# The Effect of Low-Skilled Immigration on Robotization*

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**Abstract**

I examine whether low-skilled immigration entry into manufacturing, construction and agriculture impedes the adoption of automation using industrial robots. Firstly, I show that the Mariel Boatlift in 1980 significantly stifled the adoption of robots in Miami, relative to the control regions. Then, employing an industrial robot dataset for 1980-2015, I document that low-skilled immigration and robot deployment are negatively associated across developed countries, as well as commuting zones and occupational categories within the U.S. To explain these patterns, I develop a simple task assignment model, which predicts that a short-run wage drop triggered by immigration will nudge establishments to suppress the robotization in the long-run. Employing instruments from 1940 ethnic settlement patterns, I show that an inflow of 1,000 low-skilled foreign laborers reduces adoption of robots by 2.4 robots. The result suggests that restricting immigration will potentially lead to boosting automation, accompanied by unintended rising income inequality.

*JEL Classification*: D21, E22, J15, J21, J23, J31, O14, R23
*Keywords*: immigration, automation, industrial robots, comparative advantage

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# 1 Introduction

A robot revolution is underway. Despite the consensus that routine manual-task intensive jobs are relatively immune from automation (Polanyi (2009)), recent self-learning artificial intelligence embedded in robot arms, however, leads this perception to fade. (Pratt (2015)) As the impact of robotization is recently explored by a few works (Acemoglu and Restrepo (2017), Graetz and Michaels (2017)), little is known regarding the process of how robotization itself actually proceeds, despite the growing interests in the transformational role of robotization for the production system.

In this paper, I explore the mechanism of automation process by industrial robots by advancing a hypothesis that the entry of a relatively small, but growing class of labor force, low-skilled immigration, plays a prominent role in impeding robotization by establishments. The logic behind the hypothesis is simple: low-skilled immigration reduces the wages for routine occupation labor, thus, mitigates the incentives for upgrading automation. As developed economies undergo secular labor shortage due to population aging, the reliance to foreign skills is increasingly prominent alternative in parallel to robotization, especially in the manual task-intensive sectors. In the U.S., foreign labor share has reached 15% in manufacturing, 24% in construction and 32% in agriculture, as computed from the American Community Survey, 2015 (IPUMS (2019)). While robotization is implemented by private investments, in principle, away from the public control, immigration density is controllable by admission quota of the government. The linkage of immigration on robotization is worth investigating because demographic controls could shift the nationwide technology, which instead affects the labor market. (See recent literature on automation; Autor, Levy and Murnane (2003), Autor and Dorn (2013), Acemoglu and Restrepo (2017), and Eden and Gaggl (2018), among others.)

To motivate the hypothesis, I start by documenting a cross-country descriptive link between immigration employment ratio and industrial robots adoption among developed economies. The industrial robot data draws on World Robotics Database by International Federation of Robotics (IFR (2015)), imputing the robot stocks from worldwide industrial robot sales in manufacturing, construction and agriculture worldwide. In Figure 1, I find a significantly large negative correlation between low-skilled immigration ratio and industrial robots per employment, with elasticity of -0.72. One could see that immigration-intensive countries including Saudi Arabia (SAU), Oman (OMN), Kuwait (KWT), Israel (ISR), Australia (AUS), New Zealand (NZL) and Canada (CAN) exhibit relatively lower industrial robot density, compared to less immigration-intensive, but more robot-intensive countries, including Japan (JPN) and South Korea (KOR).

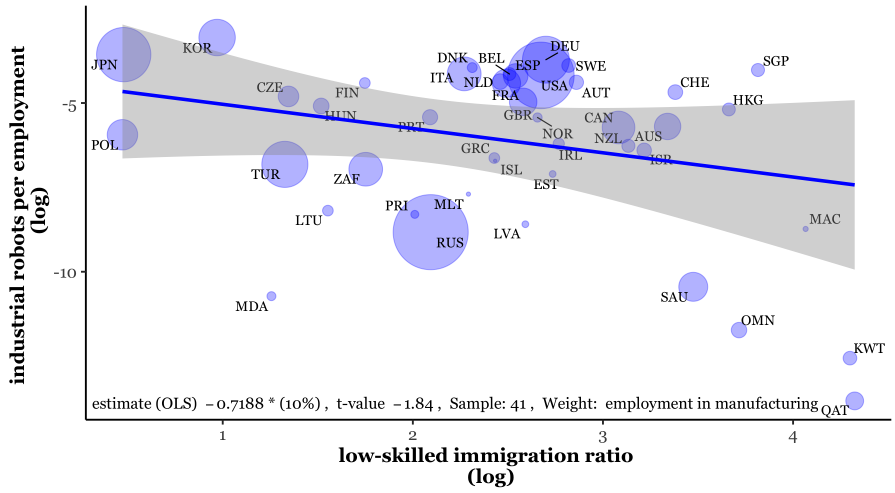


Figure 1: Low-skilled immigration and robot adoption in developed economies (2015)
*Notes*: Alphabetical labels are 3-digit country codes. Industrial robots data comes from IFR (2015). Low-skilled immigration ratio is computed as a ratio of individuals with high-school degrees or less out of the total working age population. The details are summarized in Data Appendix.

Drawing on IFR (2015), I also document the analogous within-country relationships inside the U.S., in regional-level (Figure 6) and in occupation-level (Figure 7). In Figure 6, commuting zones (CZs) with larger low-skilled immigration inflow (e.g. Miami, and the regions on the U.S.-Mexico border) exhibit lower robot density relative to regions attracting smaller low-skilled immigration inflow (e.g. the Rustbelt regions including Detroit, MI and Cleveland, OH). In Figure 7, routine occupations in manufacturing with higher immigration ratio exhibits lower robot adoption, when applications of robots and occupation task contents are juxtaposed as in Table 3.

Founded by the persuasive negative patterns across countries, regions and occupations, I rationalize the pervasive negative links by a hypothesis, arguing that low-skilled immigration entry serves as downward pressure to robotization.[1] To formalize this scenario, I develop a simple task assignment model with endogenous automation. The setup explicitly embeds robots (Acemoglu and Restrepo (2018)) and foreign labor (Grossman and Rossi-Hansberg (2008) and Ottaviano, Peri and Wright (2013)) in a task-based framework (Acemoglu and Autor (2011)).[2] An economy consists of a continuum of islands, inhabited by inelastic labor, and run by a representative plant, facing a perfectly elastic robot market with a global robot rental price. The task is alined from the most routine (easy-to-automate) end to the

[1]The reverse causality story does make sense. Perhaps, regional robotization inhibits inflows of low-skilled immigration, plausibly via lowering routine wages. I discuss this possibility in the Section.5.

[2]The model is a modified version of the framework in Yoshida (2019).

non-routine (hard-to-automate) end on the spectrum. Production factors, including robots, low-skilled foreign labor, and low-skilled domestic labor, have task-specific productivities. The central problem for establishments is to optimally allocate tasks to production factors.

The key assumption underlying the theory is comparative advantage of low-skilled immigrants over natives to routine tasks.[3] In equilibrium, this comparative advantage incentivizes plants to allocate the more routine range of tasks to immigrants compared to native counterparts.[4] The most routine task covered by foreign labor turns out to be marginally unautomated threshold task, where the marginal cost of task is equalized between industrial robots and immigrants. Thus, in this conceptual model, the optimal magnitude of automation is regulated by immigration wage relative to robot rental price.

The model illustrates the automation adjustment mediated by the local wage, triggered by foreign labor influx in the following way. Initially, the influx of low-skilled immigration mechanically lowers the foreign wage by labor supply surge. If domestic and foreign skills are well-differentiated as presumed, the initial wage drops cannot be fully offset by task reallocation from foreign labor to domestic labor. Therefore, a marginal cost of the threshold task, shaped by immigrant wage, declines. In the long run when automation is adjustable, to exploit this cost advantage, establishments adopt milder robotization. As investments to cutting-edge robots are delayed and a part of routine employment has been secured, forming a lower robot-routine occupation employment ratio, as documented in Figure 1, 6, and 7.[5]

Two socio-demographic differences in the sectors of interest (manufacturing, construction and agriculture) empirically support the comparative advantage of foreign labor to routine tasks relative to domestic labor. First, immigrants typically have lower education attainments than natives. (See Figure A1 (left)) The thinness of the formal educational base, including vocational training programs, suggests shortage of expertise. Second, immigrants are typically younger on average than natives. (See Figure A1 (right)) Manual-intensive tasks are more likely to be better performed by young, and middle-aged workers with stronger physical ability. Moreover, the age constraints work experience, and thus, their crafts re-

[3]Recently, Basso, Peri and Rahman (2017) find that natives turns relatively more competitive in the clerical works compared to immigrants, mitigating the labor market polarization by computerization. Their focus is comparative advantage of immigrants in non-tradable service occupations (eg. care givers, waiters, taxi drivers), while mine centers on manual-intensive routine occupations in manufacturing, construction and agriculture.

[4]Peri and Sparber (2009) empirically show that the modest immigration's impact on wages could be explained by comparative advantage of immigrants to natives on the manual-intensive tasks rather than communication-intensive tasks.

[5]In textbook economics, technological adjustment is delayed than labor adjustment.

main under-developed.[6] A lack of skills and experiences jointly induces plants to allocate routine range of tasks to low-skilled immigrants as laborers, more susceptible group to robots, while non-routine range of tasks are allocated to native counterparts engaged in non-routine occupation[7], fostering foreign-domestic segregation within the production operation.

Next, I test the key prediction of mitigating effect of low-skilled immigration on automation in two units of analysis, inter-temporal evolutions across regions and occupations. The routinely-invoked empirical challenge is that immigration entry to regions, occupations are non-random. To address this issue of endogeneity, I adopt an instrumental variable strategy, employing the historical settlement patterns of foreign labor force in 1940. (Altonji and Card (1991) and Card (2001)) The idea is that location choice for immigrants are substantially fueled by the ethnic network of the same ethnic group, independent from regional economic opportunities. (Munshi (2003))[8] The key identification conditions are exogeneity and exclusion restriction. Exogeneity requires that the historical settlement pattern of low-skilled immigrants in 1940 are orthogonal to the unobservable regional factors, which could also give rise to the robotization. Exclusion restriction mandates that the only channel the historical settlement pattern feeds into the robotization is through the new immigration inflow. Based on these conditions, I find that 10,000 entry of low-skilled foreign labor force ratio downshifts 2.4 robot units in the main specification. The result is contrasted with using black natives and immigrants from English-speaking countries (including Canada, Australia, India, Philippines) as alternative regressors. The estimated impacts are substantially weaker, supporting my theory that differentiation of immigrants from natives matters for the result. The finding poses a natural policy implication to immigration regulation. The limited admission quota will upshift robotization, potentially leading to immiseration of labor in the production economy.[9] The model also generates a series of testable predictions: rising ethnic inequality, together with labor share and falling robot density and labor productivity (Corollary 1). Empirical findings are consistent with these predictions.

