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Education

2019 **PhD candidate in Economics, Department of Economics, Washington University in St. Louis**
expected graduation: May 2020

2016 M.A. in Economics, Washington University in St. Louis
Courseworks: Microeconomics, Macroeconomics, Econometrics, Statistics, Mathematics

2014 M.A. in Economics, the University of Tokyo

2010 B.A. in Economics, the University of Tokyo

Research Interests

Economics of Automation, Labor economics, Immigration economics, Public Economics

Research Projects

"Immigration, Automation and the U.S. Cities: A Task-based Framework for Welfare Analysis", main dissertation chapter

"The Effect of Low-Skilled Immigration on Robotization", second chapter

"Using Local Elasticities to Derive Optimal Taxation on Robots", third chapter

"Political Risk and Negotiations: Theory and Experiments"

(Master's Thesis in University of Tokyo, Advisor: Prof. Michihiro Kandori, Lab. experiment Advisor: Prof. Brian Rogers)

Academic Services and Employment

2018 *Teaching Assistant* for Health Economics, for Prof. Grace Johnson

2018 *Teaching Assistant* for Introductory Microeconomics, for Prof. Brian Rogers

2013 *Research Assistant* and *Teaching Assistant* for International Trade (graduate), the University of Tokyo for Prof. Michal Fabinger

2013 *Teaching Assistant* for Game Theory (undergraduate, Graduate School of Public Policy), the University of Tokyo for Prof. Akihiko Matsui

2010-11 Business Analyst, Strategy Group, Management Consulting, Accenture

Scholarship

2014-19 McDonell International Scholar Academy (Sep. 2014 - Aug. 2019)

2014-19 Nakajima Memorial International Scholarship (Jul. 2014 to Jun. 2019)

Summary of my interest in AI and my current projects

June 1, 2019

I am writing up the following three papers as a dissertation as a solo-author, and plan to enter the U.S. job market this year. (The main chapter is attached after this passage.) My interest on AI lies in the impact of demography shifts (e.g. immigration, population aging) on automation adoption, and their economic and fiscal consequences.

The main paper, "**Immigration, Automation and the U.S. Cities: A Task-based Framework for Welfare Analysis**", advances a hypothesis that foreign labor inflow guides automation penetration, and develops a task-based framework for applied welfare analysis, based on Acemogulu and Restrepo (2018). In the model, tasks are allocated across machines and domestic/foreign labor along their task productivities. Comparative advantage schedules are semi-parametrically estimated from regional elasticities of immigration inflow on a set of labor market moments. Using the structural model with estimated adjustment costs of automation, I quantify the role of foreign labor to shift the automation adoption, and run a series of policy experiments, including immigration quota expansion or regulation under the plausible distributional preference of the native government.

In the second paper, "**The Effect of Low-Skilled Immigration on Robotization**", assesses how much low-skilled immigration inflow impedes industrial robotization. Employing an integrated industrial robot dataset (from IFR) from 1980-2015, the two factors are shown to display persuasive negative links across countries, occupations and commuting zones in the U.S. I rationalize the patterns by a task-based comparative advantage framework. A series of testable predictions are assessed by instrumental variable strategy on the historical immigrant settlement. I show that 1% rise of low-skilled foreign labor force ratio lowers 0.2% robot density. Short-run and long-run predictions of immigration are separately identified, exploiting dramatic change of ethnic composition of immigration inflow from 1960s to 1970s.

The third paper, "**Using Local Elasticities to Derive Optimal Taxation on Robots**", provides a task-based foundation for taxation on autonomous machines. Under the welfare state with distributional preference, I derive the formulas of optimal robot tax rates, characterized by task-specific comparative advantage, mapped to elasticity of substitution. The elasticities are estimated exploiting regional retirement from aging across the U.S. commuting zones, serving as key inputs to the welfare formula.

Immigration, Automation and the U.S. Cities: A Task-based Framework for Welfare Analysis

Masahiro Yoshida*
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May 31, 2019

Abstract

The developed economies facing secular domestic labor shortage are bound to shift two margins: admitting foreign labor or adopting labor-saving technology. This paper advances a hypothesis that foreign labor inflow guides automation penetration, and provides a task-based framework for applied welfare analysis of immigration and automation. I start by documenting that low-skilled immigration is negatively linked with robotization, while high-skilled immigration is positively associated with computerization across the U.S. commuting zones. To consistently rationalize the patterns, I build a two-sector task-based model of endogenous automation based on Acemoglu and Restrepo (2018*b*), where tasks are allocated across smart machines and domestic/foreign labor along with their task productivity. Comparative advantage schedules across factors are semi-parametrically estimated from regional-level elasticities of immigration on smart machines, routine skill prices and ethnic inequality in skill prices. For quantitative assessments, the baseline model is extended to incorporate dynamic automation choice under heterogeneous adjustments costs, reproducing size distribution evolution of establishments. Founded by the estimated adjustment costs, the welfare implications are explored for immigration policies, and a universal basic income under the distributional preference of the native government.

JEL Classification: D21, E22, H21, H25, H32, H55, J15, J21, J23, J31, O14, R23

Keywords: immigration, demography, automation, regional labor market, universal basic income

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1 Introduction

The developed economies uniformly face a secular shortage of domestic labor force from population aging. To sustain the production system, natural economic reasoning suggests two directions: admission of foreign labor force (immigration) and adoption of labor-saving technology (automation). Both are far from popular solutions for the public, because both might substitute or displace the current labor force. A large part of the literature, including Lewis (2005),Beaudry, Doms and Lewis (2010),Acemoglu and Restrepo (2017), has examined the impact of automation on labor market. Despite the surging interest of how new automation technologies affects the labor markets, little is known on the mechanism of how automation itself proceeds.[1]

To help fill this void, this paper advances a hypothesis that foreign labor inflow, an admittedly small but rising class of labor, navigates the penetration of automation in the long run. This unexplored link is important because while immigration quota is a policy variable for a nation state, penetration of automation, or investing in autonomous machines, basically proceeds in isolation from the government. Thus, immigration, as a policy driver of national demography, presumably have potentials to shift the nation-wide automation intensity. To formalize the scenario of immigration-induced automation, I develop a task-based framework for applied welfare analysis, synthesizing the roles of foreign labor and smart machines and derive a welfare implication under the social welfare function of native government. The joint investigation of foreign labor and automation is shown to be fruitful for understanding their labor market impact together with a guideline of policy prescription to a nation state.

To motivate the link between foreign labor and automation, foreign labor inflow and automation penetration are juxtaposed in the regional level in the U.S. The U.S. commuting zones provide over 700 geographical variations best suited to examine the relationships between regional labor supply and automation penetration.[2]

[1] A notable exception is Acemoglu and Restrepo (2018*a*), who formerly theorized the process in which demographic-change demography nudges the production system to adopt automation.

[2] A companion paper, Yoshida (2018) features the role of low-skilled immigrants for production robotization, a specific subtype of modern mechanization. It presents an analogous chart on the left side in Figure 1, employing more narrowly defined industrial robot dataset from IFR (2015).

Figure 1: Low-skilled immigration inflow and mechanization (1980-2015)

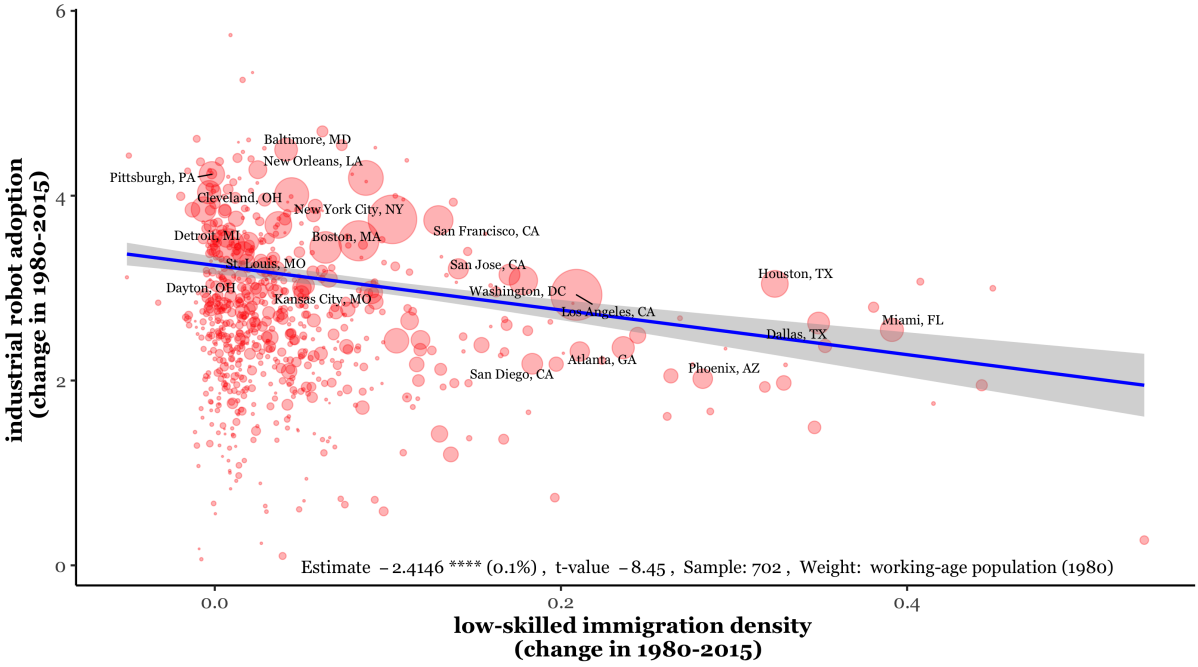
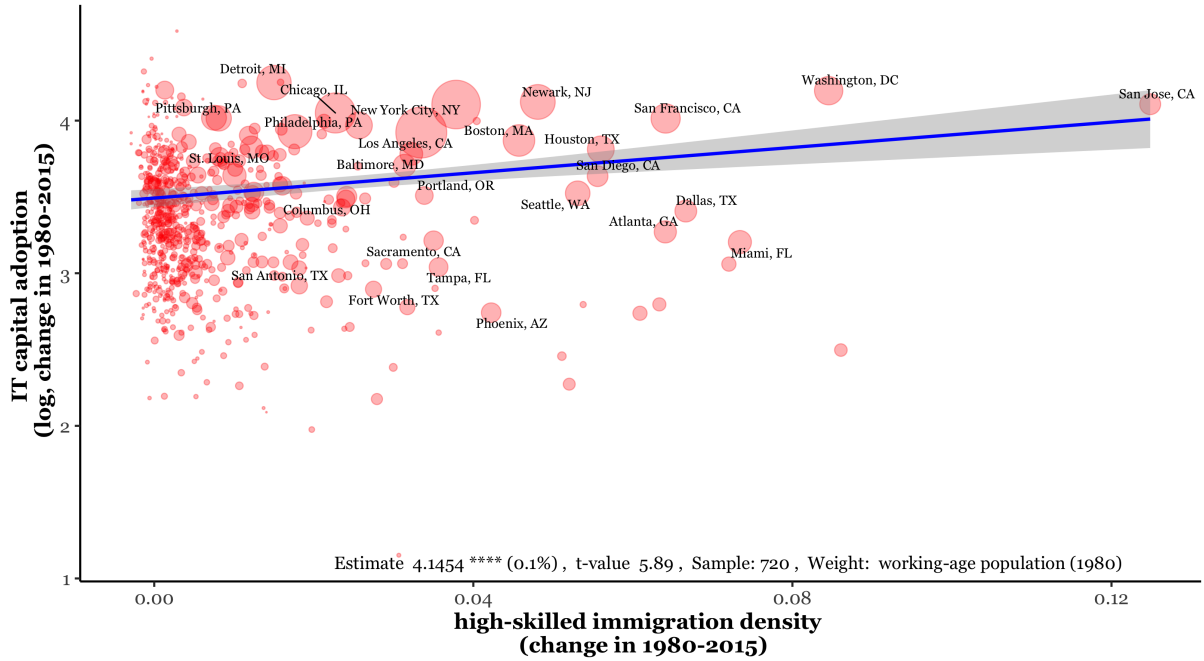


Figure 2: High-skilled immigration inflow and computerization (1980-2015)



Note: Computed from the Population Census, American Community Survey and NIPA from BEA. Commuting zones span the U.S. mainland. Robot density is captured by robot capital per production-worker. IT capital density is captured by IT capital (inclusive of hardware and software) per non-production employment.

Immigration into the U.S. is well-characterized by their polarity of skills, typically proxied by education attainment. Given the over-presence of the polar skills among immigrants, low-skilled and high-skilled and classes of immigrants are contrasted with their, plausibly, pertinent mode of automation: mechanization in production tasks and computerization in non-production tasks. As automation technology is unobservable for researchers *per se*, they are captured by capitals embodying each type of automation, industrial robots

and information technology (IT) capitals.[3]

As the two figures show, the polarized skills foreign labor inflow stands in sharp contrast to automation. The observation naturally brings me to propose a hypothesis of immigration-induced automation to bridge the two factors. The regional wage response serves as a mediating role for explaining penetration of automation: the low-skilled immigration inflow lowers the routine worker wages via substitutive forces. Thus, rationally optimizing establishments slow down mechanization in production tasks in the face of low-skilled immigration inflow. On the other hand, high-skilled immigration inflow raises demand for clerk workers via complementary forces, and thus, elevates the routine worker wages. Intuitively, larger inflow of managers or engineers require a larger back-office (e.g. secretaries/bookkeepers) to support their expert-skilled activities. For example, a secretary in San Jose, CA is more well-remunerated than in Cleveland, OH, possibly because of greater demand of back office jobs. Establishments are nudged to speed up the computerization in administrative tasks previously provided by clerk workers.

Regional units of the economy not only provide rich variations of immigration density, but it offers significant sources for unified understanding of differential modes of automation. An apparent, but non-trivial observation is that human workers armed with their knowledge and capability, are, in principle, geographically bounded in locations: workers have to reside in the regional labor markets (proxied by commuting zones), while autonomous machines are, in principle, procurable from the global capital market. Even though the access to automation technology, embodied by autonomous machines, is accessible everywhere, the figures indicate that automation might be framed as regional phenomenon, mirrored by geographic constraint of human workers.

To formalize the idea, I build a two-sector task-based model with endogenous automation based on Acemoglu and Restrepo (2018*a*), in line with Zeira (1998),Acemoglu and Autor (2011). The model features comparative advantage between autonomous machines and foreign/domestic labor over the task spectrum from routine (easy-to-automate) end to non-routine (hard-to-automate) end. The model formulates technology adjustment as task reallocation across production factors along with their relative productivity schedule. A final good is produced from material production in *plant* sector (manufacturing), and information processing in *office* sector (information service). The sectors are delineated as symmetric, but supposed to exhibit the contrasting comparative advantage schedules of foreign labor: low-skilled immigrants work as a routine worker in plant, and display comparative advantage in routine tasks, while high-skilled immigrants work non-routine worker in office, exhibit one in non-routine tasks. The model allows for richer substitution pattern across factors than conventional iso-elastic technology, by flexible matching of skills and tasks . Under some regularities, the task specialization emerges in equilibrium, which accords well with the observed distribution of immigrants across the occupation spectrum, ordered along the automatability index from Frey and Osborne (2017). (See Figure.5)

The model generates analytical links of three *local comparative advantage* (LCA, hereafter)[4] between routine-task worker and machine, the low and high skills and foreign and domestic skills and a trio of elasticities of immigration on autonomous machine deployments, routine skill prices and ethnic inequality in skill prices.

To run quantitative assessment of how immigration played a role in shifting the automation, I enrich the

[3]Recently, Eden and Gaggl (2018) highlight the role of IT capital as opposed to non-IT capital in the labor market implications.

[4]The paper explicitly distinguishes the terms: *local* and *regional*. *Local* denotes task-specific from modeling perspective, while *regional* is synonymous with geographical.

baseline model by adding dynamics and heterogeneity to explicitly feature dynamic automation adjustment of establishments. In the model, heterogeneous establishments run automation adjustments, facing expected streams of labor supply and a menu of capital prices. where establishments jointly decide when and how much to upgrade their automation intensity. The establishments incur adjustment costs when they choose to automate. The cost parameters are specified based on industry-level automatability and unobservable productivity (TFP) of the establishments, representing the taste for automation independent of their economic efficiency. The establishments rationally expect the expected skill prices across regions, driven by the labor supply streams of the region.[5] The production-side model reproduces a long-run menu of skill prices together with differential evolution of establishment size distributions.

To quantify the channel of immigration-induced automation, the identification and estimation proceeds in three steps. First, run quasi-experiments across commuting zones to recover elasticities of autonomous machine change, and routine skill price change, and ethnic inequality in skill prices with respect to immigration inflow *at regional level*. It is shown that substantial regional heterogeneity is observed in the reaction of immigration inflow. To address the routinely invoked non-randomness of immigration inflow, I exploit the strong ethnic preference of immigrants as non-economic forces to allocate a new wave of immigrants to each region, as widely implemented in immigration literature in Altonji and Card (1991), and Card (2001). As immigrants strongly prefer a larger ethnic pool (see e.g. Munshi (2003)), historical settlement patterns of ethnic groups is utilized as instruments to construct highly stable ethnically-driven waves of foreign labor, orthogonal to the regional economic opportunities.[6]

Second, I semi-parametrically identify and estimate the entire comparative advantage schedule from the distribution of immigration elasticities in each sector, obtained in the first step. Analytical mappings of elasticities and LCAs from the task-based model are utilized as moment conditions in the two-step GMM procedure.

Third, inserting the recovered technology into the dynamic full model, I estimate adjustment cost parameters for automation by simulated method of moments. Adjustment cost parameters for automation is estimated conditional on a host of observable establishment attributes, and industry-level automatability, constructed fromFrey and Osborne (2017).

Armed with the full model with the estimated technology and adjustment costs, the quantitative assessments are provided in three steps. First, I numerically evaluate how low-/high-skilled immigrants reduce or shift up the routine skill prices in each sector, and how the regional skill prices change have shifted the automation adoption. Second, the sources of economic-driven automation adjustments is decomposed into immigration and aging of the native workers in the period of 1980-2015. Next, the projection is extended to the future periods from 2015-2050, drawing on the population projection of the Census. Third, I quantify the mechanism of automation of economic-driven and non-economic factors. This could be achieved by assessing the contributions of adjustment costs to automation choices.

