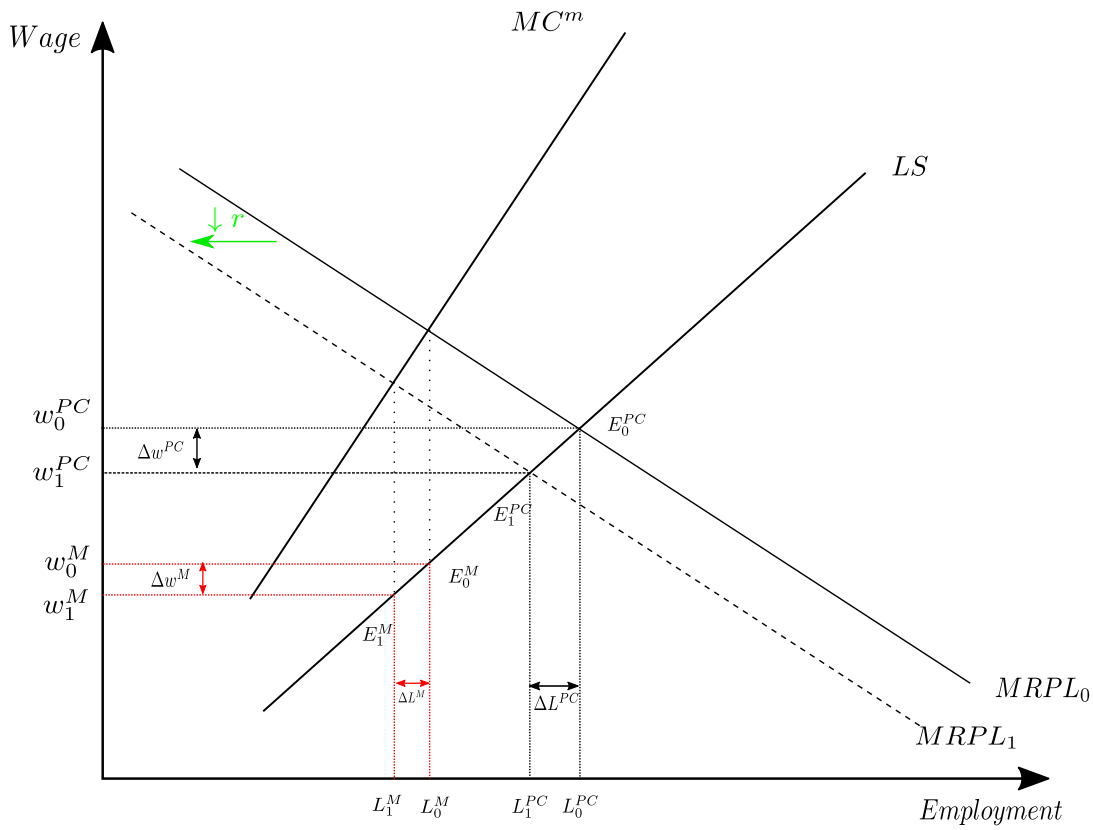
$$\frac{\partial l^{*,pc}}{\partial r} > \frac{\partial l^{*,pm}}{\partial r} > 0$$

This says that higher exposure to robots (through lower price) results in lower employment. Furthermore, the employment drop (in percentage) caused by the higher exposure is a greater, ceteris paribus, in a perfectly competitive market than in a perfectly monopsonistic market.

It is noteworthy that the change in equilibrium wages in any market in response to higher exposure to robots would strictly follow the change in equilibrium employment (in terms of the direction and the magnitude) as long as the labor supply curve is upward-sloping. Therefore, the above results also hold for wages in terms of signs and relative magnitude of effects. The most important one among them is that the wage response of monopsonistic firms is muted relative to perfectly competitive firms.

Figure 2 illustrates the above results. $MRPL$ is the marginal revenue product of labor (MRPL) which also represents the demand curve in a perfectly competitive market. $LS$ is the labor supply curve. $MC^m$ is the marginal cost of labor for a monopsonist. Assuming that robots and labor are substitutes (i.e., $f_{kl} < 0$), then the price drop for robots will increase demand for robots and, in turn, lower the MRPL. This shifts the MRPL curve from $MRPL_0$ to $MRPL_1$. Then the equilibrium moves from $E_0^{PC}$ to $E_1^{PC}$ in

*Figure 2: Wage and employment change at equilibrium in response to higher robot adoption*




the perfectly competitive market and $E_0^M$ to $E_1^M$ in the perfectly monopsonistic market.

As a result, employment and wages fall in both markets. Since the $MC^m$ curve is steeper than the $LS$ curve, employment and wages drop more to higher robot adoption in a perfectly competitive labor market than in a perfectly monopsonistic labor market (i.e., $\Delta L^{PC} > \Delta L^M$ and $\Delta w^{PC} > \Delta w^M$).

Figure 2 shows this under the assumption of $f_{kl} < 0$. On the contrary, assuming that robots and labor are complements (i.e. $f_{kl} > 0$), then the price drop for robots will increase demand for robots and, in turn, raise the MRPL. This shifts the MRPL curve right. As a result, employment and wages go up in both markets. Since the $MC^m$ curve is steeper than the $LS$ curve, employment and wages rise more due to higher robot adoption in a perfectly competitive labor market than in a perfectly monopsonistic labor market (i.e., $\Delta L^{PC} > \Delta L^M$ and $\Delta w^{PC} > \Delta w^M$).

To summarize, the theory yields three testable predictions. First, the effect of a change in robot prices (and hence robot exposure) on employment is of the same sign in both a perfectly competitive market and a perfectly competitive market, but is smaller in absolute value in a perfectly competitive market. Second, the impact of a decrease in robot price (and hence increase in robot exposure) on employment is positive (negative) if robots and labor are complements (substitutes). Third, the effects of a change in robot prices (and hence robot exposure) on wages is of the same sign as the effect on employment in both the perfectly competitive market and the perfectly monopsonistic market, i.e., wages and employment either both go

up or both go down within a given market type. Moreover, as with employment, the effect of a change in robot prices on wages is smaller in absolute value in a perfectly competitive market.

The following section renders an empirical strategy to test these theoretical predictions.

# 3 Empirical Methodology

Letting $m$ index the labor market defined as a location-by-occupation cell and $t_1 - t_0$ index the change between $t_1$ and $t_0$, I estimate the following regression at the market level:

$$\Delta y_{m,t_1-t_0} = \beta_m \, ER_{m,t_0-t_1} + X_{m,t_0} \, \delta + \gamma_o + \gamma_a + \epsilon_m \tag{8}$$

where $\Delta y_{m,t_1-t_0}$ can either be the change in employment, as a share of initial period working-age population, or the change in log annual wage in market $m$. $ER_{m,t_0-t_1}$ stands for the change in US exposure to robots across the period $t_0 - t_1$ in market $m$. It measures the change in expected per worker robot use in a market. $\gamma_o$ captures occupation fixed effects. $\gamma_a$ captures area fixed effects, and it does not have to correspond to the location used to define labor markets. $X_{m,t_0}$ controls for various demographic characteristics as well as the concentration in each labor market in the initial period. $\epsilon_m$ is a mean zero error term.

The marginal effect of robot exposure is allowed to be heterogeneous depending on the concentration level of the labor market; hence the $m$ subscript on $\beta_m$. Thus, it can be represented by

$$\beta_m = \theta_0 + \theta_1 C_m, \tag{9}$$

where $C_m$ is concentration. The model described by Equations (8) and (9) differs from Acemoglu and Restrepo (2020) in two important ways. First, while I define a labor market as a location-by-occupation cell, Acemoglu and Restrepo (2020) define a labor market as a location alone. Second, Acemoglu and Restrepo (2020) ignore possible heterogeneity by labor market concentration, implicitly constraining $\theta_1 = 0$.

Both exposure to robots and market concentration could potentially suffer from endogeneity issues. There are two reasons why exposure to robots could be endogenous. First, markets may adopt robots in response to other changes that directly affect labor demand. For instance, the wage push from workers' unions may directly affect firms' decisions on recruiting workers and adopting robots. Second, the local or regional economic shocks a market is undergoing may also affect its robot adoption. For example, a local economic recession may directly affect firms' incentives to hire and adopt robots. Regarding labor market concentration, various laws that limit monopsony power are one reason raising endogeneity concerns. The horizontal merger law is an example. It adversely affects labor demand and also lowers concentration. Another one would be labor demand shocks (or wage shocks) that affect both the left-hand side variable and

the number of firms hiring in the market, leading to different concentration levels. Finally, concentration may also be endogenous due to measurement error. The empirical measure used for concentration may be an imperfect proxy for true monopsony power due to vacancies being measured at only one point in time or shortcomings in HHI as a measure of concentration.

Endogeneity issues are addressed using IV. I closely follow Acemoglu and Restrepo (2020) to build an IV based on robot adoption of other countries to instrument US exposure to robots. Using the countries that are slightly ahead of the US in robotics helps isolate the source of variation coming from global technological advances instead of US-specific technological shocks. As for concentration, in the absence of an ideal IV, I adopt the technique from Lewbel (2012) to create heteroskedasticity-based IVs. The details on the construction of IVs are discussed in the next section.

# 4 Data and Measurement

The empirical analysis relies on multiple datasets. The primary sources of data on robots are the International Federation of Robotics (IFR) and the replication kit of Acemoglu and Restrepo (2020). The labor market concentration is collected from the supplemental materials of Azar et al. (2020b), in which they use BGT data to create this measure. Finally, labor market outcomes and demographics are obtained using the 1% annual American Community Survey (ACS) 2006 and 2014 and the 5% Census 2000 data from Integrated Public Use Micro Samples USA (IPUMS-USA) (Ruggles et al. 2010).

## 4.1 Labor Market Concentration

Labor market monopsony power is measured as the concentration level captured by HHI constructed using data on job vacancies. A market is highly concentrated when a few firms provide the majority of job positions. Before quantifying the concentration level, identifying proper boundaries for the labor market is crucial.

If a market is defined too narrowly, the available job positions outside this market, either geographically or occupationally, could be easily accessed by job seekers. The quantified concentration level would then overstate the true market power of employers. Conversely, if a market is defined too broadly, the similarity of jobs within this market is overestimated, implying the quantified concentration level would understate the true market power of employers. To proceed, I follow the definition used in Azar et al. (2020b), defining the labor market by both commuting zone and occupation. The main reason for using occupation, rather than industry, to define a labor market is that "occupation is an aspect of a job and rooted in the knowledge, skills, and abilities that workers and firms trade in the labor market" (Qiu and Sojourner, 2019). Also, Azar et al. (2020b) run a "hypothetical monopsonist test" to validate their market definition.

Given this definition of a labor market, the concentration level in each market is measured using HHI, which is a function of the squared market shares of firms. Formally, this is given by

$$HHI_m = \sum_{f \in m} s_{f,m}^2 = \sum_{f \in m} \left( \frac{Post_{f,m}}{Post_m} \times 100 \right)^2 \tag{10}$$

where $Post_{f,m}$ is the number of online job vacancies of firm $f$ in labor market $m$, $Post_m$ is the total number of online job vacancies in market $m$, and $s_{f,m}$ is firm $f$'s market share of new job vacancies posted online in market $m$. A perfectly monopsonistic market has a concentration of 10000. A perfectly competitive market has a concentration of zero. Azar et al. (2020b) utilize data from BGT to generate HHI.[8] Moreover, the authors claim that BGT has the best data quality in 2016 among all its annual data and the average concentration levels in 2016 are comparable to the average concentration levels in 2007-2015. Therefore, in the absence of publicly available data at the establishment level, I use 2016 HHI from Azar et al. (2020b) (collected from Ioana Marinescu's website) as a proxy for the concentration level in my regression period. Measurement errors on concentration caused by using a single-year and vacancy-based HHI as a proxy for true concentration in a period are addressed by the IV approach. Such measurement error is not consequential as long as the IV strategy remains valid.