[6]Regarding production workers in the occupations of interest, experience especially appears equally important because learning from experience matters for uncodified craftman types of works.

[7]This occupation group includes specialized artisans, mechanical engineers and production managers.

[8] Mexicans tend to agglomerate to the "border" states where Mexicans historically resided.

[9]The policies currently discussed include building a wall across the U.S.-Mexico border, deportation of illegal immigrants and limiting admission quota of refugees. (See Allen, Dobbin and Morten (2018))

**Literature review** The paper primarily belongs to a sizable branch of the literature of technology adoption.[10] Doms, Dunne and Troske (1997) found that plants with higher skill mix adopts wider range of technologies, using establishment-level data (Survey of Manufacturing Technology, SMT) in 1987 and 1993. The closest specification to mine is found in Lewis (2011). Employing a similar instrumental variable strategy and the SMT, he shows that low-skilled biased labor mix induced by immigration influx shrinks a variety of high-tech manufacturing technologies across Metropolitan Statistical Areas.[11] Only a few literature is investigating the adoption of robots. Acemoglu and Restrepo (2018) advocates that aging demography facilitates labor-saving technical change in a context of directed technical change (Acemoglu (2002)). The paper complements Acemoglu and Restrepo (2018) by highlighting the role of foreign labor in contrast to the domestic demography. Presidente (2017) finds the positive effect of dismissal regulation on robotization. Though IFR (2015) exclude tractors in agriculture from industrial robots, Manuelli and Seshadri (2014) show that abundant labor supply of blacks in the southern region in nineteenth century in the U.S. impeded tractor adoption.

Although the emphasis is set on the process of robotization, the paper potentially contributes to the debate on the puzzlingly mixed results on immigration's impact on wage. (See Dustmann, Schonberg and Stuhler (2016) for a survey) Many recent literature stresses the labor supply side adjustment, such as occupational switching by Colas (2016), spatial relocation by Monras (2015) and Piyapromdee (2017), education choice and labor force participation by Llull (2017). In contrast, the paper underscores adjustment of technology on the labor demand side.[12]

**Outline** The paper is structured as follows. Section 2 provides a natural experiment from Mariel Boatlift in 1980. Section 3 provides a theoretical framework to formalize the dynamic process of immigration-induced automation. Section 4 describes the data and identification strategy. Section 5, 6 conducts the analysis by regional- and occupation-level, respectively. Section 7 concludes.

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[10] Technical *adoption* is different from technical *change* in endogenous growth theory (e.g. (Romer, 1990) and directed technology change (Acemoglu, 2002)).

[11] My specification complements Lewis (2011) in two points. First, he uses establishment-level data across metropolitan areas in 1987, 1991, 1993, while I use imputed CZ-level data, covering the U.S. mainland, including non-urban areas, in 1980-2015. Second, he proxies technology as the *variety* of technologies used, while I employ *units* of robots.

[12] As a notable exception, Borjas (1999) theoretically examines a process of capital adjustment, albeit not a shift of technology, stemming from immigration inflow.

# 2 Natural Experiment: the Mariel Boatlift (1980)

This section delivers the natural experiment by the Mariel Boatlift in 1980, applying a research design of the classic study of Card (1990) to industrial robot adoption. On April 20, 1980, Fidel Castro declared that Cuban nationals wishing to move to the United States could leave freely from the port of Mariel, and around 125,000 Cubans quickly accepted the offer, and rushed to Miami. I construct low-skilled immigration inflow in 1972 to 1993 from the Current Population Survey (CPS). Following Borjas (2017), ethnicity of hispanics is used as alternative proxy of low-skilled immigrants, because CPS before 1994 does not record citizenship status. Robot density follows my extrapolation from BEA, and computation of robot density in Section 4.1.

To run the natural experiment, I set up two control groups or placebos. The first one is aggregate areas outside the Miami in the U.S. mainland. The second one is a placebo region used in Card (1990), which is a combination of MSAs sharing similar characters with Miami before 1980 (Atlanta, Los Angeles, Houston, and Tampa-St. Petersburg). The comparison between the treatment group (Miami) and the two control groups indicate that the inflow of low-skilled Cubans downshifted robot density by 8.3%.

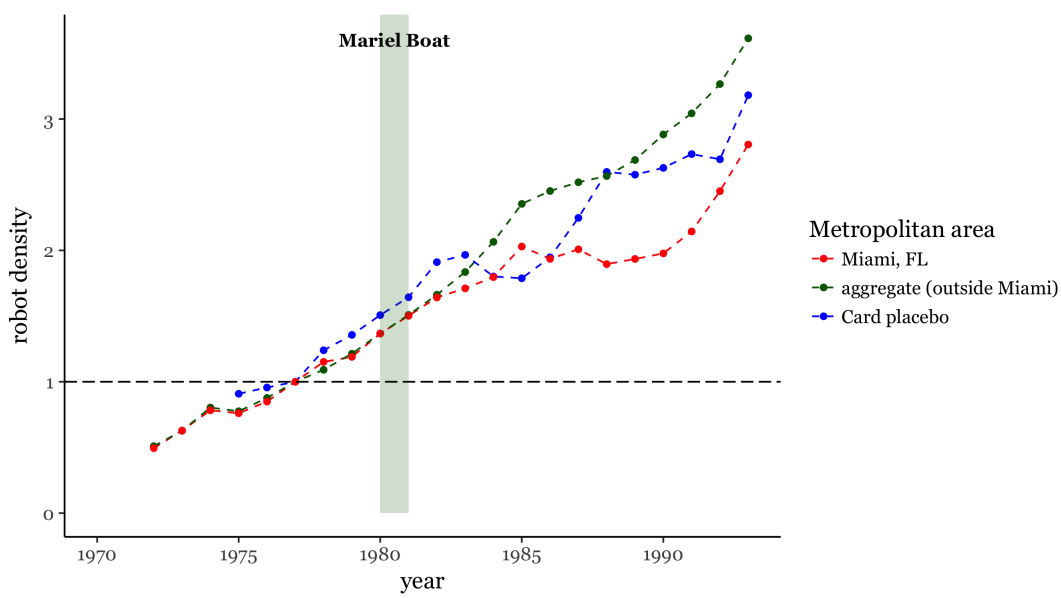


Figure 2: Robot density before and after the Mariel Boatlift (Miami vs. control regions)
*Notes: Computed from the Current Population Survey and NIPA from BEA.*

Intriguingly, after the Mariel Boatlift in 1980, Miami region records the lowest robot density at the time of 2015 as seen in Figure 6. Guided by this finding, I propose a mechanism behind the downshifting pressure of immigration on robotization, using a model presented

in the next section.

# 3 A Task-based Model with Endogenous Automation

## 3.1 Setting

The model embeds task allocation over production factors (Acemoglu and Restrepo (2018), Grossman and Rossi-Hansberg (2008)) in the spatial economy (Autor and Dorn (2013), Beaudry, Doms and Lewis (2010)). Suppose an economy consists of a continuum of islands indexed by $l$, inhabited by inelastic labor force. Assume there are three types of labor, low-skilled domestic labor $\widetilde{L^D}$, low-skilled foreign labor $\widetilde{L^F}$, and high-skilled labor $\widetilde{H}$.[13] $l$ is suppressed in this chapter for brevity, and will be explicit in the empirical part. Robot supply $R$ is perfectly elastic in a global capital market with a technologically-disciplined rental price $q$.[14] A representative plant produces a homogeneous final good (numeraire) by Cobb-Douglas combination of each task $\omega \in [0, 1]$ such that

$$Y = exp[A^{\eta}(\int_0^1 lny(\omega)d\omega)^{1-\eta}]$$

where $y(\omega)$ is a task output of $\omega$ and $A$ captures intangible capital, yielding a source of profit. The total size of task spectrum is set to measure one, and the lower-indexed task is more routine task, which is more easily to be automated.[15] [16]

Assume that each type of labor, augmented by task productivity, is perfectly substitutive in each task. Production technology of task $\omega$ is given by

$$y(\omega) = r(\omega) + \underline{a}^F(\omega)l^F(\omega) + \underline{a}^D(\omega)l^D(\omega) + \overline{a}(\omega)h(\omega)y(\omega)$$

$l^F(\omega), l^D(\omega), h(\omega)$ are low-skilled foreign, low-skilled domestic, high-skilled labor, respectively, employed in task $\omega$. Analogously, $\underline{a}^F(\omega), \underline{a}^D(\omega), \overline{a}(\omega)$ is a task-specific productivity for each class of labor, relative to the robot with a unit task-productivity.

[13] Empirically, island takes a unit of analysis, including region or occupation class.

[14] Consider robot producers competitively producing robots at marginal cost $q$ in a global capital market.

[15] One could interpret that lower-indexed task (occupation) has higher risk of automation as computed in Frey and Osborne (2017).

[16] Empirically, $H$ is represented by mechanical engineers or production managers, occupation group requiring specialized craft, while $L$ are laborers, where it is not required. See empirical definitions of occupations in Section.4.1.

**Plant's problem**

The plant maximizes profit under the resource constraints as follows.

$$max \eta Y$$

$$s.t.\ \widetilde{L^F} = \int_0^1 l^F(\omega)d\omega,\ \widetilde{L^D} = \int_0^1 l^D(\omega)d\omega,\ \widetilde{H} = \int_0^1 h(\omega)d\omega,\ R = \int_0^1 r(\omega)d\omega$$

The following comparative advantage assumptions are critical to derive the key results.

**Comparative advantage regularities**

**R1 [Labor vs. Robots]**

$\underline{a}^F(\omega), \underline{a}^D(\omega), \overline{a}(\omega)$ *are strictly increasing in* $\omega$.

This captures comparative advantage of every labor over robots for non-routine tasks.

**R2 [High-skilled vs. Low-skilled labor]**

$\dfrac{\overline{a}(\omega)}{\underline{a}^D(\omega)}$ *is strictly increasing in* $\omega$.

High-skilled labor have comparative advantage in non-routine tasks than low-skilled labor.

**R3 [Low-skilled domestic vs. Foreign labor]**

$\dfrac{\underline{a}^D(\omega)}{\underline{a}^F(\omega)}$ *is strictly increasing in* $\omega$.

Low-skilled domestic labor have comparative advantage in non-routine tasks than low-skilled foreign labor. In diagrammatic representation (Figure 3), R1-3 generate differential slopes of task-level marginal cost curves.

## 3.2 Equilibrium under the Steady State

These regularities R1-R3 and some corner conditions[17] described above engender the complete specialization of four production factors, such that each task is covered by each factor.