Then, I explore a series of policy counterfactual experiments, and their impacts to real wages, automation, labor shares and impacts the labor market. Welfare implications are examined under different social welfare weights of the domestic U.S. government. First, I examine the nationwide immigration policies spanning both

[5]The model echoes with durable good demand literature in that establishments with heterogeneous "tastes" for automation technology. (eg. Adda and Cooper (2000),Gowrisankaran and Rysman (2012))

[6]Recent econometrics literature (e.g.Borusyak, Hull and Jaravel (2018)) discusses the robustness of the exercise, regarding the credibility of Bartik-type shift-share instruments,.

low- and high-skills. Specifically, by trying out different scenarios of immigration quotas for each skill, I ask how much immigration quota is required both to remain the real wages, labor shares kept at the level of 2015 and to maximize the national welfare under a series of plausible distributional preference of the native government.[7]

Lastly, founded by the economic and fiscal impacts on two pro-employment policies with government sector, universal basic income (UBI) is simulated. UBI is unconditional social benefit to every national citizen instead of the canonical progressive social security system, and getting traction mirrored by the rise of artificial intelligence.[8] I explore a regime change to UBI, by sustaining a fiscal balance jointly by selective immigration policy. Since the micro data for social experiments is few, the ex-ante policy counterfactuals would deliver a first benchmark for designing future field experiments or more rigorous evaluation. The simulation shows that UBI strongly boosts automation, by raising reservation wages of individuals. The result suggests that UBI should be viewed as a booster to the hyper-automated economy as well as the counter-measure to the transformative automation.

The literature finds it hard to agree with a pair of elasticity of substitutions of immigrants vs. natives, and of labor vs. capitals. The paper contributes to the debates by offering an applied task-based model with a richer substitution pattern across factors, allowing for heterogeneous elasticities of substitution. The proposed semi-parametric identification and estimation procedure serves as a remedy integrating a myriad of reduced-form snapshots to recover a entire picture of comparative advantage schedule. This could also deliver a theory-grounded, but more nuanced policy prescriptions.

The paper is structured as follows. Section 2 provides a set up of the framework. Section 3 formalizes the immigration-induced automation. Section 4 describes the data. Section 5 elaborates a dynamic structural model. Section 6 delivers an identification strategy, estimation procedures, and results. Section 7 runs the decomposition exercises and policy experiments. Section 8 gives some caveats and concludes.

[7] Storesletten (2000),Lee and Miller (2000),Auerbach and Oreopoulos (1999) use an overlapping generation model to run generational accounting to examine the impact of immigration policies. Especially, a country is authorized to adjusting the skill mix of foreign labor by tweaking the allocation of visas.H-2A, H-2B, L-1 visas for low-skilled workers and H1-B visa quotas for professionally skilled immigrants. The current administration holds a plan for completing a wall on the U.S.-Mexico. to deter the illegal immigrants, most of them are low-skilled. (See e.g.Allen, Dobbin and Morten (2018))

[8] UBI has gained a new vive as a countermeasure to the looming technological unemployment against a traditional social benefit scheme. Economists, including Chris Pissarides, Peter Diamond, and Daniel McFadden, have publicly expressed their appraise. In 2016, a national referendum was held in Switzerland to adopt the UBI (albeit rejected). In 2017, Canada and Finland launches a trial, and state government in Hawaii is reported to announce a future implementation of UBI.

2 Two-sector task-based model of Endogenous Automation

2.1 Production side

Suppose an economy consists of a pair of sectors $G \in \{p, o\}$ over an array of islands l. Plant sector p runs material production and office sector o conducts information processing.[9] In each sector G, a finite number of industry g operates such that

$$P^G Y^G = \Sigma_{g \in G} P^g Y^g$$

$$P^g Y^g = \{\Sigma (P_i^g Y_i^g)^{\frac{\epsilon-1}{\epsilon}}\}^{\frac{\epsilon}{\epsilon-1}}$$

In each sector, production is operated by a finite group of establishments.[10] In each sector, a final good output is Cobb-Douglas aggregation of outputs from a continuum of task $\omega \in [0, 1]$, $y^g(\omega)$, such that

$$Y_i^g = exp(\int_0^1 lny_i^g(\omega) d\omega)$$

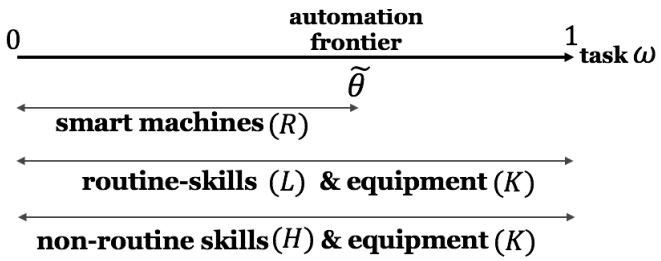


Figure 3: Technology constraints on task coverage

Notes: Automation frontier $\widetilde{\theta}$ is exogenously given in each industry.

The total size of task spectrum is set to measure one from 0 to 1. The higher-indexed task is more non-routine, meaning harder to automate. Suppose that smart machines can *technologically* automate the routine side of task $\omega \in [0, \widetilde{\theta})$, where $\widetilde{\theta^g}$ is an automation frontier, which is globally common across islands.[11]

Individuals in cell $\iota = (l, g)$ offer either low-skills $\underline{S}$ as routine occupation workers ($m = L$) and high-skills $\overline{S}$ as non-routine occupation workers ($m = H$) and are feasibly perform all tasks with equipments.

Output of each task ω is produced as following:

$$(1) \qquad y(\omega) = \begin{cases} \{A^R r(\omega) + A^L \underline{a}(\omega)\underline{s}(\omega) + A^H \overline{a}(\omega)\overline{s}(\omega)\}^\alpha k(\omega)^{1-\alpha} & (\omega \in [0, \widetilde{\theta}], \text{ automatable task}) \\ \{A^L \underline{a}(\omega)\underline{s}(\omega) + A^H \overline{a}(\omega)\overline{s}(\omega)\}^\alpha k(\omega)^{1-\alpha} & (\omega \in (\widetilde{\theta}, 1], \text{ unautomatable task}) \end{cases}$$

$\underline{s}(\omega)$ is low-skill, $\overline{s}(\omega)$ is high-skill, $r(\omega)$ is a smart machine, and $k(\omega)$ is an equipment employed in task ω. $\{\underline{a}(\omega), \overline{a}(\omega)\}$ is a series of task-specific productivities for low- and high-skills, respectively, normalized as

[9] G is often suppressed for brevity except where it is especially required. l is suppressed in this chapter for brevity, and will be explicit in the empirical part.

[10] Sectorial outputs are aggregated to produce a final good (numeraire).

[11] Acemoglu and Restrepo (2018*a*) endogenize $\widetilde{\theta}$ in directed *technological change* framework, while the paper features *technological adoption* under the technological limit.

$\underline{a}(0) = \overline{a}(0) = 1$. The task-specific productivity for capitals are set to unity so that $\{\underline{a}(\omega), \overline{a}(\omega)\}$ could be seen as relative productivities to capitals.

The low-end automatable partition $\omega \in [0, \widetilde{\theta}]$ is potentially performed by either smart machine or both skills armed with equipments. The high-end unautomatable partition $\omega \in (\widetilde{\theta}, 1]$ can only be executed only by skills armed with equipments.

In each cell ι, routine/non-routine skill prices is competitively given as $\underline{q_\iota}, \overline{q_\iota}$, respectively. In national capital markets, smart machine R and equipment K is supplied with perfect elasticity with fixed rental prices, q^R and q^K, respectively.

Each island is inhabited by citizens (natives) and non-citizens (immigrants). In both sectors, native workers work in both routine- and non-routine occupations ($m \in \{L, H\}$). In particular, in view of empirical supports (skill dispersion measured by education), presume that immigrants are engaged in routine occupations in plant sector, providing foreign low-skills $\underline{S}^F$, while in office sector, they are involved in non-routine occupations, providing foreign high-skills $\overline{S}^F$.[12] Mirrored by this foreign skill dispersion across sectors, sectors differ in nesting ethnic skills in technology, albeit symmetrically treated elsewhere; routine (non-routine) occupation is foreign-intensive in plant (office) sector, thus, low- (high-) skill is composite of distinct ethnic skills.

Formerly, analogous to the final goods, low-skill is composed of sub-task production. The

$$\underline{S} = exp[\int_0^1 ln\underline{s}(\omega')d\omega'] \text{ (plant)}, \quad \overline{S} = exp[\int_0^1 ln\overline{s}(\omega')d\omega'] \text{ (office)}$$

Each sub-task is produced from perfect substitutes of effective routine skills.

$$\begin{cases} \underline{s}(\omega') = \underline{b}^F(\omega')\underline{s}^F(\omega') + \underline{b}^D(\omega')\underline{s}^D(\omega') & \text{(plant)} \\ \overline{s}(\omega') = \overline{b}^F(\omega')\overline{s}^F(\omega') + \overline{b}^D(\omega')\overline{s}^D(\omega') & \text{(office)} \end{cases} \tag{2}$$

For tractability, the task allocation between ethnic groups is independent from the one between low- and high- skills.[13] The establishment i in industry g, sector $G \in \{p, o\}$ purchases a task output $y(\omega)$ with a marginal cost $p(\omega)$ for task $\omega \in [0, 1]$. The establishment i's problem is

$$\min_{r(\omega), k(\omega), \underline{s}(\omega), \overline{s}(\omega)} \int_0^1 p(\omega) y_i(\omega) d\omega$$

$$s.t. \;\; exp(\int_0^1 lny_i^g(\omega)d\omega) \geq Y_i^g, \;\; y_i(\omega) \text{ is given by (1)}.$$

$$\int_0^1 \underline{s}(\omega)d\omega = \underline{S}_i, \;\; \int_0^1 \overline{s}(\omega)d\omega = \overline{S}_i, \;\; \int_0^{\widetilde{\theta}} r(\omega)d\omega = R_i \;\; \int_0^1 k(\omega)d\omega = K_i$$

In plant sector, given routine skill demand $\underline{S}_i$, $\{b^D(\omega'), b^F(\omega')\}$ are ω'-based productivity for $\omega' \in [0, 1]$, the nested cost minimization problem for routine occupation manager is to minimize the skill expenditure to satisfy the skill demand from the establishment.

[12] In empirical point of view, immigrants work in both occupations. However, their presence is relatively small and it is treated in the same way as natives.

[13] This is comparable in the widespread nested-CES models.

$$min \underline{q}^{'F} \underline{S}_i^F + \underline{q}^{'D} \underline{S}_i^D$$

$$s.t.\ \underline{b}^F(\omega^{'}) \underline{s}_i^F(\omega^{'}) + \underline{b}^D(\omega^{'}) \underline{s}_i^D(\omega^{'}) \geq \underline{S}_i$$

$$s_i(\omega') \text{ is given by (2).}$$

$$\underline{S}_i^e = \int_0^1 \underline{s}_i^e(\omega^{'}) d\omega^{'} \quad (e \in \{D, F\})$$

Proposition 1 [Task price curves]

Suppose regularities R0-R3. Denote the marginal cost of routine- (non-routine) task outputs implemented by low- (high-)skills as $\underline{p}(\omega), \overline{p}(\omega)$ *given by*

$$\overline{p}(\omega) = (\frac{\overline{q}}{\overline{a}(\omega)\alpha})^{\alpha} (\frac{q^K}{1-\alpha})^{1-\alpha} \tag{3}$$

Let the marginal cost of sub-task outputs implemented by ethnic skills as $\underline{p}^{'e}(\omega^{'})$

$$\underline{p}^{'e}(\omega^{'}) = \frac{q^{'e}}{\underline{q}\underline{b}^e(\omega^{'})} \text{ (plant)}$$

2.1.1 Regularities

R0 [Skills vs. Smart machines]

Task productivities for all skills are strictly increasing in task non-routineness. Formerly,

$$d\underline{a}(\omega)/d\omega > 0 \ \ d\overline{a}(\omega)/d\omega > 0 \quad \forall \omega \in [0,1]$$

Recall that the task productivities of smart machines are set to unity. This implies that $\underline{a}(\omega)$ and $\overline{a}(\omega)$ are strictly increasing in ω and $\underline{p}(\omega), \overline{p}(\omega)$ are strictly decreasing in ω.

R1 [Low skills vs. Smart machines]

$$\frac{\underline{q}}{\underline{a}(\widetilde{\theta})} < q^R < \frac{\underline{q}}{\underline{a}(0)}$$

Intuitively, the condition implies at the automation frontier, the rental price is expensive enough so that it is economically reasonable to use low-skills. This assures that there exists θ with $0 < \theta < \widetilde{\theta}$ equalizing the task price.

$$\underline{p}(\theta) = q^R$$

R2 [Low skills vs. High skills]

$$\frac{\overline{q}}{\overline{a}(\theta)} < \frac{\underline{q}}{\underline{a}(\theta)}, \quad \frac{\overline{q}}{\overline{a}(1)} < \frac{\underline{q}}{\underline{a}(1)}$$

This assures that there exists ψ with $\theta < \psi < 1$ equalizing the task price.

$$\underline{p}(\psi) = \overline{p}(\psi)$$

In graphics of marginal cost curves, R0-R2 ensures that differential slopes of marginal cost curves.

R3 [Domestic vs. Foreign skills]

$$\frac{\underline{q}'^F}{\underline{q}'^D} \in [min(\frac{\underline{b}^D(0)}{\underline{b}^F(0)}, \frac{\underline{b}^D(1)}{\underline{b}^F(1)}),\ max(\frac{\underline{b}^D(0)}{\underline{b}^F(0)}, \frac{\underline{b}^D(1)}{\underline{b}^F(1)})]$$

There exists $\omega' = \phi$ with $\theta < \phi < 1$ such that

$$p^F(\phi) = p^D(\phi).$$

This assures a single crossing of $p^D(\omega'), p^F(\omega')$ at ϕ.

Given the regularities R0-R3, establishments turn out to follow the cutoff strategies to split the coverage of factors over the task spectrum.

Proposition 2 [Factor allocation over tasks]

Suppose the regularities R0-R3. Then, there exists an automation intensity $\theta \in (0, \widetilde{\theta}]$ *such that smart machines cover task* $\omega \in [0, \theta]$*, and occupation threshold* $\psi \in (\theta, 1)$ *such that routine-skills with equipments cover task* $\omega \in (\theta, \psi]$*, and non-routine skills with equipments cover task* $\omega \in (\psi, 1]$.

Moreover, there exists a foreign-domestic threshold $\phi \in (0, 1)$ *splitting the task coverages, where foreign and domestic skills mutually exclusively cover.* θ,ψ,ϕ *are implicitly defined as*

$$\underline{a}(\theta) = \frac{q}{q^R}, \quad \frac{\underline{a}(\psi)}{\overline{a}(\psi)} = \frac{\underline{q}}{\overline{q}}, \quad \frac{\underline{a}^F(\phi)}{\underline{a}^D(\phi)} = \frac{\underline{q}'^F}{\underline{q}'^D} \text{ (plant)} \tag{4}$$

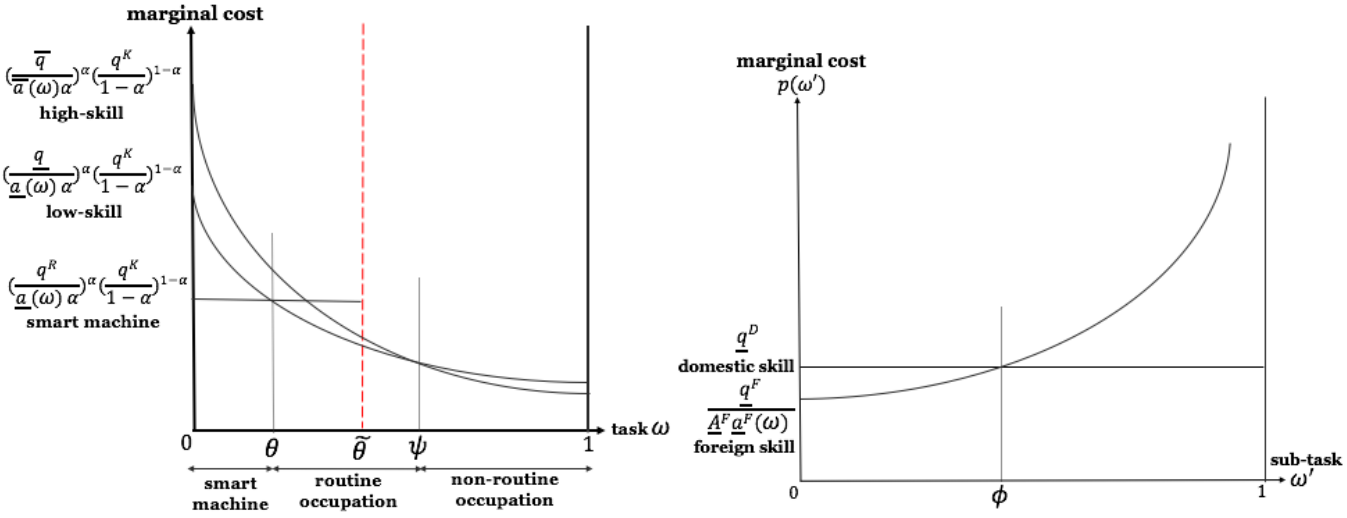
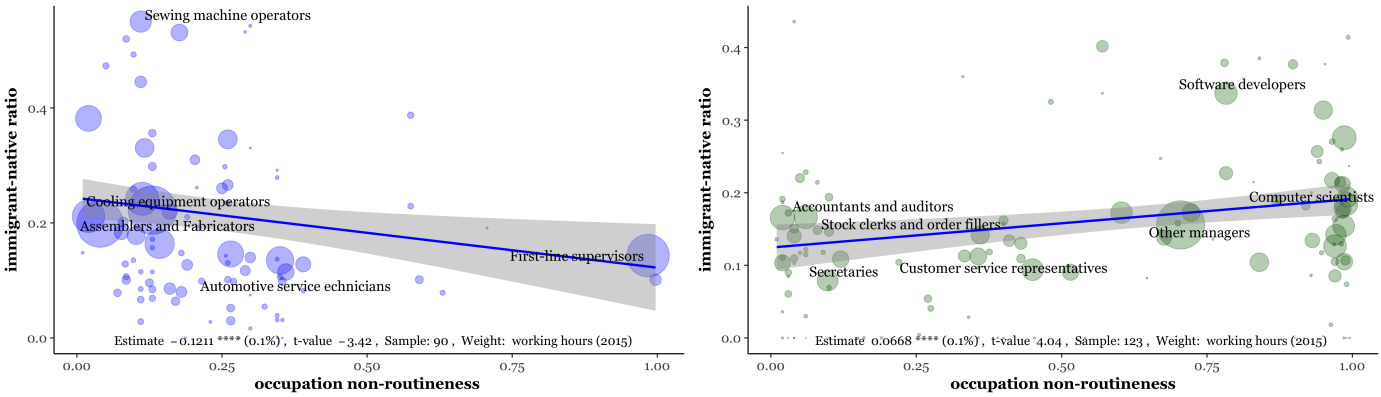


Figure 4: Equilibrium task specialization

The regularities R0-R3 ensure the specialization of factors over the task spectrum. Routine skills perform

all tasks of $\omega \in (\theta, \psi]$, and non-routine skill performs all tasks $\omega \in (\psi, 1]$. Graphically, it assures single-crossing of the marginal cost curves, and each task is implemented by either smart machines or skills with equipments.[14]

Figure 5: Occupation non-routineness and immigrant-native ratio (2015): production workers (left), non-production workers (right)



Note: Occupation non-routineness is proxied by one minus computerizable probability crafted in Frey and Osborne (2017). *Production workers, non-production workers are classified from occ2010 in American Community Survey, 2015. Production workers include production managers and mechanical engineers. Non-production workers consist of clerks (white-collar), STEM workers and managers, excluding service workers.*

To lend support to the specialization pattern in the model, a snapshot of immigration presence across the spectrum of occupations along occupation non-routineness in 2015 for production and non-production workers is presented. The non-routineness is proxied by one minus automation probability codified by Frey and Osborne (2017).[15].[16] The figure illustrates sharply contrasting presence facing the technical threat of automation in production and non-production workers. Foreign labor is characterized by polarized susceptibility to automation technology; in the production workers, routine class of occupations are, on average, immigration-intensive. In non-production workers, most non-routine class of occupations are on average, immigration-intensive relative to more routine class of workers. One could view that a pair of non-zero slopes signals comparative advantage of foreign skills against machine capabilities, upholding the comparative advantage assumptions made above.[17]

2.2 Labor supply side

As seen in the factor demand side, in each cell z (sector $G \times$ occupation $m \in \{L, H\} \times$ location l), two types occupation $m \in \{L, H\}$ are available. An individual j in the segment $z = (m, g, l)$ has a utility function

[14] At the crossing point, two factors of interest is possible. Without loss of generality, a tie-break condition can be imposed.

