

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

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Abstract

This paper revisits the longstanding question of how immigration shapes regional wages through its effects on automation. I develop a dynamic spatial framework in which tasks are allocated among industrial robots, natives, and immigrants, and semi-parametrically recover cross-factor substitution schedules from commuting-zone-level elasticities of economic outcomes with respect to immigration, instrumented by 1940 ethnic settlement patterns. Accounting for immigration-induced automation can reverse the estimated wage effects of immigration over 1980–2015. Low-skilled immigration initially reduces the wages of native workers in routine occupations but raises them in the long run by slowing automation adoption, enhancing domestic welfare. Finally, a universal basic income targeted to natives would increase reliance on both automation and immigrants by raising routine native wages.

JEL Classification: E22, J11, J31, J61, O14

Keywords: immigration, demography, automation, regional labor market

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1 Introduction

The rising concern about disruptive automation in the labor market is ubiquitous. (Brynjolfsson and McAfee (2014) and Frey and Osborne (2017)) In contrast to the current conventional view, which presumes that new technology unambiguously brings net benefits to labor by augmenting human skills, economists, including Autor and Dorn (2013) and Acemoglu and Restrepo (2017), have re-examined the labor market impacts of skill-replacing technology and found adverse effects on routine occupation workers. Nearly all the literature, however, frames automation technology as a primitive external force, and underrates this simple observation: automation is implemented by investing in autonomous machines (robots), thus, automation is a consequence of rational technology choices.¹ Overall, in conjunction with the surging public interest in how evolving automation technologies reshape the labor markets, the literature is dominated by what could be called a *technology-push* view, and relatively little is known about the mechanism regarding why, when and how much the production economy adopts the new automation technology.

To help fill this void, this paper theoretically and empirically investigates the mechanism of automation adoption, and advances the hypothesis that foreign labor inflow, a consistently increasing class of labor across the developed economies, affects the penetration of automation in the long run. If the adoption of automation is based on the cost advantage of using robots instead of human labor, then, immigration presumably has the potential to shift the human skill prices, and thus, alter the optimal magnitude of automation. This relatively unexplored link is important because immigration is a policy variable to reconfigure the national demography, and automation significantly reshapes the labor market landscape, as the recent automation literature demonstrates.² Therefore, the country could potentially navigate the adoption of automation via immigration policy.

To formalize the theory described above and quantitatively assess how immigration has played a role in shifting automation, I develop a dynamic spatial task-based model of endogenous automation based on Acemoglu and Restrepo (2018a).³ In a spatial economy, a competitive establishment with heterogeneous productivities produces a final good, com-

¹A notable exception is a recent work by Acemoglu and Restrepo (2018a), which explores how demographic change nudges the production system to develop automation, in the context of directed technical change. This paper complements their work by featuring the distinctive role of foreign labor and by adopting a more structural, empirically implementable approach.

²Except Autor and Dorn (2013) and Acemoglu and Restrepo (2017) mentioned above, see for example, Eden and Gaggl (2018).

³Ottaviano, Peri and Wright (2013) employ a similar vein of task-based model to jointly examine the interaction and impacts of immigration and offshoring, in contrast to my focus on automation.

binning tasks with different routineness (easiness-to-automate). The production factors are robots, routine skills and non-routine skills, and each skill is a composite of domestic and foreign skills. Each production factor has arbitrary task-specific factor productivities on the task spectrum, allowing for a richer cross-factor substitution pattern than conventional iso-elastic technology.

Three non-stationary drivers (immigration inflow, demographic transitions, and technological progress, proxied by quality-adjusted investment price of robots) shapes the equilibrium skill prices. Given the expected future menu of factor prices and task-specific factor productivities, the central problem for establishments is dynamically optimal task allocation. Automation is implemented by task reallocation from routine skills to robots; establishments of heterogeneous productivities decide when and how much tasks to be automated by the updated vintage of robots by paying the cost of adjustment friction,⁴ accompanied by their investments in robots.⁵

All the implications from the model are tightly disciplined by regional-level cross-factor substitution. The model yields a key relationship between elasticities of task reallocation with respect to factor prices and regional cross-factor substitution. Since elasticities of task allocation are unobservable *per se*, I analytically derive higher-level estimatable elasticities of regional economic outcomes (robot deployments, routine skill prices, and native premium of skill prices) under the steady state with respect to low-skilled (or high-skilled) immigration as functions of regional-level cross-factor substitutions. Having developed a model, the identification and estimation proceeds in three steps. First, I conduct quasi-experiments using reduced-form regressions across the CZs and years to estimate the *regional-level* elasticities of robots, routine skill price, and native premium of skill prices with respect to low- and high- skilled immigration inflow in manufacturing sector, and in information service sector, respectively, during 1980-1990, regarding this initial decade as the change under the steady state. To address the routinely invoked issue of non-randomness of regional immigration inflows, I use the location preferences of immigrants as non-market forces, as immigrants strongly prefer a neighborhood with larger numbers of people of their own ethnicity (Munshi (2003)). Operationally, I use the historical settlement patterns of 26 ethnic groups in 1940 to

⁴Adjustment costs for automation could allow for many interpretations: unions, legal labor regulations, initial learning costs, or inertia.

⁵As robots are durable, and their use is *de facto* irreversible, the decision to invest in robots inherently depends on the current menu of factor prices (both regional skill prices and national quality-adjusted investment prices), and the expected future path of menus. The model echoes with classical optimal replacement model (e.g. Rust (1987)) and durable good demand literature. (e.g. Adda and Cooper (2000), Gowrisankaran and Rysman (2012))

construct an instrument of ethnically-driven waves of foreign labor settlements, orthogonal to regional economic climates⁶ (Altonji and Card (1991), and Card (2001)). The regional reactions to immigration inflows exhibit remarkable heterogeneity, especially between urban and rural areas; the elasticities of routine occupation wages and robots with respect to immigration are more negatively skewed in rural areas than in urban areas.⁷

Second, I semi-parametrically identify and estimate the entire cross-factor substitution schedules to consistently match the series of *region-specific* immigration elasticities in each sector, as obtained in the first step. To do this, I draw on three analytical mappings, generated from the benchmark model; the *threshold-specific* substitutions of routine skills vs. robots, the substitutions of non-routine vs. routine skills, and the substitutions of foreign vs. domestic skills. I use these analytical mappings as moment conditions in a Generalized Method of Moments (GMM) procedure to consistently rationalize a trio of regional-specific elasticities of economic outcomes with respect to immigration. To the best of my knowledge, this paper is the first to empirically recover the task-specific factor productivities in the line of literature using a task-based approach.⁸

Third, after inserting these factor productivities recovered in the previous step into the dynamic model, I estimate a pair of non-convex and convex adjustment parameters for automation with a product differentiation parameter, using a Simulated Method of Moments (SMM) matched with patterns of establishment size evolutions across sectors.

Armed with the model including the estimated technology and adjustment costs, I start by quantifying the impact of immigration on the similarly-skilled native wages, both with and without effects from automation upgrading. A comparison to the counterfactual case with no immigration growth from 1980 to the baseline reveals that low-skilled immigration alone *reduced* the routine native wages by -0.05%, but *raised* the wages by +0.04% from 1980-2015 when automation adjustment is included. In contrast, high-skilled immigration alone *raised* the non-routine native wages by +0.03%, and inclusive of adjusted automation, *raised* the wages by +0.05% from 1980-2015.

The results highlight the importance of taking the dynamic effect of adjusted technology in the production system into account as well as substitution between immigrants and natives

⁶The instrumental variable strategy has been predominantly used in the immigration literature. For an extensive list, see Jaeger, Ruist and Stuhler (2018).

⁷The urban areas are the top 37 CZs accounting for the half of the labor force in 1980, and the rural areas are the other CZs.

⁸Recent related works on the task-based approach includes Peri and Sparber (2009) (immigration), Acemoglu and Restrepo (2018b) (automation), and Ottaviano, Peri and Wright (2013) (offshoring). See Acemoglu and Autor (2011) for a theoretical background.

when examining the economic impacts of immigration and crafting an immigration policy. Low-skilled immigration weakened robotization in manufacturing, and thus, raised routine native wages in the long run. The measured impacts are stronger by 4 times when the regions are limited to the top 30 CZs of the largest low-skilled immigration growth rate, showing the geographically heterogeneous impacts of immigration.⁹ In contrast, increased computerization driven by high-skilled immigration in the information service sector further benefited non-routine native workers. The findings are applicable to the welfare implication when social welfare is defined as a weighted sum of consumption utilities from labor and non-labor incomes for the U.S. citizens. Under the plausible distributional preference of the planner, I find that both low-skilled and high-skilled immigration during 1980-2015 improved the domestic welfare at the time of 2015.¹⁰

Having reproduced the rational delay of automation upgrading during the target period, 1980-2015, I extend the analysis by another 35 year future period, 2016-2050, and conduct policy experiments. First, by keeping the current immigration policy, I extend the simulation, following the demographic projections of the most recent Census ([Census Bureau \(2017\)](#)) and [Weldon Cooper Center \(2018\)](#). This could be labeled as the future baseline case.

Second, motivated by the burgeoning anti-immigration movements occurring across developed countries, I ask what would happen if future immigration is restricted in the U.S.. To consider an extreme case, I mechanically keep foreign labor in the U.S. at the projected level of 2020, and quantify the difference from the future baseline. The simulation shows that the immigration regulation is welfare-harming by -0.5% (low-skilled) and -1.9% (high-skilled) compared to the baseline at the time of 2050. The policy simulation mirrors the findings during the target period: low-skilled immigration weakens robotization, shrinking wage inequality. High-skilled immigration augments the wages of both occupation classes despite the expansion of wage inequality from greater use of computerization.

Last, motivated by the rising policy debate about a potential universal basic income (UBI) in the face of looming technological unemployment due to technological advances¹¹, I explore what would happen if a part of natives exit from the labor force by a UBI policy. Typically, a UBI is discussed as unconditional minimum (*basic*) stipend (800-1200 USD per month)

⁹These top 30 CZs account for 46% of low-skilled immigration inflow in terms of headcounts.

¹⁰I try out sensitivity analysis of welfare protocols, and the implications are stable. See Section 6.1.

¹¹Recently, UBI has gained a new vive instead of the canonical progressive social security system. Economists, including Peter Diamond and Chris Pissarides, have publicly expressed their approval. ([Forbes \(2017\)](#)) In 2016, a national referendum was held in Switzerland to vote on adopting a UBI, and it was rejected.

to be provided to every (*universal*) working-aged U.S. citizen, excluding immigrants.¹² The simulation shows that a UBI boosts automation intensity (proxied by robot task share) by 0.4-0.6%, and 1.5-2.1% across sectors, by raising routine native wages by 4.1-5.8% and 6.2-9.1%, respectively, as compared to the future baseline for 2020-2050. Parallel to the surging deployment of automation, dependency on foreign labor, which has been excluded from the UBI provision, is predicted to sharply rise by 0.5 and 0.3 p.p. in 2050 as compared to the baseline across sectors. Although a UBI is often touted as a counter-measure to massively disruptive automation, which is implicitly founded in the *technology-push* view, my model delivers a contrary perspective: a UBI would serve as a policy shock resulting in the highly automated economy.