The 2016 HHI generated by Azar et al. (2020b) is at the location-by-occupation level. It uses the 2000 CZ and the 2010 6-digit Standard Occupational Classification (SOC) system. Thus, I classify exposure to robots and covariates by 2000-CZ and SOC.[9] Table 1 shows the summary statistics for 2016 HHI. In the original data of Azar et al. (2020b), there are 267,546 markets with an average HHI of 5910. After using the necessary concordances, I have a sample of 140,615 markets with an average HHI of 5130.[10] Furthermore, other descriptive statistics of HHI from the two samples are also very similar. Table 2 lists the ten highest and the ten lowest HHI occupations. I generate the SOC-level HHI using the average of the CZ-by-SOC-level HHI weighted by CZ employment. Miners in company towns, actors, and athletes are far and away the most concentrated occupations. Except for actors and athletes, the other nine occupations seem likely to be located in non-urban areas. In contrast, the ten lowest HHI occupations regularly come from urban areas. Figure 3 demonstrates this finding by showing that the majority of the commuting zones that contain big cities are less concentrated, although highly concentrated CZs may surround them. I generate this CZ-level HHI using the average of the CZ-by-SOC-level HHI weighted by SOC employment. To make empirical results readily comprehensible, the HHI used in regressions are defined in decimals

[8] BGT is a private company providing an online job postings dataset. It captures roughly 85% of the jobs in the Job Openings and Labor Turnover Survey (JOLTS).

[9] To merge the datasets for HHI, exposure to robots, covariates, and labor market outcomes that are from different years, I recategorize their 6-digit SOC to 2010 SOC system based on the SOC crosswalk tables from IPUMS-USA. See Appendix for details.

[10] The occupations that were present in the 2006 or 2014 ACS but absent in the 2000 Census are dropped from the regression sample.

rather than percentage numbers, implying a fully concentrated market has an HHI of 1 ($1.00 \times 1.00$) rather than 10,000 ($100\% \times 100\%$)

Because HHI derived from vacancy data in 2016 is an imperfect proxy for concentration over the sample period, HHI is instrumented. Absent an obvious instrumental variable, I build one using Lewbel (2012)'s heteroskedasticity-based IV approach. Lewbel claims the potential instruments for the endogenous variable, here is $HHI$, include

$$\tilde{Z}_m \equiv (Z_m - \bar{Z}_m)\hat{u}_m, \tag{11}$$

where $Z_m$ is a subset of $X_{m,t_0}$ and fixed effects and $\hat{u}_m$ are the residuals from the first-stage regression of $HHI$ on all exogenous variables and fixed effects. Validity of the IVs requires $E[Z^{'}u^2] \neq 0$ and $E[Z^{'}\epsilon u] = 0$. That is, $Z_m$ generates heteroskedasticity in the first-stage errors but does not drive correlation between first-stage and the second-stage errors. Lewbel shows that the restrictions are satisfied if there is a homoskedastic common factor that is the sole source of correlation between $\epsilon$ and $u$, and the idiosyncratic part of $u$ is heteroskedastic with variance depending on $Z$.

To practically build this IV, I follow four steps. In the first stage, I regress the endogenous variable on all exogenous controls to predict the residual $\hat{u}_m$. Second, I target a list of controls $Z_m$ on which the variance of first-stage residual may depend. Third, I run the Breusch-Pagan test developed by Koenker (1981) on each of the $Z_m$ to check whether they are the likely contributors of heteroskedasticity. Fourth, I demean $Z_m$ to get $Z_m - \bar{Z}_m$ and interact it with residual $\hat{u}_m$. Note, if $Z_m$ includes more than one element of $X_{m,t_0}$, then the model will be over-identified, enabling the use of tests of instrument validity that implicitly test the requirement that $E[Z^{'}\epsilon u] = 0$. Moreover, tests of instrument strength implicitly test the assumption of $E[Z^{'}u^2] \neq 0$.

### 4.2 Exposure to Robots

International Organization for Standardization defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". This definition highlights the industrial robots' capability of replacing human labor in a wide range of tasks. The IFR collects information on the stock of industrial robots by industry, country, and year using surveys. Figure 4 exhibits time trends of the industrial robot stock per thousand workers for the United States, Germany, Japan, Britain, and the average of five European countries, including Denmark, Sweden, Italy, Finland, and France (EURO5). Germany and Japan are clearly two big countries leading the robotization of the world, although Japan saw a drop from six in 2000 to 4.3 in 2016. The US industrial robot stock per thousand workers has been steadily increasing since 2000, resembling the trend of the average of the EURO5 countries.

I closely follow the approach in Acemoglu and Restrepo (2020) to construct exposure to robots at the level of the local labor market. Whereas Acemoglu and Restrepo (2020) define labor markets more broadly at the CZ level, I build the exposure to robots at the CZ-by-SOC level to be in line with my market definition. Exposure to robots is denoted as

$$ER_{m,t_0-t_1} = \sum_{i \in I} l_{mi,t_0} \cdot APR_{i,t_0-t_1},$$

where $l_{mi,t_0}$ is the employment share of industry $i$ at time $t_0$ in market $m$, and

$$APR_{i,t_0-t_1} = \frac{\Delta K_{i,t_0-t_1}}{L_{i,1990}} - \frac{\Delta Y_{i,t_0-t_1}}{Y_{i,t_0}} \frac{K_{i,t_0}}{L_{i,1990}}$$

is the adjusted penetration of robots in industry $i$, in which $K_{i,t_0}$ is the number of robots in industry $i$ at time $t_0$, $L_{i,1990}$ is the employment level (in thousands) in industry $i$ in 1990 which is a much earlier time than the initial time $t_0$, $Y_{i,t_0}$ is the output of industry $i$ at $t_0$, and $\Delta K_{i,t_0-t_1}$ and $\Delta Y_{i,t_0-t_1}$ are the corresponding changes between $t_0$ and $t_1$.[11] The data source on the employment share $l_{mi,t_0}$ will be discussed in the next subsection.

The IV for exposure to robots is created based on EURO5 adjusted penetration of robots, which is

$$ER^{EURO5}_{m,t_0-t_1} = \sum_{i \in I} l_{mi,t_{-1}} \cdot APR^{EURO5}_{i,t_0-t_1} \tag{12}$$

where $l_{mi,t_{-1}}$ is the employment share of industry $i$ at time $t_{-1}$ in market $m$, and

$$APR^{EURO5}_{i,t_0-t_1} = \frac{1}{5} \sum_{j \in EURO5} \left[ \frac{\Delta K^j_{i,t_0-t_1}}{L^j_{i,1990}} - \frac{\Delta Y^j_{i,t_0-t_1}}{Y^j_{i,1990}} \frac{K^j_{i,t_0}}{L^j_{i,1990}} \right], \tag{13}$$

where $j$ represents one of the EURO5 countries. Both the $APR_{i,t_0-t_1}$ and $APR^{EURO5}_{i,t_0-t_1}$ can be obtained directly from Acemoglu and Restrepo (2020)'s replication kit. To minimize endogeneity concerns, I use the employment share $l_{mi,t_{-1}}$ from $t_{-1}$ which is a time before the initial time $t_0$. Using the countries that are slightly ahead of the US in robotization to build $APR$ helps isolate the source of variation coming from global technological advances instead of US-specific technological shocks. Further, Figure 4 shows the time trend of industrial robots per thousand workers for EURO5 countries closely resembles the time trend of the US.

Figure 5 shows the geographic distribution of exposure to robots at the CZ level between 2006 and 2014, with the US exposure to robots in Panel A and the EURO5 exposure in Panel B. I obtain the CZ-

[11] The unadjusted penetration of robots simply is the change in robot stock per thousand workers.

level exposure by averaging the market-level exposure weighted by employment. The similarity of the two distributions and trends implies a strong relevance between EURO5 exposure to robots and US exposure to robots.

### 4.3 Labor Market Outcomes and Demographics

Labor market outcomes, demographic characteristics, and employment shares used for constructing exposure to robots are obtained using the data from the IPUMS-USA.

The CZ-by-occupation labor market outcomes on the left-hand side of the empirical regression include (1) the change in employment over the periods 2006-2014 as a share of base-year (2006) CZ working-age population (multiplied by 1000);[12] (2) the change in the log average annual wage of employed for each market. I construct two dependent variables using the 2006 and 2014 1% annual ACS. Figure 6 shows the change in the employment-to-population ratio at the commuting zone level across the regression period. Panels A is based on the original ACS sample, and Panel B is based on the regression sample. In general, there are not many obvious discrepancies between the two maps. Moreover, there appears to be a negative correlation between the change in the employment-to-population ratio in Figure 6 and exposure to robots in Figure 5.

Demographic characteristics include the share of males; the share of elders (over 65); the share of the population with no college; some college; college or professional; and master or doctoral degree; the share of non-white; and the share of manufacturing industry workers. I build these measures as well as the market employment share used in the US exposure to robots from the 1% annual ACS at the base year 2006. Market employment share used for constructing the EURO5 exposure to robots is generated from the 2000 5% Census.

## 5 Results

### 5.1 Baseline Specification

Tables 3-5 and Figures 7 present the empirical results. In Table 3, I estimate the labor market effects of robots ignoring monopsony power. Tables 4 and 5 contain the main results, where Table 4 treats HHI as exogenous and Table 5 treats HHI as endogenous. In both tables, robot exposure is always treated as endogenous. Figure 7 visualizes the key results from Tables 4 and 5. I focus on the IV estimates as these are my preferred estimates given the strong belief that robots and HHI may be endogenous. But I do provide OLS estimates in Table 6 for reference.

[12] For the sake of simplification, I use "employment-to-population ratio" throughout the rest of the article.

In all specifications, standard errors are clustered at the state level, thereby allowing for arbitrary heteroskedasticity and spatial and serial correlation within states. Moreover, in each table that uses the IV approach, I report necessary IV test results, including the under-identification test, the weak identification test, the over-identification test (reported when multiple instruments are used), and the endogeneity test.[13]

### 5.1.1 Results Ignoring Monopsony Power

I begin by replicating Acemoglu and Restrepo (2020)'s baseline specification in my framework, ignoring labor market concentration. I want to access the effect of changing the definition of a labor market from a CZ in Acemoglu and Restrepo (2020) to a CZ-by-occupation cell. Table 3 presents, under different specifications, the IV estimates of the effect of exposure to robots on employment and wages. Columns (1) and (2) present the employment results, and columns (3) and (4) present the wage results.