[15] Frey and Osborne (2017) explores the future of jobs, predicting that 47% of the jobs are technically displaceable by automation. They cover both production workers (e.g. assembly line workers) and non-production office workers (e.g. secretaries). A purely technical feasibility for automation is rigorously examined, mixing interviews to experts and machine learning technique.

[16] The polarized distribution echoes with education attainment distribution, shown in **??** on page ??. low-skilled (high schools graduates and below) and expert-skilled (above bachelors) immigrants over-represent.

[17] Peri and Sparber (2009) document immigration presence across occupation spectrum along task character composition compiled in ONET, which has been often used since Autor, Levy and Murnane (2003). They show that immigrants agglomerate relatively in manual and analytically intensive occupations. As shown in Appendix, automation probability from Frey and Osborne (2017) and these task measures from ONET are strongly correlated.

$$U(C_j, L_j) = \underbrace{\frac{(C_j - \underline{C_l})^{1-\eta}}{1-\eta} - exp(b_j)\frac{{L_j}^{1-\gamma}}{1-\gamma}}_{\equiv \widehat{U}(C_j, L_j)} + \epsilon_j^z$$

where C_j is consumption, $\underline{C_l}$ is subsistence consumption level (e.g. residence) in location l, and b_j is individual taste for leisure. Consumption and disutility for labor is assumed to be additive-separable. ϵ_j^z is a segment-level taste idiosyncrasy following i.i.d. Type-1 extreme value distribution.

Every individual has fixed amount of aggregate time endowment $\widetilde{L_j}$. G_j is non-labor income. The problem is solve below. Now suppose that the second stage is solved and indirect utility $\widehat{U}(C_j, L_j)$ is derived, the first stage is solved backward. The first-order condition yields the familiar marginal rate of substitution (MRS) condition:

$$MRS = \frac{exp(z_j)L_j^{\gamma}}{(w_j^z L_j^z + G_j)^{\eta}} = w_j^z \tag{5}$$

2.3 Equilibrium

Given a menu of regional skill prices and national rental prices for capitals, the establishment chooses automation intensity $\theta \in [0, \widetilde{\theta}]$, skill threshold ψ, and ethnic skill threshold ϕ.

Definition 1 [Equilibrium conditions]

Given the task productivity schedule $\{a(\omega), b(\omega')\}$ *and capital rental price* q^R, q^K *in sector* G*, and skill prices in location* l*, the establishment* $i \in \iota = (G, g, l)$*, maximizes the profit by optimally allocating the tasks by specifying automation intensity* θ*, occupation threshold* ψ*, and ethnic threshold*ϕ *such that* θ, ψ *and* ϕ *are characterized by (4).*

Labor supply choice: $L_j^z = argmax_{z, L_j \in [0, \widetilde{L}]} U(C_j^z, L_j^z)$

Skill market clearing:

$$\underbrace{\Sigma_{i \in z} \int_{\theta}^{\psi} \underline{s_i^e}(\omega')d\omega'}_{\text{ethnic-skill demands}} = \underbrace{\Sigma_{j \in \iota} \underline{s_j^{e,z}} L_j = \underline{S_z^e}}_{\text{ethnic-skill supply}} (e \in \{D, F\})$$

$$\underbrace{\Sigma_{i \in z} \int_{\psi}^{1} \overline{s_i}(\omega)d\omega}_{\text{high-skill demands}} = \underbrace{\Sigma_{j \in \iota} \overline{s_j} L_j = \overline{S_z}}_{\text{high-skill supply}}$$

Capital market clearing:

$$\underbrace{\Sigma_{i \in \iota} \int_{0}^{\theta} r(\omega)d\omega}_{\textit{aggregate smart machine demands}} = R_\iota, \qquad \underbrace{\Sigma_{i \in \iota} \int_{\theta}^{1} k(\omega)d\omega}_{\textit{aggregate equipment demands}} = K_\iota$$

Proposition 2 [Equilibrium]

Suppose the regularities $R0-R3$ holds. Then, an equilibrium uniquely exists. The aggregate production is given by

$$Y_i = B(\theta,\psi)\{(\frac{R_i}{\theta})^{\theta}(\frac{\underline{S}_i}{\psi-\theta})^{\psi-\theta}(\frac{\overline{S_i}}{1-\psi})^{1-\psi}\}^{\alpha}{K_i}^{1-\alpha}$$

where

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

Skill prices:

$$q = \frac{(q^{'F})^{\phi}(q^{'D})^{1-\phi}}{B^{'}(\phi)}, \underline{S}_i = \frac{(\psi-\theta)Y}{\underline{q}},\ \overline{q} = \frac{(1-\psi)\alpha Y}{\overline{S}_i},\ q^{'e} = \frac{\Lambda^{'Le} q\underline{S}_i}{q\underline{S^e}} \tag{6}$$

where

$$B^{'}(\phi) \equiv exp[\int_{0}^{\phi} lnb^{F}(\omega^{'})d\omega^{'} + \int_{\phi}^{1} lnb^{D}(\omega^{'})d\omega^{'}]$$

Capital allocation:

$$R = \frac{\theta Y}{q^R},\ K = \frac{(1-\psi)(1-\alpha)Y}{q^K}$$

Labor supply is implicitly characterized by (5).

Aggregation of individual skills

$$\Sigma_{j\in\iota} s_j^e L_j I_j^{m=L} = S^e, \Sigma_{j\in\iota} s_j L_j I_j^{m=H} = \overline{S}$$

Skill prices depend on skill employment, task interval, and the aggregate production. The factor income maps with task interval.

2.3.1 Planner's problem

Definition [Social welfare]

The social welfare function (SWF) in a nation state is a weighted average of curved utilities across citizens and non-citizens such that

$$SWF(t) = \frac{\chi\Sigma_j I_j^{e=D}\Upsilon(U(C_{j,t},L_{j,t});\delta) + (1-\chi)\Sigma_j I_j^{e=F}\Upsilon(U(C_{j,t},L_{j,t});\delta)}{N_t^D + N_t^F}$$

where utility is transformed as

$$\Upsilon(U(C_{j,t},L_{j,t});\delta) = \frac{(expU(C_{j,t},L_{j,t}))^{\delta}-1}{\delta}$$

$$\chi \in [0,1], \delta \leq 0$$

$U(C, L)$ is a utility function (parameterized in 2.2). δ captures inequality preference and χ captures a degree of native preference of a nation state. The planner's problem is to maximize the social welfare by policy instruments, in particular, immigration quotas for each skills.

$$max_{\Delta \underline{N}^F, \Delta \overline{N}^F} \Delta SWF(t)$$

2.4 Local comparative advantage and Technology adjustments

Technology adjustments from factor price changes. In response to factor price changes, the establishment adjusts extensive-margin technologies by reallocating tasks to production factors.

Definition 1 [Local comparative advantage]

Local comparative advantage (LCA, hereafter) *of low-skills over smart machines, of high-skills over low-skills in task non-routineness at task ω is defined respectively as*

$$LCA^{L,R}(\omega) \equiv \frac{d\underline{a}(\omega)/d\omega}{\underline{a}(\omega)}, \quad LCA^{H,L}(\omega) \equiv \frac{d\overline{a}(\omega)/d\omega}{\overline{a}(\omega)} - \frac{d\underline{a}(\omega)/d\omega}{\underline{a}(\omega)}$$

Analogously, LCA of domestic skills over foreign skills in task non-routineness at sub-task ω' is defined as

$$LCA^{F,D}(\omega') \equiv \frac{db^F(\omega')/d\omega'}{b^F(\omega')}$$

Recall that without loss of generality

$$a^R(\omega) = 1 \; \forall \omega, \;\; b^D(\omega') = 1 \; \forall \omega',$$

[18]

Proposition [Local comparative advantage and extensive-margin technology adjustment]

Extensive-margin technology adjustment to a marginal factor price change hinges on local comparative advantage. Specifically, the automation intensity is adjusted as

$$\frac{d\theta}{dln\underline{q}} = -\frac{d\theta}{dlnr^R} = LCA^{L,R}(\theta)^{-1}$$

Routine-/non-routine skill adjustments over tasks and ethnic skill adjustments over sub-tasks are given by

$$\frac{d\psi}{dln\underline{q}} = -\frac{d\psi}{dln\overline{q}} = LCA^{H,L}(\psi)^{-1}, \quad \frac{d\phi}{dlnq^D} = -\frac{d\phi}{dlnq^F} = LCA^{D,F}(\phi)^{-1}$$

Intuitively, when two factors are well-differentiated, adjustments get smaller.

[18] Equivalently, $\frac{a^z(\omega)}{a^{z'}(\omega)}$ is is strictly increasing.

Lemma [Marginal cost and task productivity growth]

The diminishing rate of marginal cost is negatively proportional to growth rate of task productivities.

$$\frac{\dot{\underline{p}}(\omega)}{\underline{p}(\omega)} = -\frac{\dot{\underline{a}}(\omega)}{\underline{a}(\omega)}, \quad \frac{\dot{\overline{p}}(\omega)}{\overline{p}(\omega)} = -\alpha\frac{\dot{\overline{a}}(\omega)}{\overline{a}(\omega)}$$

holds.

Proof.

$$\dot{\underline{p}}(\omega) \equiv \frac{d\underline{p}(\omega)}{d\omega} = -\underline{p}(\omega)(\frac{\dot{\underline{a}}(\omega)}{\underline{a}(\omega)}) \Longrightarrow \frac{\dot{\underline{p}}(\omega)}{\underline{p}(\omega)} = -\frac{\dot{\underline{a}}(\omega)}{\underline{a}(\omega)}$$

$$\dot{\overline{p}}(\omega) \equiv \frac{d\overline{p}(\omega)}{d\omega} = \overline{p}(\omega)\frac{d(\overline{a}(\omega))^{-\alpha}}{d\omega} = -\alpha\overline{p}(\omega)\frac{\dot{\overline{a}}(\omega)}{\overline{a}(\omega)} \Longrightarrow \frac{\dot{\overline{p}}(\omega)}{\overline{p}(\omega)} = -\alpha\frac{\dot{\overline{a}}(\omega)}{\overline{a}(\omega)}$$

‖

The relative slopes of marginal cost curves corresponds with comparative advantage across the factors of interest. Larger comparative advantage is represented by wider disparity of slopes of marginal cost curves.

- Automation adjustment

Automation adjustment is operationalized by task allocation between routine skills and smart machines. A routine skill price and rental price of smart machines jointly shifts the automation intensity.

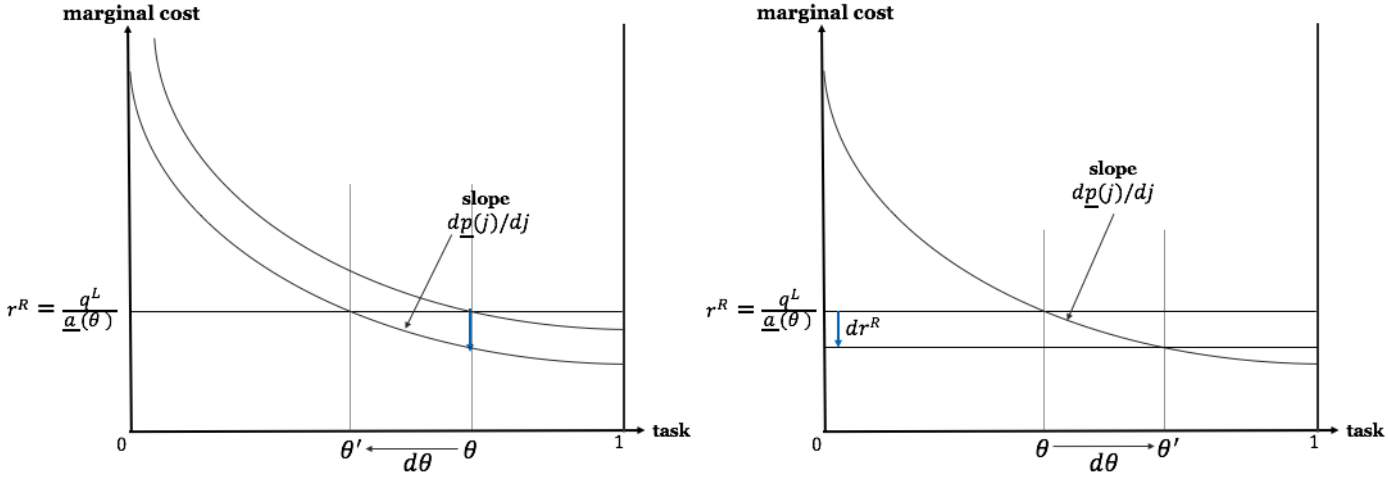


Figure 6: Marginal response of θ in routine skill price (left) / rental price of smart machines (right)

By the graphical relationships,

$$d\theta \mid \dot{\underline{p}}(\theta) \mid = \frac{d\underline{q}}{\underline{a}(\theta)} \Longrightarrow \frac{d\theta}{d\underline{q}} = \frac{1}{-\dot{\underline{p}}(\theta)\underline{a}(\theta)} > 0$$

$$d\theta \mid \dot{\underline{p}}(\theta) \mid = -dr^R \Longrightarrow \frac{d\theta}{dr^R} = \frac{1}{\dot{\underline{p}}(\theta)} < 0$$

holds. The elasticities of automation with respect to factor prices are

$$\frac{d\theta}{dln\underline{q}} = \frac{d\theta}{d\underline{q}}\underline{q} = \frac{\underline{q}}{-\dot{\underline{p}}(\theta)\underline{a}(\theta)} = -\frac{\underline{p}(\theta)}{\dot{\underline{p}}(\theta)} = \left(\frac{\underline{a}(\dot{\theta})}{\underline{a}(\theta)}\right)^{-1} = LCA^{L,R}(\theta)^{-1} > 0$$

$$\frac{d\theta}{dlnr^R} = \frac{d\theta}{dr^R}r^R = \frac{r^R}{\dot{\underline{p}}(\theta)} = \frac{\underline{p}(\theta)}{\dot{\underline{p}}(\theta)} = -\left(\frac{\underline{a}(\dot{\theta})}{\underline{a}(\theta)}\right)^{-1} = -LCA^{L,R}(\theta)^{-1} < 0$$

- Labor (skill) adjustment

Labor (skill) adjustment is manifested in two layers: routine- vs. non-routine and foreign vs. domestic skills. Skill adjustment is operationalized by task reallocation between routine- and non-routine skills under establishment managers. A pair of skill price changes jointly shifts the occupation threshold. Likewise, ethnic skill adjustment is operationalized by sub-task reallocation between ethnic skills under the occupation manager. A pair of ethnic skill price changes jointly shifts the ethnic threshold.