**Proposition 1. [Complete Specialization of Tasks]**

*The regularities including R1-R3 and (1) are imposed. Then, there exists an automation threshold $\theta \in (0, \widetilde{\theta})$ such that robots cover task $\omega \in [0, \theta]$ and labor covers task $\omega \in (\theta, 1]$. There exists a foreign-domestic threshold task $\phi \in (\theta, 1)$ such that low-skilled foreign labor covers task $\omega \in (\theta, \phi]$ and low-skilled domestic labor cover task $\omega \in (\phi, \psi]$. There exists a skill threshold task $\psi \in (\phi, 1)$ such that low-skilled labor covers task $\omega \in (\theta, \psi]$ and high-skilled labor covers task $\omega \in (\psi, 1]$. $\theta, \phi, \psi$ are characterized by*

$$\underline{a}^F(\theta) = \frac{\underline{w}^F}{q}, \ \frac{\underline{a}^F(\phi)}{\underline{a}^D(\phi)} = \frac{\underline{w}^F}{\underline{w}^D}, \ \frac{\overline{a}(\psi)}{\underline{a}^D(\psi)} = \frac{\overline{w}}{\underline{w}^D}.$$

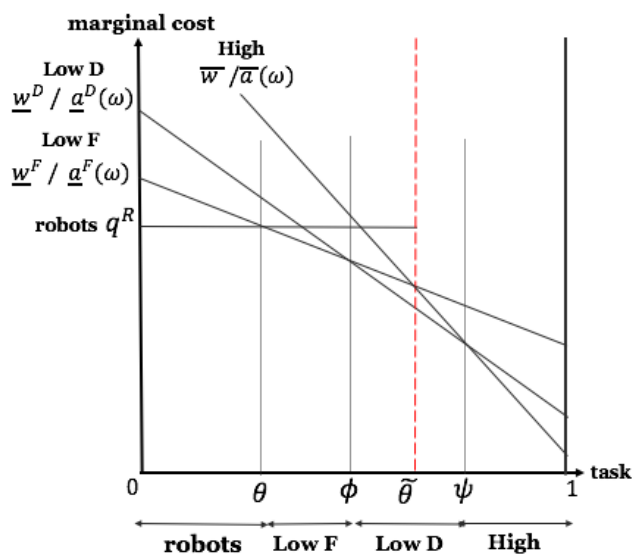


Figure 3: Steady state equilibrium with complete specialization of tasks

The equilibrium under the complete specialization is defined as follows. A representative plant maximizes the profit by optimally matching factors and tasks, by specifying the

[17] To generate single-crossing of marginal cost curves, the following corner conditions are imposed. (For proofs, see Yoshida (2019))

$$\frac{\phi-\theta}{\theta}\frac{1}{\underline{a}(\widetilde{\theta})} < \frac{\widetilde{L}^F}{R} < \frac{\phi-\widetilde{\theta}}{\widetilde{\theta}}\frac{1}{\underline{a}(0)}, \frac{(\phi-\theta)\underline{a}^D(\theta)}{(\psi-\phi)\underline{a}^F(\theta)} < \frac{\widetilde{L}^F}{\widetilde{L}^D} < \frac{(\phi-\theta)\underline{a}^D(\psi)}{(\psi-\phi)\underline{a}^F(\psi)}, \frac{(\psi-\phi)\overline{a}(\phi)}{(1-\psi)\underline{a}^D(\phi)} < \frac{\widetilde{L}^D}{\widetilde{H}} < \frac{(\psi-\phi)\overline{a}(1)}{(1-\psi)\underline{a}^D(1)} \tag{1}$$

automation threshold $\theta$, foreign-domestic threshold $\phi$, and skill threshold $\psi$ under the labor supply constraint.

**Definition 1. [Equilibrium Conditions]**

*The regularities are imposed. Given the comparative advantage schedule* $\underline{a}^F(\omega), \underline{a}^D(\omega), \overline{a}(\omega)$ *with inelastic labor supply and* factor prices $\{\underline{w}^F, \underline{w}^D, \overline{w}, q^R\}$*, the firm in each island maximizes the profit by choosing task thresholds*

$$\theta, \phi, \psi = argmax \eta Y$$

*Factor market clearing:*

$$\widetilde{L^F} = \int_\theta^\phi l^F(\omega)d\omega, \widetilde{L^D} = \int_\phi^\psi l^D(\omega)d\omega, \widetilde{H} = \int_\psi^1 h(\omega)d\omega, R = \int_0^\theta r(\omega)d\omega$$

Following the steps in Yoshida (2019), the equilibrium is characterized by the following closed-form equation.[18]

**Proposition 2. [Equilibrium under the Optimal Task Allocation]**

*Suppose the regularities holds. Then, an equilibrium uniquely exists. The aggregate production is given by*

$$Y = B(\theta, \phi, \psi)(\frac{R}{\theta})^\theta(\frac{\widetilde{L^F}}{\phi - \theta})^{\phi-\theta}(\frac{\widetilde{L^D}}{\psi - \phi})^{\psi-\phi}(\frac{\widetilde{H}}{1-\psi})^{1-\psi}$$

*where*

$$B(\theta, \phi, \psi) \equiv exp[\int_\theta^\phi ln(\underline{a}^F(\omega))d\omega + \int_\phi^\psi ln(\underline{a}^D(\omega))d\omega + \int_\psi^1 ln(\overline{a}(\omega))d\omega]$$

*Wages:*

$$\underline{w}^F = \frac{(\phi - \theta)\eta Y}{\widetilde{L^F}}, \ \underline{w}^D = \frac{(\psi - \phi)\eta Y}{\widetilde{L^D}}, \ \overline{w} = \frac{(1-\psi)\eta Y}{\widetilde{H}}$$

*Robots in operation:*

$$R = \frac{\theta \eta Y}{q}$$

In the islands with inelastic labor supply, the impact on the labor market is shaped by wage responses. Note that wages depend on labor supply, task coverage, and the aggregate production level.

[18] Observe that unit task range yields an aggregate technology with constant returns to scales.

## 3.3 Low-skilled Immigration Entry and Adjustment of Robotization

The following assumption is an intermediate milestone to run the comparative statics below.

**A1 [Sufficient Differentiation between Domestic and Foreign Labor]**

$$\frac{\underline{a}^{F\dot{}}(\theta)}{\underline{a}^{F}(\theta)} \gg 0, \quad \frac{\underline{a}^{D\dot{}}(\phi)}{\underline{a}^{D}(\phi)} \gg \frac{\underline{a}^{F\dot{}}(\phi)}{\underline{a}^{F}(\phi)}, \quad \frac{\overline{a}^{\dot{}}(\phi)}{\overline{a}(\phi)} \gg \frac{\underline{a}^{D\dot{}}(\phi)}{\underline{a}^{D}(\phi)} \tag{2}$$

These conditions ensure that low-skilled domestic labor, low-skilled domestic labor, and robots are sufficiently well differentiated between each other at each task thresholds. (2) states that at the foreign-domestic threshold, the low-skilled foreign and domestic labor are sufficiently differentiated. (2) claims that at the automation threshold, low-skilled foreign labor are sufficiently differentiated from robots.

Now, it is ready to run comparative statics in response to immigration shock. Immigration to the entire economy is regulated by a national policy, and each island takes low-skilled immigrant entry as given. Whenever the marginal effect is considered in the short-run, long-run, and aggregate of short-run and long-run, I write $()_{short}, ()_{long}$ and $()_{agg}$, respectively.

### 3.3.1 Short-run

In the short run, suppose a new wave of low-skilled immigration enters each island, and a plant is not allowed to adjust automation threshold $\theta$.[19] Substitution effect is induced from the mechanical wage shifts from the surge in foreign labor supply.

When comparative advantages conditions (2) are satisfied, the following shifts occur in order. (1) wage drop by immigration shock. (2) scale effect from immigration. (3) Task reallocation between low-skilled domestic and foreign labor, $(\frac{d\phi}{dln\widetilde{L^F}})_{short} > 0$. (4) wage feedbacks from task demand shifts. (5) Task reallocation between low-skilled domestic labor and high-skilled labor, $(\frac{d\psi}{dln\widetilde{L^F}})_{short} > 0$. (the number (0)-(5) corresponds to the Figure 5)

Low-skilled immigrant inflow expands the task coverage, substituting low-skilled domestic labor, because the plant exploits the relative cost advantage of low-skilled foreign labor, driven by competing shifts of wages: immediate drop of low-skilled immigrant wage by labor supply effect, and the instant rise of low-skilled native wage by growth effect.

Under (2), the wage impact on wages from low-skilled immigration entry in the short-run is given by

[19] Textbook economics states that automation (capital) adjustment is delayed than labor adjustments.

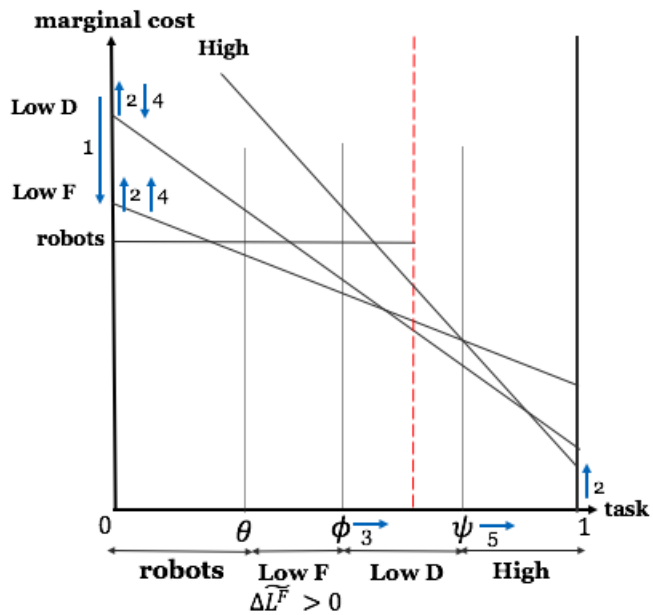


Figure 4: Equilibrium shifts in the short-run

$$(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{short} < 0, \quad (\frac{dln\underline{w}^D}{dln\widetilde{L^F}})_{short} > 0, \quad (\frac{dln\overline{w}}{dln\widetilde{L^F}})_{short} > 0. \tag{3}$$

Thus, low-skilled immigration dampen the wage of the same class, but lifts up the wage of native workers via production boost. The short-run wage shifts induce task reallocation by shifting $\psi$ and $\phi$, which partially counteract the initial wage movements. As long as immigrants and natives are sufficiently differentiated as in (2), it can be shown that their initial wage shifts cannot be offset or reversed by subsequent labor adjustment.

### 3.3.2 Long-run

In the long run, a plant is allowed to tweak the automation level under the common automation frontier, facing the short-run changes of marginal cost curves over tasks.