Column (1) contains only census division dummies as covariates.[14] The estimated effect of -0.047 ($s.e. = 0.008$) indicates a statistically significant negative relationship between exposure to robots and the change in employment. This estimate suggests that an additional robot per thousand workers leads to a 0.047 ($\times 10^{-3}$) decline in the employment-to-population ratio. In addition to census division dummies, column (2) incorporates demographic characteristics and occupation fixed effects. The estimate in column (2) says an additional robot per thousand workers leads to a 0.044 ($\times 10^{-3}$) decline in the employment-to-population ratio. Relative to the initial period of 2006 mean of employment-to-population ratio, 0.003, this estimate implies a 1.5% drop in employment. The specification in Acemoglu and Restrepo (2020) most analogous to that used here yields an estimate of -0.39 percentage points. Relative to the mean of CZ-level employment-to-population ratio in their initial period of 1990, 0.35, this estimate implies a 1.1% drop in employment.

On the wage side, the parsimonious specification with only census dummies included is presented in column (3). In column (4), I control for census dummies, demographic characteristics, and occupation fixed effects. The wage results provide evidence that wages are also negatively related to exposure to robots. The point estimate of -0.007 ($s.e. = 0.004$) in column (4) suggests one additional robot per thousand workers leads to a 0.7% lower average annual wage. The specification in Acemoglu and Restrepo (2020) most analogous to that used here yields an estimate of -0.008. It suggests one additional robot per thousand

[13] The under-identification test reports p-value of the Kleibergen-Paap LM statistic, with the null hypothesis being that the equation is under-identified. The weak-identification test reports the Kleibergen-Paap Wald F statistic, with the null hypothesis being that excluded instruments are correlated with the endogenous regressors, but only weakly. The over-identification test uses the Sargan-Hansen test, with the null hypothesis being that the instruments are uncorrelated with the error terms, i.e., valid instruments. The endogeneity test reports p-value of the chi-square statistic, with the null hypothesis being that the specified endogenous regressors can actually be treated as exogenous.

[14] I want to make my specifications close enough to the ones in Acemoglu and Restrepo (2020). Hence, I imitate their use of census division dummies rather than state fixed effects which will be included in my main results specifications to capture various location factors.

workers leads to a 0.8% lower average annual wage.

In summary, the similarity between the results here and those presented in Acemoglu and Restrepo (2020) demonstrates that the estimated labor market impacts of robots are robust to the more disaggregate definition of a labor market used here. Furthermore, these results confirm the Acemoglu and Restrepo (2020) findings that exposure to robots has adverse effects on both employment and wages.

### 5.1.2 Results Incorporating Monopsony Power

This subsection focuses on Tables 4-6 and Figure 7. All three tables present the employment results in columns (1) and (2) and the wage results in columns (3) and (4). All the columns contain HHI, occupation fixed effects, and market-level demographic characteristics as covariates. Instead of census division dummies, state fixed effects are included in columns (2) and (4) to better control for occupation-invariant area factors. Because the marginal effect of exposure to robots is no longer constant in the primary specifications, but rather varies with HHI, Figure 6 plots the marginal effects as a function of HHI. The results from columns (2) and (4) in Table 4 are displayed in panels (a) and (c) of Figure 7. The results from columns (2) and (4) in Table 5 are displayed in panels (b) and (d) of Figure 7.

The results treating exposure to robots endogenous and HHI exogenous are presented in Table 4. In all columns, the results of the under-identification test suggest that I reject that the equations are under-identified at the 5% significance level; the results of the weak identification test results imply I reject the null that the instruments only are weakly correlated with the endogenous regressors at the 5% significance level. The results of the endogeneity test from columns (1) and (2) show that I reject the null that the instrumented variables can be treated as exogenous variables in the employment equations at the 5% significance level. Finally, the results of the endogeneity test from columns (3) and (4) show that I fail to reject the null that the instrumented can be treated as exogenous variables in the wage equations at the 5% significance level.

In column (1), the estimated effect of exposure to robots on the change in the employment-to-population ratio is -0.067 ($s.e. = 0.022$) in perfectly competitive markets and -0.025 ($s.e. = 0.017$) in fully concentrated markets. Moreover, a one standard deviation increase in HHI leads to a decline in the employment-to-population ratio of 0.014 ($s.e. = 0.01$). Equivalently, adopting one additional robot per thousand workers in a perfectly competitive market reduces the employment-to-population ratio by 2.2%. Importantly, this adverse impact becomes weaker as labor market concentration rises.[15] In a perfectly monopsonistic market, where there is only one employer, adopting one additional robot per thousand workers lowers the employment-to-population ratio by only 0.8%.

[15] $2.2\% \approx -0.067 \times 10^{-3}/0.003$, where 0.003 is the average market employment, as a share of CZ working-age population in 2006.

Column (2) adds state fixed effects. This has only a minor effect on the coefficients of interest, which now equal -0.066 ($s.e.$ = 0.017) in perfectly competitive markets and -0.017 ($s.e.$ = 0.019) in perfectly monopsonistic markets. Moreover, a one standard deviation increase in HHI leads to a decline in the employment-to-population ratio of 0.016 ($s.e.$ = 0.01). Equivalently, the adoption of one additional robot per thousand workers reduces its employment-to-population ratio by 2.2% in a perfectly competitive market and 0.6% in a perfectly monopsonistic market. Further, this adverse impact becomes weaker as the concentration level rises. These estimates also imply that adopting one additional robot displaces 18 workers on average for perfectly competitive markets but does not significantly affect employment in perfectly monopsonistic markets.[16] From another perspective, for two markets with a one-standard-deviation difference on HHI, their employment gap is reduced (or increased) by four due to the adoption of one more robot.[17] Compared to the average employment drop caused by one additional robot adoption for a labor market, which is seven, this effect on the gap is nontrivial.[18]

Panel (a) in Figure 7 shows how the marginal effect of exposure to robots on the change in the employment-to-population ratio varies by concentration levels in column (2). Grey areas mark the 95% confidence intervals. Negative and statistically significant effects of robots are found in labor markets with a concentration level below 8000. Furthermore, this adverse effect is declining in HHI, becoming less obvious and statistically insignificant when HHI exceeds 8000. The employment results in Columns (1) and (2) are consistent with the theory under the assumption of robots and labor being substitutes.

Columns (3) and (4) yield similar estimates (in terms of point estimates and standard errors) for log average annual wages. Incorporating state fixed effects does not significantly change the estimates. In column (4), the estimated effect of exposure to robots on the change in log average annual wages is -0.008 ($s.e.$ = 0.004) in perfectly competitive markets and equals -0.003 ($s.e.$ = 0.005) in fully concentrated markets. Moreover, a one standard deviation increase in HHI leads to a decline in log average annual wages of 0.002 ($s.e.$ = 0.001). Equivalently, one additional robot adoption per thousand workers lowers the annual wage by 0.8% in perfectly competitive markets and 0.3% in perfectly monopsonistic markets. This adverse effect declines (in absolute value) by 0.05% for each one-thousand HHI increase. The marginal effects of robots on annual wages under different concentration levels in column (4) are depicted in panel (c) of Figure 7. The precision of the estimates in the model for wages is not as strong as it is for employment. However, we can still see a negative relationship between exposure to robots and wage changes, whether the markets are concentrated or not. And importantly, this negative effect becomes less prominent when HHI is high. Again, the wage results also correspond to what the theory characterizes under the circumstances

[16] $18 \approx 0.066 \times 10^{-3} \times \frac{1000}{985} \times 265900$, where 985 is the average number of employment in a labor market and 265900 is the average number of working-age population in a commuting zone.

[17] $4 \approx 0.049 \times 10^{-3} \times 0.336 \times \frac{1000}{985} \times 265900$, where 0.336 is the standard deviation of HHI.

[18] $7 \approx 0.049 \times 10^{-3} \times 0.513 \times \frac{1000}{985} \times 265900$, where 0.513 is the mean of HHI.

that robots and labor are substitutes.

Table 5 reports the IV estimates when both the exposure to robots and HHI (as well as the interaction) are treated as endogenous variables. Applying the method in Lewbel (2012), I build heteroskedasticity-based IVs to instrument HHI. In columns (1) and (2), the Lewbel IVs are constructed using the share of the population with college or professional degrees and the share of manufacturing workers. Columns (3) and (4) use the share of elders (over 65) and the share of manufacturing workers to generate the Lewbel IVs. The under-identification test, the weak identification test, and the endogeneity test yield the same results as in Table 4 at the 5% level of significance. Moreover, the over-identification tests in all four columns fail to reject the validity of the instruments.

Column (2) presents the key results for employment. The point estimate of the effect of exposure to robots on employment equals -0.060 ($s.e.$ = 0.012) in perfectly competitive markets and -0.025 ($s.e.$ = 0.016) in perfectly monopsonistic markets. And the coefficient on interaction term, which equals 0.035 ($\hat{\theta}_1 = 0.035$, $s.e. = 0.019$), suggests that a one standard deviation increase in HHI leads to a decline in the employment-to-population ratio of 0.016 ($s.e.$ = 0.010). This is equivalent to say that the adoption of one additional robot per thousand workers reduces its employment-to-population ratio by 2% in a perfectly competitive market and 0.8% in a perfectly monopsonistic market. Further, this adverse impact becomes weaker as the concentration level rises. These estimates also imply that adopting one additional robot displaces 16 workers on average for perfectly competitive markets but does not significantly affect employment in perfectly monopsonistic markets. From another perspective, for two markets with a one-standard-deviation difference on HHI, their employment gap is reduced (or increased) by three due to the adoption of one more robot. Compared to the average employment drop caused by one additional robot adoption for a labor market, which is 5, this effect on the gap is nontrivial.

Panel (b) in Figure 7 shows how the marginal effect of exposure to robots on the change in the employment-to-population ratio varies by concentration levels in column (2). Grey areas mark the 95% confidence intervals. Negative and statistically significant effects of robots are found in labor markets with a concentration level below 8400. Furthermore, this adverse effect is declining in HHI, becoming less obvious and statistically insignificant when HHI exceeds 8400. The employment results in Columns (2) are consistent with the theory under the assumption of robots and labor being substitutes.

For the key result on wages in column (4), the estimated effect of exposure to robots on the change in log average annual wages is -0.009 ($s.e.$ = 0.004) in perfectly competitive markets and equals -0.002 ($s.e.$ = 0.005) in fully concentrated markets. Moreover, a one standard deviation increase in HHI leads to a decline in log average annual wages of 0.002 ($s.e.$ = 0.002). Equivalently, one additional robot adoption per thousand workers lowers the annual wage by 0.9% in perfectly competitive markets and 0.3% in perfectly monopsonistic markets. This adverse effect declines (in absolute value) by 0.07% for each

one-thousand HHI increase. The marginal effects of robots on annual wages under different concentration levels in column (4) are depicted in panel (c) of Figure 7. The precision of the estimates in the model for wages is not as strong as it is for employment. However, we can still see a negative relationship between exposure to robots and wage changes, whether the markets are concentrated or not. And importantly, this negative effect becomes less prominent when HHI is high. Again, the wage results in column (4) are in line with what the theory predicts.

Note that the endogeneity tests in the wage results of both Table 4 and 5 fail to reject that the exposure to robots, HHI, and their interactions term are jointly exogenous. Therefore, for reference, I report the OLS estimates for both employment and wages in Table 6. The OLS regressions in Table 6 have the same specifications as in Table 4. Incorporating state fixed effects does not significantly change the estimates. Hence I will briefly talk about the results in columns (2) and (4). For the employment results in column (2), I do not find statistically significant robot effects under any concentration levels. Moreover, the point estimates are much different from IV estimates obtained in Table 4 and 5. This deviation from the theory is expected since the endogeneity test results in Tables 4 and 5 all indicate we should not consider robot exposure and HHI as exogenous in the employment specifications.