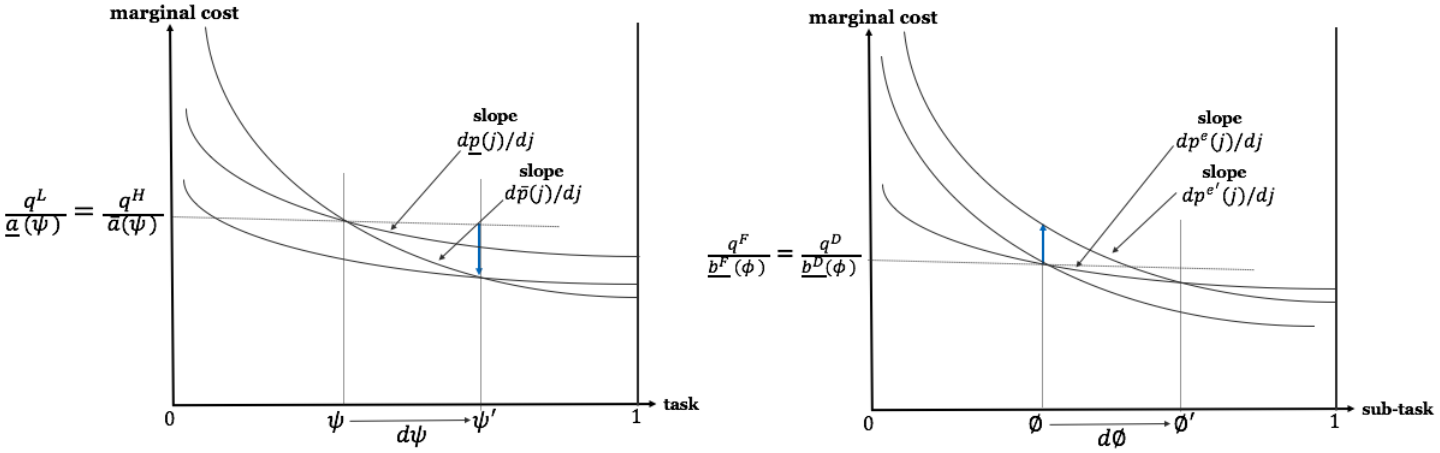


Figure 7: Marginal response of ψ to low-skill price change (left) and marginal response of ϕ to ethnic skill price change (right)

By the graphical relationships, for ethnic group e,

$$d\phi \mid \dot{p^D}(\phi) - \dot{p^F}(\phi) \mid = \frac{-dq^e}{b^e(\theta)} \Longrightarrow \frac{d\phi}{dq^e} = \frac{1}{\{\dot{p^e}(\phi) - \dot{p^{e'}}(\phi)\}\underline{b^e}(\phi)}$$

holds.

$$\frac{d\phi}{dlnq^e} = \frac{d\phi}{dq^e}q^e = \frac{q^e}{\{\dot{p^D}(\phi) - \dot{p^F}(\phi)\}\underline{b^F}(\phi)} = \frac{p^e(\phi)}{\dot{p^D}(\phi) - \dot{p^F}(\phi)}$$
$$\underset{p^D(\phi)=p^F(\phi)}{=} \left(\frac{\dot{p^D}(\phi)}{p^D(\phi)} - \frac{\dot{p^F}(\phi)}{p^F(\phi)}\right)^{-1} = -\left(\frac{\dot{b^D}(\phi)}{b^D(\phi)} - \frac{\dot{b^F}(\phi)}{b^F(\phi)}\right)^{-1} \equiv -LCA^{D,F}(\phi)^{-1}$$

3 Comparative Statics of Immigration Inflow

This chapter shows the equilibrium shifts in response to immigration inflow in both sectors. Timeline is depicted in the following figure. In the short run, labor adjustment occurs in the response to immigration inflow. In the long run, automation adjustment, in turn, triggers labor adjustment. The welfare is evaluated based on the resulting state of the labor market.

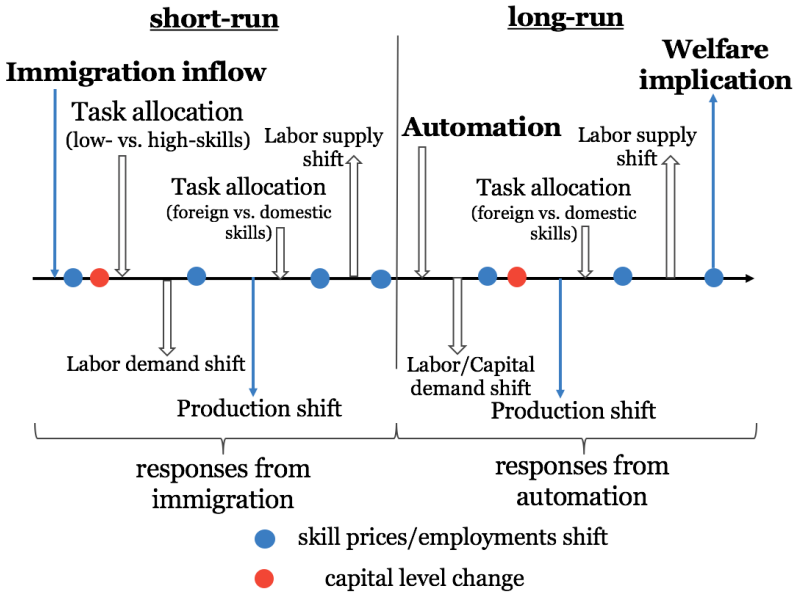


Figure 8: Timeline of events

Note:

The expansion (not shift) of labor supply curve occurs from the change of entry into the occupation class. This include immigration inflow and demographic change (e.g. retirement with aging). Suppose immigration inflow is homogeneous as existing immigration.

Proposition [Immediate shocks from Immigration inflows]

The immigration inflows expands the skill supply curves. The results are characterized by the skill/employment elasticity of skill inflow given by

$$\frac{dln\underline{q}}{dln\underline{S}^F} = -\frac{dln\underline{S}}{dln\underline{S}^F} = -\Lambda^{LF}\underline{\Phi^F} \text{ (plant)}$$

$$\frac{dln\overline{q}}{dln\overline{S}^F} = -\frac{dln\overline{S}}{dln\overline{S}^F} = -\Lambda^{HF}\overline{\Phi}^F \text{ (office)}$$

The skill supply curve expands.

3.1 Short-run

In the short run, immigration inflow coupled with domestic demography shift occurs. Suppose an establishment is only allowed to run labor adjustment over tasks by shifting a pair of thresholds,ψ and ϕ. Task reallocation is induced by the mechanical skill price responses driven by immigration inflow.

Suppose rental price of smart machine q^R is fixed. When $LCA^{H,L}(\psi)$ is sufficiently large, the following occurs by order in the plant (or office, respectively) sector.

1. Low-skilled (or High-skilled) immigration inflow lowers (or raises) low-skill price $\underline{q}$ and raise a high-skill price $\overline{q}$.
2. Occupation threshold ψ expands (or shrinks).
3. Low-skill price $\underline{q}$ rises (or falls), while high-skill price $\overline{q}$ falls (or rises).

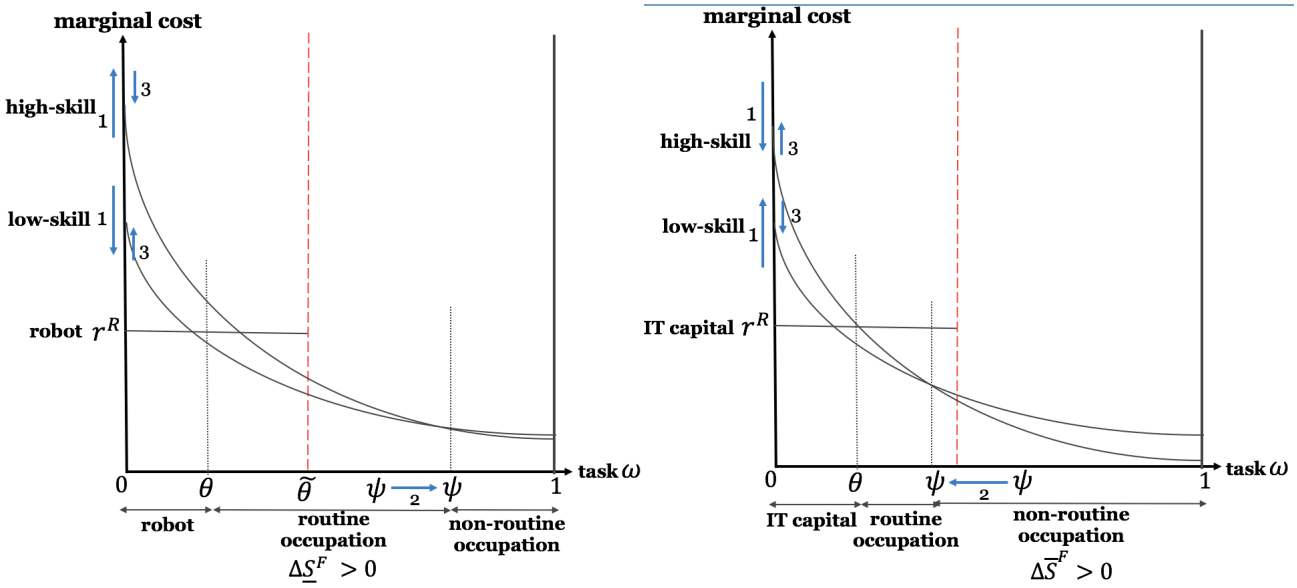


Figure 9: Short-run (left: plant, right: office)

As the foreign labor supply rises, the low-skill price mechanically declines, this leads to a price advantage, raising the production. The production expansion upshifts demand for routine skills, raising low-skill prices.

In office sector, the high-skill foreign labor supply induces lower high-skill price. This leads to a price advantage, raising the production and raising both low-skill and high-skill prices.

The inflow of immigration drops the foreign skill, lowering (or upshifting) the aggregate foreign-intensive skill price in each sector. The rise of production raises the demand for other factors, including non foreign intensive skills. The competing movement between two skill prices nudges establishments to shift their occupation threshold. As a result of task reallocation, factor demand between skills shift. Thus, more foreign-intensive skills are demanded so that skill prices rises in ethnic skill markets. In turn, this would push up the foreign-intensive skill price. Then, occupation manager reallocates the sub-tasks. This mechanism is formalized in Proposition 3 and 4 as follows.

Proposition 3 [Foreign labor entry and reallocation of tasks and sub-tasks]

Suppose θ is fixed, and the regularities R0-R3 are imposed. And suppose that $LCA^{H,L}(\psi)$ is sufficiently large. Then, the occupation threshold is adjusted as

$$(\frac{d\psi}{dln\underline{S}^F})_{short} = LCA^{H,L}(\psi)^{-1}(\overline{\Phi}\alpha\Lambda^L + 1)\underline{\Phi}^F > 0 \quad \text{(plant)}$$
$$(\frac{d\psi}{dln\overline{S}^F})_{short} = -LCA^{H,L}(\psi)^{-1}(\underline{\Phi}\alpha\Lambda^H + 1)\overline{\Phi}^F < 0 \quad \text{(office)}$$

The ethnic threshold is adjusted as

$$(\frac{d\phi}{dln\underline{S}^F})_{short} = LCA^{F,D}(\phi)^{-1}[\underbrace{-\Lambda^{LF}\underline{\Phi}^F}_{\text{mechanical}} + (\underline{\Phi}^F - \underline{\Phi}^D)\{\underbrace{\alpha\Lambda^L\underline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{1}{\Lambda^L}(\frac{d\psi}{dln\underline{S}^F})_{short}}_{\text{substitution effect}}\}] > 0 \quad \text{(plant)}$$
$$(\frac{d\phi}{dln\overline{S}^F})_{short} = LCA^{F,D}(\phi)^{-1}\{\underbrace{-\Lambda^{HF}\overline{\Phi}^F}_{\text{mechanical}} + (\overline{\Phi}^F - \overline{\Phi}^D)\underbrace{\frac{-1}{\Lambda^H}(\frac{d\psi}{dln\overline{S}^F})_{short}}_{\text{substitution effect}}\} < 0 \quad \text{(office)}$$

In the short-run, the immigration impact to the routine price involves the effect of two adjustments in addition to the mechanical drop of the immigration shock.

Proposition 4 [Foreign labor entry and routine skill price]

Suppose that θ is fixed, and $LCA^{H,L}(\psi)$ is sufficiently large. Then, the elasticity of routine skill price with respect to immigration inflow is

$$(\frac{dln\underline{q}}{dln\underline{S}^F})_{short} = \underbrace{-\Lambda^{LF}\underline{\Phi}^F}_{\text{mechanical drop}} + \underline{\Phi}\{\underbrace{\alpha\Lambda^L\underline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{1}{\Lambda^L}(\frac{d\psi}{dln\underline{S}^F})_{short}}_{\text{skill substitution}}\} + \underbrace{(\underline{\Phi}^F - \underline{\Phi}^D)(\frac{d\phi}{dln\underline{S}^F})_{short}}_{\text{ethnic substitution}} < 0 \text{ (plant)}$$

where

$$\underline{\Phi} \equiv \{\phi\underline{\Phi}^F + (1-\phi)\underline{\Phi}^D\}$$

$$(\frac{dln\underline{q}}{dln\overline{S}^F})_{short} = \underline{\Phi}\{\underbrace{\alpha\Lambda^H\overline{\Phi}^F}_{\text{growth effect}} + \frac{1}{\Lambda^L}\underbrace{(\frac{d\psi}{dln\overline{S}^F})_{short}}_{\text{skill substitution}}\} > 0 \text{ (office)}$$

If low-skills and high-skills are locally sufficiently differentiated, low-skill prices decline while high-skill prices rise. In plant sector, low-skilled immigration inflow lowers the skill price level of routine workers, but raises the low-skill price. In office sector, high-skilled immigration inflow raises the low-skill price.

In the short-run, task allocation shifts in response with the short-run skill price shock. As long as low-skills and high-skills are sufficiently differentiated, the initial shock cannot be completely offset by the subsequent task reallocation.

3.2 Long-run

In the long run, an establishment attempts to tweak the automation intensity. Suppose the short-run predictions (in Proposition.4), the following occurs by order in the plant (or office, respectively) sector.

1. Automation intensity θ shifts downwards (upwards).
2. Low-skill price $\underline{q}$ declines (rises) by shrinkage (expansion) of task interval.
3. A pair of skill prices $\underline{q}, \overline{q}$ downshifts (upshifts) due to production shift.

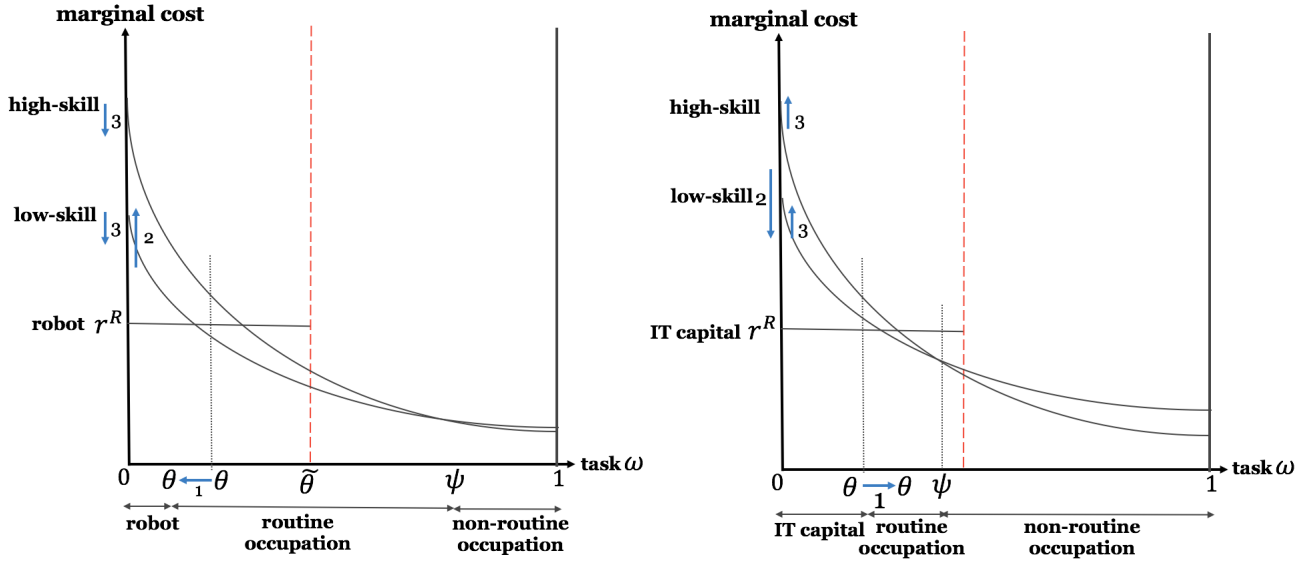


Figure 10: Long-run (left: plant, right: office)

In plant sector, if low-skilled immigration inflow decreases low-skill price, and the automation intensity shifts downward. In office sector, high-skilled immigration inflow raises the low-skill price, and the automation intensity shifts upward.

Proposition 5 [Immigration-induced automation]

Suppose θ is adjustable, and Proposition.4 holds. Then, the automation intensity is adjusted as

$$\left(\frac{d\theta}{dln\underline{S}^F}\right)_{long} = \underbrace{\left(\frac{\partial\theta}{\partial ln\underline{q}}\right)_{long}}_{>0}\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{short} < 0 \text{ (plant)} \quad \left(\frac{d\theta}{dln\overline{S}^F}\right)_{long} = \underbrace{\left(\frac{\partial\theta}{\partial ln\underline{q}}\right)_{long}}_{>0}\left(\frac{dln\underline{q}}{dln\overline{S}^F}\right)_{short} > 0 \text{ (office)}$$

Proposition 6 [Foreign labor entry and reallocation of tasks and sub-tasks]

Suppose θ is adjustable, and the regularities R0-R3 are imposed. Then, the occupation threshold is adjusted as

$$(\frac{d\psi}{dln\underline{S}^F})_{long} = LCA^{H,L}(\psi)^{-1}\frac{\underline{\Phi}}{\Lambda^L}(\frac{d\theta}{dln\underline{S}^F})_{long} < 0 \text{ (plant)}$$
$$(\frac{d\psi}{dln\overline{S}^F})_{long} = LCA^{H,L}(\psi)^{-1}\frac{\underline{\Phi}}{\Lambda^L}(\frac{d\theta}{dln\overline{S}^F})_{long} > 0 \text{ (office)}$$

The ethnic threshold is adjusted as

$$(\frac{d\phi}{dln\underline{S}^F})_{long} = -LCA^{F,D}(\phi)^{-1}(\underline{\Phi}^D - \underline{\Phi}^F)\frac{1}{\Lambda^L}\{-(\frac{d\theta}{dln\underline{S}^F})_{long} + (\frac{d\psi}{dln\underline{S}^F})_{long}\} \text{ (plant)}$$
$$(\frac{d\phi}{dln\overline{S}^F})_{long} = LCA^{F,D}(\phi)^{-1}(\overline{\Phi}^F - \overline{\Phi}^D)\frac{-1}{\Lambda^H}(\frac{d\psi}{dln\overline{S}^F})_{long} < 0 \text{ (office)}$$

3.3 Net impact of immigration via Automation adjustment

The mechanism of the main interest, net impact of immigration via automation is summarized by the change of cell-level robot adoption and regional skill prices.