The paper is structured as follows. Section 2 shows motivating evidences, delivers a perspective on mechanisms of automation, and positions a related literature within the perspective. Section 3 provides a setup and equilibrium of the framework. The framework under the steady state delivers analytical formula of the economic impacts of immigration via automation adjustment. Section 4 describes the data sources, and their salient patterns. Section 5 delivers an identification strategy, outlines the estimation procedures, and reports the results obtained. Section 6 quantitatively assesses each channel, accompanied by decomposition exercises by multiple forces. Section 7 reports policy experiments. Section 8 concludes.

2 Understanding the Mechanism of Automation by Linking Immigration and Automation

2.1 Motivating graphics

To motivate the hypothesis, I juxtapose foreign labor inflow and automation penetration at the U.S. regional level. The U.S. commuting zones (CZs, developed by Tolbert and Sizer (1996)) provide 722 geographically consistent units suitable for tracking the relationships between immigration inflow and automation penetration. Immigration inflow is stably asymmetric across the CZs¹³, generating a large cross-region labor supply shocks to the aging

¹²Unsurprisingly, the largest obstacle preventing the adoption of a UBI is the massive expenditure necessary. To finance a UBI, I consider a regime of heavier taxation of high-income earners, a sizable part of whom belong to the information service sector.

¹³From 1980-2015, the mean growth rate of working-age immigration (employed in Figure.1 and 2) is more than double the median. (low-skilled, 5.0% (mean) vs. 2.4% (median), high-skilled, 3.4% (mean) vs. 1.5% (median), implying a remarkably skewed regional immigration inflow. See Figure.13 for a geographic

demography, which proceeds in more uniformly across regions, and is mirrored by declining geographic mobility for the native population (Notowidigdo (2011)).

It is well-known that immigrants into the U.S. are characterized by their polarity of skill levels (See Data Appendix). Due to the salient skill dispersion among the immigrants, they are categorized as low-skilled or high-skilled, according to their education attainments.¹⁴ I contrast each class of foreign labor according to their plausibly pertinent mode of automation across two sectors: the robotization of production tasks in manufacturing and the computerization of non-production tasks in information service. As automation technology is unobservable *per se*, it is proxied by the capital embodying each mode of automation, namely, industrial robots and information technology (IT) capital.¹⁵

As Figure 1 and 2 shows, the magnitude of immigration inflow with different skill levels robustly stands in sharp contrast to their pertinent mode of automation; that is, low-skilled immigration negatively correlates to robotization, but high-skilled immigration is positively correlated with computerization.¹⁶ This observation guides my hypothesis to bridge the two factors, by highlighting the key mediating role of regional routine wages: low-skilled immigration inflow reduces the routine wages by providing an over-supply of routine skills. Thus, establishments would use less robots in production tasks.¹⁷ On the other hand, high-skilled immigration inflow raises the demand for complementary routine tasks, and thus, elevates the routine wages. Establishments would heighten the computerization of routine tasks previously provided by routine labor.¹⁸

illustration.

¹⁴In Figure 1 and 2, immigrants with high-school diplomas or less are *low-skilled*, while those with bachelor's and higher degrees are *high-skilled*. For the rest of the analysis, *high-skilled* immigration is extended to incorporate immigrants with some college education.

¹⁵Eden and Gagli (2018) emphasize the distinct roles of IT capital as opposed to non-IT capital in their welfare calculations.

¹⁶Figure 2 interprets IT capitals as skill-replacing to routine skills. but it could be also interpreted as skill-augmenting to non-routine skills in the context of skill-capital complementarity. (e.g. Krusell et al. (2000), Autor, Levy and Murnane (2003), Autor and Dorn (2013)). My model explicitly distinguishes two forms of IT capitals by robots and equipments.

¹⁷A companion paper, Yoshida (2019) examines whether low-skilled immigration inflow impedes robotization, using a more narrowly defined industrial robot dataset from IFR (2015). The paper examines manufacturing, construction and agriculture.

¹⁸Intuitively, a larger inflow of managers or engineers require a larger back office (e.g. secretaries, book-keepers) to support their expert skill level activities. For example, a secretary in San Jose, CA is better paid than one in Flint, MI, possibly because of more abundant demand for administrative jobs.

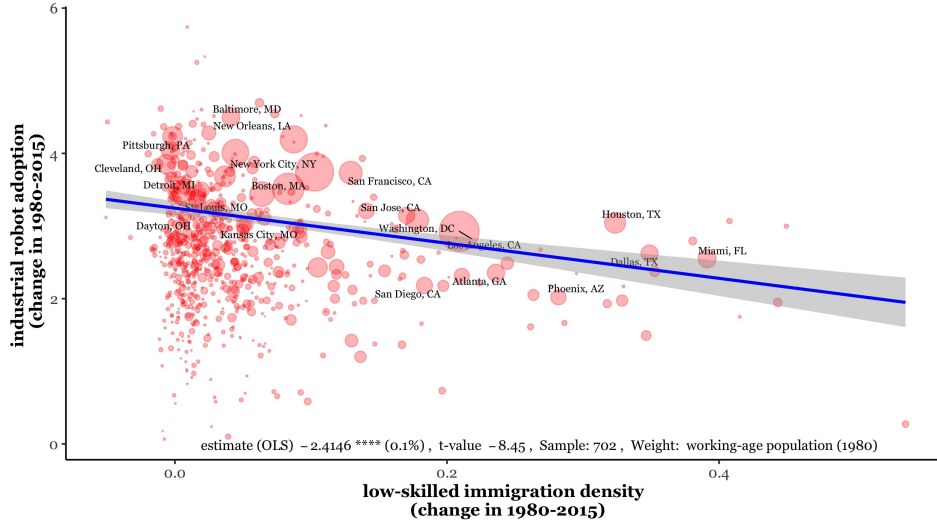


Figure 1: Low-skilled immigration inflow and robotization (1980-2015)

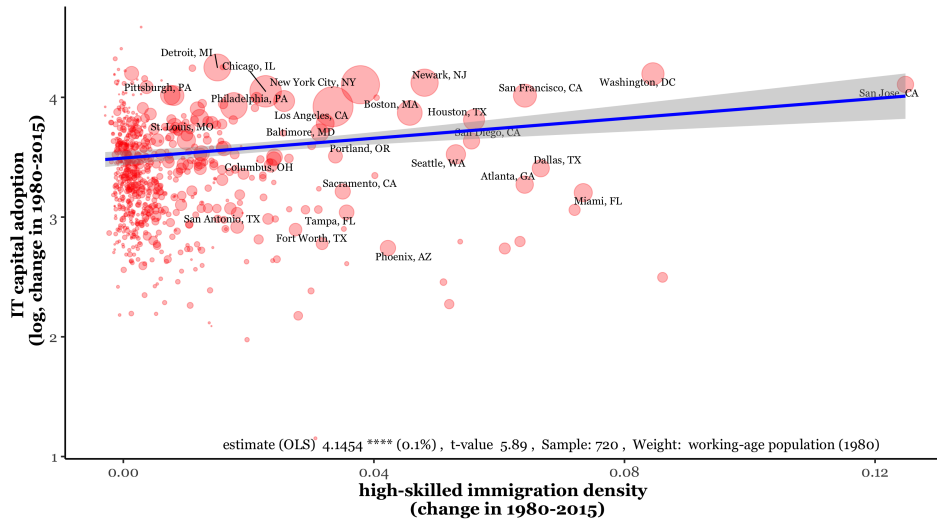


Figure 2: High-skilled immigration inflow and computerization (1980-2015)

Notes: Computed from the Population Census (1980), American Community Survey (2015) and National Income and Production Accounts from the Bureau of Economic Analysis. Individuals with high-school degrees or less are *low-skilled*, while those with bachelor's and higher degrees are *high-skilled*. Robot adoption is measured by industrial robots per production worker. IT capital adoption is captured by IT capitals per non-production employment. Regressions are weighted with CZ-level working-age population in 1980, as depicted by the size of each bubble. Shaded areas are 99% confidence intervals. For details of the data source, see Section 4.

Given that autonomous machines follow the law of one price in the global capital market, Figure 1 indicates that automation could be framed as regional phenomena induced by regional heterogeneous wages molded by the geographic and demographic constraints of

human workers.¹⁹

2.2 Why does automation occur?: the mechanism of automation

To organize the hypothesis on the interaction of immigration and automation, I craft a conceptual chart, Figure 3, which summarizes the mechanism of automation. I sequentially divide the mechanism into three channels, drivers of automation, captured by (1) and (2) and the consequences of automation, as by (3). (4) represents the aggregate effect of immigration on the labor market.²⁰

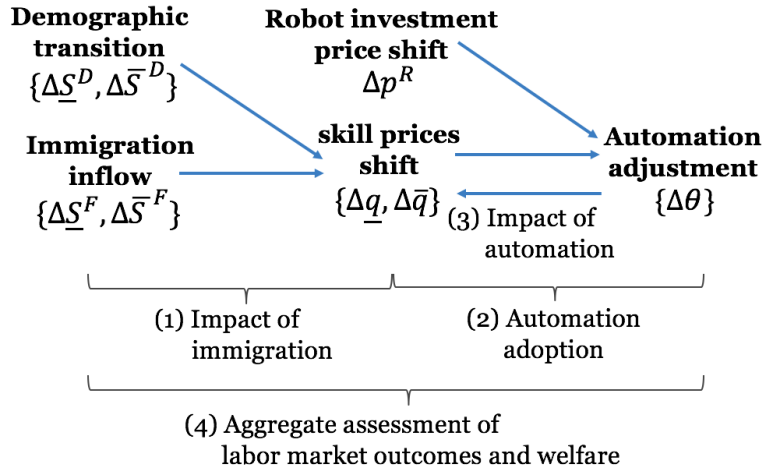


Figure 3: Mechanism of automation

Notes: Robot investment price is quality-adjusted so that it proxies the technological progress of automation. S denotes skills, q denotes skill prices, and the upper-line and lower-line corresponds to non-routine and routine skills, respectively. Formal definitions are given in Section 3.

First, in the short run and under a fixed level of automation, immigration affects skill prices in conjunction with demographic change. The effect of immigration inflow on skill prices *without* effects from adjusted automation is given by:

$$\chi_1 = \left. \frac{dq}{d\widehat{S^F}} \right|_{\theta} \quad (1)$$

¹⁹Research shows that routine occupation workers exhibit less mobility (Notowidigdo (2011)), and their wages are presumably more vulnerable to regional demographic change. Moreover, when adopting automation, establishments will be plausibly more sensitive to routine workers' wages rather than non-routine workers' wages.

²⁰Theoretically, declining robot investment price augments skill prices via investment-specific technology changes, independently from adoption of automation. (Greenwood, Hercowitz and Krusell (1997)) This channel is also included in the quantitative model.

where $q \in \{\underline{q}, \bar{q}\}$ represents skill prices including routine and non-routine occupations, $\widehat{S^F}$ is low- or high-skilled foreign skills, and θ is automation intensity, as defined below in Section 3.