In terms of the wage results in column (4), the estimated effect of exposure to robots on the change in log average annual wages is -0.003 ($s.e. = 0.001$) in perfectly competitive markets and 0.001 ($s.e. = 0.002$) in fully concentrated markets. Moreover, a one standard deviation increase in HHI leads to a decline in log average annual wages of 0.001 ($s.e. = 0.001$). Equivalently, one additional robot adoption per thousand workers lowers the average annual wage by 0.3% in perfectly competitive markets but increases the average annual wage by 0.1% in perfectly monopsonistic markets. The robot effect declines (in absolute value) by 0.04% for each one-thousand HHI increase. Nevertheless, the negative and statistically significant effects of robots are found in competitive markets. And this negative effect becomes less prominent and less statistically significant when HHI is high. The wage results using OLS are still in line with the theoretical predictions.

To conclude, either treating HHI as endogenous or exogenous, the empirical results for both employment and wages work extremely well to align with the theoretical implications when assuming robots and labor are substitutes (i.e., $f_{kl} < 0$). Although the findings in Acemoglu and Restrepo (2020) are informative, my results indicate they miss an important source of heterogeneity, which is labor market monopsony. Finally, my results also have strong implications for public policies. For example, any policy changes designed to limit labor market monopsony (e.g., reforming laws pertaining to the use of non-compete agreements, raising the minimum wage, enforcing the antitrust laws) may unintendedly increase the adverse effects of greater exposure to robots on labor market outcomes in the future.

## 5.2 Robustness and Extension

Tables 7-10 and Figures 8 and 9 provide the results for robustness check, where Table 7 attempts alternative Lewbel IVs and Table 8 reexamines the specifications from Table 5 but excluding fully concentrated markets from the sample. Figures 8 shows the key results from Tables 7 and 8. Tables 9 and 10 and Figure 9 show the results of weighted regressions where weights are the 2000 market employment with specifications same to Tables 4 and 5.

**Alternative Lewbel IVs.** One may wonder whether my results are sensitive to the particular choice of Lewbel IVs. Thus Table 7 uses alternative sets of heteroskedasticity-based IVs for HHI. For the employment results in columns (1) and (2), the Lewbel IVs are constructed using the share of the population with no college degrees and the share of manufacturing workers. For the wage results in columns (3) and (4), the Lewbel IVs are based on the share of the population with master's or doctoral degrees and the share of manufacturing workers. Given that all controls and fixed effects remain the same as previous tables, both employment and wage results vary little relative to the results from Table 5. Panels (a) and (c) in Figure 8 display the results from columns (2) and (4) respectively, which are quite similar (in terms of point estimates and confidence intervals) to panels (b) and (d) in Figure 7.

**Excluding fully concentrated markets.** There are a significant number of labor markets that are fully concentrated; there is only a single firm with vacancies in a particular occupation in a given CZ. To check whether my estimates are sensitive to excluding these markets, Table 8 reports the results of the specifications from Table 5 but excluding all fully concentrated markets. The exclusion leads to a 19% loss of observations in the employment regression sample and a 15% loss of observations in the wage regression sample. Panels (b) and (d) in Figure 8 exhibit the results from columns (2) and (4). As shown in both estimates in column (2) and the figure in panel (b), the effects of exposure to robots on the change in the employment-to-population ratio are nearly identical to Table 5. However, I can not estimate a statistically significant effect of robots on wages in either highly concentrated markets or competitive markets. Nevertheless, the point estimates of robots on wages are still negative, and the magnitude of this negative effect is still decreasing in market concentration.

**Weighted regressions.** My preferred analysis weights all labor markets equally. Alternatively, one may wish to weight them according to their employment. This is done in Tables 9 and 10. I obtain the estimates by replicating the identical specifications from Tables 4 and 5 but using weighted regressions where the weights are labor market employment (i.e., CZ-by-SOC) in 2000. The left two panels in Figure 9 show

the results from columns (2) and (4) in Table 9, and the right two panels show the results from columns (2) and (4) in Table 10. Unlike the unweighted regression results, the wage estimates are more precise than the employment results in the weighted regression results. Nevertheless, the two key results from the weighted regression results also hold in the weighted regression results.

# 6 Conclusion

The race between humans and robots has long been a hot topic. After the Covid-19 pandemic, scientists are compelled to think seriously about the possible acceleration of automation. However, when investigating the force robots have been exerting on labor markets, researchers typically overlook the labor market monopsony power, which dramatically lowers the labor cost. For example, monopsonistic firms may not be willing to displace as many workers as they would otherwise be in perfectly competitive markets. For the first time, this paper studies the relationship between the effects of robots on labor market outcomes and labor market monopsony.

I use a simple theoretical analysis to show that robot exposure always has a more substantial impact (in absolute values) on labor market outcomes in a perfectly competitive market relative to a perfectly monopsonistic market. Based on data from the IPUMS-USA, IFR, and supplementary materials of Acemoglu and Restrepo (2020) and Azar et al. (2020b), my empirical results confirm this theoretical prediction. Using the vacancy-based HHI as a substitute to capture the extent of monopsony, I find a significantly negative effect of exposure to robots on labor market outcomes in less concentrated labor markets and a less harmful and statistically insignificant effect of robots in highly concentrated labor markets.

This study also has strong implications for public policies. With the growing labor market imperfection, the government is implementing various policies to limit employers' market power. However, these actions may indirectly affect the process of labor market automation. For example, any policy changes designed to limit labor market monopsony (e.g., reforming laws pertaining to use of non-compete agreements, raising the minimum wage, enforcing the antitrust laws) may unintendedly increase the adverse effects of greater exposure to robots on labor market outcomes in the future.

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# 7 Appendix

## Reclassification

The 2000 5% Census, the 2006 and 2014 1% annual ACS provide several options on industry classification for data requester to report. The IFR reports data on the stock of industrial robots at the country level as well as industry breakdowns for each country. However, instead of following existing industry classification, they divide industries into 19 categories. Among those 19 industries, 13 are manufacturing industries, including food and beverage, textile and apparel, paper and printing, plastics and chemicals, wood and furniture, basic metals, metal products, industrial machinery, electronics, mineral, shipbuilding and aerospace, automotive, miscellaneous manufacturing. The other 6 are nonmanufacturing industries: agriculture, forestry and fishing; mining; construction; services; utilities; education, research and development. This way of classification is much more aggregated than most of the existing systems. In this paper, I adopt the IFR approach to classify industries. Thus, I recategorize the Census and ACS industries based on the IFR industries classification system.

As for occupations and regions, I use standard occupational classification (SOC) and commuting zone 2000 (CZ) for classifying because Marinescu's data reports HHI at the CZ-by-SOC level. Moreover, their reported SOC codes are most close to 2010 SOC, used in the 2014 1% annual ACS to classify occupations. But the 2000 Census and the 2006 ACS reports the occupational code according to the 2000 SOC system. Therefore, I use the 2010 SOC as my occupation classification system. Thus, I reclassify the SOC codes in the 2000 Census and the 2006 ACS based on the 2010 SOC system.

## Imputation

All three samples (the 2000 5% Census, the 2006 and 2014 1% annual ACS) from IPUMS are weighted samples. Industry codes, occupation codes, and demographics are accurately reported in them. The only blurry variable is the region identifier. In order to identify the CZ for each individual, it is essential to know to which county a respondent belongs. However, the smallest identifiable geographic unit is the PUMA, containing at least 100,000 persons. It suggests high chances that a county can not be identified if its population is less than 100,000.[19]

I do the following to impute the CZ code for each observation: First, I extract the observations I do not have to work with, including those with county reports and those whose "PUMA" and "state" codes together can uniquely identify a CZ. The rest of the observations can only be identified through a PUMA-state cell. Using the PUMA-to-county crosswalk table with PUMA-county population reports and the county-to-CZ crosswalk table, I then distribute to each unidentified county a weight that is equal

[19] PUMAs do not cross state boundaries.

to its population share in the PUMA-state cell it belongs to. This new weight represents the probability that a person in a certain PUMA-state cell comes from the county associated with the weight. Next, by multiplying the new weights with the person weights in the raw data, I disaggregate each observation that only reports its PUMA-state code to multiple observations that report their county code and new person weights. Finally, since observations either have a CZ code or a county code, I can assign each of them a CZ code according to the county-to-CZ crosswalk.

Table 1: Summary Statistics

| Variable | Level | Obs | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| **Outcomes** | | | | | | |
| Change in employment-to-population ratio ($\times 10^3$) | $CZ \times SOC$ | 140615 | $-0.085$ | 2.992 | $-44.675$ | 106.253 |
| Change in average annual wage | $CZ \times SOC$ | 115024 | 6604.703 | 221912.54 | -135000 | 166461.5 |
| **Explanatory variables** | | | | | | |
| Exposure to robots | $CZ \times SOC$ | 140615 | 0.689 | 2.650 | 0.003 | 33.661 |
| IV Exposure to robots | $CZ \times SOC$ | 140615 | 0.526 | 1.244 | -1.017 | 18.815 |
| HHI (original sample, $\times 10^4$) | $CZ \times SOC$ | 267546 | 0.591 | 0.347 | 0.0003 | 1 |
| HHI (regression sample, $\times 10^4$) | $CZ \times SOC$ | 140615 | 0.513 | 0.336 | 0.0004 | 1 |
| **Covariates** | | | | | | |
| Market employment in 2006 | $CZ \times SOC$ | 140615 | 984.671 | 3766.263 | 0.017 | 215686 |
| Market employment in 2014 | $CZ \times SOC$ | 140615 | 1020.148 | 4103.282 | 0 | 254073 |
| CZ population in 2006 ($\times 10^5$) | $CZ$ | 708 | 4.225 | 11.14 | 0.012 | 178 |
| CZ working-age population in 2006 ($\times 10^5$) | $CZ$ | 708 | 2.659 | 7.045 | 0.007 | 1.11 |
| Employment-to-population ratio in 2006 | $CZ \times SOC$ | 140615 | 0.003 | 0.005 | 0 | 0.092 |
| Average annual wage in 2006 | $CZ \times SOC$ | 115024 | 35119 | 21246 | 2400 | 140000 |
| Share of male | $CZ \times SOC$ | 140615 | 0.554 | 0.387 | 0 | 1 |
| Share of elders (age¿65) | $CZ \times SOC$ | 140615 | 0.055 | 0.137 | 0 | 1 |
| Share of non-college | $CZ \times SOC$ | 140615 | 0.404 | 0.359 | 0 | 1 |
| Share of some college | $CZ \times SOC$ | 140615 | 0.073 | 0.159 | 0 | 1 |
| Share of college or professional | $CZ \times SOC$ | 140615 | 0.192 | 0.287 | 0 | 1 |
| Share of master or doctorate | $CZ \times SOC$ | 140615 | 0.073 | 0.194 | 0 | 1 |
| Share of non-white | $CZ \times SOC$ | 140615 | 0.145 | 0.235 | 0 | 1 |
| Share of manufacturing workers | $CZ \times SOC$ | 140615 | 0.141 | 0.296 | 0 | 1 |

NOTES. The employment-to-population ratio in the table refers to the CZ-by-SOC employment, as a share of CZ-level working-age population.