Proposition 7 [Immigration and Smart machines deployment]

Suppose the regularities are imposed.

$$(\frac{dlnR}{dln\underline{S}_F})_{agg} = \underbrace{\alpha\Lambda^L\underline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{1}{\Lambda^R}(\frac{d\theta}{dln\underline{S}_F})_{long}}_{\text{displacement effect}} \text{ (plant)}$$

$$(\frac{dlnR}{dln\overline{S}^F})_{agg} = \underbrace{\alpha\Lambda^H\overline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{1}{\Lambda^R}(\frac{d\theta}{dln\overline{S}^F})_{long}}_{\text{displacement effect}} \text{ (office)}$$

Proposition 8 [Immigration and Low-skill price]

$$(\frac{dln\underline{q}}{dln\underline{S}_F})_{agg} = \underbrace{-\Lambda^{LF}\underline{\Phi}^F}_{\text{mechanical}} + \underline{\Phi}\{\underbrace{\alpha\Lambda^L\underline{\Phi}^F}_{\text{growth effect}} + \frac{-1}{\Lambda^L}\underbrace{(\frac{d\theta}{dln\underline{S}^F})_{net}}_{\text{displacement}} + \frac{1}{\Lambda^L}\underbrace{(\frac{d\psi}{dln\underline{S}^F})_{net}}_{\text{skill substitution}}\} + \{\underline{\Phi}^F - \underline{\Phi}^D\}\underbrace{(\frac{d\phi}{dln\underline{S}^F})_{net}}_{\text{ethnic substitution}} \text{ (plant)}$$

$$(\frac{dln\overline{q}}{dln\overline{S}^F})_{agg} = \underline{\Phi}\{\underbrace{\alpha\Lambda^H\overline{\Phi}^F}_{\text{growth effect}} + \frac{-1}{\Lambda^L}\underbrace{(\frac{d\theta}{dln\underline{S}^F})_{net}}_{\text{displacement}} + \frac{1}{\Lambda^L}\underbrace{(\frac{d\psi}{dln\overline{S}^F})_{net}}_{\text{skill substitution}}\} \text{ (office)}$$

The result is reflected in the contrasting association with capital density, illustrated by Figure 2. In plants, low-skilled immigration inflow lower the robot density. In offices, high-skilled immigration inflow raise the smart machine (software) density. As low- (high-) skilled immigrant enters the region, skill price declines (rises) and the smart machine density shrinks (rises). This explains the negative association between immigration density and robot adoption across regions.

Proposition 9 [Immigration and Ethnic inequality in skill prices]

$$(\frac{dln(\underline{q}^F/\underline{q}^D)}{dln\underline{S}^F})_{net} = \underbrace{-\Lambda^{LF}\underline{\Phi}^F}_{\text{mechanical effect}} \underbrace{+(\frac{\underline{\Phi}^F}{\Lambda^{LF}}+\frac{\underline{\Phi}^D}{1-\Lambda^{LF}})(\frac{d\phi}{dln\underline{S}^F})_{net}}_{\text{ethnic subsitution effect}} + \underbrace{(\underline{\Phi}^F-\underline{\Phi}^D)\alpha\Lambda^L\underline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{\underline{\Phi}^F-\underline{\Phi}^D}{\Lambda^L}\{(\frac{d\psi}{dln\underline{S}^F})_{net}-(\frac{d\theta}{dln\underline{S}}}_{\text{substitution and displacement effe}}$$

$$(\frac{dln(\overline{q}^F/\overline{q}^D)}{dln\overline{S}^F})_{net} = \underbrace{-\Lambda^{HF}\overline{\Phi}^F}_{\text{mechanical effect}} \underbrace{+-(\frac{\overline{\Phi}^F}{\Lambda^{HF}}+\frac{\overline{\Phi}^D}{1-\Lambda^{HF}})(\frac{d\phi}{dln\overline{S}^F})_{net}}_{\text{ethnic subsitution effect}} + \underbrace{(\overline{\Phi}^F-\overline{\Phi}^D)\alpha\Lambda^H\overline{\Phi}^F}_{\text{growth effect}} + \underbrace{\frac{\overline{\Phi}^D-\overline{\Phi}^F}{\Lambda^H}(\frac{d\psi}{dln\underline{S}^F})_{net}}_{\text{substitution effect}} \text{ (office)}$$

3.4 Simulated elasticities

I show that the model generates a mapping between LCAs and a trio of elasticity with respect to immigration inflow. Suppose high skills and low skills gets more locally differentiated. The routine workers cannot substitute non-routine workers, thus, the low-skill immigration impact on the low-skill price ($\epsilon^{\underline{q}}$) gets smaller in plant sector. Likewise, because the non-routine occupation cannot substitute routine-occupations, the high-skill immigration impact on low-skill prices ($\epsilon^{\underline{q}}$) gets larger due to the growth effect in office sector. Because the degree of low-skill price elasticity ($\epsilon^{\underline{q}}$) is positively associated with the robot deployment (ϵ^R), the slope is analogously directed via automation.

Suppose low skills get more locally differentiated from smart machines. Then, smart machines cannot substitute routine workers (decreasing ϵ^R), and consequently, the impact to routine skill price is smaller. (increasing $\epsilon^{\underline{q}}$). The graphical presentation of Proposition 7 and 8 are shown below.

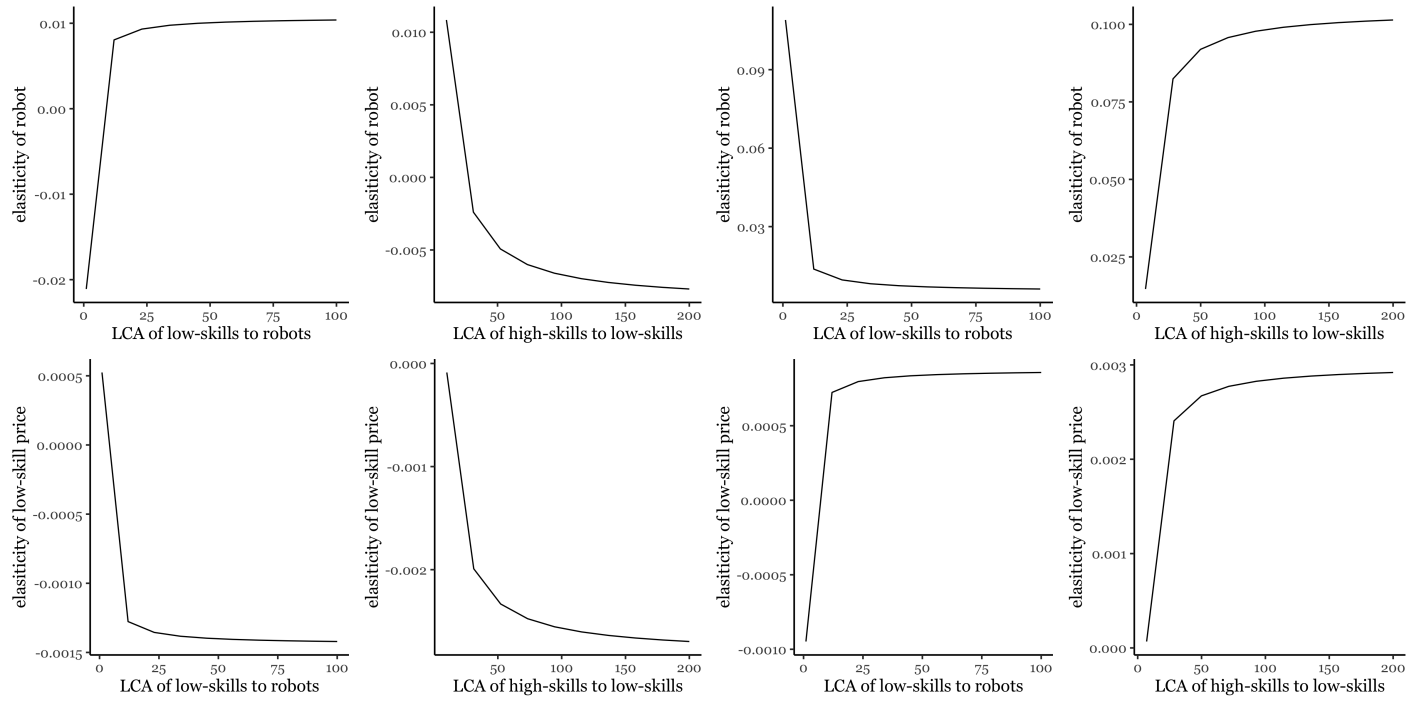
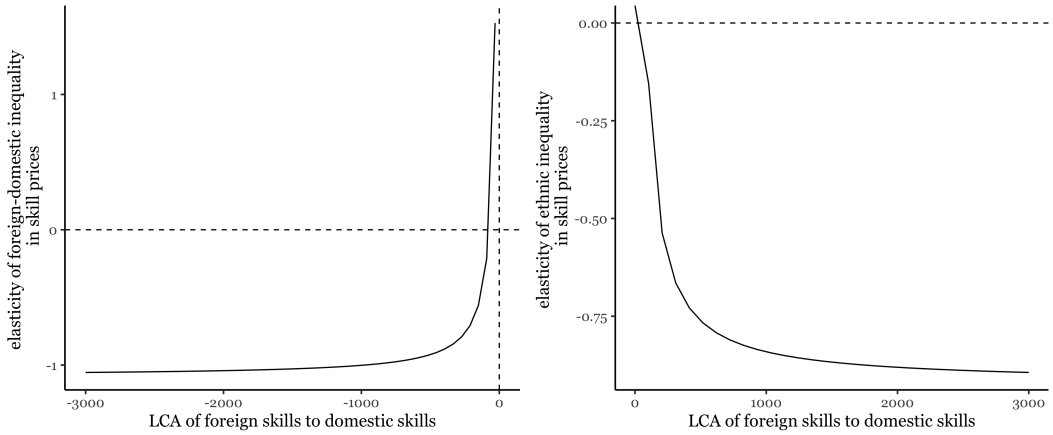


Figure 11: baseline case: simulated elasticity with respect to a pair of LCA (plant (top), office (bottom)
Note: As supposed in Proposition 4, a sufficiently large range of $LCA^{H,L}(\psi)$ is imposed.

Ethnic substitution and elasticities with respect to immigration

I simulate how the elasticity on the domestic price with respect to immigration is sensitive to the LCA of foreign skills compared to domestic skills. When foreign skills gets more differentiated from domestic skills, ethnic inequality exacerbates in plant sector, but mitigates in office sector, because immigration inflow gets less likely to substitute domestic skills.

Figure 12: Simulated elasticity of ethnic inequality in skill prices with respect to LCA of foreign skills to domestic skills (plant (left), office (right)



4 Data

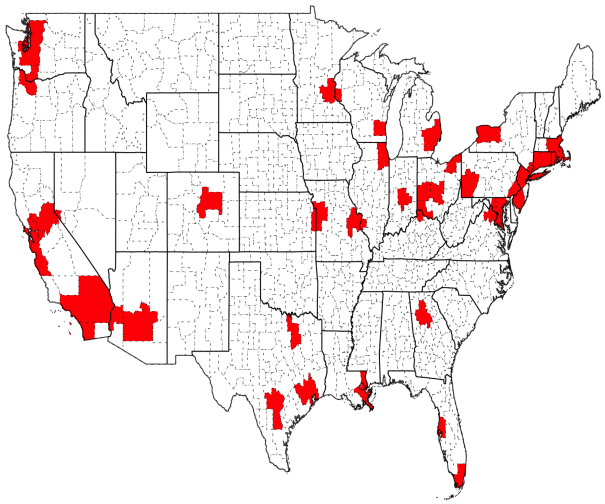
The primary data sources and proxy making are described. The further details are relegated to Data Appendix.

4.1 Unit of analysis

Plant sector covers manufacturing, while office sector corresponds to information service sector (professional service, finance service, business service, personal service) from BEA. County business patterns adopts SICs from 1980 to 1997, and NAICS from 1998-2015.

Units $\iota = (l, g')$ is a tuple, characterized by region l and industry g' in sector g. I focused on 722 commuting zones in the main land, excluding Hawaii and Alaska. I pick up *urban* areas as a combination of commuting zones, accounting for the half of the labor force at 1980. The rest of the area outside of the urban commuting zone is classified as *rural*.

Figure 13: Urban (red zones) vs. rural (state area excluding red zones)



Notes: *Computed from Current Population Survey via IPUMS USA(Steven Ruggles and Sobek (2010)) In the year 1993 and before, CPS does not contain "birthplace", thus excluded. Occupation category is classified according to the harmonized variable of "occ2010". "blue" indicates production workers in manufacturing. "white" represents clerk workers. A worker is defined as an immigrant if he was foreign-born and is non-citizen. Self-employed workers are excluded from the category of service occupations.*

4.2 Capitals

I use NIPA from BEA, which has been extensively employed in macroeconomics. It provides physical capitals and information capitals, from the consistent data ground during all the years of interest, 1980-2015. The literature also provides quality indices. As automation (both mechanization and computerization) is unobservable per se, it is captured by automation-embodying physical capitals. The barrier for measurement is separating smart machines and equipments, as specified in the conceptual model.

I overcome this empirical barrier respectively in each sector. First, in manufacturing sector, I explore which combination of capital categories in NIPA best correspond with industrial robots from IFR. Recent automation literature (e.g. Acemoglu and Restrepo (2017),Graetz and Michaels (2017)) uses the World

Robotics, Industrial Robots from IFR (2015) to measure industrial robots. [19]

Through a cross-validation exercise, a pair of *"metalworking machines"* and *"special industry machines"* is found to best match the industrial robots from IFR. (See Data Appendix)

In information service sector, the information technology (IT) capital plays a vital role. Anecdotal evidence suggests that most of IT automation-embodying capitals belong to mainframe computers, system integrator, custom software, own-account software, which are supposed to be used "off-hands" in the corporate business. The results remain robust in several alternative choices of category.[20][21]

Founded by the data categorization, I compute proxies for capital levels for each cell. A key identification assumption imposed is no within-cell heterogeneity in automation intensity at the baseline year:[22]

$$\theta^{g'}_{i,t_0} = \theta^{g'}_{\iota,t_0} = \theta^{g'}_{l,t_0} \quad \forall i \in \iota \in l$$

This presumes that no automation friction at the baseline year 1980. Also, no labor adjustments throughout the paper.

$$\psi^{g'}_{i,t_0} = \psi^{g'}_{\iota,t_0} = \psi^{g'}_{l,t_0} \forall i \in \iota \in l$$

Due to constant returns to scales technology,

$$M^{g}_{\iota,t_0} = \Sigma_{i\in\iota} M^{g}_{i,t_0} = \Sigma_{i\in\iota} A_i \underline{M}^{g}_{\iota,t_0}$$

where $M_i \in \{R_i, K_i\}$ is a quality-adjusted capital units, nominal values denominated by quality-adjusted prices. For all regions l, l' in sector g, the following relationships hold:

$$\frac{K^{g}_{\iota,t_0}}{K^{p}_{\iota',t_0}} \underset{(1)}{=} \frac{r^{g,K}_{t_0} K^{g}_{\iota,t_0}}{r^{g,K}_{t_0} K^{g}_{\iota',t_0}} \underset{(2)}{=} \frac{\underline{W}_{\iota,t_0} + \overline{W}_{\iota,t_0}}{\underline{W}_{\iota',t_0} + \overline{W}_{\iota',t_0}}, \quad \frac{R^{g}_{\iota,t_0}}{R^{g}_{\iota,t_0}} \underset{(1')}{=} \frac{r^{g,R}_{t_0} R^{g}_{\iota,t_0}}{r^{g,R}_{t_0} R^{g}_{\iota',t_0}} \underset{(2')}{=} \frac{\underline{W}_{\iota,t_0} + \overline{W}_{\iota,t_0} + V^{g,K}_{\iota,t_0}}{\underline{W}_{\iota',t_0} + \overline{W}_{\iota',t_0} + V^{g,K}_{\iota',t_0}}$$

$(1), (1')$ comes from common rental prices of the national capital market. $(2), (2')$ stem from Proposition 3. Thus, the cell-level capital in each sector is computed as

$$K^{g}_{\iota,t_0} = \Sigma_{g'} \frac{\underline{W}_{\iota,t_0} + \overline{W}_{\iota,t_0}}{\underline{W}_{g',t_0} + \overline{W}_{g',t_0}} K^{p}_{g',t_0}, \quad R^{g}_{\iota,t_0} = \Sigma_{g'} \frac{\underline{W}_{\iota',t_0} + \overline{W}_{\iota',t_0} + V^{g,K}_{\iota',t_0}}{\underline{W}_{g',t_0} + \overline{W}_{g',t_0} + + V^{g,K}_{g',t_0}} R^{g}_{g',t_0}$$

For the detailed empirical exercise, see Data Appendix.

Capital investment and rental prices

This sub-chapter computes the capital rental prices.

[19] Due to its narrow definition of industrial robots, their proxies only cover a very tiny fraction of physical capital, not suited for nation-wide analysis.

[20] It appears that IT capitals have dual-faceted roles in the literature. A line of literatures make IT capitals embody routine-replacing computerization, while other stream of literature treats it as skill-augmenting. (e.g. Beaudry, Doms and Lewis (2010),Akerman, Gaarder and Mogstad (2015)) A body of literature incorporate both in the context of skill-capital complementarity. (e.g. Krusell et al. (2000),Autor, Levy and Murnane (2003),Autor and Dorn (2013)) Figure 2 depicts IT capital as skill-replacing, embodying automation in non-production tasks. Both skill-replacing and skill-augmenting fronts of IT capital will be explicitly included in the model below.

[21] No outside data source to capture smart machines R is available.

[22] Acemoglu and Restrepo (2017) adopts a similar imputation strategy of commuting zone-level industrial robots.

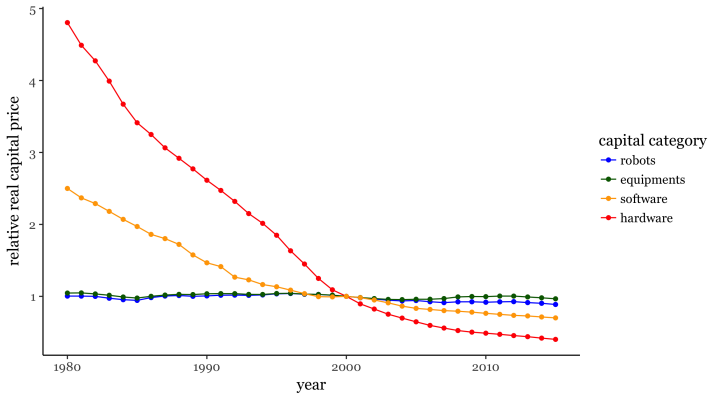


Figure 14: capital investment price

Several differences between physical and information capitals are worth noting. First, quality-adjusted investment prices of physical capital prices are relatively stable, while information capitals plummet over time. Second, information capital exhibits a larger depreciation rate than .