In the long run, technology is the choice variable of producers. Second, the routine skill price changed from the first channel, and guides the automation intensity in parallel to the evolution of quality-adjusted investment price of robots. The effect of routine skill price change on automation intensity is given by:

$$\chi_2 = \frac{d\theta}{d\underline{q}} \quad (2)$$

where $\underline{q}$ denotes routine skill prices. Third, in turn, the induced automation change affects the skill prices. The effect of automation adjustment to skill price is given by:

$$\chi_3 = \frac{dq}{d\theta} \quad (3)$$

Summing up (1),(2) and (3), the aggregate effect of immigration on skill prices are formulated as

$$\frac{dq}{d\widehat{S^F}} = \underbrace{\chi_1}_{\text{direct effect}} + \underbrace{\chi_2 \times \chi_3}_{\text{indirect effect via automation adjustment}}. \quad (4)$$

The key empirical challenge is to quantitatively assess each channel of χ_1, χ_2 and χ_3 . One can see that what makes this mechanism intractable is the fact that the equilibrium skill price changes serve both the drivers and the consequences of automation. To distinguish these effects, this circularity guides me to develop a unified structural model that regards regional immigration inflow as a driving force from the labor supply side.

2.3 Literature Review

The paper encompasses the intersection of three related lines of literature, each of which could be mapped on Figure 3. First, this paper is related to a small stream of papers bridging labor supply and technology adoption. (e.g. [Beaudry, Doms and Lewis \(2010\)](#), [Manuelli and Seshadri \(2014\)](#), [Akerman, Gaarder and Mogstad \(2015\)](#)) My hypothesis about the manufacturing sector most closely echoes those of [Lewis \(2005\)](#) and [Lewis \(2011\)](#), by exploring the negative effect of low-skilled immigration to technology adoption, using micro-level plant data in metropolitan areas. My hypothesis about the information service sector complements the work by [Basso, Peri and Rahman \(2017\)](#), who analyze the role of low-skilled immigration in the non-tradable service sector on labor market polarization by adopting computerization. This paper features high-skilled immigration into the tradable service

sector; [Beaudry, Doms and Lewis \(2010\)](#) explores the effect of high-skilled labor on computer adoption across metropolitan areas. This stream of papers do not explicitly frame their technology as labor-saving automation. Also, they consider the link (1) and (2) in Figure 3, but does not explicitly split the channel into the two by mediating with routine occupation wages.

Second, this paper belongs to the immigration literature (e.g. [Card and Peri \(2016\)](#), [Ottaviano and Peri \(2012\)](#), and [Borjas \(1995\)](#)), exploring the aggregate effect of (4), mapped by (4) in Figure 3. The literature is characterized by the intensive focus on immigration impacts on native wages ([Dustmann, Schonberg and Stuhler \(2016\)](#)), and this paper complements the papers in the stream by highlighting the dynamic impact from adjustment of automation, indexed by (3) in Figure 3. Moreover, this paper allows for regionally heterogeneous impacts of immigration by heterogenous substitution patterns across tasks. All of the papers in this stream use the canonical constant elasticity of substitution (CES) protocols as a theoretical framework, and do not adopt a task-based approach.

Third, this paper complements the automation literature. As stressed in the introduction, the recent automation literature (e.g. [Autor, Levy and Murnane \(2003\)](#), [Autor and Dorn \(2013\)](#), [Acemoglu and Restrepo \(2017\)](#), [Eden and Gaggl \(2018\)](#)) is founded by the *technology-push* view, and focuses on the channel of (3) in Figure 3. In contrast, I highlight the mechanics of why automation occurs as well as its feedbacks on the labor market.

Overall, no literature jointly analyze the channel of (1)-(4). My framework elucidates the processes of (1) and (2) and incorporates the feedback effects of automation adjustment from (3) to evaluate the aggregate impact of immigration, (4). The quantitative assessment of each channel is presented in Section 6.

3 Dynamic Spatial Model of Endogenous Automation

To quantify how immigration accounts for regional automation adoption, and how automation affects the regional labor markets, I develop a dynamic spatial task allocation model with endogenous automation. The model is characterized by three features. First, under the rationally expected transition of skill prices and a perfectly-foreseen path of constantly declining quality-adjusted prices of robots, automation upgrading is run by forward-looking establishments, accompanied by investments to robots with the latest vintage. Note that the model implements automation as task reallocation from routine labor to robots, conceptually distinct from the canonical mode of technological progress proxied by declining quality-adjusted prices of robots.

Second, as is common in capital investment literature, an establishment incurs sunk costs

in both non-convex and convex forms, whenever they adjust automation technology. As automation is factor-biased technical change, adjustment costs of automation conceptually accommodate both capital adjustment (e.g., robot installation, learning) and labor adjustment costs (e.g., layoff costs, renegotiation costs), sufficiently proxying the non-economic frictions of adjusting automation.

Third, an establishment has their factor-neutral unobservable total factor productivities (TFP), which could influence automation upgrading, accompanied by frictional investments.²¹ As a result of differential upgrading behaviors due to heterogeneous productivities, establishments with newer vintages enable lower final good prices, and achieve larger market shares, substituting the market share with establishments with older vintages.

3.1 Setup

Suppose a country consists of an array of islands (regions) l . Production is operated by a finite group of establishments, indexed by i . Time is an infinite horizon, starting at the initial year $t = 0$.²² Establishment i in region l in year t competitively produces a nationally traded final good, $Y_{i,t}$. Each island is inhabited by individuals, indexed by j with citizenship $e_j \in \{F, D\}$, consisting of natives ($e_j = D$) and immigrants ($e_j = F$). On the consumption side, consumption for individual j , $\widehat{C}_{j,t}$ is a CES combination of differentiated final products from every establishment i in the country, $\widehat{C}_{j,i,t}$, formulated as

$$\widehat{C}_{j,t} = \{\sum_i (\widehat{C}_{j,i,t})^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1}}$$

where $\sigma > 1$ is an elasticity of substitution.²³ The final aggregate consumption good $\widehat{C}_{j,t}$ is set to be numeraire. On the production side, an establishment i produces the final aggregate good by

$$\widehat{Y}_{i,t} = (A_{i,t})^\eta (Y_{i,t})^{1-\eta}$$

where η is an intellectual property share, stemming from an unobservable productivity, $A_{i,t}$, and $Y_{i,t}$ is a deterministic baseline production. $A_{i,t}$ follows a persistent AR(1) evolution such

²¹In this context, TFP could be well-interpreted as intangible knowledge assets inside the establishment, or the firm it belongs to, including intellectual patents, management know-hows, and engineering knowledge accumulated, which plausibly affects the adoption of the frontier automation technology.

²² l, i and t are often suppressed for brevity, except where especially required.

²³When $\sigma > 1$, if automation lowers the final good price relative to the sectoral aggregate price, the production value is upshifted.

that

$$\ln A_{i,t+1} = \xi_t + \rho \ln A_{i,t} + \epsilon_{i,t}$$

where ξ_t is an annual TFP shifter, $\rho \in (0, 1)$ is a stationarity parameter, and $\epsilon_{i,t}$ is identically and independently distributed (i.i.d.) shock drawn from a standard normal distribution.

Task allocation A final good is produced from a continuum of tasks $\omega \in [0, 1]$, a continuous, differentiable, and closed interval with measure one. $Y_{i,t}$ is produced from unit-elastic aggregation of output from task ω , $y(\omega)$ such that

$$Y = \exp\left(\int_0^1 \ln y(\omega) d\omega\right). \quad (5)$$

²⁴ Competitive labor market in island l offers either routine skills $\underline{S}$ from routine occupation workers and non-routine skills $\bar{S}$ from non-routine occupation workers. $y(\omega)$ is specified as follows:

$$y(\omega) = \{A^R r(\omega) + \underline{A} \underline{a}(\omega) \underline{s}(\omega) + \bar{A} \bar{a}(\omega) \bar{s}(\omega)\}^\alpha k(\omega)^{1-\alpha} \quad (6)$$

where $\underline{s}(\omega)$ is routine skills, $\bar{s}(\omega)$ is non-routine skills, $r(\omega)$ is robots, and $k(\omega)$ is capital equipment employed in task ω . $\{\underline{a}(\omega), \bar{a}(\omega)\}$ are series of task-specific factor productivities for routine- and non-routine skills, respectively, normalized as $\underline{a}(0) = \bar{a}(0) = 1$. $A^R, \underline{A}, \bar{A}$ are factor-augmenting productivities for robots, routine skills, and non-routine skills, respectively. Without loss of generality, $\underline{A}$ is normalized to unity. $1 - \alpha$ is intensity of capital equipment. Lower bars indicate variables of routine occupations, while upper bars show those of non-routine occupations.

Analogous to the relationships between final goods and tasks, I construct a nested structure of aggregate skills and sub-tasks (Figure 4). Specifically, an aggregate skill $\hat{S} \in \{\underline{S}, \bar{S}\}$ is unit-elastic aggregation of output from a sub-task $\omega' \in [0, 1]$, $\hat{y}(\omega')$ such that

$$\hat{S} = \exp\left[\int_0^1 \ln \hat{y}(\omega') d\omega'\right].$$

Production from each sub-task is perfect substitutes of effective foreign and domestic skill productions such that

$$\hat{y}(\omega') = \widehat{A^F} \widehat{a^F}(\omega') \widehat{s^F}(\omega') + \widehat{A^D} \widehat{a^D}(\omega') \widehat{s^D}(\omega') \quad (7)$$

²⁴ Acemoglu and Restrepo (2018b) features primarily shifting of the technology frontier (most non-routine task automatable from the engineering point of view) in directed *technical change* framework, while the paper endogenizes *technology adoption* of the realized automation.

where $\{\widehat{a^D}(\omega'), \widehat{a^F}(\omega')\}$ are sub-task productivities for $\omega' \in [0, 1]$, and $\widehat{A^F}, \widehat{A^D}$ are factor-augmenting productivities of sub-tasks for domestic and foreign skills, respectively. Without loss of generality, $\widehat{A^D}$ is set to unity.

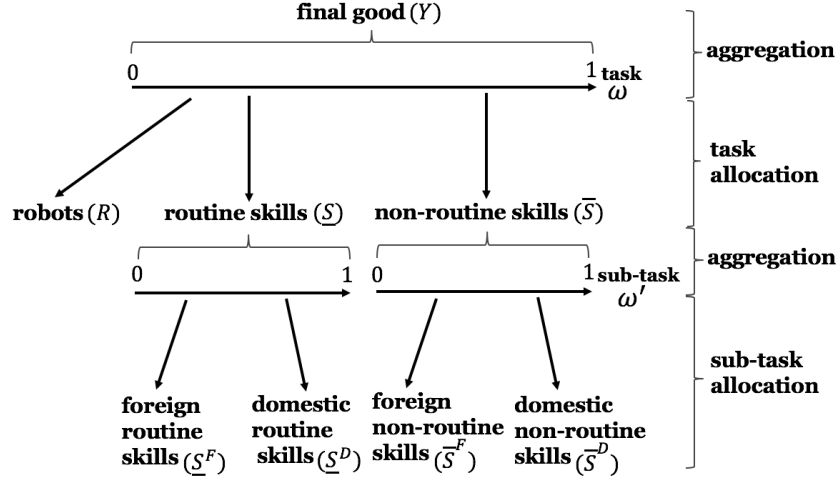


Figure 4: Nested structure of task allocation

Notes: Note that after tasks are allocated to $R, \underline{S}, \bar{S}$, each factor is combined with equipments, K to produce task outputs.