When A1 (2) are satisfied, the following shifts occur in order. (0) A robot rental price declines. (1) Together with the short-run price drop, automation shifts downwards, and the task range by low-skilled foreign labor expand. (2) Low-skilled immigration wage rises. (3) task reallocation between domestic and foreign labor. (4) Low-skilled native wage rises. (5) task reallocation between low-skilled domestic labor and high-skilled labor. (the number (0)-(5) corresponds to the Figure 5)

**Long-run level of robotization** Suppose a quality-adjusted price of robot $q$ declines, and now, $\theta$ is adjustable in the long-run. Then,

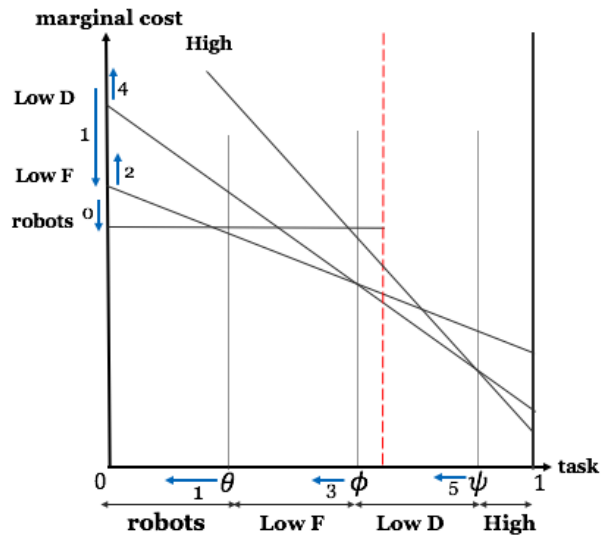


Figure 5: Equilibrium shifts in the long-run

$$(\frac{d\theta}{dln\widetilde{L^F}})_{long} = \underbrace{\frac{\partial\theta}{\partial ln\underline{w}^F}}_{>0}\underbrace{(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{short}}_{<0(3)} < 0 \tag{4}$$

holds. This proposition formalizes the immigration-induced automation. As shown above, low-skilled immigration inflow reduces their wages, with rental price of robots fixed. Thus, the automation gets weakened.

**Long-run wage rebound by adjusted robotization** Suppose $\theta$ is adjustable with the regularities R1-R3 imposed. Then,

$$(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{long} > 0, \quad (\frac{dln\underline{w}^D}{dln\widetilde{L^F}})_{long} > 0, \quad (\frac{dln\overline{w}}{dln\widetilde{L^F}})_{long} > 0$$

holds.

$$(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{long} = (\frac{dlnY}{dln\widetilde{L^F}})_{long} + (\frac{dln(\psi-\theta)}{dln\widetilde{L^F}})_{long} = \underbrace{(\frac{\partial Y}{\partial\theta})_{long}}_{=0}\underbrace{(\frac{d\theta}{dln\widetilde{L^F}})_{long}}_{<0} + \underbrace{(\frac{dln(\psi-\theta)}{dln\widetilde{L^F}})_{long}}_{>0(4)} > 0$$

$$(\frac{dln\underline{w}^D}{dln\widetilde{L^F}})_{long} = (\frac{dlnY}{dln\widetilde{L^F}})_{long} + (\frac{dln(1-\psi)}{dln\widetilde{L^F}})_{long} = \underbrace{(\frac{\partial Y}{\partial\theta})_{long}}_{=0}\underbrace{(\frac{d\theta}{dln\widetilde{L^F}})_{long}}_{<0\ (4)} + \underbrace{(\frac{dln(1-\psi)}{dln\widetilde{L^F}})_{long}}_{>0} > 0$$

$$(\frac{dw^{HD}}{dln\widetilde{L^F}})_{long} = (\frac{dY}{dln\widetilde{L^F}})_{long} = 0$$

Low-skilled immigration wage rises due to task range expansion by weakened automation. High-skilled domestic workers undergo upshifts in wages. In response with the long-run wage rebound in low-skilled immigrants, the relative cost advantage of low-skilled foreign labor diminishes. Consequently, the coverage of low-skilled domestic labor expands back, raising their wage.[20]

### 3.3.3 Testable Predictions

Empirically, short-run and long-run phenomenons are infeasible to distinguish, because a continuous waves of low-skilled immigrants enter the economy, in contrast to one-shot big wave. What is observed is the aggregate impact on wages, the sum of short-run and long-run effects as follows.

**Proposition 3. [Aggregate Impact on Wages]**

*Suppose the regularities R1-R3, (2) are imposed. Then,*

$$(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{agg} < 0, \quad (\frac{dln\underline{w}^D}{dln\widetilde{L^F}})_{agg} > 0, \quad (\frac{dln\overline{w}}{dln\widetilde{L^F}})_{agg} > 0 \tag{5}$$

*holds.*[21]

Thus, the initial wage drop for low-skilled immigrants lingers despite its long-run rebound. As long as robots and immigrants are sufficiently differentiated ((2)), the wage drop in the short run cannot be counterbalanced by long-run automation adjustment. The both native wages rises due to their short-run wage growth by growth effect. Additionally, the low-skilled domestic worker wage rises in the long run as well. Furthermore, the model also generates four testable predictions as follows.

**Corollary 1. [Testable Predictions]**

---

[20] Rigorously, another wage shift takes place after the task reallocation. However, the further chain-reaction adjustment after the task reallocation is second-order, thus, omitted.

[21] This is because (2) implies that

$$(\frac{dln\underline{w}^F}{dln\overline{L^F}})_{agg} = \underbrace{(\frac{dln\underline{w}^F}{dln\overline{L^F}})_{short}}_{\ll 0} + \underbrace{(\frac{dln\underline{w}^F}{dln\overline{L^F}})_{long}}_{>0} < 0 \; (\frac{dln\underline{w}^D}{dln\overline{L^F}})_{agg} = \underbrace{(\frac{dln\underline{w}^D}{dln\overline{L^F}})_{short}}_{\gg 0} + (\frac{dln\underline{w}^D}{dln\overline{L^F}})_{long} > 0, \; (\frac{dln\overline{w}}{dln\overline{L^F}})_{agg} = \underbrace{(\frac{dln\overline{w}}{dln\overline{L^F}})_{short}}_{>0}$$

holds.

*Suppose the regularities R1-R3. Then, under (2),*

,

$$(\frac{dln(\underline{w}^F/\underline{w}^D)}{dln\widetilde{L^F}})_{agg} < 0 \text{ (ethnic inequality in wages)} \tag{6}$$

$$\frac{dln\{R/(L^D + L^F)\}}{dln\widetilde{L^F}} < 0 \text{ (robot density)} \tag{7}$$

$$\frac{dln\{Y/(L^D + L^F + H)\}}{dln\widetilde{L^F}} < 0 \text{ (labor productivity)} \tag{8}$$

*holds. Moreover,*

$$\frac{dln\{(\underline{w}^F L^F + \underline{w}^D L^D + \overline{w} H^D)/Y\}}{dln\widetilde{L^F}} > 0 \text{ (low-skilled labor share)} \tag{9}$$

*unambiguously holds.*

(6)-(9) characterize the effect of low-skilled immigration. (6) represents expanding foreign-domestic wage inequality, which is an immediate corollary of (5). (7) captures a negative impact on robot density. (8) states that labor productivity rises with low-skilled immigration entry. (9) indicates that labor share unambiguously rises with low-skilled immigration entry. This is directly attributable to the result that automation level shifts downward, because labor share is negatively proportional to the automation threshold.[22] I test these predictions separately across regions (Section.5) and occupations (Section.6).

# 4 Empirical Design

## 4.1 Data

**Immigration and labor** This paper employs Integrated Public Use Microdata Samples (IPUMS (2019)) of the Decennial Census for the 1980, 1990, and 2000 and American Community Survey for every year from 2005 to 2015[23]. The analysis is restricted to working-age individuals aged from 16 to 64 without full-time students. Individuals are low-skilled if their education attainment is high school diplomas and below. The rest of the individuals are high-skilled. Following Borjas (2003), an immigrant is defined as foreign-born non-citizen including naturalized citizens and natives are the rest of the people in the U.S.

[22]The model negatively links labor share with automation intensity such that $(\underline{w}^F\widetilde{L^F}+\underline{w}^D\widetilde{L^D}+\overline{w}\overline{H^D})/Y = 1-\theta$.

[23]For 2001-2004, no detailed geographic information (public-use metropolitan area, PUMA), is available to be connected with CZs. These years are dropped from the analysis.

**Industrial robots** I draw on World Robotics Database by IFR (2015), documenting sales and imputed stocks across countries, industries and applications of robots.[24] IFR (2015) defines an industrial robot as *"an automatically controlled, reprogrammable, and multipurpose [machine]"*. Although this definition excludes other types of capitals which could be labor-replacing, the definition permits consistent measurement of industrial robots across units of analysis.[25]

Two caveats on the industrial robot data are worth noting. First, IFR (2015) only covers industrial robots in manufacturing, construction and agriculture, presumably because the service robots (e.g. robots of transportation, care giving, receptionist, personal care) are still in the infancy.[26] Second, the data covers *general purpose* robots, excluding *dedicated industrial* robots.

IFR (2015) delivers robot stock datasets by U.S. industry-level only after 2004. To construct an industry-level industrial robot operation stocks in these three sectors throughout the period of 1980-2015, I crosslink the IFR robot data and industry-level physical capital in National Income and Product Accounts (NIPA) from Bureau of Economic Analysis (BEA), predominantly used in macro economics. Yoshida (2019) finds that IFR robots data is most likely captured by a unique combination of *metal working machines* and *special-industry machines* in BEA. Founded the correlation between installations of industrial robots in IFR and capital investments in BEA, I use non-parameteric method to backcast missing data in previous years, 1980-2003, accompanied by cross-validation exercises.

## 4.2 Identification Strategy

I estimate the impact of low-skilled immigration on robotization, their joint impacts on wages, by exploiting the large variation of evolutions in low-skilled immigration inflow across units (regions or occupations). In reality, however, immigration inflow to each unit is far from random so that self-selection of immigration are likely to be correlated with unobserved determinants of robotization and wages. To address this endogeneity, I adopt an instrumental variable strategy, constructing ethnic-driven immigration labor supply shocks. (Altonji

[24]The data is recently used in robotization literature, including Graetz and Michaels (2017), Acemoglu and Restrepo (2017) and Presidente (2017).

[25]For example, in agriculture, tractors are not included as robots.

[26]IFR issues another version of service robots, but the numeric information is scarce compared to industrial robots.

and Card (1991) and Card (2001)) [27]The idea is that self-selection of immigrants is substantially influenced by existing agglomeration of ethnic enclaves. The instrument exploits the residential preference of immigrants for a large enclave of immigrants from the same ethnic group. Immigration networks play substantial roles in their location or occupation choices of incoming immigrants because these networks facilitate the job search process and assimilation to the new culture, especially when the workers have relatively poor social status (e.g. low education attainment or no professional licenses in the host country) and no employment history in a host country. (Munshi (2003)) Operationally, the instrument allocates new waves of immigrants of each ethnic group, based on the historical distribution of the same ethnic group across regions or occupations in 1940. Formally, the instruments in unit $z$ and year $t$ from the base year $t_0$ based on an ethnic mix in the reference year $\underline{t}$ that predates $t_0$ can be written as

$$IV = \Sigma_{e \in E} \frac{L^e_{z,\underline{t}}}{L^e_{\underline{t}}} \frac{\Delta L^e_t}{L^D_{t_0} + L^F_{t_0}}$$

where $E$ is a set of ethnic groups in the reference period $\underline{t} = 1940$ and $\Delta$ captures from the change in period $t$ from the baseline period $t_0 = 1980$.[28] $\frac{L^e_{z,\underline{t}}}{L^e_{\underline{t}}}$ captures the settlement share of unit $z$ of ethnic group $e$ population in $\underline{t}$.