4.3 Labor

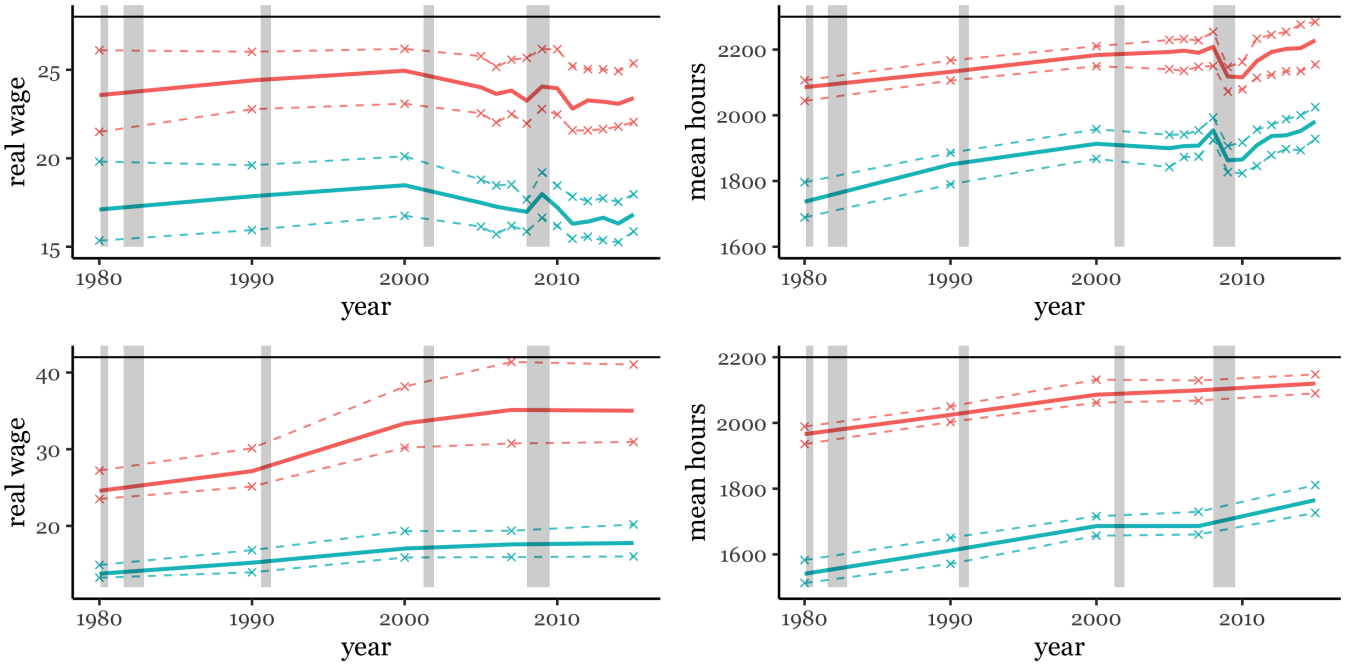
The dataset for labor is a repeated cross-section data from the Decennial Population Census and American Commuting Survey (ACS) in 1980, 1990, 2000, 2005-2015 as benchmark years from the Integrated Public Use Microdata Samples (IPUMS)(Steven Ruggles and Sobek., 2017) The analysis is restricted to working-age individuals from 16 to 64. An immigrant is defined as foreign-born, non-citizen (including naturalized citizen) and natives are the rest of the people in the US.

In manufacturing sector, production workers are on the key interest. Guided by the model, the production workers are classified into *routine* occupations ($m = L$, e.g. laborers) and *non-routine* occupations ($m = H$, e.g. frontline factory managers and mechanical engineers) In the information service sector, most of employees are non-production workers. They are split into *routine* occupations ($m = L$, e.g. white-collar workers) and *non-routine* occupations ($m = H$, e.g. managers and engineers). Occupation category is split according to the ONET classification.

In the year 1993 and before, CPS does not contain "birthplace". In plant sector, I use *"Hispanic origins"* as alternative proxies, following Borjas.

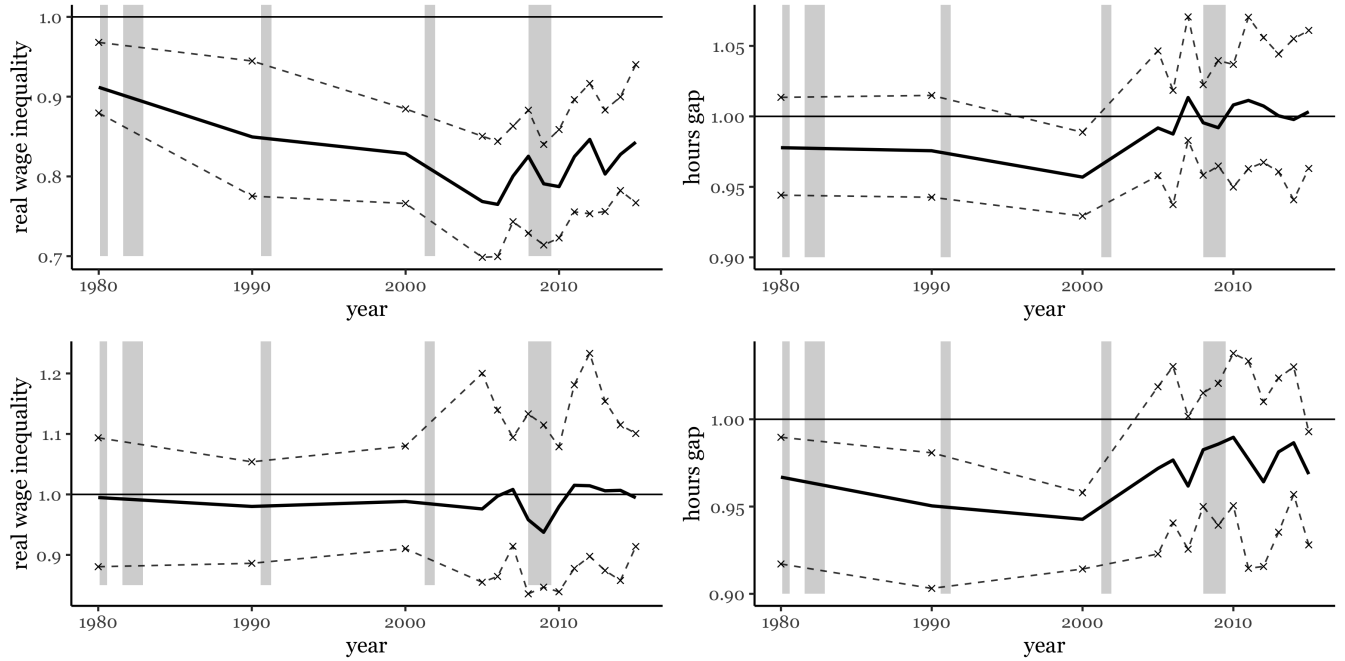
The Figure 16 graphically shows that immigration inflow is highly dispersed across commuting zones. Skill rental prices are estimated. Computed from Current Population Survey via IPUMS USA.*Steven Ruggles and Sobek (2010)* Shaded years are NBER recession periods.

Figure 15: Real wage and working hours trend by occupation class (Right: real wage, left: mean working hours, top: manufacturing, bottom: information service, 1980-2015)



Notes: *Red lines are non-routine occupations, while green ones are routine occupations. Solid lines track median across units, while dashed lines are top 25, 75 quantiles.*

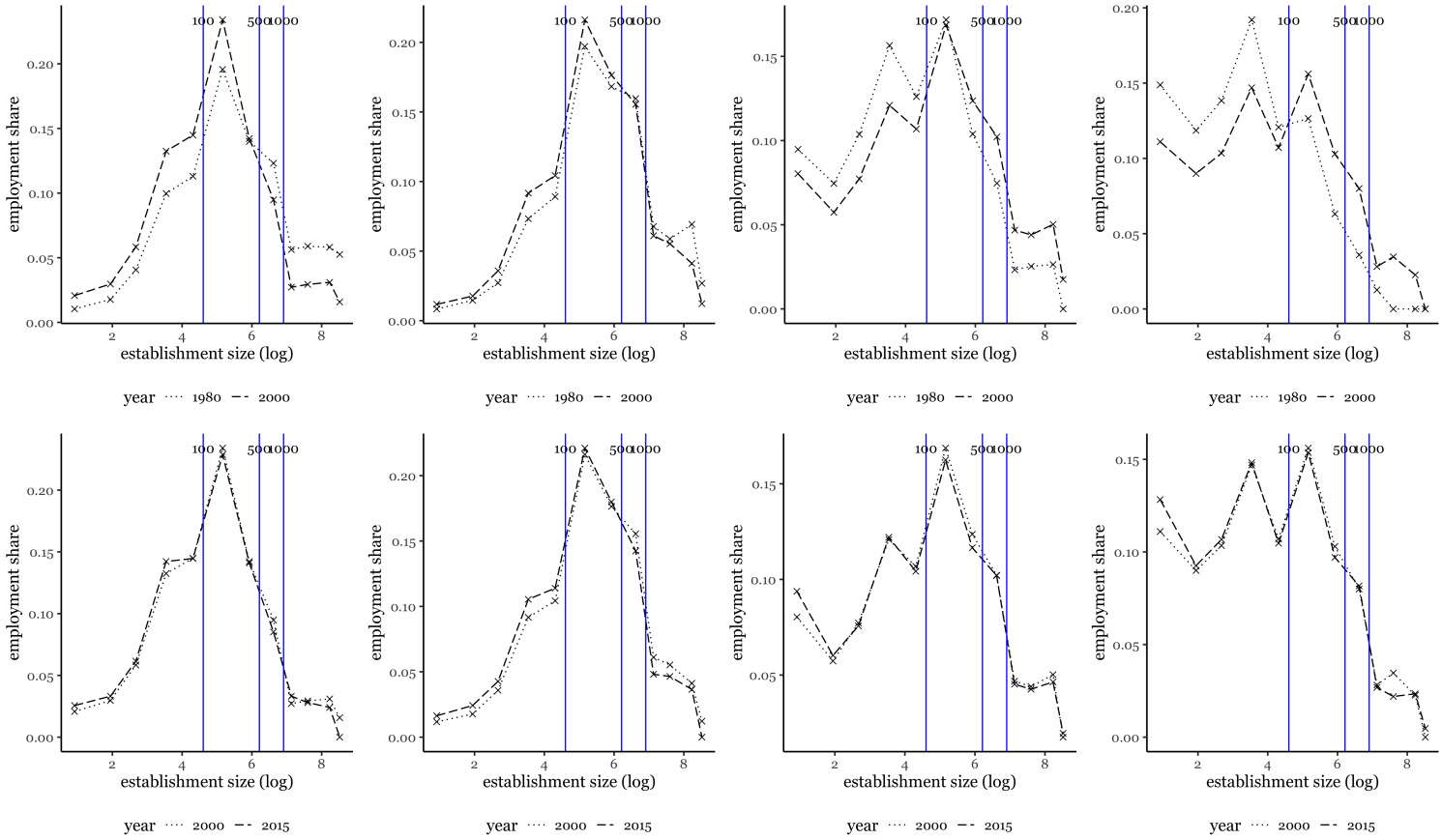
Figure 16: Ethnic wage inequality by occupations (median across commuting zones)



Notes: *In the year 1993 and before, CPS does not contain "birthplace", thus excluded.*

4.3.1 Size distribution

Figure 17: Employment share by sector (urban vs. rural, 1980 vs. 2000, 2000 vs. 2015)



The two proxies capture the distribution of employment shares of each size class. gini coefficient represents employment concentration of large establishments. (It is highly correlated with mega-establishments share), while skewness represents the asymmetry of the distribution.

Suppose automation decreases size in plant (displacement effect dominates). If automation is primarily driven by high-productive plants (negatively large β_A), the gini would fall and skewness would rise. On the other hand, market competition drives up gini and decreases skewness, because productive plants by automation gain larger market shares.

Since skill price and productivity (measured by TFP) are higher in urban areas than rural areas and, automation is more strongly induced in urban areas. This will induce decline of mean size.

Suppose automation raises size in office (growth effect dominates). If automation is primarily driven by high-productive plants (negatively large β_A), the gini would rise and skewness would fall (more flatter distribution). On the other hand, analogous to the plant sector, market competition drives up gini and decreases skewness, because productive plants by automation gain larger market shares.

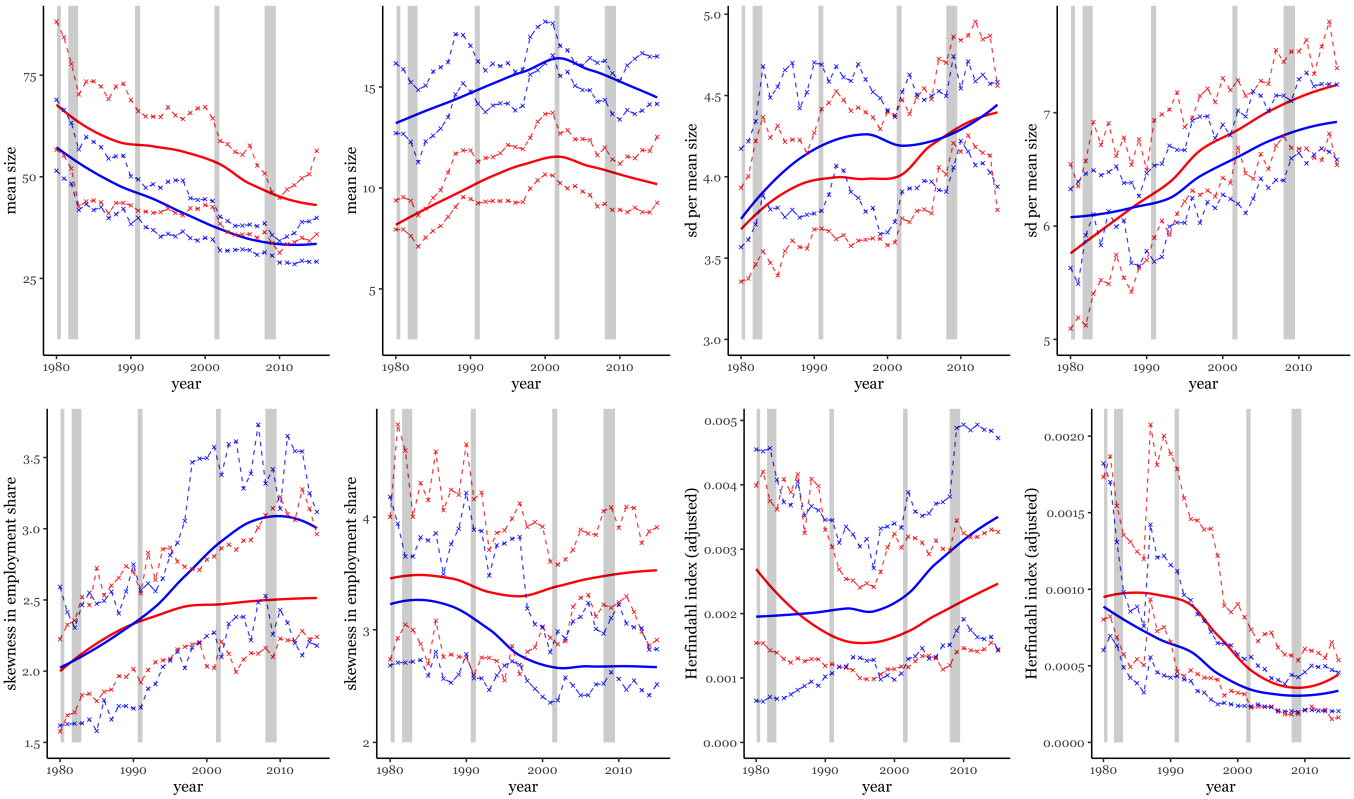
Since skill price and productivity (measured by TFP) are higher in urban areas than rural areas and, automation is more strongly induced in urban areas. This will induce rise of mean size. However, after 2000, the growth effect of automation turns to be counteracted by displacement effect, and the automation does not affect the office employment share distribution.

The mean plant size is monotonically decreasing, while mean office size is increasing in 1980-2000, and decreasing in 2000-2015.

The decline of plant is chiefly driven by the shrinkage of mega-size plants. (initially productive mega-sized plants underwent intensive automation) In 1980-2000, it was augmented by the shrinkage of small and middle sized plants. (by competition effect from intensified automation)

The rise in mean size employment in office in 1980-2000 appears to be driven by the expansion of office sizes. (growth effect of automation matters) Decline in mean size employment in office after 2000 appears uniformly occur, consistent with the stable the employment share distribution.

Figure 18: Mean, standard deviation per mean of the establishment size, and skewness of their employment shares (manufacturing (left) and information service (right), urban (blue) vs. rural (red), 1980-2015)



5 Dynamic Structural Model

To jointly explain the patterns described in the last chapter, and assess how immigration accounts for automation adoption, via the mechanism stress in the paper, I develop a dynamic stochastic structural model.

5.1 Factor demand side

I model automation adjustment as dynamic instead of repeated optimization of task allocations. I adopt the dynamic automation decision for three reasons. First, as is commonly presumed in investment literature, capitals are durable, and partially irreversible poor secondary market. Its profitability inherently depends not only on the *current* skill price, but the *future* path of skill price as well. The expectation of future skill prices matter for the current technology adoption.[23] This makes the establishments consider the future profitability under the current technology.

Second, investments are affected by business cycles. In booms, investments are typically boosted, while in recessions, they get suppressed.

Third, the factor prices are also non-stationary. In particular, fundamental evolution of demography and technologies naturally nudge establishments to forecast the trends of factor prices.

The conceptual model is enriched along the following realistic dimensions. First, establishments are better reformulated in the dynamic setting as capital owners rather than capital renters.[24] Second, establishment pays heterogeneous automation adjustment costs in both non-convex and convex forms. The non-economic forces of automation is sufficiently proxied by adjustment cost, where establishments are set to pay when they adjust the automation intensity. As automation is inherently factor-biased, adjustment costs for automation accommodates both capital adjustment (e.g. robot installation, learning) and labor adjustments costs (e.g. layoff, renegotiation). Observable heterogeneity of the cell (e.g. technological automatability, export intensity, product variety) is incorporated to examine their relative contributions to adjustment costs.