Dynamic automation problem Establishments periodically employs labor skills from the regional labor market, rents equipments from the global capital market, and owns robots via investments.²⁵ Shaped by regional immigration inflow and demographic transition in island l , a menu of routine and non-routine skill prices, $q_l, \bar{q}_l$, respectively, is competitively given. Assume that establishments rationally expect a skill price trajectory of routine and non-routine skills with nativity distinction in each sector. In nationwide capital markets, robot R and equipment K are elastically supplied with quality-adjusted investment prices of robots, p^R and rental prices q^K , respectively. Assume that establishments have perfect foresight of $\{p^R, q^K\}$.²⁶

Task allocation rule is characterized by $\Lambda_t = \{\Lambda_t^R, \Lambda_t^L, \Lambda_t^H, \widehat{\Lambda}_t^e\}$ ($e \in \{D, F\}$), where $\Lambda_t^R, \Lambda_t^L, \Lambda_t^H, \widehat{\Lambda}_t^e \subset (0, 1)$ is a set of tasks allocated to robots, routine skills, non-routine skills,

²⁵Note that automation shifts with friction, and investment is implemented without friction. Even when automation is not upgraded, investment to robots occurs to compensate for depreciation to retain the production. Regarding equipment, one could alternatively model establishments investing to equipment. However, this is mathematically equivalent to rental price payment equal to compensation for depreciation under the perpetuate inventory method.

²⁶This assumption is conventional in the investment literature that capitals are produced with marginal cost pricing, almost exclusively shaped by technological forces. (e.g. Moore's law)

and a set of sub-tasks allocated to foreign or domestic skills at period t , respectively. The periodic profit at period t is specified as

$$\begin{aligned} \Pi_{i,t}(\mathbf{X}_t, A_{i,t}, \Lambda_{i,t} \mid \Theta) = & \underbrace{P_{i,t} \widehat{Y}_{i,t}}_{\text{revenue}} - \underbrace{(q_{l,t} S_{i,t} + \bar{q}_{l,t} \bar{S}_{i,t})}_{\text{payment to skills}} \\ & - \underbrace{p_i^R I_{i,t}^R}_{\text{investments to robots}} - \underbrace{\mathbb{I}(|\Lambda_{i,t}^R| > |\Lambda_{i,t-1}^R|) c(\mathbf{X}_t, \Lambda_{i,t}^R, \zeta, \tau) P_{i,t-1} \widehat{Y}_{i,t-1}}_{\text{adjustment costs payment}} \end{aligned}$$

where $\mathbf{X}_t$ is a set of all observable state variables (a history of task allocation $\{\Lambda_{i,t}\}$ and factor prices $\{q_{l,t}, \bar{q}_{l,t}, p_t^R, q_t^K\}$), $\Theta = \{\zeta, \tau, \sigma, \xi_t, \rho\}$ as a set of parameters to be estimated, $P_{i,t}$ is a final good price, $I_{i,t}^R$ is i 's investment to robots in period t , $\mathbb{I}(\cdot)$ is an indicator function and $c(\mathbf{X}, \theta, \zeta, \tau)$ is adjustment cost function per production value at the previous period, $t - 1$. $|\Lambda^R|$ captures an size of task share allocated to robots. To simplify the analysis, automation upgrading is irreversible and the intensity level could only be allowed to be rising monotonically over time.²⁷

Investment into robots $I_{i,t}^R$ is specified by task allocation $\Lambda_{i,t}$ along with the following the law of motion, since task allocation, especially automation choice, determines the robot demand.

$$I_{i,t}^R = R_{i,t}(\Lambda_{i,t}) - (1 - \delta^R) R_{i,t-1}(\Lambda_{i,t-1}) \quad (8)$$

Note that investment to robots occurs both from task reallocation and from depreciation δ^R . Following the line of adjustment cost literature (e.g., [Cooper and Haltiwanger \(2006\)](#)), adjustment cost function is parameterized by non-convex and convex adjustment parameters, ζ and τ such that

$$c(\mathbf{X}, \theta, \zeta, \tau) = \underbrace{\zeta}_{\text{non-convex costs}} + \underbrace{(|\Lambda^{R'}| > |\Lambda^R|)^2 \tau}_{\text{convex costs}}.$$

τ is interacted by a square of expansion of robot task share.

Since technology is constant returns to scale, optimization problem for every establishment is isomorphic with respect to the production value. Introduce $\pi_{i,t}(\mathbf{X}_t, A_{i,t}, \Lambda_{i,t} \mid \Theta)$ as a normalized profit function, denominated by their standard production value, $P_{i,t-1} \widehat{Y}_{i,t-1}$

²⁷This is not so restrictive because under the environment that quality-adjusted prices is constantly declining and skill prices are relatively stable, establishments' behaviors are only incentivized to upgrading. Alternatively, allowing for frictional downgrading does not severely alter the result.

such that

$$\pi_{i,t}(\mathbf{X}_t, A_{i,t}, \Lambda_{i,t} \mid \Theta) \equiv \frac{\Pi_i(\mathbf{X}_t, A_{i,t}, \Lambda_{i,t} \mid \Theta)}{P_{i,t-1} \widehat{Y_{i,t-1}}}.$$

Using Bellman's principle of optimality, a forward-looking establishment's problem is recursively defined as dynamic task allocation problem; a value function is recursively defined as a

$$V(\mathbf{X}, A) = \max_{\Lambda} \pi(\mathbf{X}, A, \Lambda \mid \Theta) + \beta \int V(\mathbf{X}', A') dF_{\Lambda}(\mathbf{X}', A' \mid \mathbf{X}, A)$$

where β is a common discount factor for establishments and $F_{\Lambda}(\mathbf{X}', A' \mid \mathbf{X}, A)$ is a choice Λ -dependent transition distribution. In a lower level, an establishment statically minimizes the cost to satisfy the demand of aggregate skills $\widehat{S}$:

$$\begin{aligned} & \min_{\widehat{\Lambda}^F, \widehat{\Lambda}^D} \widehat{q^F} \widehat{S^F} + \widehat{q^D} \widehat{S^D} \\ & s.t. \exp\left\{\int_0^1 \ln \widehat{y}(\omega') d\omega'\right\} \geq \widehat{S}, \text{ where } \widehat{y}(\omega') \text{ is given by (7).} \\ & \widehat{S^e} = \int_0^1 \widehat{s^e}(\omega') d\omega' \quad (e \in \{D, F\}) \end{aligned}$$

In the higher level, an establishment optimally allocates production factors over a spectrum of tasks, anticipating a trajectory of skill prices and quality-adjusted capital prices. In the lower level, occupation manager minimizes the skill expenditure to satisfy the aggregate skill demand $\widehat{S}$ from the establishment manager to employ the best mix of foreign and domestic skills.

3.2 Equilibrium

To highlight the non-degenerate equilibrium, I impose a set of regularity conditions. These weak regularities are routinely imposed in the task-based literature. ([Grossman and Rossi-Hansberg \(2008\)](#), [Acemoglu and Autor \(2011\)](#), and [Ottaviano, Peri and Wright \(2013\)](#), among others)

R0 [Task productivities of skills]

Task (or sub-task) productivities for human skills (foreign skills) are strictly increasing (or decreasing) and continuously differentiable in task non-routineness. Formerly,

$$d\underline{a}(\omega)/d\omega > 0 \quad d\bar{a}(\omega)/d\omega > 0 \quad d\widehat{a^F}(\omega')/d\omega' < 0 \quad \forall \omega, \omega' \in [0, 1]$$

holds.

Brackets are for sub-tasks. Recall that the task-specific productivities of robots and sub-task productivities for domestic skills are set to unity across all (sub-) tasks. The former part regularity implies that task-specific productivities of human skills are strictly increasing when tasks become more non-routine, compared to robots. This naturally comes from the definition of task routineness (easiness-to-automate). The latter part states that sub-task productivities for foreign skills are strictly decreasing when sub-tasks become more non-routine. This simply serves to capture differentiation between foreign and domestic skills across sub-tasks.²⁸ Three additional regularities, R1-R3²⁹ are imposed to regulate the balance of relative cost efficiency of three pairs of production factors to ensure every factor is employed in some non-empty tasks. R0, together with these corner conditions R1-R3, establishments follow the cutoff strategies to split the task spectrum across factors.

Proposition 1. [Optimal Task Allocation over Production Factors]

Suppose the regularities R0-R3. Then, there exists an automation intensity $\theta \in (0, 1)$ and an occupation threshold $\psi \in (\theta, 1)$ such that $\Lambda^R = [0, \theta]$, $\Lambda^L = (\theta, \psi]$, and $\Lambda^H = (\psi, 1]$ holds.³⁰ Moreover, there exists an immigration threshold $\phi \in (0, 1)$ such that $\widehat{\Lambda}^F = [0, \phi]$ and $\widehat{\Lambda}^D \in (\phi, 1]$ holds.³¹ Under no friction of adjusting automation, θ, ψ and ϕ are implicitly defined to satisfy

$$\frac{a(\theta)}{A^R} = \frac{q}{q^R}, \quad \frac{a(\psi)}{\bar{A}\bar{a}(\psi)} = \frac{q}{\bar{q}}, \quad \frac{\widehat{A}^F \widehat{a}^F(\phi)}{\widehat{a}^D(\phi)} = \frac{\widehat{q}^F}{\widehat{q}^D}. \quad (9)$$

where robot rental price q^R is computed as $q^R = \delta^R p^R$ using a depreciation δ^R .³²

²⁸The normalization in sub-tasks loses no generality. For example, one could run the analogous argument even if $da^F(\omega')/d\omega' > 0$ or normalize sub-task productivities of foreign skills as unity instead of domestic skills. This would require a variant of R3, but the subsequent argument would be unaffected.

²⁹Three regularities specifies the range of routine skills relative to robots, of routine skills relative of non-routine skills, of foreign skills relative to domestic skills in effective terms as $\frac{\psi - \theta}{\theta} \frac{A^R}{\underline{a}(1)} < \frac{S}{R} < (1 - \psi) A^R$ (R1), $\frac{(\psi - \theta) \bar{A} \bar{a}(\theta)}{(1 - \psi) \underline{a}(\theta)} < \frac{S}{\bar{S}} < \frac{(\psi - \theta) \bar{A} \bar{a}(1)}{(1 - \psi) \underline{a}(1)}$ (R2), and $\frac{\phi}{(1 - \phi) \widehat{A}^F} < \frac{\widehat{S}^F}{\widehat{S}^D} < \frac{\phi}{(1 - \phi) \widehat{A}^F \widehat{a}^F(1)}$ (R3). In Model Appendix, I show that R1-R3 is rewritten as corner conditions, graphically assuring single-crossing of marginal cost curves, used in Proposition 1.

³⁰Each factor is combined with equipments by intensity $1 - \alpha$.

³¹Without loss of generality, a tie-break condition is imposed at the crossing point on the atomless task (or sub-task) spectrum.