Table 2: Most and Least Concentrated Occupations

| **Highest HHI Occupations** | | |
|---|---|---|
| SOC | Title | HHI |
| 475040 | Mining Machine Operators | 8935.168 |
| 272099 | Entertainers and Performers, Sports and Related Workers | 8799.437 |
| 514023 | Rolling Machine Setters, Operators, and Tenders, metal and Plastic | 8714.308 |
| 453000 | Fishing And Hunting Workers | 8642.778 |
| 492096 | Electronic Equipment Installers and Repairers, Motor Vehicles | 8535.555 |
| 432099 | Communications Equipment Operators | 8392.442 |
| 435053 | Postal Service Mail Sorters, Processors, and Processing Machine Operators | 8392.119 |
| 516021 | Pressers, Textile, Garment, and Related Materials | 8327.19 |
| 519196 | Paper Goods Machine Setters, Operators, and Tenders | 8278.166 |
| 516063 | Textile Knitting and Weaving Machine Setters, Operators, and Tenders | 8190.465 |
| **Lowest HHI Occupations** | | |
| 434051 | Customer Service Representatives | 167.5584 |
| 414010 | Sales Representatives, Wholesale and Manufacturing | 177.0424 |
| 151030 | Computer Software Engineers | 238.4284 |
| 132051 | Financial Analysts | 306.1723 |
| 291123 | Physical Therapists | 349.187 |
| 411011 | First-Line Supervisors of Retail Sales Workers | 349.4099 |
| 151081 | Network Systems and Data Communications Analysts | 372.3035 |
| 291111 | Registered Nurses | 374.8477 |
| 112020 | Marketing and Sales Managers | 415.8779 |
| 132011 | Accountants and Auditors | 416.4309 |

NOTES. The ten most and least concentrated occupations under the 2010 Standard Occupational Classification (SOC) system. Only non-military occupations are counted. The SOC-level HHI is the average of market-level HHI weighted by employment over regression sample.

*Table 3: Effects of robots on employment and wages: IV estimates*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.047*** | -0.044*** | -0.005*** | -0.007* |
| | (0.008) | (0.012) | (0.002) | (0.004) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Underidentification | 0.000 | 0.001 | 0.000 | 0.002 |
| Weak identification | 369.393 | 51.323 | 341.722 | 43.902 |
| Endogeneity | 0.000 | 0.004 | 0.574 | 0.145 |
| Census divisions | ✓ | ✓ | ✓ | ✓ |
| Demographics | | ✓ | | ✓ |
| Occupation fixed effects | | ✓ | | ✓ |

NOTES. Table 3 presents the IV estimates of the effects of exposure to robots on employment and wages for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. I instrument the US exposure to robots using the EURO5 exposure to robots. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 4: Effects of robots on employment and wages in concentrated markets: endogenous ER; exogenous HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.067*** | -0.066*** | -0.009*** | -0.008** |
| | (0.022) | (0.017) | (0.003) | (0.004) |
| HHI*Exposure to Robots | 0.042 | 0.049* | 0.003 | 0.005 |
| | (0.030) | (0.029) | (0.004) | (0.004) |
| HHI | -0.576*** | -0.582*** | 0.022 | -0.004 |
| | (0.074) | (0.079) | (0.013) | (0.010) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Underidentification | 0.000 | 0.000 | 0.001 | 0.001 |
| Weak identification | 34.251 | 33.044 | 27.902 | 26.341 |
| Endogeneity | 0.005 | 0.004 | 0.282 | 0.449 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

NOTES. Table 4 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. In all columns, I instrument the US exposure to robots using the EURO5 exposure to robots and treat HHI exogenous. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wage. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 5: Effect of robots on employment and wages in concentrated markets: endogenous ER and HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.064*** | -0.060*** | -0.011** | -0.009* |
| | (0.017) | (0.012) | (0.004) | (0.004) |
| HHI*Exposure to Robots | 0.037* | 0.035* | 0.006 | 0.007 |
| | (0.020) | (0.019) | (0.006) | (0.006) |
| HHI | -0.698*** | -0.669*** | 0.015 | -0.013 |
| | (0.088) | (0.089) | (0.029) | (0.029) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Underidentification | 0.006 | 0.006 | 0.005 | 0.003 |
| Weak identification | 15.075 | 14.056 | 17.067 | 18.027 |
| Overidentification | 0.790 | 0.381 | 0.994 | 0.830 |
| Endogeneity | 0.005 | 0.010 | 0.418 | 0.580 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

NOTES. Table 5 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. In all columns, I instrument US exposure to robots using EURO5 exposure to robots, and HHI using a heteroskedasticity-based IV set. The set in the employment regressions contains the share of the population with college or professional degree and the share of manufacturing workers. The set in the wage regressions includes the share of elders (over 65) and the share of manufacturing workers. Column 1 and 2 present results for employment-to-CZ-working-age-population ratio. Column 3 and 4 present results for log annual wage. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 6: Effect of robots on employment and wages in concentrated market: OLS*

| | OLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.005 | -0.005 | -0.004** | -0.003** |
| | (0.007) | (0.006) | (0.002) | (0.001) |
| HHI*Exposure to Robots | 0.006 | 0.008 | 0.005* | 0.004* |
| | (0.009) | (0.009) | (0.003) | (0.002) |
| HHI | -0.545*** | -0.548*** | 0.022* | -0.003 |
| | (0.067) | (0.071) | (0.013) | (0.010) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

NOTES. Table 6 presents the OLS estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 7: Alternative Lewbel IVs: endogenous ER and HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.065*** | -0.060*** | -0.011** | -0.008* |
| | (0.018) | (0.013) | (0.004) | (0.004) |
| HHI*Exposure to Robots | 0.038* | 0.036* | 0.006 | 0.007 |
| | (0.020) | (0.019) | (0.005) | (0.006) |
| HHI | -0.701*** | -0.662*** | 0.016 | -0.008 |
| | (0.092) | (0.092) | (0.029) | (0.028) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Under identification | 0.008 | 0.007 | 0.005 | 0.009 |
| Weakidentification | 13.899 | 13.172 | 13.790 | 11.569 |
| Overidentification | 0.535 | 0.215 | 0.090 | 0.112 |
| Endogeneity | 0.004 | 0.008 | 0.519 | 0.615 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

NOTES. Table 7 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. In all columns, I instrument the US exposure to robots using the EURO5 exposure to robots, and HHI using a heteroskedasticity-based IV set. The set in the employment regressions contains the share of the population with no college degree and the share of manufacturing workers. The set in the wage regressions includes the share of population with master or doctoral degree and the share of manufacturing workers. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 8: Without fully concentrated markets: endogenous ER and HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.068*** | -0.060*** | -0.007 | -0.005 |
| | (0.022) | (0.017) | (0.004) | (0.004) |
| HHI*Exposure to Robots | 0.042 | 0.041 | -0.001 | 0.001 |
| | (0.033) | (0.031) | (0.006) | (0.006) |
| HHI | -0.725*** | -0.726*** | 0.039 | 0.008 |
| | (0.088) | (0.090) | (0.034) | (0.035) |
| Observations | 113633 | 113633 | 97083 | 97083 |
| Underidentification | 0.010 | 0.011 | 0.000 | 0.008 |
| Weak identification | 17.689 | 15.748 | 42.810 | 20.651 |
| Overidentification | 0.525 | 0.288 | 0.512 | 0.977 |
| Endogeneity | 0.011 | 0.017 | 0.302 | 0.549 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

NOTES. Table 8 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. The fully concentrated markets are excluded from the sample. In all columns, I instrument the US exposure to robots using the EURO5 exposure to robots, and HHI using a heteroskedasticity-based IV set. The set in the employment regressions contains the share of the population with college or professional degree and the share of manufacturing workers. The set in the wage regressions includes the share of elders (over 65) and the share of manufacturing workers. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 9: Weighted regressions: endogenous ER; exogenous HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.084*** | -0.043 | -0.009*** | -0.004*** |
| | (0.029) | (0.031) | (0.002) | (0.001) |
| HHI*Exposure to Robots | 0.096*** | 0.071** | 0.005 | 0.004 |
| | (0.031) | (0.030) | (0.003) | (0.003) |
| HHI | -1.772*** | -1.591*** | 0.014 | 0.006 |
| | (0.177) | (0.185) | (0.014) | (0.010) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Underidentification | 0.001 | 0.001 | 0.001 | 0.001 |
| Weak identification | 120.204 | 108.445 | 124.693 | 111.332 |
| Endogeneity | 0.000 | 0.007 | 0.454 | 0.939 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

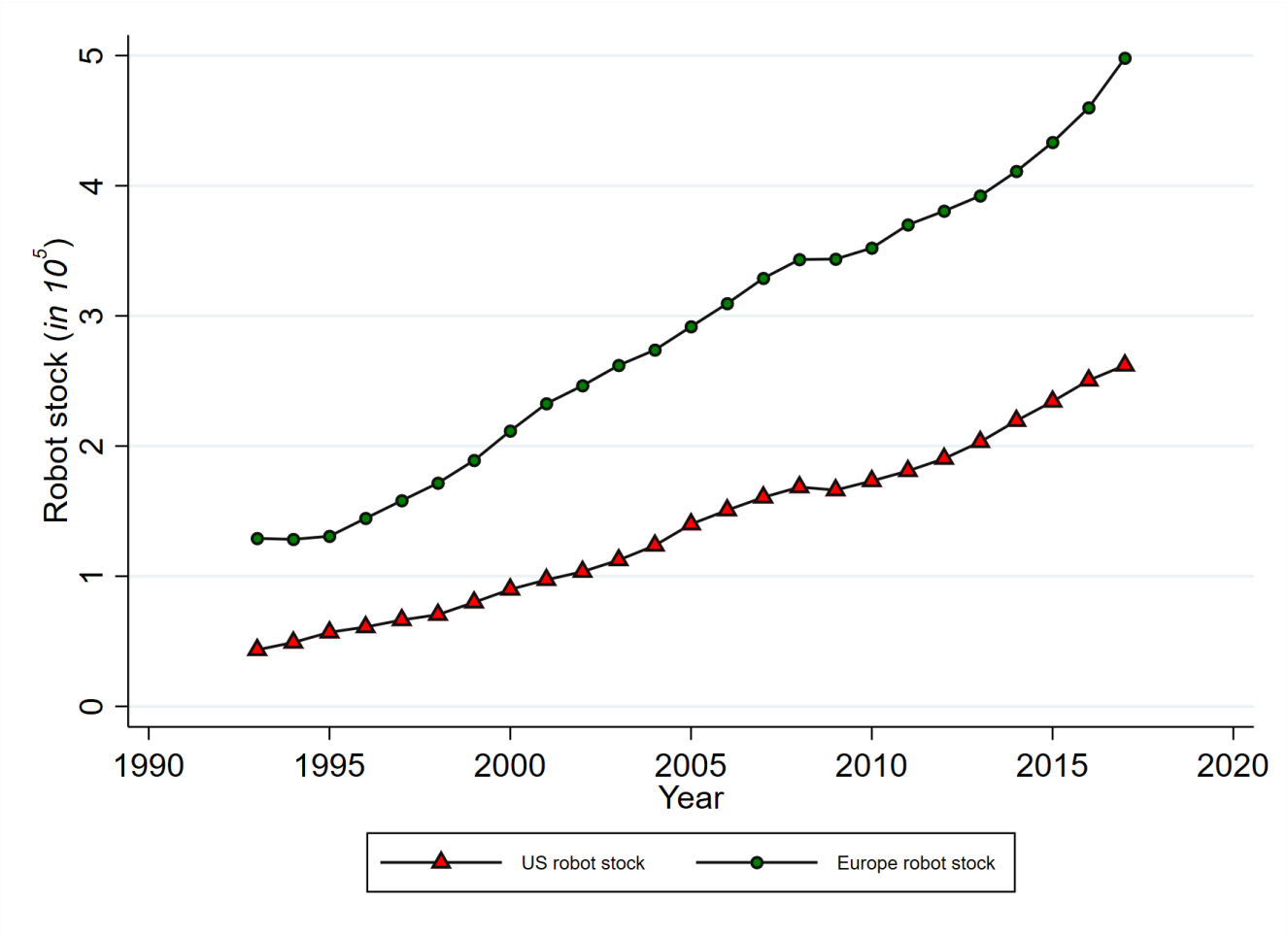
NOTES. Table 9 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. Regressions are weighted by the market-level employment. In all columns, I instrument the US exposure to robots using the EURO5 exposure to robots and treat HHI exogenous. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