Third, establishment has their own factor-neutral productivities (TFP), which potentially affect the adjustment costs as well.

Setup

Time is infinite horizon, and discretized, starting at the initial period $n = 0$. Establishment i at cell $\iota = \{l, g\}$, sector $G \in \{p, o\}$, produces a final good. Production function for establishment i is reformulated as

$$Y_{i,n}^{g} = (A_{i,n})^{1-\eta}(X_{i,n})^{\eta}$$

where $X_{i,n}$ is a baseline production function as

$$X_{i,n} = B(\theta_{i,n}, \psi_{i,n})\left(\frac{R_{i,n}}{\theta_{i,n}}\right)^{\theta_{i,n}}\left(\frac{\underline{S}_{i,n}}{\psi_{i,n} - \theta_{i,n}}\right)^{\psi_{i,n}-\theta_{i,n}}\left(\frac{\overline{S}_{i,n}}{1-\psi_{i,n}}\right)^{(1-\psi_{i,n})\alpha}\left(\frac{K_{i,n}}{1-\psi_{i,n}}\right)^{(1-\psi_{i,n})(1-\alpha)} \tag{7}$$

[23] This resonates with durable goods consumption in industrial organization or marketing literature, where consumers rationally decide when to purchase the new durable good products and preference for product attributes conditional on consumer characteristics are examined. (e.g. Hendel (1999),Gowrisankaran and Rysman (2012))

[24] Rental service market for industrial robots or information capital remains poor. In light of policy implementation, investments, not operative stock values, serve as basis for fiscal policies on capital investments.

and

$$B(\theta_{i,n}, \psi_{i,n}) = exp[\int_{\theta_{i,n}}^{\psi_{i,n}} ln(\underline{a}(\omega))d\omega + \alpha \int_{\psi_{i,n}}^{1} ln(\overline{a}(\omega))d\omega]$$

$\epsilon_{i,n}$ is an idiosyncratic shock in location l and $A_{i,n}$ is a time-invariant total factor productivity (TFP), such that persistent establishment productivity follows an AR(1) process with auto-regressive parameter η

$$\epsilon_{i,l,n} = \epsilon_{i,l,n-1} + \eta_{l,n} + \sigma_{l,n} u_{in}$$

The periodic profit function at period n is

$$\pi_{i,n}(\theta_{i,n}, \frac{q}{q^R}_{i,n}) = PY_{i,n}(\theta_{i,n}, \epsilon_{i,n}) - \underbrace{\Sigma_M p^M_{i,n} I^M_{i,n}}_{\text{investments}} - \underbrace{(\Sigma_e q^e_{l,n} S^e_{i,n} + \overline{q}_{l,n} \overline{S}_{i,n})}_{\text{labor compensation}} \tag{8}$$

Technology choice is accompanied by investments by the law of motion of capital $M \in \{R, K\}$.

$$I^M_{i,n} = M_{i,n+1} - (1 - \delta^M_n) M_{i,n} \tag{9}$$

Because labor adjustment between foreign-domestic tasks is frictionless, the threshold ψ, ϕ is set every period to reflect the skill price inequality to satisfy (4). Since regional skill prices are equalized, $\psi_{i,n} = \psi_{\iota,n} = \psi_{l,n}, \phi_{i,n} = \phi_{\iota,n} = \phi_{l,n}$ for every $i \in \iota \in l$.[25]

Dynamic automation choice

A forward-looking establishment is making dynamic investment decisions by choosing automation intensity θ, rationally anticipating a price trajectory, of smart machine price, equipment rental price and skill prices. Each independently chooses an where the superscripts refer to *adjust* $(A, \theta_{i,n} \neq \theta_{i,n-1})$ or *no adjust* $(N, \theta_{i,n} = \theta_{i,n-1})$ the automation. Cyclical shock is factor-neutral, while automation choice is factor-biased. These value functions are given by

$$V^A(\theta, \frac{q}{q^R}) = \pi(\theta, \frac{q}{q^R}) - \{F + (\theta^{'} - \theta)^2 g\}\Pi X + \beta \mathbb{E}[V(\theta^{'}, (\frac{q}{q^R})^{'})]$$

$$V^N(\theta, \frac{q}{q^R}) = \pi(\theta, \frac{q}{q^R}) + \beta \mathbb{E}[V(\theta^{'}, (\frac{q}{q^R})^{'})]$$

where F, g are non-convex and convex adjustment costs proportional to the baseline production.[26] Π captures heterogeneity in observable attributes $\mathbf{x}$ and unobservable productivity A.[27]Π is parameterized as

$$\Pi = F + \beta^A A + \epsilon$$

Adjustment costs directly feed into their intervals of automation upgrading. Automation adjustment F

[25]The baseline model predicts that same regional skill price and investment price (and rental price), the threshold is common for all establishments in the same region.

[26]Note that automation shift is costly, while investment itself is made frictionless.

[27] A captures intangible assets including intellectual patents, trade secrets, and management know-hows.

captures notions of factor adjustments: both capital adjustment cost (e.g. robot installation) and labor adjustment cost associated with labor displacement (e.g. dismissal payment), with regard to automation.

The establishment i raises automation intensity if and only if

$$V^A(\theta, \frac{q}{q^R}) > V^N(\theta, \frac{q}{q^R})$$

Given this optimal automation decision, a discrete automation choice is specified as

$$V(\theta, \frac{q}{q^R}) = max\{V^A(\theta, \frac{q}{q^R}), V^N(\theta, \frac{q}{q^R})\} \; \forall \theta, \frac{q}{q^R}$$

Forecasting of factor price

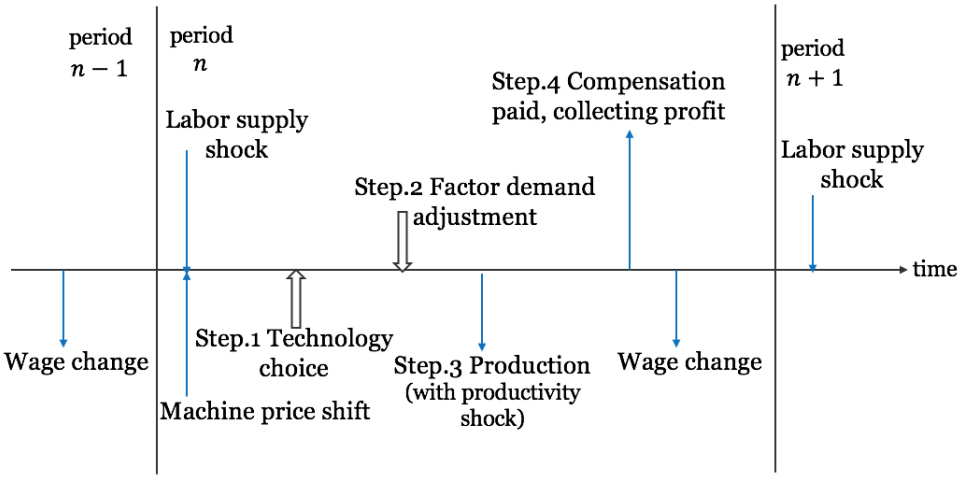
Establishments rationally expect that the future labor supply entry and a skill price trajectory.

Suppose that establishments form a rational expectation for labor supply entry of each class of workers. It is unlikely that establishments perfectly calculate the location choice as the labor model states. The expectation formation of both parties in the economy not only reduces computational burden, but behaviorally more preferable and realistic, given the bounded rationality of agents. Establishments have perfect foresights in investment capital prices.

Timeline of events

In view of rigidity of skill prices during a short period, regional skill prices are adjusted only once at the end of the cycle. The following procedure is iterated until the economy reaches the target period $n = N$.

Figure 19: Timeline of events



Several caveats are worth noting. Several features, such as human capital accumulation, credit constraint of establishments, and entries/exits of establishments are excluded.

5.2 Adjustment costs and Size distribution

In the equilibrium upgrading interval, the discounted sum of mismatch losses is equalized with one-shot adjustment cost. The tradeoff is a loss from skill-task mismatch and adjustment cost payment.

An idiosyncratic productivity shock is utilized. A "good" shock facilitates investment with large amounts, while a "bad" shock induces smaller, or zero investments.

Cheaper price with frequent upgrading cycles versus expensive price with less-frequent upgrading cycles. The more unobservable abilities they have, the less adjustment costs they pay.

- Higher F induces the overall labor share, and pro-cyclicality. (overshooting force)

High F implies longer intervals, the automation intensity is more likely to be smaller from the regional optimum level. When the boom happens (good cyclical shock), the fixed cost property of adjustment cost leads to increasing return to scales.[28]

- Higher g affects the overall labor share, and against pro-cyclicality. (undershooting force)
- Negatively larger TFP parameter β^A reduces the mega share, increase the small share, and decreases Herfindahl index (less concentration)
- Industry- (regional-) level parameters capture industry- (regional-) level variations

[28] Employing the plant-level data, Doms, Dunne and Troske (1997) Bernard, Jensen and Schott (2006) documents the dramatic heterogeneity in automation adoption. The large firms tend to adopt the advanced automation technologies.

6 Identification and Estimation

This chapter summarizes a strategy for identification and report estimation results on factor demand and supply sides, respectively.

Factor demand side

The identification in the factor demand side consists of the following two stages. The key primitives are intensive margin of technology to capture the economic forces to govern automation and dynamic parameters for automation adjustment to capture non-economic frictions of automation.

In Stage.1, extensive-margin of technology (task thresholds) at the baseline year is recovered. These serve as inputs to estimate primitive intensive-margin of technology.

Given the recovered technology in Stage.1, in Stage.2, the adjustment costs for automation together with market competition structure are estimated by replicating the key features of cross-sectional variation of the evolution of the size distributions by the dynamic automation choice model.

Stage.1: Recover the technology

To start with, task thresholds (extensive-margin technology) are recovered in the baseline year, 1980. Analogously in the previous chapter, automation is presumed to be frictionlessly adopted by every establishment in the baseline year; no heterogeneity in automation intensity within cells. The following procedure is designed to recover task-specific productivities.

Extensive-margin of technology

Proposition [Extensive-margin technology and Factor shares]

At the baseline year, task thresholds across production factors and equipment intensity are identified from factor shares such that

$$\theta_{l,t_0} = \frac{\chi^R_{l,t_0}}{1-\chi^K_{l,t_0}},\ \psi_{l,t_0} = 1 - \frac{\chi^H_{l,t_0}}{1-\chi^K_{l,t_0}},\ \phi_{l,t_0} = \chi'^F_{l,t_0},\ \alpha_{l,t_0} = 1-\chi^K_{l,t_0}$$

The task thresholds are identified by labor/capital income, and foreign/domestic labor incomes, respectively. The result immediately comes from (6), shown in Proposition 3.

In the later periods after the $t > t_0 = 1980$, due to heterogeneous adjustment costs, task thresholds start to diverge across establishments.

Intensive-margin of technology

Stage 1-1 Region-specific elasticities with respect to immigration inflow

As shown in Proposition 6 and 7, mappings between two primitives and two elasticities with respect to immigration are given by

$$\epsilon^R = f^1(LCA^{L,R}(\theta), LCA^{H,L}(\psi), LCA^{F,D}(\phi)) \quad \epsilon^{\underline{q}} = f^2(LCA^{L,R}(\theta), LCA^{H,L}(\psi), LCA^{F,D}(\phi))$$

where f^1, f^2 are non-linear functions. This non-linear simultaneous equations are approximately linearized in the following reduced-form.

$$y_{\iota,t_0} = \beta^z_{0,\iota} + \beta^z_{1,\iota}\frac{\Delta S^F_{\iota,t_0}}{S^F_{\iota,t_{-1}} + S^D_{\iota,t_{-1}}} + \beta^z_{2,\iota}\theta_{\iota,t_0}\frac{\Delta S^F_{\iota,t_0}}{S^F_{\iota,t_{-1}} + S^D_{\iota,t_{-1}}} + \beta^z_{3,\iota}\psi_{\iota,t_0}\frac{\Delta S^F_{\iota,t_0}}{S^F_{\iota,t_{-1}} + S^D_{\iota,t_{-1}}} + \varepsilon^z_{\iota,t_0} \tag{10}$$

where

$$t_0 = 1980, \quad t_{-1} = 1970, \quad y \in \{\frac{\Delta R_\iota}{\underline{S}^D_{t_{-1}} + \underline{S}^F_{t_{-1}}}, \frac{\Delta \underline{q}_l}{\underline{q}_{l,t_{-1}}}\}$$

Cell-specific elasticity with respect to immigration is

$$\epsilon^z_\iota = \beta^z_1 + \beta^z_2\frac{\chi^R_{t_0}}{\alpha} + \beta^z_3(1 - \frac{\chi^H_{t_0}}{\alpha})$$

As is often evoked in the literature, endogeneity problem of immigration inflow into the cell ι arises. Econometrically, $logS^F_{t_0,\iota}$ and unobservable terms ε^y_l are correlated. To address this issue, I use ethnic settlement patterns in 1970 as instrument for immigration entry. (Card,1991) Formally, following the immigration literature[29], the instrument for the inflow of immigrants into $\iota \in l$ from the reference year $t = 1970$ to year t is given by

$$IV_{l,t} = \Sigma_{e'}\frac{N^{e'}_{l,1970}}{N^{e'}_{1970}}\frac{\Delta N^{e'}_t}{\widetilde{N^D_{1970}} + \widetilde{N^F_{1970}}}$$

where e' is an ethnic group in the reference year $t = 1970$ and Δ captures the change from the reference year $t = 1970$ to year t of interest.[30] $\frac{N^{e'}_{l,1970}}{N^{e'}_{1970}}$ captures the settlement ratio of a region l of ethnic group e' population in 1970. The instrument essentially allocates a new wave of immigrants of an ethnic group, following the historical distribution of the same ethnic group.

[29]The strategy with the instrument have been predominantly used in the immigration literature. (e.g.Altonji and Card (1991),Card (2001)) See Jaeger, Ruist and Stuhler (2018)for an extensive list of literatures.

[30]Ethnic groups included in the Census1970 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 the size of working-age population)

		manufacturing	information service
task share	robot	0.043 (.013)	0.011 (.0017)
	routine	0.647 (.07)	0.475 (.0437)
	non-routine	0.307 (.063)	0.514 (.044)
	foreign share	0.031 (.051)	0.011 (.019)
equipment intensity		0.122 (.045)	0.048 (.006)

Uncompensated labor supply elasticity	low-skill (foreign)	low-skill
	low-skill (domestic)	high-skill (foreign)
	high-skill	high-skill (domestic)

Figure 20: Table for summary statistics in each sector

Note: To get the uncompensated elasticity, run the regression, using the cross-section individual data (Census/ACS) in 1980.

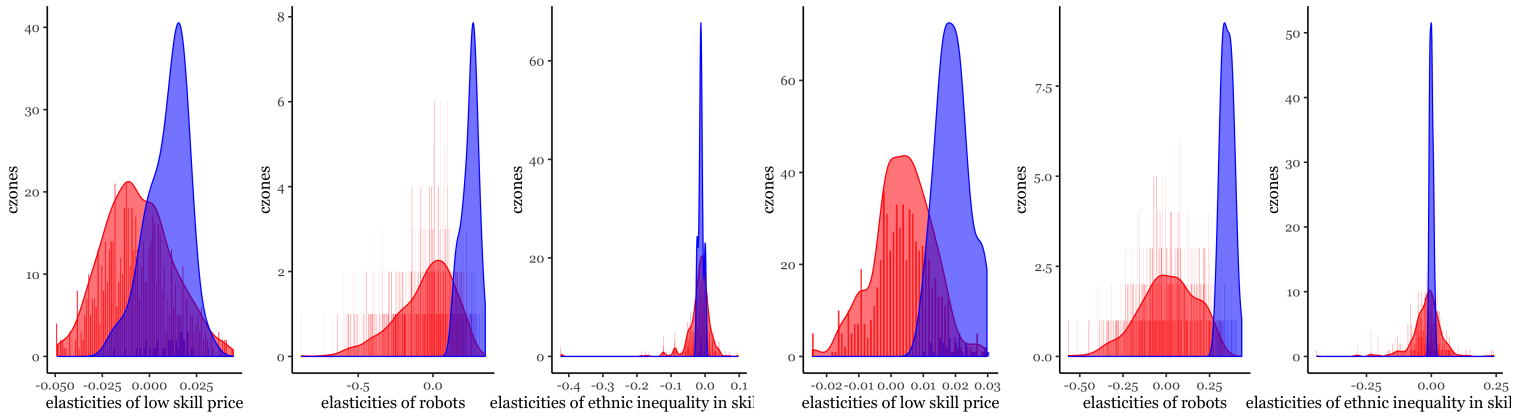
$$logL_i^z = \beta_0 + \beta_1 logw_i^z + \beta_2 logNLI_i + \beta_3 X_i + \epsilon_i$$

Figure 21: Reduced-form estimation results

		manufacturing			information service	
year		routine skill price	robot		routine skill price	robot
1970-1980	immigrant (low-skill)	1.105 (.238)***	3.842 (1.230)**	immigrant (high-skill)	0.102 (.045)*	-2.639 (.712)***
	robot share share (log)	0.308 (.060)*	0.975 (.311)*	robot share share (log)	0.020 (.0079)*	-0.616 (.124)***
	non-routine share (log)	0.122 (.062) ***	0.606 (.322)'	non-routine share (log)	0.012 (.029)	0.043 (.455)
	state fixed effects	Yes	Yes		Yes	Yes
	sample size	715	715		721	721
		location-specific elasticity			location-specific elasticity	
	median	-0.015	0.031	median	0.0019	0.1356
	sd	0.092	0.322	sd	0.003	0.0618
	max	0.320	1.179	max	0.0118	0.341
	min	-0.246	-0.811	min	-0.0064	-0.129

*Notes: *** p<0.1 %; ** p<1 %; * p<5 %, ' p<10 %.*

Figure 22: Distribution of a trio of region-specific elasticities of immigration in 1980 (top: manufacturing, right: information service)



Notes: "Urban" and "rural" area follows a definition in Chapter 5.