³²This is a special case of a perpetuate inventory method with no rental markets, nor financial markets. (See, for example, Barkai (2016))

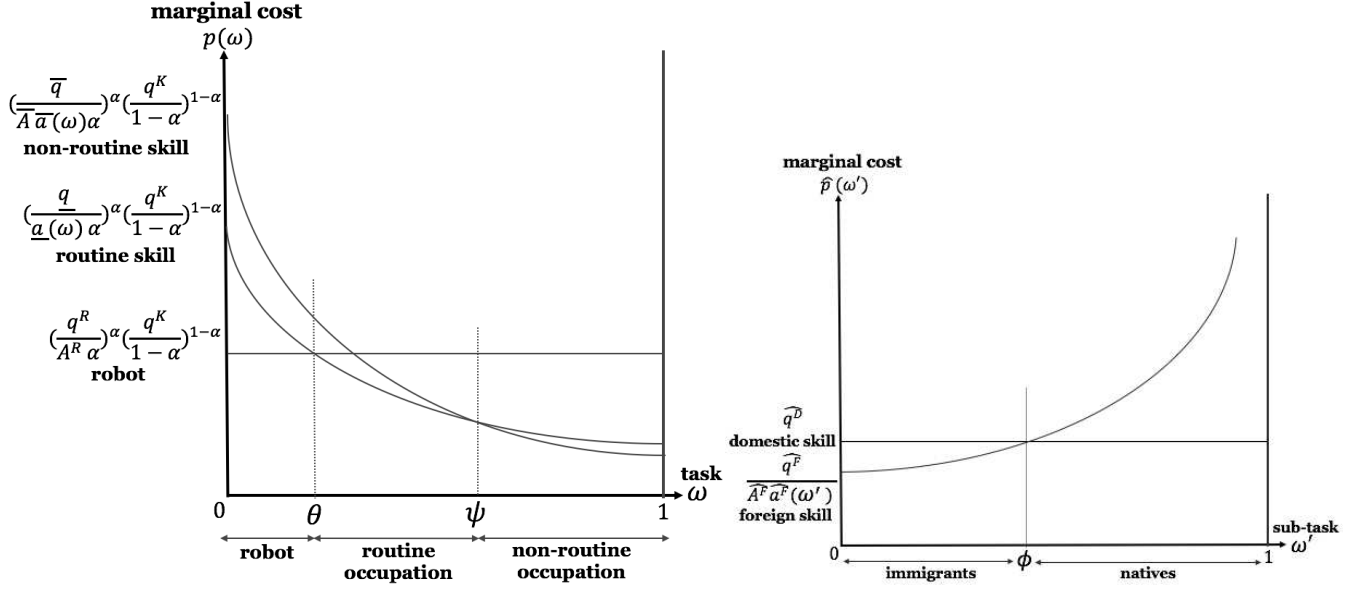


Figure 5: Equilibrium task allocation (left: upper level tasks, right: lower level sub-tasks)
Notes: q^R is imputed rental price of robots such that $q^R \equiv \delta^R p^R$.

Proposition 1 states that given the task productivities and factor-augmenting productivities (intensive-margin of technology) and a menu of regional skill prices, national rental prices of equipments, and national investment price of robots, the optimal task allocation is characterized by a trio of task thresholds (extensive-margin of technology), automation intensity $\theta \in (0, 1)$, occupation threshold ψ , and immigration threshold ϕ .

Graphically, the regularities R0-R3 ensure the specialization of factors over the task spectrum in Figure 5. Since most affordable factors are allocated to each task, robots perform the most routine range, routine skills cover a middle range, and non-routine skills cover the most non-routine range. In the low-level sub-tasks, foreign skills cover the routine range, and domestic skills cover the non-routine range. Given Proposition 1, the marginal cost function of each task when tasks are exclusively allocated to each factor is explicitly formulated as a function of factor price and (sub-) task productivity. Denote the marginal costs of routine- (non-routine) task outputs by routine- (or non-routine) skills as $\underline{p}(\omega), \bar{p}(\omega)$, respectively. Then, some algebra yields

$$\bar{p}(\omega) = \left(\frac{\bar{q}}{A\bar{a}(\omega)\alpha}\right)^\alpha \left(\frac{q^K}{1-\alpha}\right)^{1-\alpha}, \quad \underline{p}(\omega) = \left(\frac{q}{a(\omega)\alpha}\right)^\alpha \left(\frac{q^K}{1-\alpha}\right)^{1-\alpha}. \quad (10)$$

Analogously, let the marginal cost of sub-task outputs implemented by ethnic skills as

$\widehat{p}^e(\omega')$. Then,

$$\widehat{p}^e(\omega') = \frac{\widehat{q}^e}{\widehat{A^e a^e}(\omega')} \quad (e \in F, D) \quad (11)$$

holds. Given the regularities and the optimal task allocation policy, the dynamic equilibrium is defined as follows. The formulation of marginal costs will be used as an analytical device to examine the sensitivity of task reallocation in response to factor price changes in Section 3.5.

Assume that as in the benchmark model, the establishment vintage is the same as the frontier level in the baseline year $t_0 = 1980$ such that $p_{i,t_0}^R = p_{t_0}^R \quad (\forall i)$. As shown in Figure 14, quality-adjusted robot price is monotonically decreasing such that for $t < t'$, $p_t^R > p_{t'}^R$. Once $\theta' > \theta$ is chosen at period t , the vintage of automation technology is updated from s to t where $t > s$ is the current vintage of automation, indexed by i 's last year of upgrading.

$$p_{i,t}^R = \begin{cases} p_t^R & (i \text{ upgrades}) \\ p_s^R & (i \text{ does not upgrade}) \end{cases} \quad (12)$$

Whenever i adjusts automation intensity θ , the vintage is taken to the frontier level. Thus, automation adjustment involves not only expansion of automation intensity $\theta' - \theta$ but capital deepening by vintage upgrading (from s to t). The higher vintage of automation is reflected by lower imputed rental price of robots, serving to the affordable final good price in the partially differentiated good market. i 's imputed robot rental price at period t is $q_{i,t}^R = \delta^R p_{i,t}^R$.

Definition 1. [Dynamic Task Allocation Equilibrium]

Impose the regularities of R0-R3. Then, given the skill prices $\widehat{q}_l^e, \widehat{q}_l$ in region l , equipment rental price q^K and investment price of robots p^R , the equilibrium requires (a)-(d):

(a) *Optimal task allocation:* Given task and sub-task productivity schedule $\{\underline{a}(\omega), \bar{a}(\omega), \widehat{a}^e(\omega')\}$, an establishment i in island l , maximizes the profit by optimally allocating the tasks by specifying automation intensity θ , occupation threshold ψ , and immigration threshold ϕ . ψ and ϕ are characterized by (9).

(b) *Regional skill market clearing:*

$$\begin{aligned} \text{(i)} \quad & \underbrace{\sum_{i \in l} \int_0^1 \widehat{s}_i(\omega) d\omega}_{\text{aggregate skill demand}} = \underbrace{\sum_{j \in l} \widehat{s}_j}_{\text{aggregate skill supply}} \\ \text{(ii)} \quad & \underbrace{\sum_{i \in l} \int_0^1 \widehat{s}_i^e(\omega') d\omega'}_{\text{domestic/foreign skill demand}} = \underbrace{\sum_{j \in l} \widehat{s}_i^e L_j^l}_{\text{domestic/foreign skill supply}} = \widehat{S}_l^e \quad (e \in \{D, F\}) \end{aligned}$$

(c) Nationwide capital market clearing:

$$(i) \underbrace{\sum_{i \in I} \int_0^\theta r_i(\omega) d\omega}_{\text{robot demand}} = R_l, \quad (ii) \underbrace{\sum_{i \in I} \int_0^1 k_i(\omega) d\omega}_{\text{equipment demand}} = K_l$$

(d) Nationwide goods market clearing:

$$\underbrace{\sum_j \widehat{C_{j,i,t}}}_{\text{final goods demand}} = \underbrace{\widehat{Y_{i,t}}}_{\text{final goods supply}} \quad \forall i$$

In dynamic equilibrium under frictional adjustment of automation, automation intensity, θ not necessarily follows a frictionless benchmark shown in Proposition 1. Observe that in the spatial economy, the skill market of the aggregate skills and foreign (domestic) skills regionally clears (*a la* Autor and Dorn (2013), and Beaudry, Doms and Lewis (2010), among others) and the capital market clears nationwide. Recall that final goods are tradable nationwide with imperfect product differentiation. Based on the equilibrium definition, nationwide prices, allocations and productions are formulated as follows.

Proposition 2. [Equilibrium Outcomes]

Suppose the regularities R0 – R3 hold. Then, a dynamic task allocation equilibrium uniquely exists. A deterministic production $Y_{i,t}$ is given by

$$Y_{i,t} = B(\theta_{i,t}, \psi_{l,t}, \alpha_l \mid A_l^R, \bar{A}_l, \{\underline{a}(\omega), \bar{a}(\omega), \widehat{a^F}(\omega')\}) \left\{ \left(\frac{R_{i,t}}{\theta_{i,t}} \right)^{\theta_{i,t}} \left(\frac{\underline{S}_{i,t}}{\psi_{l,t} - \theta_{i,t}} \right)^{\psi_{l,t} - \theta_{i,t}} \left(\frac{\bar{S}_{i,t}}{1 - \psi_{l,t}} \right)^{1 - \psi_{l,t}} \right\}^{\alpha_l} K_{i,t}^{1 - \alpha_l}$$

and a final good price $P_{i,t}$ depends on i 's vintage of robots proxied by $q_{i,t}^R = \delta p_{i,s}^R$.

$$P_{i,t} = \frac{\{(q_{i,s}^R)^{\theta_{i,t}} \underline{q}_{l,t}^{\psi_{l,t} - \theta_{i,t}} \bar{q}_{l,t}^{1 - \psi_{l,t}}\}^{\alpha} (q_t^K)^{1 - \alpha_l}}{\alpha_l^{\alpha_l} (1 - \alpha_l)^{1 - \alpha_l} B(\theta_{i,t}, \psi_{l,t}, \alpha_l)}$$

where $B(\theta_{i,t}, \psi_{l,t}, \alpha_l) = \{(A_i^R)^{\theta_{i,t}} (\bar{A}_i)^{1 - \psi_{l,t}}\}^{\alpha_l} \exp[\alpha_l \{\int_{\theta_{i,t}}^{\psi_{l,t}} \ln \underline{a}(\omega) d\omega + \int_{\psi_{l,t}}^1 \ln \bar{a}(\omega) d\omega\}]$ holds. Aggregate skill allocation:

$$\underline{S}_{i,t} = \frac{(\psi_{l,t} - \theta_{i,t}) \alpha_l P_{i,t} Y_{i,t}}{\underline{q}_{l,t}} \quad \bar{S}_{i,t} = \frac{(1 - \psi_{l,t}) \alpha_l P_{i,t} Y_{i,t}}{\bar{q}_{l,t}} \quad (13)$$

Skill prices:

$$\widehat{q}_{l,t} = \frac{(\widehat{q}_{l,t}^F)^{\phi_{l,t}} (\widehat{q}_{l,t}^D)^{1-\phi_{l,t}}}{B'(\phi_{l,t})}, \quad \widehat{q}_{l,t}^F = \frac{\phi_{l,t} \widehat{q}_{l,t} \widehat{S}_{i,t}}{\widehat{S}_{i,t}^F}, \quad \widehat{q}_{l,t}^D = \frac{(1-\phi_{l,t}) \widehat{q}_{l,t} \widehat{S}_{i,t}}{\widehat{S}_{i,t}^D}$$

where

$$B'(\phi_{l,t}) = (\widehat{A}_l^F)^{\phi_{l,t}} \exp\left[\int_0^{\phi_{l,t}} \ln \widehat{a}^F(\omega') d\omega'\right]$$

holds. *Equipment allocation:*

$$K_{i,t} = \frac{(1-\alpha_l) P_{i,t} Y_{i,t}}{q_t^K}$$

Aggregation of individual skills:

$$\sum_{j \in l} \widehat{s}_{j,t} = \widehat{S}_{l,t}, \quad \sum_{j \in l} \widehat{s}_{j,t}^e = \widehat{S}_{l,t}^e$$

A proof is relegated to Model Appendix. Note that establishments with wider $\theta_{i,t}$ and lower $q_{i,t}^R$ with a newer vintage enables lower final good price $P_{i,t}$, yielding larger market shares under the imperfectly differentiated market with $\sigma < 1$. Skill incomes of each occupation class are shaped by task thresholds, $\theta_{i,t}, \psi_{l,t}$ and $\phi_{l,t}$, which characterizes adjustments of technology. As a combination of these skill incomes constitute the basis of the social welfare (discussed in Section 6), the welfare implication is directly tied to task reallocation.