The two identification conditions, exogeneity and exclusion restriction are imposed. The exogeneity necessiates that the unobserved factors attracting immigrants to unit $z$ in $\underline{t}$ are orthogonal to changes in the relative economic incentives offered by the two zones in the following periods. Exclusion restriction requires that the only channel through which immigrant distribution in $\underline{t}$ affects robot adoption after $t \geq t_0$ is its effect on the actual distribution of low-skilled immigrants across units. Analogous to the regional-level selection, the immigration entry to each occupation is endogenous. Although the method is traditionally used in regional units, I apply the aforementioned identification strategy into occupation level.[29]

[27]The strategy with the instrument is predominantly used in the immigration literature. See Jaeger, Ruist and Stuhler (2018)for an extensive list of literatures.

[28]Ethnic groups included in the Census 1940 are: Mexico, Central America, Central Europe, South America, Caribbean, India, China, Philippines, Africa, Vietnam, Japan and East Asia, Canada and Other North America, UK and Ireland, Southern Europe, Cuba, Middle East, Other Southeast Asia, Korea, Other Southwest Asia, Western Europe, Australia and New Zealand and Northern Europe. (ordered by working-age population)

[29]The historically immigrant-intensive occupations typically attract the immigrants more because of cheaper entry cost of the occupations. (Ottaviano and Peri (2008))

### 4.3 Econometric Specification

The main econometric specification comes from (7) in Corollary 1. The simplest main specification is formulated as

$$log(\frac{\Delta R_{z,t}}{L^D_{z,t} + L^F_{z,t}}) = \alpha log(\frac{\Delta \widetilde{L^F_{z,t}}}{\widetilde{L^D_{z,t}} + \widetilde{L^F_{z,t}}}) + \epsilon_{z,t}.$$

for unit $z$ and year $t$. The outcome variable is robot units per routine labor employment. Since the automation threshold $\theta$ is unobservable in data, the technical change is gauged by automation-embodying capitals, in particular, robot $R$. The main explanatory variable is increase of low- skilled immigrant workers relative to low-skilled labor force during the period from $t$ to $t+1$ in the sector of interest.[30] The prediction of $\alpha < 0$, a negative robotization elasticity of immigration, would empirically support the hypothesis of immigration-induced automation.

## 5 Regional-level Analysis

### 5.1 Data and Specification

The period of the analysis spans from 1980 to 2015, covering the prominent immigration boom from Mexico, due to the Peso Crisis in 1994. As a geographic unit of analysis, I use Commuting Zones (CZ) (Tolbert and Sizer (1996))[31] Compared to traditionally-used regional units, Metropolitan Statistical Areas (MSAs), CZ yields two payoffs. Firstly, it has 722 regional variation covering the U.S. mainland, in contrast to approximately 220 MSAs. Secondly, CZ is geographically consistent over time by design, while MSA underwent frequent adjustment of boundaries. To map the CZs onto the geographic units in Census, and ACS, I draw on crosswalks with connection weights from Dorn (2009), respectively bridging 1990 CZs and Census County Groups in 1980, Public Use Micro Areas (PUMAs) in 1990 and after.

[30] Card and Peri (2016) suggest a potential drawback on the traditionally used measure of a difference of immigrant labor ratio between different periods. $(\frac{\Delta \widetilde{L^F_{z,t+1}}}{\widetilde{L^D_{z,t+1}} + \widetilde{L^F_{z,t+1}}} - \frac{\Delta \widetilde{L^F_{z,t}}}{\widetilde{L^D_{z,t}} + \widetilde{L^F_{z,t}}})$ I follow Card and Peri - type ratio, although both indices are highly correlated and the choice does not affect the result.

[31] Autor and Dorn (2013), Autor, Dorn and Hanson (2013) employ CZs.

**Translate robots in industry-level into regional-level** Following the linking strategy founded by the model, CZ $l$' s labor income share in industry $g$ is to be used as informative weights to translate industry-level robot data into regional proxies. CZ $l$ in year $t$ from the base year $t_0 = 1980$ is given by

$$\frac{\Delta R_{l,t}}{L^D_{l,t} + L^F_{l,t}} = \frac{\Delta R_{l,t}}{L_{l,t}} = \frac{\Sigma_g \Delta R_{l,g,t}}{L_{l,t}} = (\Sigma_g \frac{\underline{W}_{l,g,t_0}}{\underline{W}_{g,t_0}} \Delta R_{g,t})/L_{l,t} = \Sigma_g \frac{\underline{W}_{l,g,t_0}}{\underline{W}_{g,t_0}} \frac{\Delta R_{g,t}}{L_{l,t}}$$

where $g$ is industry code in IFR and $\underline{W}_{l,t}$ is labor income for routine occupation workers in CZ $l$, industry $g$, and in year $t$ is defined as

$$\underline{W}_{l,t} \equiv \underline{w}^F L^F_{l,t} + \underline{w}^D L^D_{l,t}$$

The third equality holds, because by the model's prediction, for all $g$,

$$\frac{R_{l,g,t_0}}{R_{l',g,t_0}} = \frac{\theta_{l,g,t_0} Y_{l,g,t_0}}{\theta_{l',g,t_0} Y_{l',g,t_0}} = \frac{Y_{l,g,t_0}}{Y_{l',g,t_0}} = \frac{\underline{W}_{l,g,t_0}}{\underline{W}_{l',g,t_0}}$$

holds. Thus,

$$\Delta R_{l,g,t} \approx \frac{\underline{W}_{l,g,t_0}}{\Sigma_l \underline{W}_{l,g,t_0}} \Sigma_l \Delta R_{l,g,t} = \frac{\underline{W}_{l,g,t_0}}{\underline{W}_{g,t_0}} \Delta R_{g,t}$$

holds. At the baseline year ($t = t_0$) before the immigration boom, the automation threshold $\theta_{l,g,t_0}$ in industry $g$ is common across regions $l$ such that

$$\theta_{l,g,t_0} = \theta_{l',g,t_0} \ (\forall\, l \neq l'),\ \underline{W}_{l,g,t_0} = (\psi_{g,t_0} - \theta_{l,g,t_0}) \eta Y_{l,g,t_0}$$

holds. Figure 6 graphically shows the relationship between rise in low-skilled immigration and industrial robot adoption in 1980-2015.

Now, I test a pair of two econometric equations, capturing immigration-induced automation. $y \in \{\frac{R_{l,t}}{L^D_{l,t} + L^F_{l,t}}, w^a\}$where $a \in \{LF, LD, H\}$

$$log(y_{l,t}) = \alpha log(\frac{\widetilde{L^F_{l,t}}}{\widetilde{L^D_{l,t}} + \widetilde{L^F_{l,t}}}) + \zeta_{s,t} + \epsilon_{l,t} \tag{10}$$

where $l$ is CZ, year $t \in \{1980, 1990, 2000, 2004 - 2015\}$, and $\zeta_{s,t}$ is a state-year fixed effect. Setting $y = \frac{R_{l,t}}{L^D_{l,t} + L^F_{l,t}}$ explores the impacts of low-skilled immigration on industrial robots, embodying the automation. Taking $y = w^a$, I regress the wage for each class of labor with the low-skilled immigration.

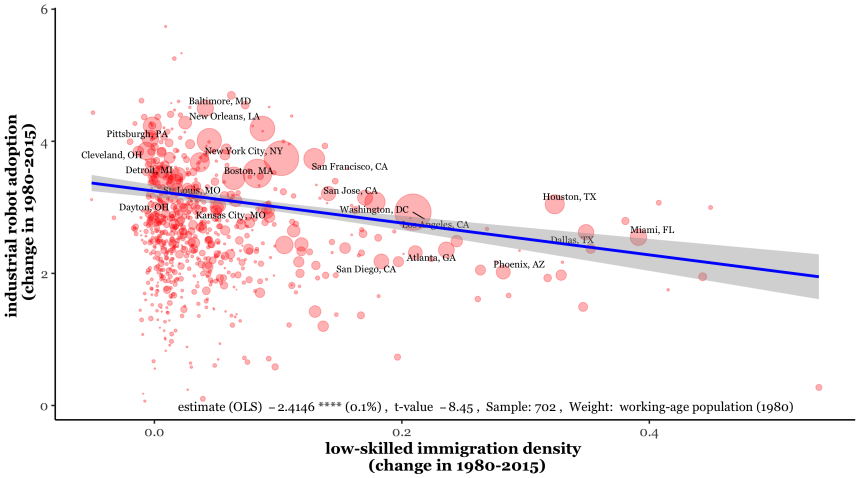


Figure 6: Low-skilled immigration inflow and robot adoption by CZs in the U.S. (1980-2015)
*Notes:* Computed from the Population Census, American Community Survey and IFR (2015). Years included: 1980, 1990, 2000, 2005-2015. Low-skilled immigration ratio is computed by a ratio of low-skilled immigrants per CZ labor force. Robot density is log of industrial robot units per 10,000 production workers in the manufacturing, construction and agriculture. For derivation of CZ-level robot density, see Section.5.1.

## 5.2 Results

**Robot adoption** I regress the robots per routine working hours with respect to immigration inflow across CZ in each sector. Identification conditions and instrument construction follows Section 4. $\alpha < 0$ in manufacturing empirically backs up the hypothesis of immigration-induced automation. The main specification (6) in Table 1 finds that 1 percentage point increase in immigrant ratio drives 0.2 percentage drop in robot density. The results supports (2), in that immigrants and natives are well-differentiated.

The impact of low-skilled immigrants are contrasted with other class of labors with the same skill level and ages: native blacks and immigrants from English-speaking countries. The impacts are robust, but weaker, supporting my core assumption of sufficient differentiation between low-skilled immigrants and natives. Immigrants from non-English speaking countries (e.g. Mexico and South America) have substantially weaker language proficiency than both native blacks, and supposedly, immigrants from English-speaking countries (e.g. Canada, the UK, India, Philippines). [32] Their linguistic disadvantage leads to a smaller choice set of occupations, forming a poor bargaining power with fewer outside options. Natives and immigrants with proficient English ability would have wider outside options of communication-intensive service jobs (e.g. call center agents, clerk workers).

[32]This is alined with the long-run trend that immigrants disproportionately work in manufacturing, construction and agriculture and STEM sectors, where non-language intensive occupations are more abundant.