Stage.1-2: Semi-parametrically identify and estimate a LCA functions from the region-specific elasticities

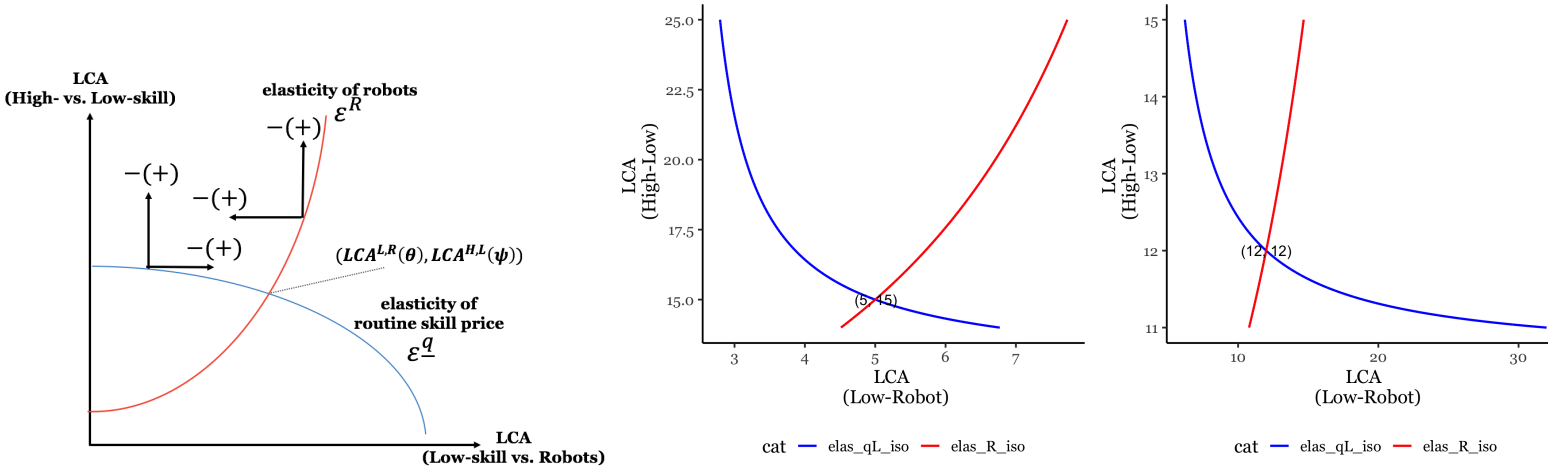
The discrepancies of reduced-form results are accommodated, and leveraged as a useful source of identification by the proposed framework with flexible substitution patterns.[31]

Using the equations derived from the model, a series of elasticities are translated to corresponding LCAs.

Proposition [Local comparative advantages and a pair of elasticities with respect to immigration]

In each cell, given a LCA of foreign skills to domestic skills, a pair of LCAs of low-skills to smart machines, and of low-skills to high-skills are just-identified from elasticities of smart machine deployment and routine skill price with respect to immigration.

Figure 23: Identify a pair of LCAs



Notes: *left: a conceptual chart for identification in baseline equilibrium in plant sector, parenthesis is for office sector. middle: simulation in plant, right: simulation in office.*

$$\left(\frac{dlnR}{dln\underline{S}^F}\right)_{agg} = \underbrace{\frac{\partial\left(\frac{dlnR}{dln\underline{S}^F}\right)_{net}}{\partial\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{short}}}_{\propto LCA^{L,R}(\theta)^{-1}} \underbrace{\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{short}}_{\propto LCA^{H,L}(\psi)^{-1}}$$

$$\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{agg} = \underbrace{\frac{\partial\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{net}}{\partial\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{short}}}_{\propto LCA^{L,R}(\theta)^{-1}, LCA^{H,L}(\theta)^{-1}} \underbrace{\left(\frac{dln\underline{q}}{dln\underline{S}^F}\right)_{short}}_{\propto LCA^{H,L}(\psi)^{-1}}$$

[31] Rigorously, LATE from quasi-experiments are used to proxies of MTE of immigration inflow. See Heckman and Vytlacil (2005) for a theoretical background.

Moment conditions

Each region l is characterized by a tuple of $(\theta_l, \psi_l, \phi_l)$. Derive $3N$ moment conditions (1)-(3) as sufficient conditions for identify parameter set,

$$\boldsymbol{\Theta} = \{LCA_l^{L,R}(\omega), LCA_l^{H,L}(\omega), LCA_l^{F,D}(\omega)\}$$

$$\begin{cases} \epsilon_l^R = m_l^1(LCA_l^{L,R}(\omega), LCA_l^{H,L}(\omega), LCA_l^{F,D}(\omega') \mid \theta_l, \psi_l, \phi_l) & (1) \\ \epsilon_l^{\underline{q}} = m_l^2(LCA_l^{L,R}(\omega), LCA_l^{H,L}(\omega), LCA_l^{F,D}(\omega') \mid \theta_l, \psi_l, \phi_l) & (2) \\ \epsilon_l^{\underline{q}^F/\underline{q}^D} = m_l^3(LCA_l^{L,R}(\omega), LCA_l^{H,L}(\omega), LCA_l^{F,D}(\omega') \mid \theta_l, \psi_l, \phi_l) & (3) \end{cases}$$

To facilitate the estimation, task productivity functions (and LCA functions) are common across regions. (but *realized* LCAs differ across regions due to heterogeneous task thresholds). Also, LCA functions are polynomially parameterized by $\boldsymbol{\beta} = \{\boldsymbol{\beta_j^L}, \boldsymbol{\beta_j^H}, \boldsymbol{\beta_j^F}\}$ such that

$$LCA^{L,R}(\omega) = \Sigma_{j=0}^K \beta_j^L \omega^j, \quad LCA^{H,L}(\omega) = \Sigma_{j=0}^K \beta_j^H \omega^j, \quad LCA^{F,D}(\omega') = \Sigma_{j=0}^K \beta_j^F \omega'^j$$

Then, the procedure is reduced to estimate the parameters $\boldsymbol{\Theta} = \boldsymbol{\beta}$ (3K) using other moment conditions (1)-(3).

$$min_{\Theta} \overline{\boldsymbol{g}}_N(\boldsymbol{\Theta})' \boldsymbol{W} \overline{\boldsymbol{g}}_N(\boldsymbol{\Theta})$$
$$s.t. \ \ \overline{\boldsymbol{g}}_N(\boldsymbol{\Theta}) = \frac{1}{N} \Sigma_{l=1}^N \boldsymbol{g}_l(\boldsymbol{\Theta})$$

where $\boldsymbol{g}_l(\boldsymbol{\Theta})$ is $3N \times 1$ vector-valued function of $3K \times 1$ vector $\boldsymbol{\Theta}$ such that $\boldsymbol{g}_l(\boldsymbol{\Theta}) = \begin{bmatrix} \boldsymbol{g^1} \\ \boldsymbol{g^2} \\ \boldsymbol{g^3} \end{bmatrix}$ and

$$\begin{cases} g_l^1 = \epsilon_l^R - m_l^1(\boldsymbol{\beta} \mid \theta_l, \psi_l, \phi_l) & (1) \\ g_l^2 = \epsilon_l^{\underline{q}} - m_l^2(\boldsymbol{\beta} \mid \theta_l, \psi_l, \phi_l) & (2) \\ g_l^3 = \epsilon_l^{\underline{q}_l^F/\underline{q}_l^D} - m_l^3(\boldsymbol{\beta} \mid \theta_l, \psi_l, \phi_l) & (3) \end{cases}$$

Observe that moment conditions exceed the number of parameters: $3K < 3N$ ($N = 722$). Once $\boldsymbol{\Theta}$ is estimated, one could recover the entire series of task productivities $\{\underline{a}(\omega), \overline{a}(\omega), \underline{a}^F(\omega)\}$ using the definition of LCAs.

Recover baseline factor-augmenting productivities

Given the $\{\underline{a}(\omega), \overline{a}(\omega), \underline{a}^F(\omega)\}$, baseline task productivity for robots, high-skills and foreign skills A^R, A^H, A^F are recovered using a set of single-crossing conditions ((4),(4)):

$$A_\iota^R = \frac{q_{R,t}}{\underline{q}_{\iota,t}/\underline{a}(\theta_{\iota,t})}, \ A_\iota^H = \frac{\overline{q}_{\iota,t}/\overline{a}(\psi_{\iota,t})}{\underline{q}_{\iota,t}/\underline{a}(\psi_{\iota,t})}, \ \underline{A}_\iota^F = \frac{\underline{q}^F/\underline{a}^F(\phi)}{\underline{q}^D/\underline{a}^D(\phi)}$$

Results

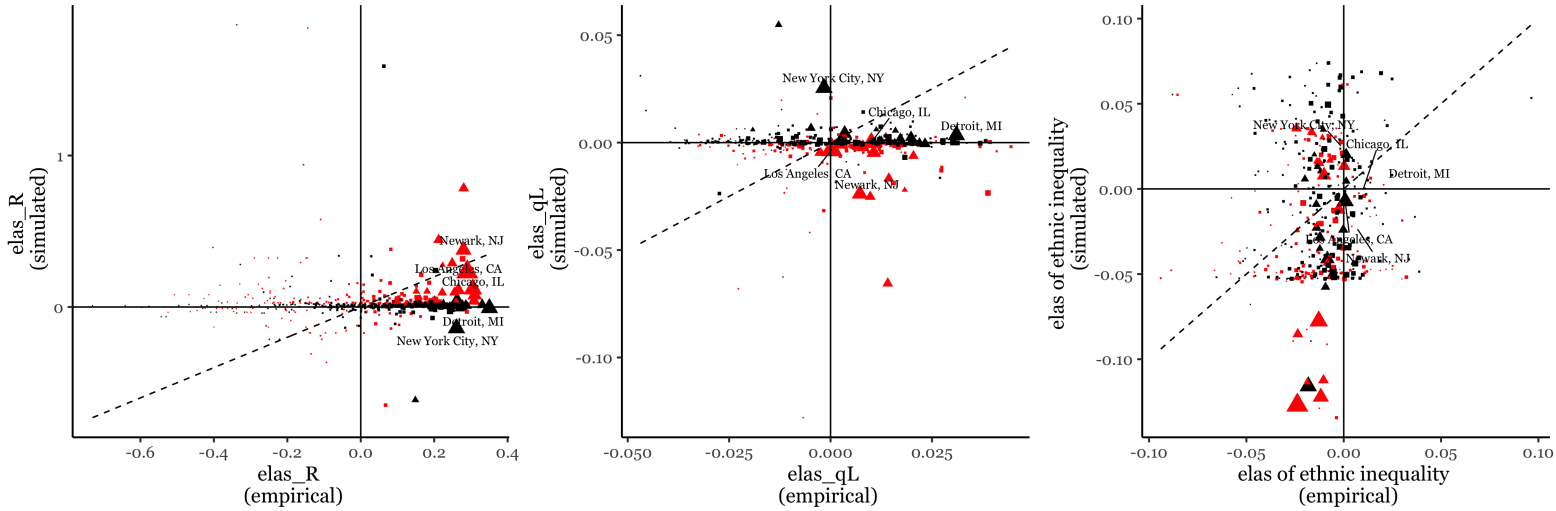
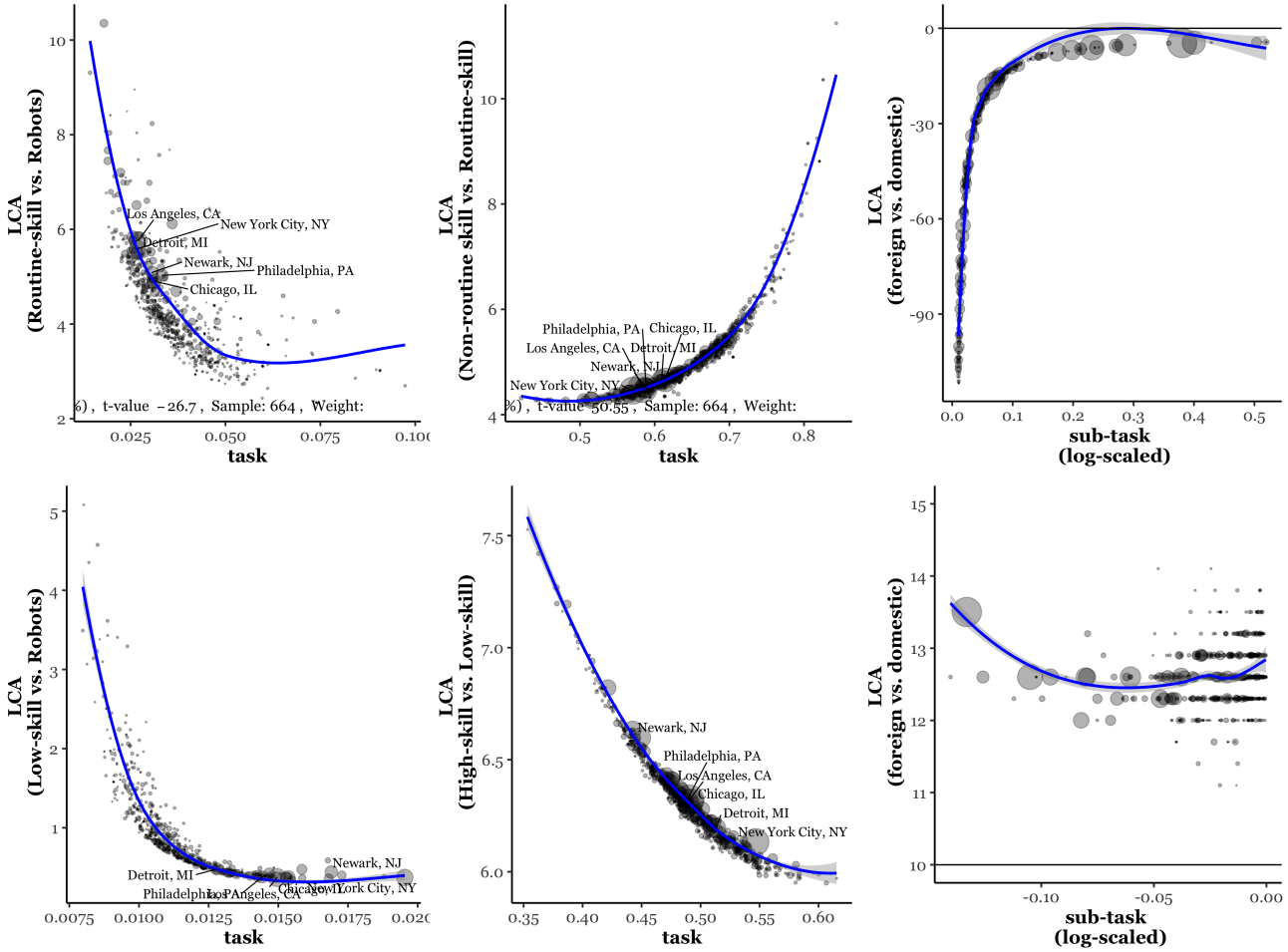


Figure 24: Estimated LCA functions (top: manufacturing, bottom: information service)



year	sector	technology		robot	high-skill	low-skill	foreign skill
1980	manufacturing	baseline		0.091 (.0038)	3.099 (5.187)	1 (normalized)	1.271 (.4349)
		task productivity (log)	100 percentile	0 (normalized)	5.82	2.51	-3.43
			50 percentile	0 (normalized)	1.37	1.23	-1.72
	information service	baseline		0.087 (.0453)	0.023 (.0221)	1 (normalized)	1.508 (.7982)
		task productivity (log)	100 percentile	0 (normalized)	20.46	13.59	
			50 percentile	0 (normalized)	7.42	3.41	

Figure 25: Summary table for productivities $\{A^R, A^H, A^F\}$ and $\{\underline{a}(\omega), \overline{a}(\omega)\}$

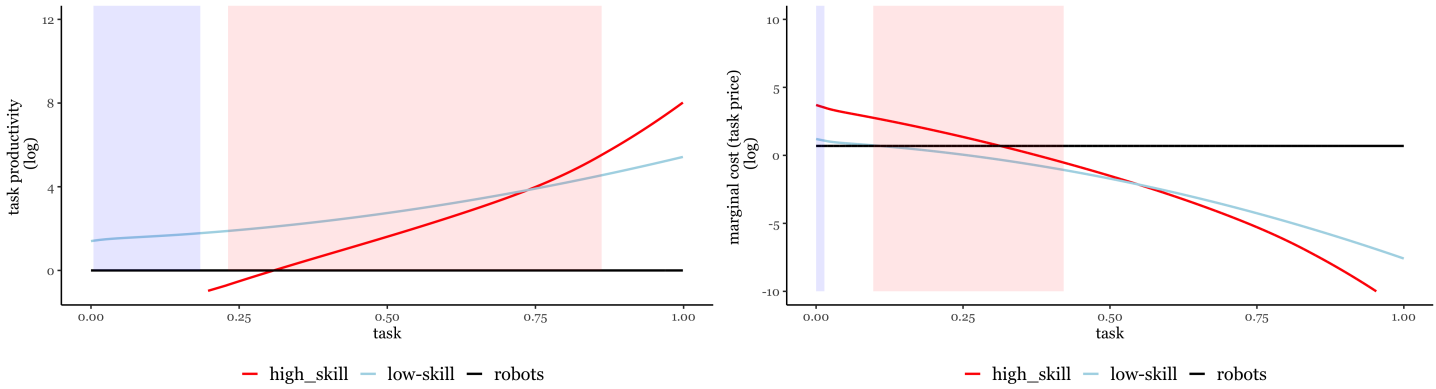


Figure 26: Inferred task-level productivities (left) and marginal costs (right) in 1980 of a representative commuting zone (plant)

Note: The task positions of crossing points corresponds with model-generated task thresholds, θ and ψ.

Stage.2: Recover the adjustment costs for automation

Estimate the adjustment parameters of automation. Non-economic components of automation is identified and estimated by regional variation of size distribution evolution of establishments. For arbitrary values of parameters, $\Theta = \{F, g, \boldsymbol{\beta^X}, \beta^A\}$, the discrete-continuous dynamic choice dynamic programming problem is solved and policy functions are generated.

Using these policy functions, generate the model-driven data. Using the model-driven data, compute simulated moments $\Psi^s(\Theta)$, as opposed to data moments, Ψ^d. The estimate $\widehat{\Theta}$ minimizes the weighted distance between the actual moments Ψ^d and simulated moments $\Psi^s(\Theta)$. Formally, I solve

$$min_{\Theta}[\Psi^d - \Psi^s(\Theta)]' W [\Psi^d - \Psi^s(\Theta)]$$

The evidence indicates that productivity of establishments differs across regional labor markets.

7 Quantitative Assessments

7.1 Labor-pull or Technology-push?: mechanism of automation

7.2 Surplus assessment

8 Policy Experiments

9 Concluding Remarks

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