3.3 Solving the model

The key trade-off of automation upgrading is production benefit from automation versus fixed lumpy adjustment cost. A policy function is characterized by a threshold rule as follows. In the baseline year of 1980, automation is presumed to be adopted without friction to the regionally optimal level by every establishment. Automation intensities and vintages depart to diverge across establishments within and across regions.

Proposition 3. [Automation Upgrading Policy]

Optimal automation upgrading policy is characterized by a threshold rule such that

$$\begin{cases} \text{Upgrade} & (\theta < \widehat{\theta}(\mathbf{X}, A, \Delta Q_{i,t-1})) \\ \text{Not} & (\theta \geq \widehat{\theta}(\mathbf{X}, A, \Delta Q_{i,t-1})) \end{cases}$$

where a cutoff automation intensity $\widehat{\theta}(\mathbf{X}, A, \Delta Q_{i,t-1})$ is function of state variables $\mathbf{X}$, A and

a trend of automation-independent price aggregate price $\Delta Q_{i,t-1}$, where $Q_{i,t}$ is an automation-independent price bundle such that

$$Q_{i,t} \equiv \frac{(\underline{q}_t)^{\alpha\psi_{l,t}} (\bar{q}_t/\bar{A})^{\alpha(1-\psi_{l,t})} (q^K)^{1-\alpha}}{P_t \alpha^\alpha (1-\alpha)^{1-\alpha} \exp\{\alpha(\int_0^{\psi_{l,t}} \ln \underline{a}(\omega) d\omega + \int_{\psi_{l,t}}^1 \ln \bar{a}(\omega) d\omega)\}}.$$

where $P_t \equiv (\sum P_{i,t}^{1-\sigma})^{\frac{1}{1-\sigma}}$ is the aggregate good price in the final good market. Specifically, the policy is sufficiently governed by unobservable state A and other reduced observable states $\mathbf{X}_t$ of

$$\mathbf{X}_t = \left\{ \underbrace{\theta_{i,t-1}}_{\text{automation intensity}}, \underbrace{\frac{q_{i,t-1}^R}{\underline{q}_{t-1}}}_{\text{vintage value relative to routine skill price}} \right\}.$$

A proof is in the Model Appendix. Proposition 3 states that conditional on dynamic trends in economic cost environments (e.g. non-routine skill prices, equipment rental prices), automation upgrading is characterized by the current automation intensity and the vintage value relative to the routine skill price.

3.4 Adjustment costs and size distribution

This sub-section summarizes the role of three dynamic parameters: adjustment parameters and a product differentiation parameter on the evolution of establishment size distributions. In Figure 6, the horizontal line illustrates hump-shaped employment share along employment size on the horizontal line. Productive establishments are initially large, and frequently conduct upgrading automation by paying the non-convex cost. Simulation under the plausible range of parameters show that higher intensity of automation shrinks the employment size of establishments including routine- and non-routine occupations.

Diminishing non-convex cost expands more automation upgraders, facilitating a balanced downward shift. Diminishing convex cost extends upgrading intensity, $\theta' - \theta$, skewing the size distribution to the left. Finally, intensified competition accelerates the market share substitution from automation, spreading the size distribution. This is summarized as follows:

1. *Smaller* non-convex costs ζ expands the range of automation upgraders. It *decreases* mean and skewness (upward-biased) but *increases* dispersion and concentration due to inequality in upgrading cycles.
2. *Smaller* convex adjustment cost τ suppresses the automation intensity θ among the upgraders. It *decreases* the mean, dispersion and concentration but *increases* skewness.

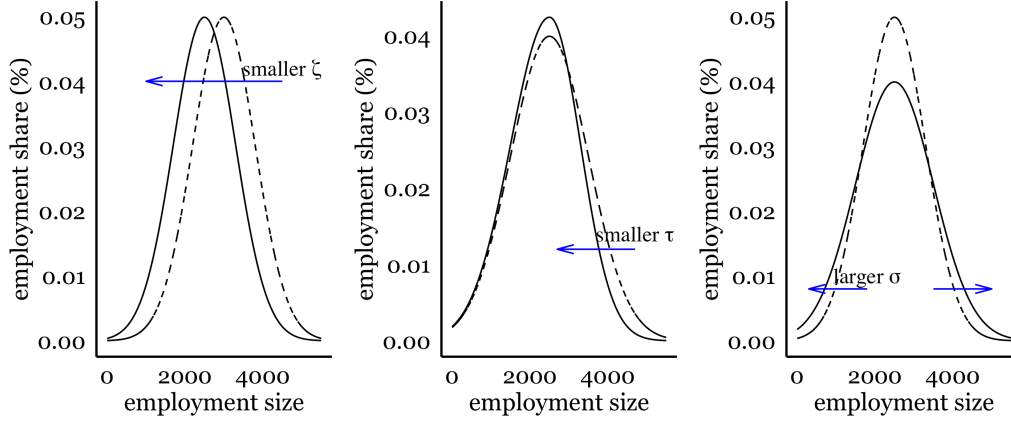


Figure 6: The roles of key parameters on the size distribution (conceptual chart) (left: smaller ζ , middle: smaller τ , right: larger σ)

3. *Larger* price competition σ governs the profitability of automation by substituting market shares. It *increases* dispersion and concentration but *decreases* skewness. (indeterminate on mean) Carefully keeping directions of parameter changes in mind, this simulation is summarized as the following table.

Table 1: The roles of key parameters on the size distribution moments (table)

dynamic parameters	role	Moments in evolution in size distribution			
		mean (magnitude)	sd per mean (dispersion)	skewness (asymetry)	HHI (concentration)
non-convex costs (ζ)	shrink range of upgraders	+	-	+	-
convex costs (τ)	suppress intensity of automation	+	+	-	+
competition (σ)	expand gains of automation	0	+	-	+

3.5 Comparative Advantage Schedule and Technology Adjustments

In response to factor price changes, an establishment adjusts extensive-margin technologies by optimally reallocating tasks over production factors, characterized by task thresholds. This sub-section formalizes the technology adjustments based on the task-specific comparative advantage defined below.

Definition 2. [Comparative Advantage]

Comparative advantage (CA, hereafter) of routine skills over robots, of non-routine skills over routine skills in task non-routineness at task ω is defined respectively

as³³

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

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

$$CA^{F,D}(\omega') \equiv \frac{\widehat{da^F}(\omega')/d\omega'}{\widehat{a^F}(\omega')}.$$

Intuitively, CA of factor 1 over factor 2 is a productivity growth rate of factor 1 relative to factor 2 when an assigned task is marginally more non-routine. Now, the elasticity of technological adjustment with respect to factor prices is directly tied to CAs as follows.

Proposition 4. [Comparative Advantage and Extensive-margin Technology Adjustment]

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

$$\frac{d\theta}{d \ln \underline{q}} = -\frac{d\theta}{d \ln q^R} = \alpha CA^{L,R}(\theta)^{-1} > 0.$$

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

$$\frac{d\psi}{d \ln \underline{q}} = -\frac{d\psi}{d \ln \bar{q}} = \alpha CA^{H,L}(\psi)^{-1} > 0, \quad \frac{d\phi}{d \ln \widehat{q^D}} = -\frac{d\phi}{d \ln \widehat{q^F}} = CA^{F,D}(\phi)^{-1} < 0.$$

Elasticity of technological change in response to factor price shifts are shown to be linked to CAs at respective thresholds across factors. These links are important because any equilibrium shifts including task reallocation involves information of CAs. The intuition of Proposition 4 is simple: when two factors are well-differentiated, adjustments become smaller in magnitude. CA at the task thresholds governs how sensitive task reallocation is in response to changes in factor prices. Next, I provide a sketch of Proposition 4 separately in two adjustments.

³³Recall the normalization of task productivities of robots and domestic skills such that

$$a^R(\omega) = 1 \quad \forall \omega \in [0, 1], \quad \widehat{a^D}(\omega') = 1 \quad \forall \omega' \in [0, 1].$$

Automation adjustment

The elasticity of automation intensity with respect to a routine skill price and rental price of robot is formulated.

$$\begin{cases} \frac{d\theta}{d \ln \underline{q}} = \frac{d\theta}{d \underline{q}} \underline{q} = \frac{\underline{q}}{-\dot{\underline{p}}(\theta) \underline{A} \underline{a}(\theta)} = \frac{\underline{p}(\theta)}{-\dot{\underline{p}}(\theta)} > 0 \text{ (wage-driven automation)} \\ \frac{d\theta}{d \ln q^R} = \frac{d\theta}{d q^R} q^R = \frac{q^R}{\dot{\underline{p}}(\theta) A^R} = \frac{\underline{p}(\theta)}{\dot{\underline{p}}(\theta)} < 0 \text{ (technology-driven automation)} \end{cases}$$

The first one shows a mechanism of automation adoption, driven by changes in skill prices, while the second one expresses technology-driven automation via declining rental price of robots, though both are mathematically isomorphic. The second equality in each equation comes from graphical relationships in Figure 7, showing the response of θ in the marginal move of $q^R, \underline{q}$, respectively. The third equality comes from single-crossing of marginal costs of routine skills and robots, $\underline{p}(\theta) = \frac{q^R}{A^R}$. To save space, define a notation of $\dot{x}(\omega^*) \equiv \frac{dx(\omega)}{d\omega} \big|_{\omega=\omega^*}$. Thus, the elasticities of automation with respect to factor prices are

$$\frac{d\theta}{d \ln \underline{q}} = -\frac{d\theta}{d \ln q^R} = \left(\frac{\underline{p}(\theta)}{-\dot{\underline{p}}(\theta)} \right)^{-1} = \alpha \left(\frac{\underline{a}(\theta)}{\underline{a}(\theta)} \right)^{-1} = \alpha C A^{L,R}(\theta)^{-1} \underset{R0}{>} 0$$

holds.³⁴

Labor adjustment

The elasticity of occupation threshold with respect to a routine skill price and rental price of robot is formulated as

$$\begin{cases} \frac{d\psi}{d \ln \underline{q}} = \frac{d\psi}{d \underline{q}} \underline{q} = \frac{\underline{q}}{\{\bar{\underline{p}}(\psi) - \dot{\underline{p}}(\psi)\} \underline{a}(\psi)} = \frac{\underline{p}(\psi)}{\bar{\underline{p}}(\psi) - \dot{\underline{p}}(\psi)} < 0 \\ \frac{d\psi}{d \ln \bar{q}} = \frac{d\psi}{d \bar{q}} \bar{q} = \frac{\bar{q}}{-\{\bar{\underline{p}}(\psi) - \dot{\underline{p}}(\psi)\} \bar{a}(\psi)} = \frac{-\bar{\underline{p}}(\psi)}{\bar{\underline{p}}(\psi) - \dot{\underline{p}}(\psi)} > 0 \end{cases}$$

The second equality in each equation comes from graphical relationships in Figure 8, showing the response of ψ in the marginal move of $\underline{q}, \bar{q}$, respectively. The third equality comes from

³⁴The third equality comes from some algebra, using the formula of $p(\omega)$; $\frac{dp(\omega)}{d\omega} = p(\omega) \frac{d(a(\omega))^{-\alpha}}{d\omega} = -\alpha p(\omega) \frac{\dot{a}(\omega)}{a(\omega)}$. Derivation is analogous in paragraph of labor adjustment below.