Table 1: Immigration inflow and automation adoption (1980-2015)

| | OLS | | | IV | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Low-skilled Immigrants | -33.7 *** | -30.8 | -11.1 *** | -27.4 *** | -64.0 * | -24.8 *** |
| | (5.73) | (21.4) | (2.37) | (5.43) | (37.1) | (4.31) |
| Share of Low-skilled Black natives | 2.2 | 18.8 | -6.96 * | -91.0 ** | 78.1 * | -23.3 * |
| | (3.17) | (11.9) | (4.05) | (36.6) | (45.5) | (13.4) |
| Fixed effects: | | | | | | |
| czone + year fixed effects | No | Yes | No | No | Yes | No |
| state × year fixed effects | No | No | Yes | No | No | Yes |
| Adjusted R-squared | 0.046 | 0.791 | 0.721 | 0.044 | 0.790 | 0.718 |
| Observations | 8,652 | 8,652 | 8,652 | 8,652 | 8,652 | 8,652 |

*Notes:* years (1980,1990, 2000, 2004-2015) × 721 CZs. (excluding New Orleans) All models include an intercept and are weighted by employment hours in each period. Standard errors clustered at the state × year level are reported in parentheses.
*** p<1 %; ** p<5 %; * p<10 %

**Impact on wages** The model indicates that low-skilled immigration entry lowers the foreign routine wage and raises the domestic routine wages. I find the decline in foreign routine wages and rise in domestic routine wages, consistent with the model prediction under sufficient foreign-domestic comparative advantage.

The specification (1), (2) and (6) in Table 2 corresponds with predictions provided in Proposition . An average wage for low-skilled production workers is given by

$$w^{mean} = \frac{\underline{w}^F L^F + \underline{w}^D L^D}{L^F + L^D} = \gamma \underline{w}^F + (1-\gamma)\underline{w}^D \ (\gamma \equiv \frac{L^F}{L^F + L^D}).$$

$$\begin{aligned}\frac{dlnw^{mean}}{dln\widetilde{L^F}} &= \frac{1}{\gamma \underline{w}^F + (1-\gamma)\underline{w}^D}\{(\frac{d\gamma}{dln\widetilde{L^F}}\underline{w}^F + \gamma\frac{d\underline{w}^F}{dln\widetilde{L^F}}) + (\frac{d(1-\gamma)}{dln\widetilde{L^F}}\underline{w}^D + (1-\gamma)\frac{d\underline{w}^D}{dln\widetilde{L^F}})\} \\ &= \{\gamma \underline{w}^F \underbrace{\frac{dln\underline{w}^F}{dln\widetilde{L^F}}}_{>0} + (1-\gamma)\underline{w}^D \underbrace{\frac{dln\underline{w}^D}{dln\widetilde{L^F}}}_{>0} - \gamma(1-\gamma)\underbrace{(\underline{w}^D - \underline{w}^F)}_{\text{initial gap}>0}\}/w^{mean}\end{aligned}$$

The elasticity of low-skilled immigration entry is a weighted average of elasticities to wage of each class net of initial wage gap. It depends on the initial share $\gamma$ and initial wage $\underline{w}^F$. If the initial foreign labor share (captured by $\gamma \underline{w}^F$) is large, the aggregate impact is heavily driven by the immigration wage drop.

This results potentially conflict with a part of earlier works. The negative results appear

Table 2: Low-skilled immigration's impacts on wages

| | | Routine occupations | | | Non-routine occupations | | |
|---|---|---|---|---|---|---|---|
| | state × year | immigrant | native | aggregate | immigrant | native | aggregate |
| Estimation | fixed effect | (1) | (2) | (3) | (5) | (6) | (7) |
| OLS | No | -0.487 *** | 0.447 *** | -0.449 *** | -0.247 ** | 1.143 *** | 0.502 *** |
| | | (0.080) | (0.074) | (0.053) | (0.101) | (0.086) | (0.066) |
| | Yes | -0.473 *** | 0.625 *** | -0.167 ** | -0.473 *** | 0.625 *** | 0.635 *** |
| | | (0.132) | (0.074) | (0.065) | (0.132) | (0.074) | (0.063) |
| IV | No | -0.811 *** | 0.899 *** | -1.099 *** | -0.811 *** | 0.899 *** | 0.556 ** |
| | | (0.103) | (0.217) | (0.116) | (0.103) | (0.217) | (0.196) |
| | Yes | -2.467 *** | -0.04 | -2.738 *** | -2.205 ** | 1.369 *** | -1.144 * |
| | | (0.416) | (0.539) | (0.502) | (0.754) | -(0.374) | (0.609) |

*Note:* Independent Variable: log (low-skilled immigrant employment / total employment). Dependent Variable: log (target labor force / total labor force) N=10,094 (12 time periods (1980, 1990, 2000, 2005-2015) × 721 CZs). Samples with zero low-skilled immigration ratio are excluded. All models include an intercept and are weighted by employment in each period. Standard errors clustered at the state × year level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

to come from my focus on foreign laborer in the sectors of manufacturing, construction and agriculture.[33]

# 6 Occupational-level Analysis

In the model, the routine occupation consists of an interval of relatively routine tasks. In reality, the routine occupation category includes a list of occupations, specialized in a unique production operation. In this section, I split the routine occupation into finer occupation categories to examine whether immigration entry to occupation impedes adoption of industrial robots, which might be labor-replacing in the occupations.

**Link occupations and industrial robot applications** IFR (2015) records industrial robot stocks by engineering application in production operation. To uncover a correspondence between immigration density and robot adoption by occupation level, I link occupation categories and robot applications via task characters as follows. I aggregate up the engineering application codes of industrial robots in 2004-2015 from IFR (2015) into eight major task categories: moulding, machine tending, final product handling, welding, painting, pro-

[33]In this vein in local service workers (e.g. care-givers, housekeepers), Cortes (2008) and Cortes and Tessada (2011) found that low-skilled immigrants entry reduces the similarly-skilled native wages.

cessing, assembling and cleaning. Then, based on occupation descriptions for production workers from ONET, Bureau of Labor Statistics (BLS), I manually construct a crosswalk between production worker occupations in manufacturing and robot in each application.[34]

Table 3: Correspondence between occupations and industrial robot applications

| Occupation (ONET) | | Task | | Industrial Robot (IFR) | |
|---|---|---|---|---|---|
| **ID** | **Occupation (example)** | **Task ID** | **Category** | **ID** | **Application** |
| 8040 | Metal Furnace Operators, Tenders, Pourers, and Casters | 1 | **Moulding** | 111 | Handling operations for metal casting |
| 8100 | Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic | | | 112 | Handling operations for plastic moulding |
| | | | | 113 | Handling operations for stampinglorgingi bending |
| 7940 | Rolling Machine Setters, Operators, and Tenders, metal and Plastic | 2 | **Machine tending** | 114 | Handling operations at machine tools |
| 8310 | Pressers, Textile, Garment, and Related Materials | | | 115 | Machine tending for other processes |
| 8740 | Inspectors, Testers, Sorters, Samplers, and Weighers | 3 | **Final product handling** | 116 | Handling operations for measurement, inspection, testing |
| 8800 | Packaging and Filling Machine Operators and Tenders | | | 117 | Handling operations for palletizing |
| | | | | 118 | Handling operations for packaging, picking and placing |
| 8140 | Welding, Soldering, and Brazing Workers | 4 | **Welding** | 160 | Welding and soldering (all materials) |
| 8810 | Painting Workers and Dyers | 5 | **Painting** | 170 | Dispensing |
| 8650 | Crushing, Grinding, Polishing, Mixing, and Blending Workers | 6 | **Processing** | 190 | Processing |
| 7720 | Electrical, Electomics, and Electronmechanical Assembers | 7 | **Assembling** | 200 | Assembling and disassembling |
| 8300 | Laundry and Dry-Cleaning Workers | 8 | **Cleaning** | 301 | Cleanroom for FPD |
| 8860 | Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders | | | 302 | Clcanroom for semiconductors |
| | | | | 303 | Cleanroom for others |

*Notes*: I split handling operations (auxiliary operation aside from the main production process) into three categories: welding, moulding and machine tending.

Some caveats on cross-linking are worth noting. Firstly, guided by the model, I focus on the workers directly engaged in production process, excluding non-routine occupation workers, who are immune from the direct threat of automation. Secondly, I also exclude some artisan-type occupations because the task description was widespread so that one-on-one connection with a particular type of robots is difficult.

Figure 7 illustrates how the immigration increase from 1980 affects the industrial robot density at 2014.[35] I find a negative link between the immigrant ratio and robot density, captured by robot units per production worker. The within-production process analysis in occupation level provides deeper support to support my hypothesis of immigrant-induced automation.

[34]Rigorous description of occupation task contents from ONET helps mapping production occupations and the eight major tasks.

[35] Aggregate industrial robots stocks in 1980 in IFR (2015) are sufficiently small, so plausibly set zero.

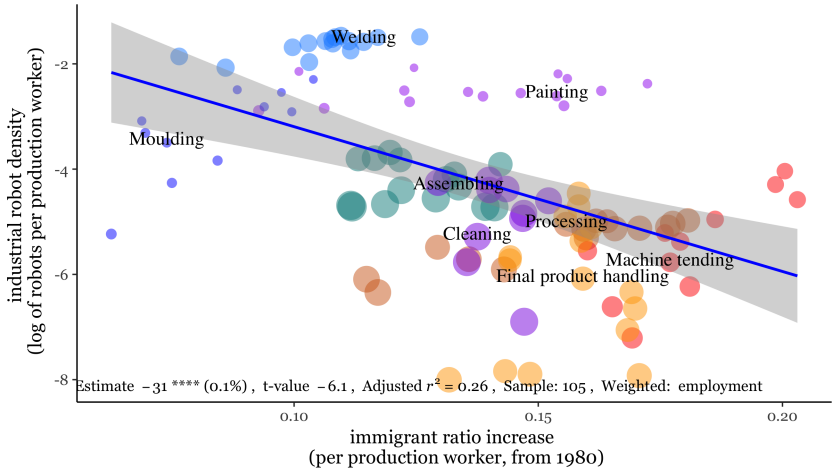


Figure 7: Immigration entry and robot adoption by occupation class in the U.S. manufacturing

*Notes*: Author's cross-linking from occupation codes in O*NET and robot application codes in IFR (2015). (Table.3) Immigration ratio is computed by a ratio of immigrants per employment by each occupation. Robot density is robot units per employment in each occupation.

# 7 Concluding Remarks

In this paper, I examine whether low-skilled immigration entry impedes production automation, particularly by industrial robots. By employing the instrumental variable strategy on historical immigrant presence to industrial robot adoption in regional and occupation levels in the U.S, I find that 10,000 inflow of low-skilled foreign labor force lowers 2.4 industrial robot units. A simple task-based model indicates that sufficient differentiation of low-skilled foreign labor to comparably educated domestic labor rationalizes the patterns. The assumption appears to be plausible in other advanced economies, including E.U. countries, where low-skilled immigrants (or refugees) from less developed economies are substantially distinct from equally-educated host country labor in terms of education and ages (and related work experiences). The other series of testable predictions are consistent with data.