*Table 10: Weighted regressions: endogenous ER and HHI*

| | TSLS | | | |
|---|---|---|---|---|
| | Employment | | Wages | |
| | (1) | (2) | (3) | (4) |
| Exposure to Robots | -0.079*** | -0.037 | -0.009*** | -0.006*** |
| | (0.024) | (0.026) | (0.002) | (0.001) |
| HHI*Exposure to Robots | 0.076* | 0.041 | 0.009** | 0.011** |
| | (0.038) | (0.045) | (0.004) | (0.005) |
| HHI | -2.392*** | -1.891*** | 0.001 | -0.008 |
| | (0.250) | (0.285) | (0.028) | (0.023) |
| Observations | 140615 | 140615 | 115024 | 115024 |
| Underidentification | 0.000 | 0.000 | 0.000 | 0.000 |
| Weak identification | 12.681 | 21.133 | 35.358 | 30.993 |
| Overidentification | 0.619 | 0.561 | 0.237 | 0.560 |
| Endogeneity | 0.000 | 0.021 | 0.172 | 0.222 |
| Occupation fixed effects | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ |
| State fixed effects | | ✓ | | ✓ |

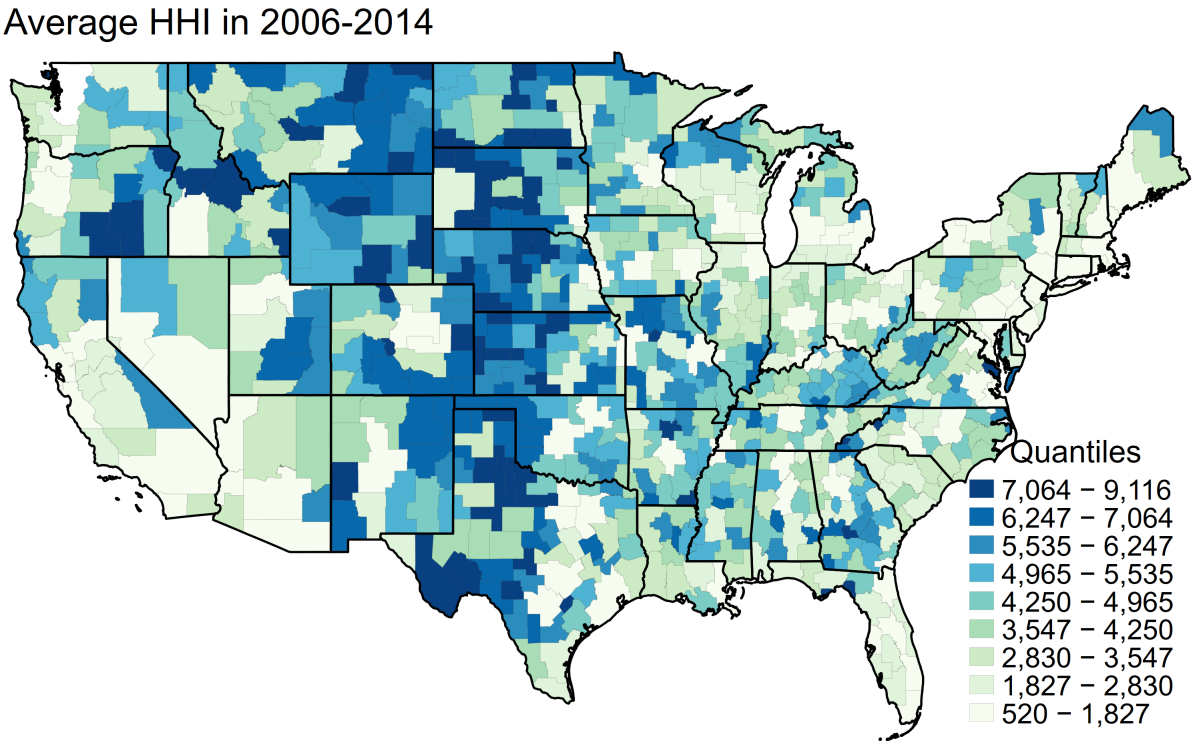
NOTES. Table 10 presents the IV estimates of the marginal effects of exposure to robots on employment and wages under different concentration levels for 2006-2014. Each labor market is defined as a CZ-by-occupation cell. Regressions are weighted by the market-level employment. In all columns, I instrument the US exposure to robots using the EURO5 exposure to robots, and HHI using a heteroskedasticity-based IV set. The set in the employment regressions contains the share of the population with college or professional degree and the share of manufacturing workers. The set in the wage regressions includes the share of elders (over 65) and the share of manufacturing workers. Columns 1 and 2 present results for employment-to-CZ-working-age-population ratio. Columns 3 and 4 present results for log annual wages. The demographic characteristics include the share of male, the share of elders (over 65), the share of the population with no college, some college, college or professional, and master or doctoral degree, the share of non-white, and the share of manufacturing industry workers. The under-identification test reports p-value of the Kleibergen-Paap LM statistic. The weak identification test reports the Kleibergen-Paap Wald F statistic. The over-identification test reports p-value of the Hansen J statistic. The endogeneity test reports p-value of the chi-square statistic. Standard errors are clustered at the state level. * p <.10, ** p< .05, *** p<.01.

Figure 1: Industrial Robot Stock



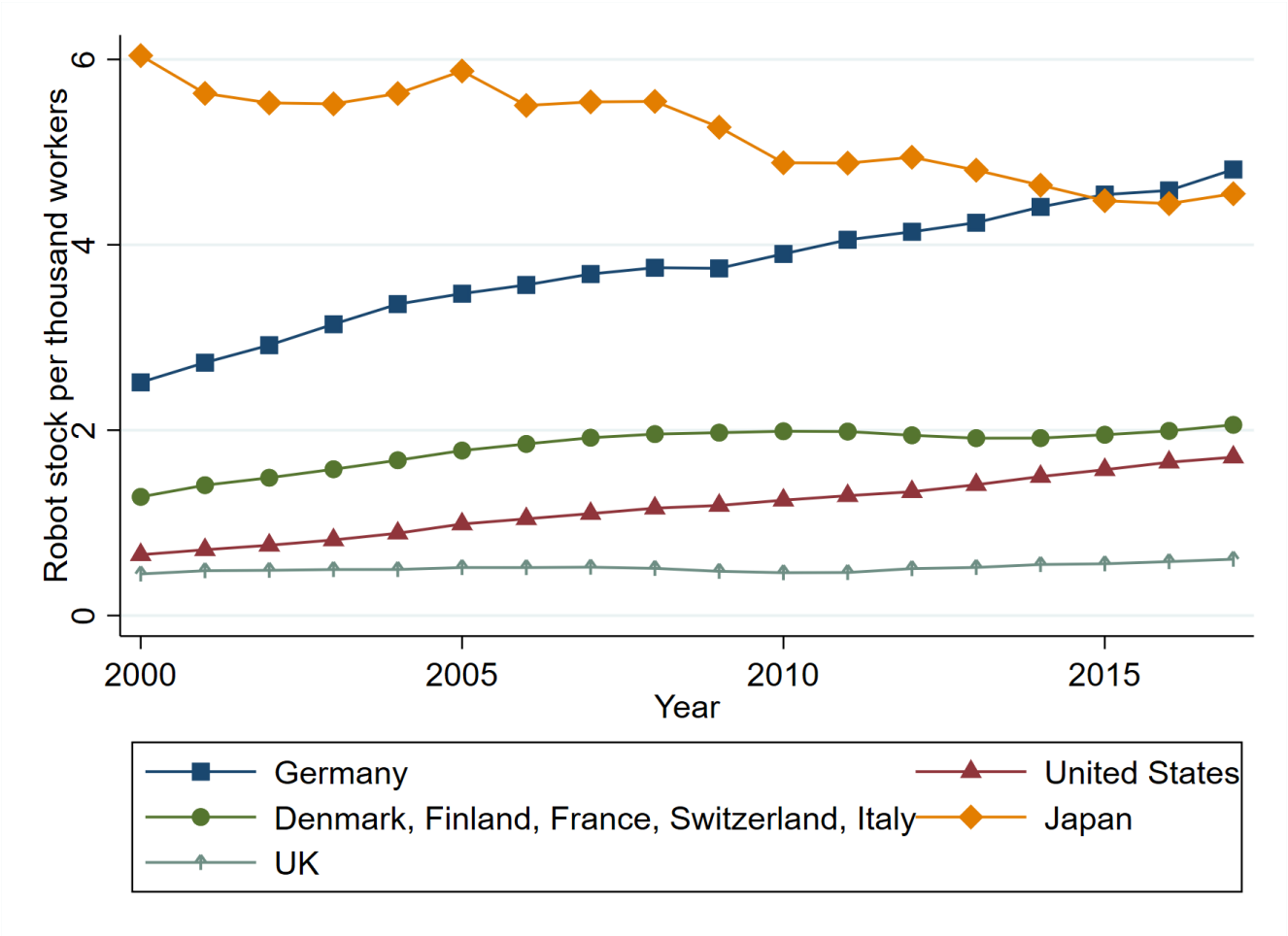

*NOTES*. Figure 1 displays the operational industrial robot stock in Europe and the US in 1993-2017. The robot stock data are obtained from the International Federation of Robotics (IFR).