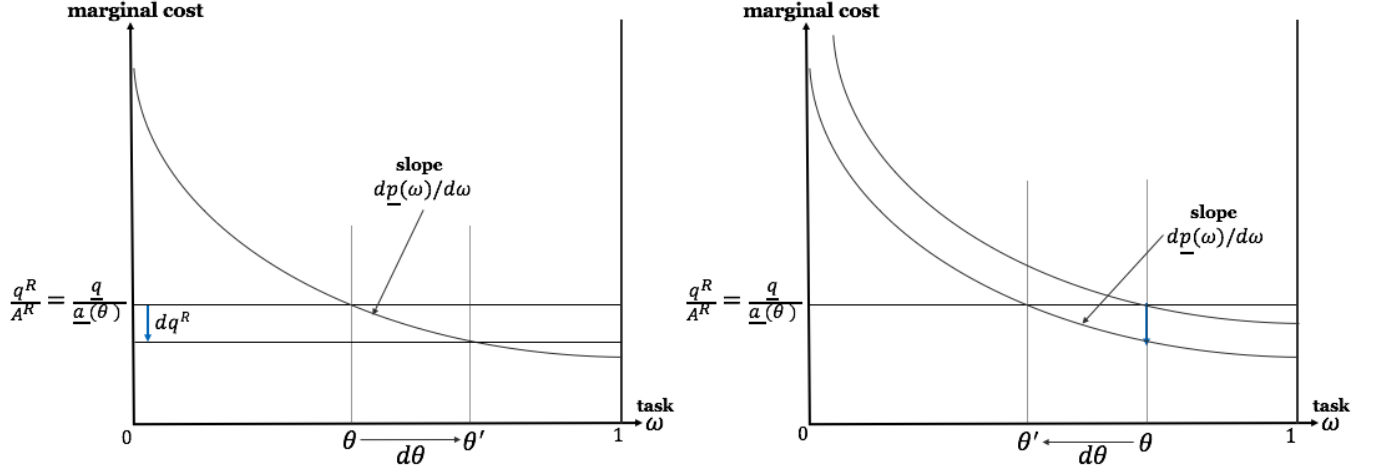


Figure 7: Marginal response of θ in routine skill price change (left), in rental price of robots change (right)

single-crossing of marginal costs, of non-routine and routine-skills $\bar{p}(\psi) = \underline{p}(\psi)$. Thus, the elasticities of labor adjustment with respect to factor prices are

$$\frac{d\psi}{d \ln \bar{q}} = -\frac{d\psi}{d \ln \underline{q}} = \left(\frac{\bar{p}(\psi)}{\underline{p}(\psi)} - \frac{\underline{p}(\psi)}{\bar{p}(\psi)} \right)^{-1} = -\alpha \left(\frac{\bar{a}(\psi)}{\underline{a}(\psi)} - \frac{\underline{a}(\psi)}{\bar{a}(\psi)} \right)^{-1} = \alpha C A^{H,L}(\psi)^{-1} \underset{\text{R0,R2}}{>} 0.$$

Replacing ψ with ϕ , $\underline{q}$ with $\widehat{q^F}$ and $\bar{q}$ with $\widehat{q^D}$, the same argument holds in the lower level sub-task reallocation. Analogously,

$$\frac{d\phi}{d \ln \widehat{q^F}} = -\frac{d\phi}{d \ln \widehat{q^D}} = C A^{F,D}(\phi) \underset{\text{R0,R3}}{<} 0$$

holds.

3.6 Comparative Statics of Immigration Inflow

Using the task-based mechanics, this section analytically explores endogenous adjustment of automation and labor market dynamics in response to immigration inflow. To make the model tractable, I consider the steady state without frictions for adjusting automation. The timeline of events is depicted in Figure 9. In the short run, immigration inflow triggers labor adjustments including ethnic skill adjustment, while automation technology remains unchanged. In the long run, automation adjustment is jointly induced by short-run routine skill price shifts and by technological drops of imputed rental prices of robots, accompanied by further labor adjustments. Social welfare is evaluated based on the consequent labor market

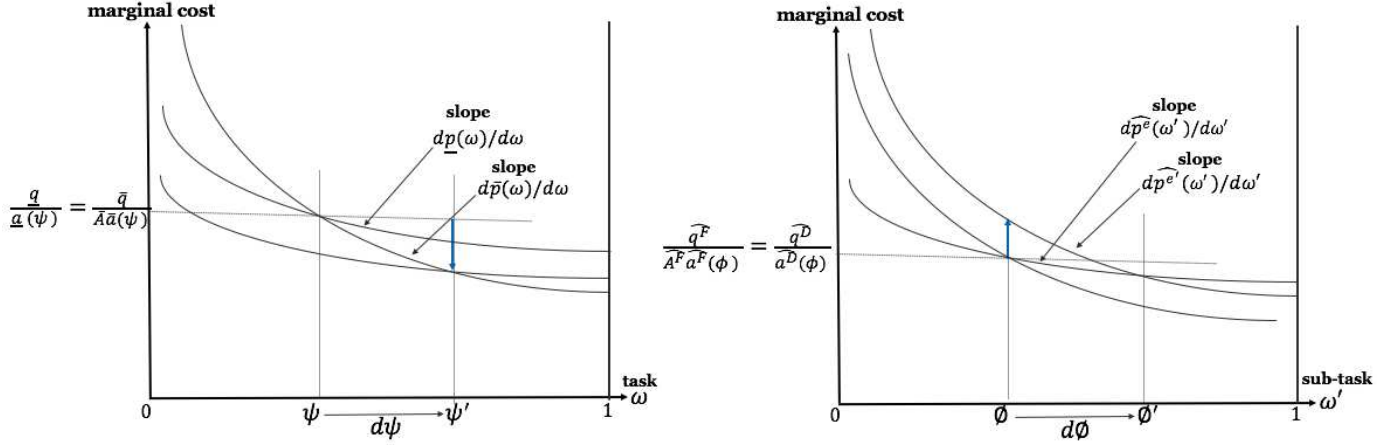


Figure 8: Marginal response of ψ to routine skill price change (left), of ϕ to domestic and foreign skill price change (right)

outcome in the long run, which will be evaluated in Section 6.1. The detailed analytical steps are in the Model Appendix.

Guided by empirical distribution patterns of immigrants of differential skills across sectors³⁵, I consider the labor market impact of low-skilled and high-skilled immigration separately in manufacturing (or plant) and information service (or office), separately. Let us presume that low-skilled immigrants provide foreign routine skills $\underline{S}^F$ and engage in routine occupations in the plant sector, and high-skilled immigrants provide foreign non-routine skills $\overline{S}^F$, and engage in non-routine occupations in the office sector. Mirrored by the foreign skill dispersion across sectors, sectors are symmetrically treated, albeit distinct in nesting foreign and domestic skills in technology; routine (or non-routine) occupation is foreign-intensive in the plant (or office) sector, thus, routine- (or non-routine-) skill is a composite of distinct foreign and domestic skills. To save space, I redefine the notations for symmetric formulation across sectors, wherever applicable as follows. For any variable $z \in \{S, q, A, a(\omega), \dots, \text{etc.}\}$ in each sector, define ethnic-variable $\hat{z}^e$ for $e \in \{F, D\}$, immigration-intensive aggregate

³⁵Empirically, plant and office sectors correspond with manufacturing and information service sectors, respectively. (See Section 4.1) In terms of education attainment, a dominant part of immigrants are low-skilled in manufacturing, and high-skilled in information service. Moreover, when occupations are aligned with routineness, proxied by automatability index from Frey and Osborne (2017), I found prominent concentration of immigrants in routine occupations in manufacturing, and non-routine occupations in information service. (See Data Appendix for details.) Immigrants in non-routine occupation in plant, and routine occupation in office are modeled equivalently as native counterparts.

variable $\hat{z}$, and non-immigrant intensive aggregate variable $\tilde{z}$ as follows

$$\begin{cases} \hat{z}^e \equiv \underline{z}^e, \hat{z} \equiv \underline{z}, \tilde{z} \equiv \bar{z} & (\text{plant}) \\ \hat{z}^e \equiv \bar{z}^e, \hat{z} \equiv \bar{z}, \tilde{z} \equiv \underline{z} & (\text{office}). \end{cases} \quad (14)$$

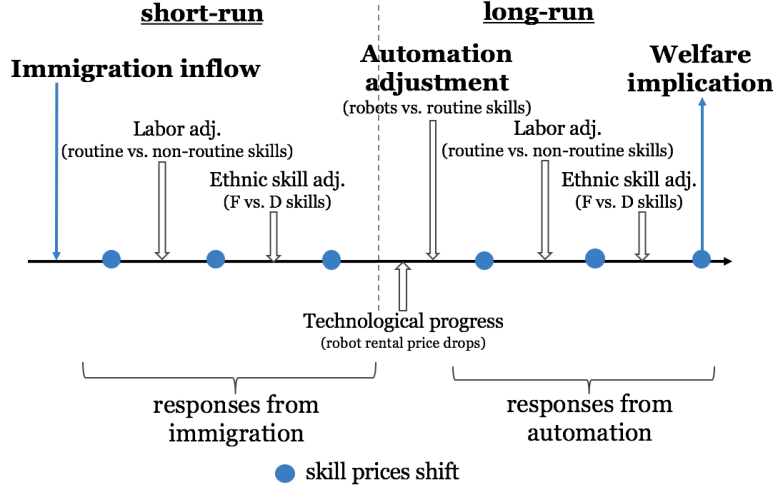


Figure 9: Timeline of events

Notes: Timeline is common across sectors. adj. denotes adjustment.

3.6.1 Short run

Labor market response to immigration inflow At the beginning of the economy, suppose that immigration inflow enters island l . (l is implicit throughout this section). The immigration inflow expands foreign skill supply curves by self-selection into each occupation class. In conceptual model, suppose for simplicity that low-skilled immigration enters a routine occupation in manufacturing, while high-skilled immigration enters a non-routine occupation in information service.³⁶ Suppose in the short run, an establishment is only allowed to run labor adjustments over tasks by shifting a pair of thresholds ψ and ϕ .