Although the exercise does not include general equilibrium consideration, the result suggests that contractive immigration policies (e.g. limitation of admission quota) would induce a consequence of unintended routine labor immiseration and rising inequality, spurred by long-run intensified robotization.[36]

Lastly, the focus on manufacturing, construction and agriculture stems both from prominent presence of immigration, but also bounded by the availability of industrial robot

[36]Using a structural approach, a companion paper, **?** explores a welfare implication, allowing for flexible cross-factor substitution schedules.

datasets. The promising avenue would be routine manual service occupations, which entails one of the highest immigration densities, and are increasingly susceptible to looming automation technology.[37] Mirrored by the solid expansion of the routine service occupations, the analysis appears intriguing.

[37]Notable examples include dichotomies between professional drivers vs. self-driving taxies and trucks, caregivers vs. nursing robots, and janitors vs. cleaning robots.

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# Contents

# A Appendix

## A.1 Educational attainment and age across nativities

Foreign labor is less educated than domestic labor. (Figure A.1, left) While high-school diploma (12 year education) is a mode in both classes of labor, a distribution of foreign labor is significantly left-skewed. Foreign labor has a wider share in prime-aged (aged 31-50) labor force than domestic labor. (Figure A.1, right)

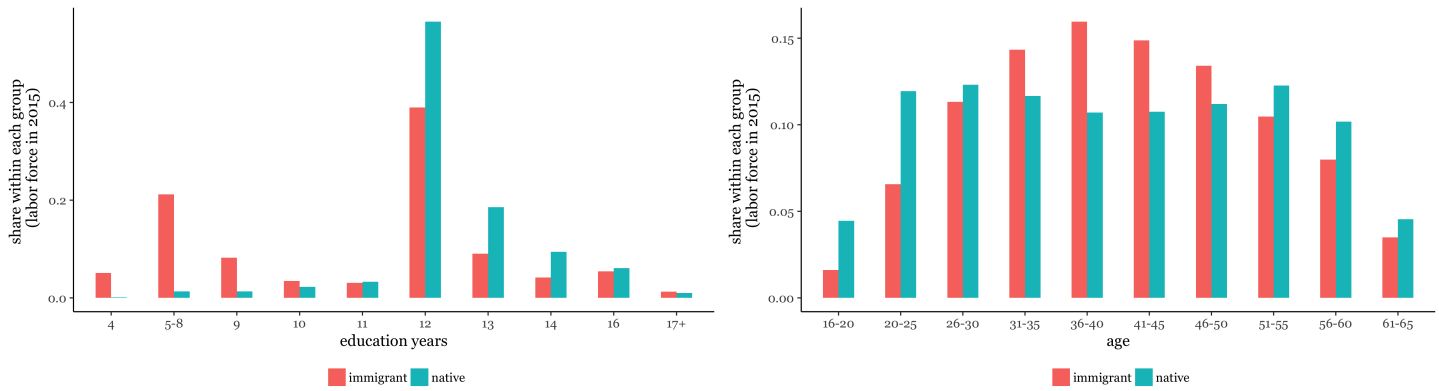


Figure A.1: Distribution of educational attainment (left), age (right): foreign vs. domestic labor (2015)

*Notes*: Computed from ACS, 2015. Focused on manufacturing, construction and agriculture.

## A.2 Foreign-domestic employment ratio by occupations in the U.S.

Agriculture, construction and production workers (blue-collar) in manufacturing exhibits a highest immigrant employment share.

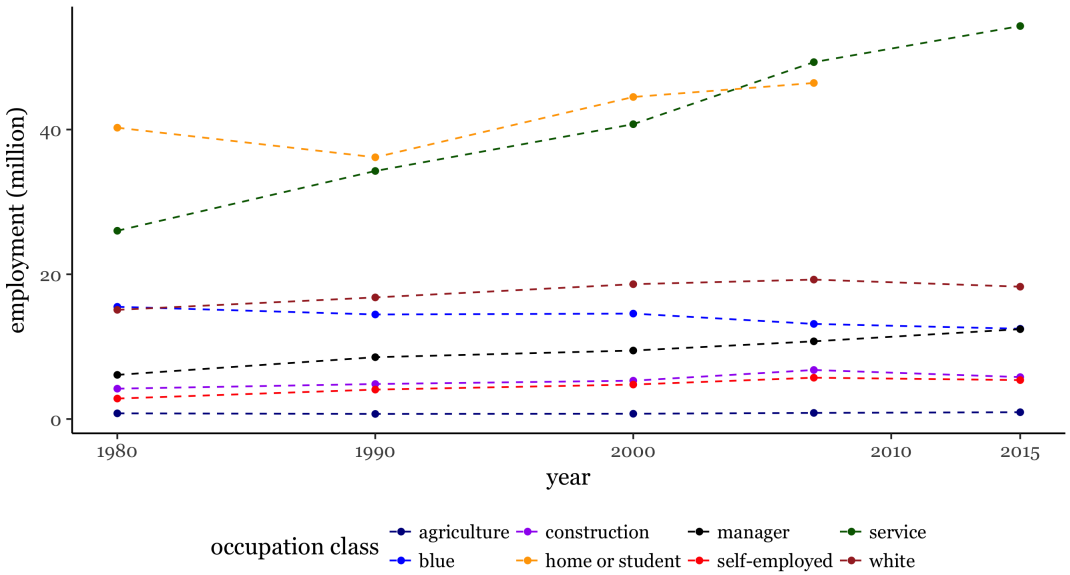


Figure A.2: Foreign-domestic employment ratio by occupations in the U.S. (1994-2015)
*Notes*: Computed from Current Population Survey via IPUMS (2019). Occupation category is classified according to the harmonized variable of "occ2010". *Blue* indicates production workers in manufacturing. *white* represents clerk workers. Self-employed workers are excluded. In the year 1993 and before, CPS does not contain *birthplace*, thus excluded.

## A.3 Occupation automatability and foreign presence

Immigration presence across the spectrum of occupations along the non-routineness in 2015 for production workers is presented. Figure A.3 illustrates sharply contrasting presence of foreign labor in the occupation spectrum among production workers. To appropriately map the model into empirics, non-routineness in occupation is proxied by one minus computerizable probability crafted in Frey and Osborne (2017). (used in Figure A.3, A.1)[38] Foreign labor is characterized by contrasting concentration along the occupation spectrum; among the production occupations, routine class of occupations are, on average, immigration-intensive.

[38] Frey and Osborne (2017) cover both production workers and non-production workers across sectors. A purely technical feasibility for automation is systematically codified in a form of numeric index, based on interviews to technology experts. Peri and Sparber (2009) document immigration presence across occupation spectrum along task routineness, crafted from characteristics codified in ONET. They show that immigrants agglomerate relatively in manual and analytically intensive occupations. Automation probability from Frey and Osborne (2017) and the task characteristics from ONET are found to be strongly correlated.

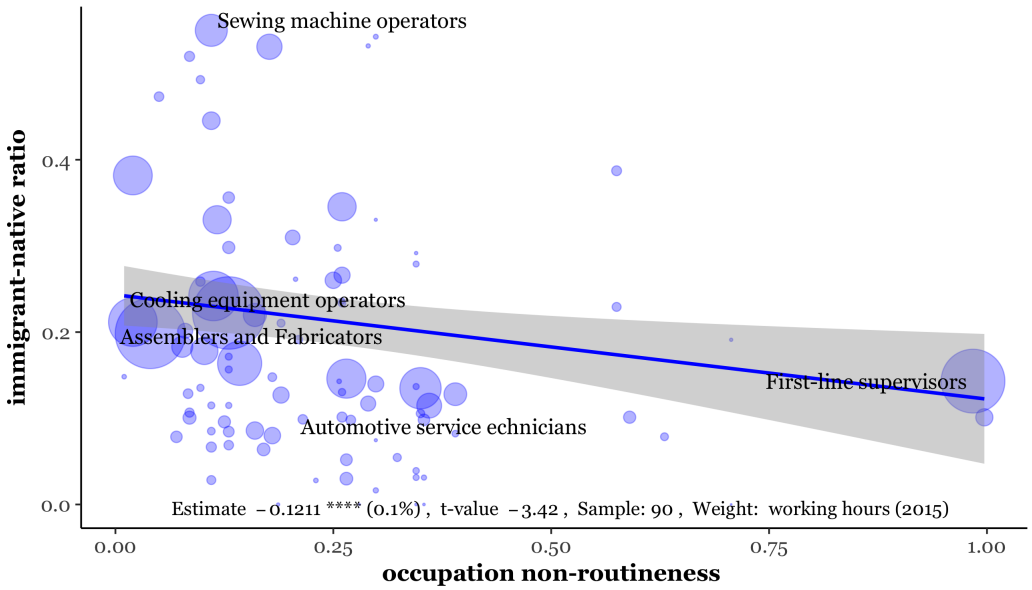


Figure A.3: Occupation non-routineness and immigrant-native ratio (2015) (production workers in manufacturing sector)

*Note:* Production workers are detected from *occ2010* in ACS, 2015. The bubble size captures working hours in 2015. Shaded areas are 99% confidence intervals.

The following table lists up the most and least non-routine occupations, and records immigrant-native ratio, computed by working hours. In 92 production occupations, the average foreign-domestic ratio in top 10 is 0.123 and is 0.211 in bottom 10.