Figure 3: Labor Market Concentration



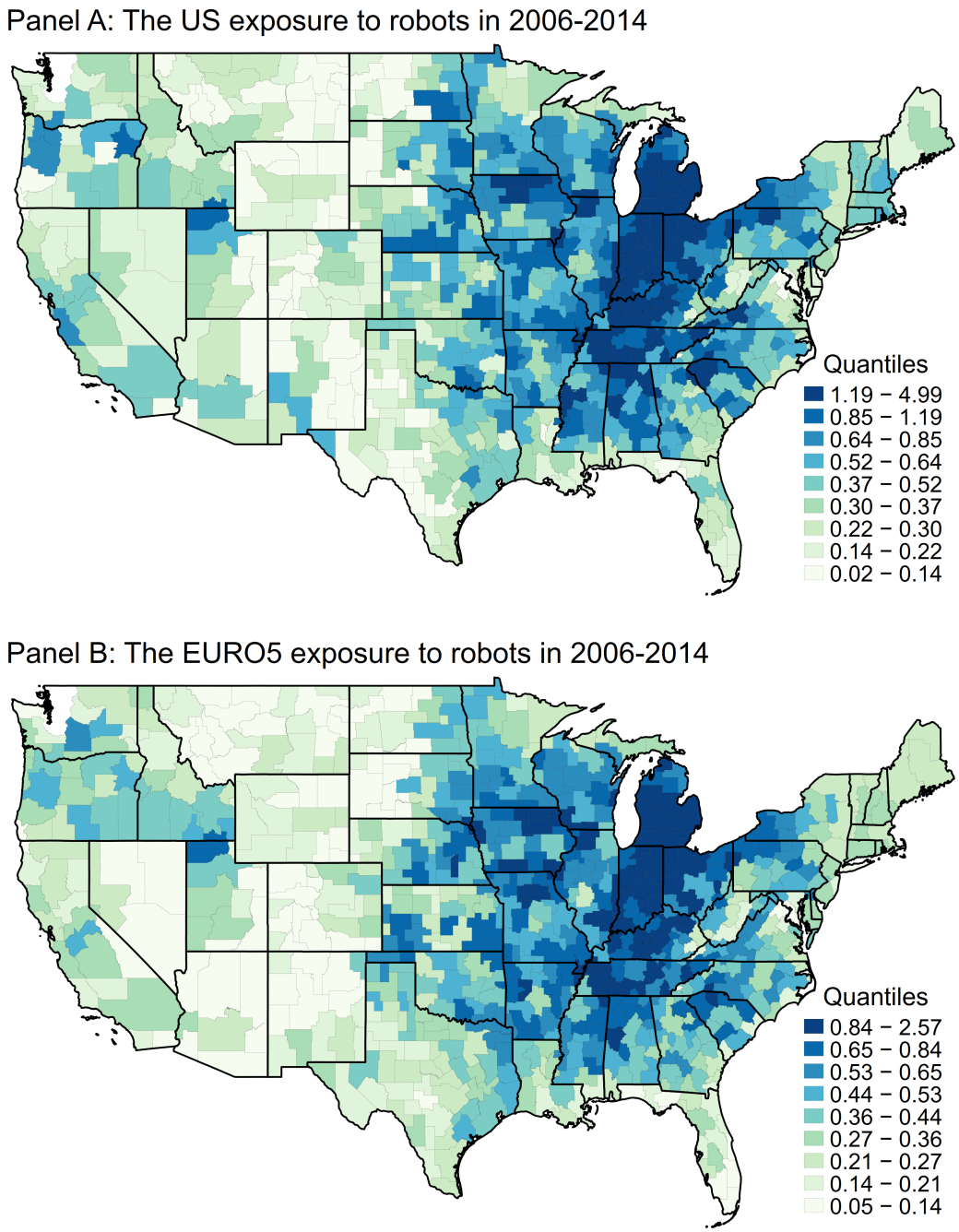

*NOTES.* Figure 3 – Geographic distribution of average HHI across 2006-2014 at the CZ level. HHI is ranged from 0 to 10000. The CZ-level HHI is the weighted average of the CZ-by-SOC-level HHI from Ioana Marinescu's website where the weights are employment in CZ-by-occupation cells.

Figure 4: Industrial Robot Stock



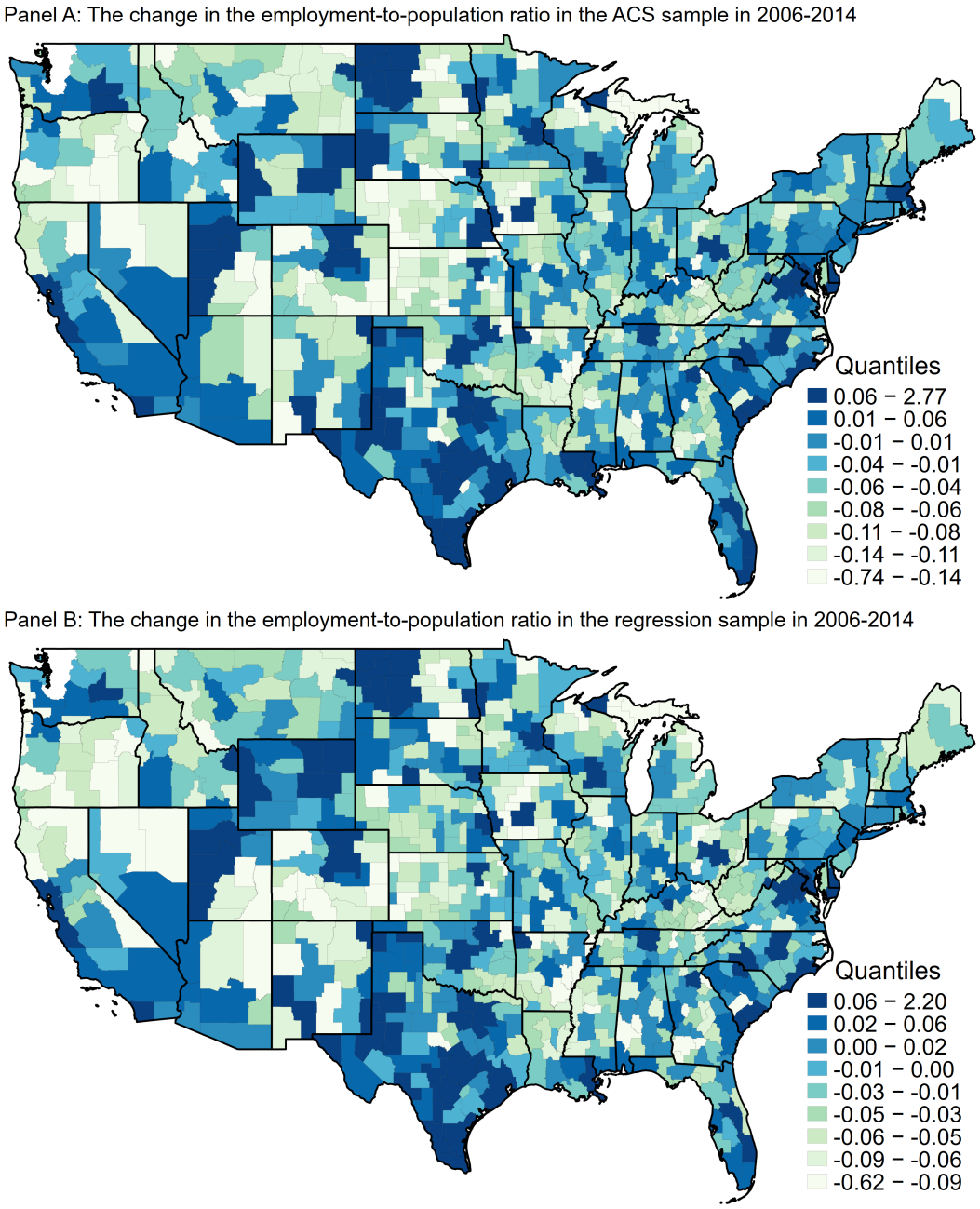

*NOTES.* Figure 4 displays the operational industrial robot stock per thousand workers at the country level over the period 2000-2017. The robot stock data are obtained from the International Federation of Robotics (IFR).

Figure 5: Exposure to Robots




*NOTES.* Figure 5 – Geographic distribution of Exposure to Robot (ER) at the CZ level, 2006-2014. In panel A, ER is built from the US industrial robot stock. In panel B, ER is built from the EURO5 countries (Denmark, Finland, France, Switzerland, Italy) industrial robot stock.

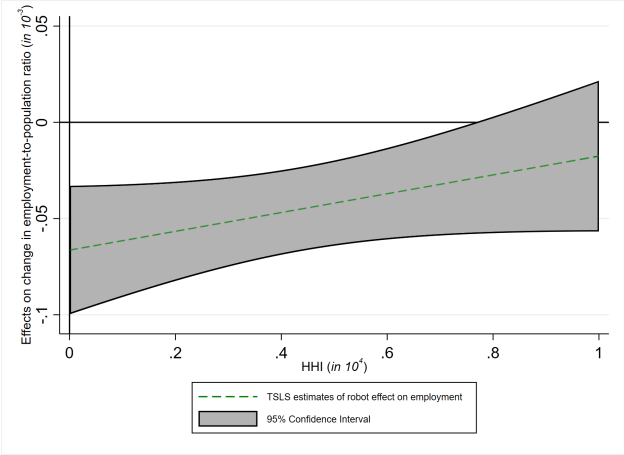
Figure 6: Employment Changes



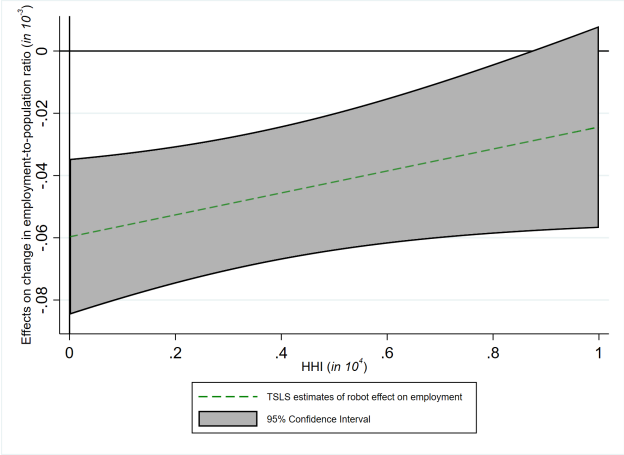

*NOTES.* Figure 6 – Geographic distribution of the change in the employment-to-working-age-population ratio at the CZ level, 2006-2014. Panel A displays the employment-to-population ratio where the CZ-level employment comes from original annual ACS data. Panel B displays the employment-to-population ratio where CZ-level employment comes from the regression sample.

*Figure 7: The effects of exposure to robots on labor market outcomes under different market concentration levels*

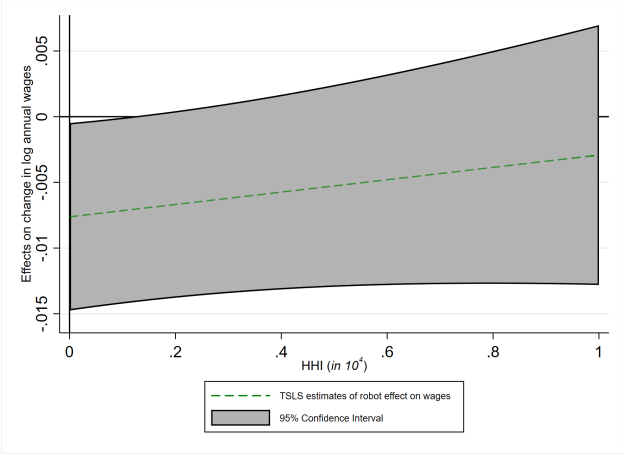
*(a) Employment effects vs HHI: endo ER, exo HHI*