Table A.1: Top/Bottom 10 non-routine occupations and foreign-domestic ratio (2015, production workers)

| non-routine ranking | non-routineness | occ2010 | employment (2015) | immigration ranking | foreign-domestic ratio |
|---|---|---|---|---|---|
| 1 | 0.997 | First-Line Supervisors of Mechanics, Installers, and Repairers | 310,319 | 80 | 0.088 |
| 2 | 0.984 | First-Line Supervisors of Production and Operating Workers | 1,046,961 | 50 | 0.141 |
| 3 | 0.707 | Telecommunications Line Installers and Repairers | 183,692 | 71 | 0.102 |
| 4 | 0.707 | Electrical Power-Line Installers and Repairers | 133,895 | 88 | 0.064 |
| 5 | 0.630 | Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders | 17,727 | 30 | 0.203 |
| 6 | 0.590 | Structural Metal Fabricators and Fitters | 35,067 | 76 | 0.095 |
| 7 | 0.575 | Upholsterers | 36,787 | 9 | 0.338 |
| 8 | 0.575 | Textile, Apparel, and Furnishings workers, nec | 26,028 | 15 | 0.315 |
| 9 | 0.390 | Computer Control Programmers and Operators | 112,602 | 62 | 0.121 |
| 10 | 0.390 | Water Wastewater Treatment Plant and System Operators | 92,883 | 89 | 0.060 |

| routine ranking | non-routineness | occ2010 | employment (2015) | immigration ranking | foreign-domestic ratio |
|---|---|---|---|---|---|
| 1 | 0.010 | Photographic Process Workers and Processing Machine Operators | 34,966 | 67 | 0.104 |
| 2 | 0.020 | Inspectors, Testers, Sorters, Samplers, and Weighers | 1,036,717 | 32 | 0.186 |
| 3 | 0.020 | Packaging and Filling Machine Operators and Tenders | 434,374 | 7 | 0.362 |
| 4 | 0.040 | Assemblers and Fabricators, nec | 1,427,682 | 31 | 0.197 |
| 5 | 0.050 | Jewelers and Precious Stone and Metal Workers | 51,956 | 6 | 0.369 |
| 6 | 0.070 | Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders | 31,104 | 84 | 0.076 |
| 7 | 0.077 | Crushing, Grinding, Polishing, Mixing, and Blending Workers | 118,651 | 35 | 0.181 |
| 8 | 0.080 | Cabinetmakers and Bench Carpenters | 54,300 | 28 | 0.209 |
| 9 | 0.083 | Prepress Technicians and Workers | 30,083 | 54 | 0.137 |
| 10 | 0.085 | Sawing Machine Setters, Operators, and Tenders, Wood | 42,874 | 69 | 0.103 |

*Notes*: Ranking is made based on 92 production occupations. (2 occupations are excluded due to lack of Frey-Osborne index)

## A.4 Cross-country analysis

This section documents a data description and manipulation in a country-level analysis in Figure 1. The cross-country robot data is constructed by combining a print version (physical book, 1981-1992) and a digital version (1993-2015) of the World Robotics Database from IFR (2015). Given my emphasis on differentiation between foreign and domestic labor, I focus on advanced countries, many of which are OECD. The data of Canada (2011-2015) and Russia (1993-2003) looks unreliable, and are excluded.

TableA.2 summarizes the cross-country data.

Table A.2: Cross-country data availability

| ranking | name | code | print version | diginal version | robot stock (2015) | ranking | name | code | print version | diginal version | robot stock (2015) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | **Japan** | JPN | 1981-1992 | 1993-2015 | 286,554 | 23 | Finland | FIN | 1981-1992 | 1993-2015 | 4,124 |
| **2** | **USA** | USA | 1981-1992 | 1993-2015 | 234,245 | 24 | South Africa | ZAF | NA | 1999-2015 | 3,604 |
| **3** | **Canada** | CAN | 1981-1992 | NA | NA | 25 | Portugal | PRT | NA | 1993-2015 | 3160 |
| **4** | **Korea** | KOR | 1981-1992 | 1993-2015 | 210,458 | 26 | Russia | RUS | NA | 2004-2015 | 2,872 |
| **5** | **Germany** | DEU | NA | 1993-2015 | 182,792 | 27 | Hong Kong | HKG | | 2005-2015 | 2,817 |
| **6** | **Italy** | ITA | 1981-1992 | 1993-2015 | 61,282 | 28 | Israel | ISR | NA | 1999-2015 | 1,080 |
| **7** | **Taiwan** | TWN | 1982-1992 | 1993-2015 | 49,230 | 29 | Norway | NOR | 1981-1992 | 1993-2015 | 1,068 |
| **8** | **France** | FRA | 1981-1992 | 1993-2015 | 32,161 | 30 | New Zealand | NZL | NA | 2005-2015 | 990 |
| **9** | **Spain** | ESP | 1981-1992 | 1993-2015 | 29,718 | 31 | Ireland | IRL | NA | 2002-2015 | 763 |
| **10** | **United Kingdom** | GBR | NA | 1993-2015 | 17,469 | 32 | Greece | GRC | NA | 1999-2015 | 446 |
| **11** | **Sweden** | SWE | 1981-1992 | 1993-2015 | 11,857 | 33 | Estonia | EST | NA | 2003-2015 | 97 |
| **12** | **Czech Republic** | CZE | NA | 1993-2015 | 11,238 | 34 | Lithuania | LTU | NA | 2004-2015 | 93 |
| **13** | **Netherland** | NLD | NA | 1993-2015 | 9,739 | 35 | Saudi Arabia | SAU | | 2006-2015 | 81 |
| **14** | **Singapore** | SGP | NA | 1993-2015 | 9,301 | 36 | UAE | UAE | | 2005-2015 | 66 |
| **15** | **Poland** | POL | 1981-1992 | 1993-2015 | 8,136 | 37 | Iceland | ISL | NA | 2004-2015 | 23 |
| **16** | **Belgium** | BEL | NA | 1993-2015 | 7,989 | 38 | Latvia | LVA | NA | 2006-2015 | 22 |
| **17** | **Turkey** | TUR | NA | 1999-2015 | 7,940 | 39 | Malta | MLT | NA | 2005-2015 | 17 |
| **18** | **Austria** | AUT | 1981-1992 | 1993-2015 | 7,859 | 40 | Macau | MAC | | 2005-2015 | 10 |
| **19** | **Australia** | AUS | 1981-1992 | 1993-2015 | 7,742 | 41 | Oman | OMN | | 2006-2015 | 6 |
| **20** | **Switzerland** | CHE | 1981-1992 | 1993-2015 | 6,258 | 42 | Moldova | MDA | NA | 2010-2015 | 5 |
| **21** | **Denmark** | DNK | 1981-1992 | 1993-2015 | 5,459 | 43 | Kuwait | KWT | | 2005-2015 | 2 |
| **22** | **Hungary** | HUN | 1981-1992 | 1993-2015 | 4,784 | 44 | Qatar | QAT | | 2011-2015 | 1 |

*Notes*: Crafted from IFR (2015). Puerto Rico is included in United States.

The data is combination of print and digital version of IFR (2015). Low-skilled immigration ratio in a country-level is calculated as

$$\text{Low-skilled immigration ratio} = \underbrace{\text{foreign population ratio}}_{\text{from WDI}} \times \underbrace{\frac{\text{working-aged ratio (immigrants)}}{\text{working-aged ratio (total)}}}_{\text{from OECD}}$$
$$\times \underbrace{\frac{\text{immigrant participation ratio}}{\text{total participation ratio}}}_{\text{from OECD}} \times \underbrace{\text{low-skilled share among immigrants}}_{\text{from IPUMS-international}}.$$

Participation ratio of male and female comes from OECD. Because industrial robots are dominant in manufacturing, the denominator is manufacturing employment. Cross-country robot density is computed as

$$\text{robot density} = \frac{\underbrace{\text{industrial robot stock (units)}}_{\text{from IFR}}}{\underbrace{\text{total labor force}}_{\text{from WDI}} \times (1 - \underbrace{\text{unemployment ratio}}_{\text{from WDI}}) \times \underbrace{\text{manufacturing employment ratio}}_{\text{from WDI}}}.$$

Unemployment ratio and manufacturing ratio, separately of male and female, are taken from WDI.

## A.5 Low-skilled immigration entry and short-run wage impact after task reallocation

In short-run, suppose $\theta$ is fixed.

$$(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{short} = \underbrace{(\frac{dlnY}{dln\widetilde{L^F}})_{short}}_{\text{growth effect}} - \underbrace{\frac{dln\widetilde{L^F}}{dln\widetilde{L^F}}}_{\text{demography effect}} + \underbrace{(\frac{\partial lnY}{\partial \phi})_{short}}_{=0}\underbrace{(\frac{d\phi}{dln\widetilde{L^F}})_{short}}_{>0} + \underbrace{(\frac{dln(\phi-\theta)}{dln\widetilde{L^F}})_{short}}_{\text{substitution effect}}$$

$$= \underbrace{\eta(\phi-\theta)-1}_{<0} + \underbrace{(\frac{dln\phi}{dln\widetilde{L^F}})_{short}}_{>0} < 0 \text{ (if and only if A1 is satisfied)}$$

$$(\frac{dln\underline{w}^D}{dln\widetilde{L^F}})_{short} = \underbrace{(\frac{dlnY}{dln\widetilde{L^F}})_{short}}_{\text{growth effect}} + \underbrace{(\frac{\partial lnY}{\partial \psi})_{short}}_{=0}\underbrace{(\frac{\partial \psi}{\partial ln\widetilde{L^F}})_{short}}_{>0} + \underbrace{(\frac{dln(\psi-\phi)}{dln\widetilde{L^F}})_{short}}_{\text{substitution effect}}$$

$$= \eta(\phi-\theta) - \underbrace{(\frac{dln\phi}{dln\widetilde{L^F}})_{short}}_{>0} > 0 \text{ (if and only if A1 is satisfied)}$$

Note that if A1 is violated, it is possible that the short-run wage effect is reversed due to stronger substitution effect.

$$(\frac{dln\overline{w}}{dln\widetilde{L^F}})_{short} = \underbrace{(\frac{dlnY}{dln\widetilde{L^F}})_{short}}_{\text{growth effect}} + \underbrace{(\frac{\partial lnY}{\partial \psi})_{short}}_{=0}\underbrace{(\frac{d\psi}{dln\widetilde{L^F}})_{short}}_{>0} = \eta(\phi-\theta) > 0$$

## A.6 Proofs of Corollary 1 [Comparative statics]

*Proof.*

Since$R = \frac{\theta\eta Y}{q}$,

$$\frac{dln(R/(L^F+L^D))}{dln\widetilde{L^F}} = \frac{dlnY}{dln\widetilde{L^F}} + \frac{dln\theta}{dln\widetilde{L^F}} - \underbrace{\frac{dln(L^F+L^D)}{dln\widetilde{L^F}}}_{=\frac{\widetilde{L^F}}{L^F+L^D}\sim small} = \phi-\theta+\underbrace{\frac{\partial ln\theta}{\partial ln\underline{w}^F}}_{\gg 0 \text{ (A1-1)}}\underbrace{(\frac{dln\underline{w}^F}{dln\widetilde{L^F}})_{short}}_{<0} < 0$$

$$\frac{dln\{Y/(L^F+L^D+H)\}}{dln\widetilde{L^F}} = \underbrace{(\frac{dlnY}{dln\widetilde{L^F}})_{agg}}_{\eta(\phi-\theta)>0} - \underbrace{\frac{dln(L^F+L^D+H)}{dln\widetilde{L^F}}}_{=\frac{\widetilde{L^F}}{L^F+L^D+H}\sim small} > 0$$

Similarly,

$$\frac{dln\{Y/(L^F+L^D)\}}{dln\widetilde{L^F}} = (\underbrace{\frac{dlnY}{dln\widetilde{L^F}}}_{\eta(\phi-\theta)>0})_{agg} - \underbrace{\frac{dln(L^F+L^D)}{dln\widetilde{L^F}}}_{=\frac{\widetilde{L^F}}{L^F+L^D}\sim small} > 0$$

$$s^L = \frac{\underline{w}^F L^F + \underline{w}^D L^D + \overline{w}H}{Y} = (1-\theta)\eta \implies \frac{dlns^L}{dln\widetilde{L^F}} = \underbrace{\frac{dlns^L}{d\theta}}_{-\eta<0}\underbrace{\frac{d\theta}{dln\widetilde{L^F}}}_{<0} > 0$$

,