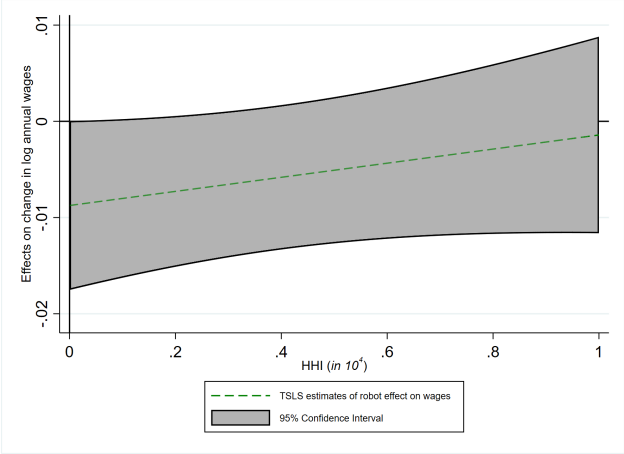

*(b) Employment effects vs HHI: endo ER, endo HHI*




*(c) Wage effects vs HHI: endo ER, exo HHI*



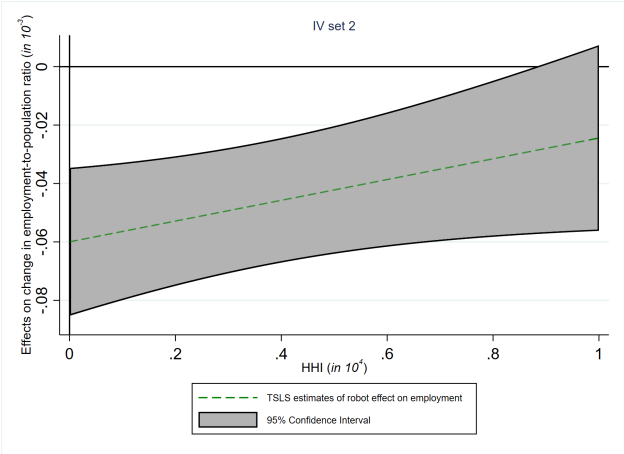

*(d) Wage effects vs HHI: endo ER, endo HHI*



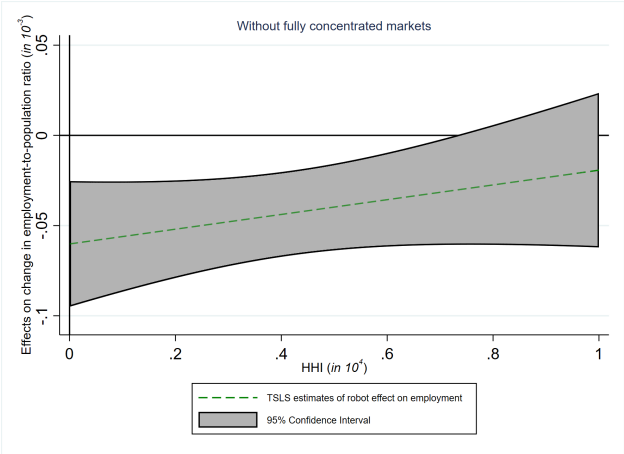

*NOTES.* Figure 7 demonstrates the marginal effects of exposure to robot on labor market outcomes under different concentration levels for the period 2006-2014. Each labor market is defined as a CZ-by-occupation cell. In all panels, I control for demographic characteristics, occupation fixed effects, and state fixed effects and instrument the US exposure to robots using the EURO5 exposure to robots. Panels (a) and (b) present the employment results. Panels (c) and (d) present the wage results. HHI is treated exogenous in panels (a) and (c) and endogenous in (b) and (d). In panel (b), I instrument HHI using the Lewbel IV built on the share of the population with college or professional degree and the share of manufacturing workers. In panel (d), I instrument HHI using the Lewbel IV built on the share of elders and the share of manufacturing workers. Standard errors are clustered at the state level.

*Figure 8: The effects of exposure to robots on labor market outcomes under different market concentration levels*

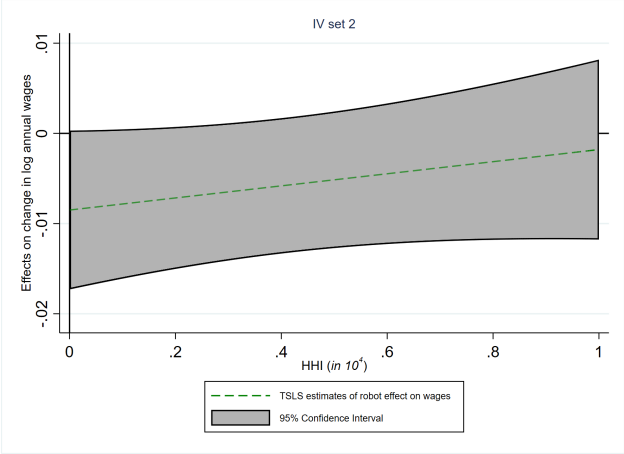
*(a) Employment effects vs HHI: endo ER, endo HHI*



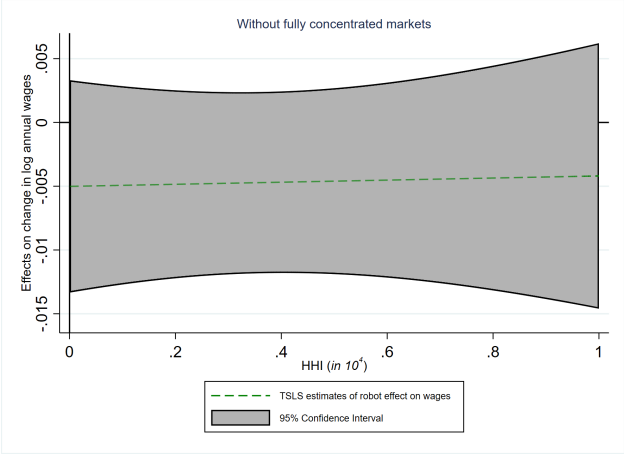

*(b) Employment effects vs HHI: endo ER, endo HHI*




*(c) Wage effects vs HHI: endo ER, endo HHI*



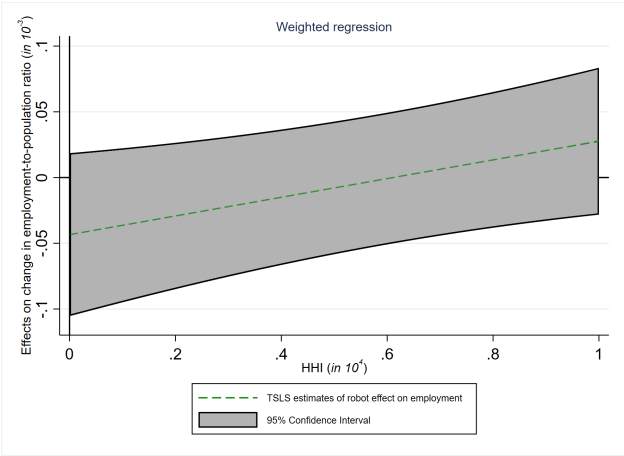

*(d) Wage effects vs HHI: endo ER, endo HHI*



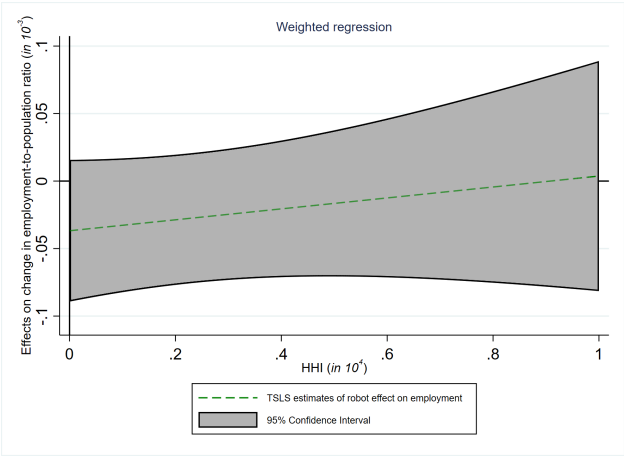

*NOTES.* Figure 8 presents the marginal effects of exposure to robot on labor market outcomes under different concentration levels for the period 2006-2014. Each labor market is defined as a CZ-by-occupation cell. In all panels, I control for demographic characteristics, occupation fixed effects, and state fixed effects and instrument the US exposure to robots using the EURO5 exposure to robots, HHI using heteroskedasticity-based IV. Panels (a) and (b) present the employment results. Panels (c) and (d) present the wage results. In panels (a) and (c), the fully concentrated markets are excluded from sample. The Lewbel IVs are built on the the share of the population with college or professional degree and the share of manufacturing workers in panel (a), the share of elders and the share of manufacturing workers in panel (b), the share of population with no college degree and the share of manufacturing workers in panel (c), and the share of population with master or doctoral degree and the share of manufacturing workers in panel (d). Standard errors are clustered at the state level.

*Figure 9: The effects of exposure to robots on labor market outcomes under different market concentration levels*

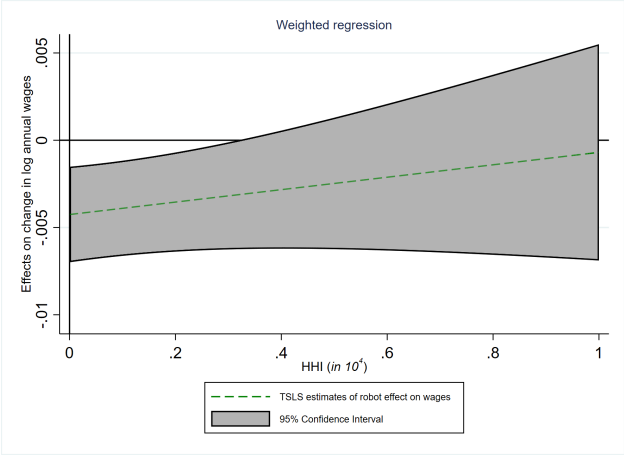
*(a) Employment effects vs HHI: endo ER, exo HHI*



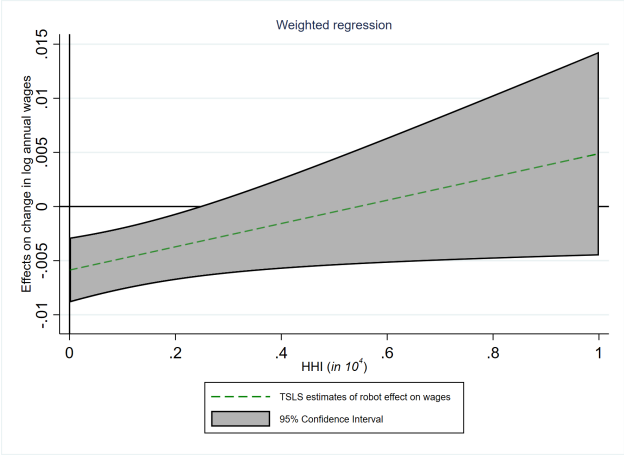

*(b) Employment effects vs HHI: endo ER, endo HHI*




*(c) Wage effects vs HHI: endo ER, exo HHI*




*(d) Wage effects vs HHI: endo ER, endo HHI*




*NOTES.* Figure 9 demonstrates the marginal effects of exposure to robot on labor market outcomes under different concentration levels for the period 2006-2014. Each labor market is defined as a CZ-by-occupation cell. Regressions are weighted by the 2000 market-level employment. In all panels, I control for demographic characteristics, occupation fixed effects, and state fixed effects and instrument the US exposure to robots using the EURO5 exposure to robots. Panels (a) and (b) present the employment results. Panels (c) and (d) present the wage results. HHI is treated exogenous in panels (a) and (c) and endogenous in (b) and (d). In panel (b), I instrument HHI using the Lewbel IVs built on the share of the population with college or professional degree and the share of manufacturing workers. In panel (d), I instrument HHI using the Lewbel IVs built on the share of elders and the share of manufacturing workers. Standard errors are clustered at the state level.