When non-routine skills are sufficiently differentiated from routine skills (i.e., $CA^{H,L}(\psi)$ is sufficiently large) at the occupation threshold, a series of gross equilibrium shifts are shown to occur by the following order in the plant (or office, respectively, italics in square brackets) as depicted in Figure 10. Step 1: Low-skilled [*High-skilled*] immigration inflow drops a routine skill price $\underline{q}$ [*non-routine skill price $\bar{q}$*]. Step 2: Both routine skill price $\underline{q}$ and non-routine skill price $\bar{q}$ are upshifted due to production shift. Step 3: Occupation threshold

³⁶This assumption is relaxed and self-selection rule into each occupation class is estimated in 3.3.

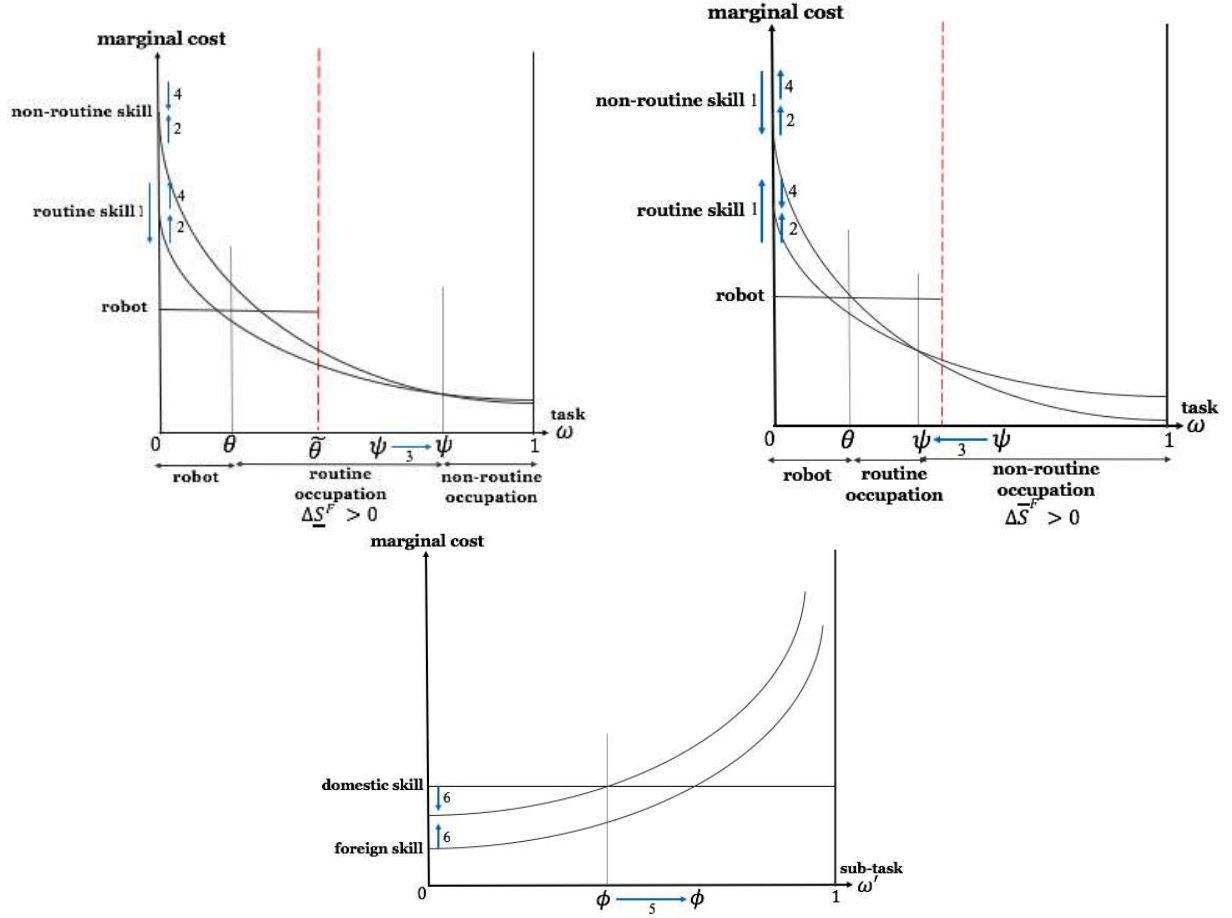


Figure 10: Short run (upper-left: tasks in plant, upper-right: tasks in office, bottom: sub-tasks in both sectors)

ψ expands [shrinks]. Step 4: Routine skill price $\underline{q}$ rises [falls], while non-routine skill price $\bar{q}$ falls [rises]. Step 5: Immigration threshold ϕ expands. Step 6: Domestic skill price $\hat{q}^D$ falls, while foreign routine skill price $\hat{q}^F$ rises. Formerly, under the fixed automation intensity, short-run transition of skill prices are shaped by three effects of immigration defined as follows.

Definition 3. [Labor supply, Scale, and Substitution Effects of Immigration]

Labor supply effect is mechanical impacts of immigration shocks on skill prices, such that $\frac{\partial q^{occ}}{\partial \hat{S}^F}$. Scale effect is impacts of immigration shocks on skill prices from production level change from labor supply effect, such that $\frac{\partial q^{occ}}{\partial Y} \frac{\partial Y}{\partial \hat{q}^F} \frac{\partial \hat{q}^F}{\partial \hat{S}^F}$. Occupational and foreign substitution effect is impacts of immigration shocks on skill prices from task reallocation across factors between non-routine and routine skills, $\frac{\partial q^{occ}}{\partial \psi} \frac{\partial \psi}{\partial \hat{S}^F}$ and factors between foreign

and domestic skills, $\frac{\partial \widehat{q}^e}{\partial \phi} \frac{\partial \phi}{\partial \widehat{S}^F}$, respectively.

Immigration and labor adjustments The immigration inflow mechanically diminishes the foreign skill price, downshifting the aggregate foreign-intensive skill price in each sector. In particular, the routine skill price drops in plant, and non-routine skill price drops in office. (Step 1, *labor supply* effect) On the other hand, the mechanical drops of skill prices lead to cost advantage for establishments, expanding production. This induced production growth expands demand for both routine and non-routine skills, augmenting their skill prices in turn. (Step 2, *scale* effect) Suppose θ is fixed, and R0-R3 are imposed. Then, induced by the forces, establishments run a pair of labor adjustments by changing the occupation and immigration thresholds as follows.

$$\begin{aligned} \left(\frac{d\psi}{d \ln \widehat{S}^F}\right)_{short} &= \pm \alpha C A^{H,L}(\psi)^{-1} \left\{ \underbrace{\widehat{\Phi} \alpha \widehat{\chi}}_{\text{scale effect}} + \underbrace{1}_{\text{labor supply effect}} \right\} \phi \widehat{\Phi}^F \\ \left(\frac{d\phi}{d \ln \widehat{S}^F}\right)_{short} &= C A^{F,D}(\phi)^{-1} \left[\underbrace{\phi \widehat{\Phi}^F}_{\text{labor supply effect}} + (\widehat{\Phi}^F - \widehat{\Phi}^D) \left\{ \underbrace{\alpha \widehat{\chi} \widehat{\Phi}^F}_{\text{scale effect}} \pm \underbrace{\frac{1}{\widehat{\chi}} \left(\frac{d\psi}{d \ln \widehat{S}^F}\right)_{short}}_{\text{occupational substitution effect}} \right\} \right] \end{aligned}$$

where $\pm$ applies to plant and office, respectively. Φ is defined as a function of uncompensated labor supply elasticity of any factor of interest, ϵ_U , such that $\Phi \equiv (\epsilon_U + 1)^{-1}$.³⁷ Φ captures the reactions of labor supply side for each factor. χ is a task interval such that $\underline{\chi} \equiv \psi - \theta$ and $\overline{\chi} \equiv 1 - \psi$ for both sectors. Recall the notation rule (14) also applies to the two. Intuitively, in the higher task level, demographic effect lowers the immigration-intensive skills, while scale effect augments the non-immigration intensive skills, expanding the task range of immigration-intensive occupation. In the sub-task level, mechanical labor supply shift from immigration inflow dominates the sub-task allocation, expanding the task range of foreign skills.³⁸

Immigration and routine skill prices After this task reallocation, factor demands shift to utilize relatively more foreign-intensive skills. Then, the occupation manager reallocates sub-tasks to exploit the relative cost advantage of foreign skills by expanding the foreign skill coverage, ϕ . The short-run labor market consequence is characterized by routine skill

³⁷Define $\widehat{\Phi} \equiv \{\phi \widehat{\Phi}^F + (1 - \phi) \widehat{\Phi}^D\}$ in plant.

³⁸Effects from the higher task-level, scale effect and occupation substitution effect, affect both foreign and domestic skills, thus, are second order, regulated by differential labor supply propensities of foreign and domestic groups, $\widehat{\Phi}^F - \widehat{\Phi}^D$.

price changes as follows.

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

$$\left(\frac{d \ln \underline{q}}{d \ln \hat{S}^F}\right)_{short} = \underbrace{\Phi \{ \alpha \hat{\chi} \phi \Phi^F \}}_{\text{scale effect}} + \underbrace{\frac{1}{\chi} \left(\frac{d \psi}{d \ln \hat{S}^F}\right)_{short}}_{\text{occupational substitution effect}} \quad (15)$$

$$+ \mathbb{I}(G = p) \left\{ \underbrace{-\phi \Phi^F}_{\text{labor supply effect}} + \underbrace{(\Phi^F - \Phi^D) \left(\frac{d \phi}{d \ln \underline{S}^F}\right)_{short}}_{\text{foreign substitution effect}} \right\} \begin{cases} < 0 & \text{(plant)} \\ > 0 & \text{(office)} \end{cases} \quad (16)$$

where $\mathbb{I}(G = p)$ is an indicator function of belonging to the plant sector. The task allocation in favor of routine occupations (larger ψ) and scale effect would upshift the short run routine price. Only in the plant sector, mechanical effect from immigration inflow (labor supply effect) is added.³⁹

When $CA^{H,L}(\psi)$ is sufficiently large, low-skilled immigration inflow lowers the routine skill price in the plant sector, while high-skilled immigration inflow raises the routine skill price in the office sector. Intuitively, when non-routine skills are sufficiently differentiated from routine skills at the occupation threshold, labor supply effect in the plant (or scale effect in office) cannot be completely offset by the induced second-order substitution effects from task reallocation.

3.6.2 Long run: Unintended Consequence of Immigration Inflows

In the long run, an establishment re-optimizes the automation intensity, guided by the change of routine skill prices relative to the current robot rental price. Suppose the short-run predictions (15), a series of gross equilibrium shifts are shown to occur by the following order in the plant (or office, respectively, *italics in square brackets*) sector.

The following Step 1-3 occurs in the long run as depicted in Figure 11. Before Step 1, robot rental price q^R drops and $\underline{q}$ has changed in the short run. The relative price change $\frac{\underline{q}}{q^R}$ drives the automation adjustment in Step 1. Step 1: Automation intensity θ falls [*rises*]. Step 2: Routine skill price $\underline{q}$ upshifts [*downshifts*] by expansion [*shrinkage*] of task interval. Step 3: A pair of skill prices $\underline{q}, \bar{q}$ downshifts [*upshifts*] due to production shift. Note that adjustment over sub-tasks are abstracted because it is second-order in magnitude.

³⁹ Analogous to the previous footnote, the ethnic substitution effect is of second-order.

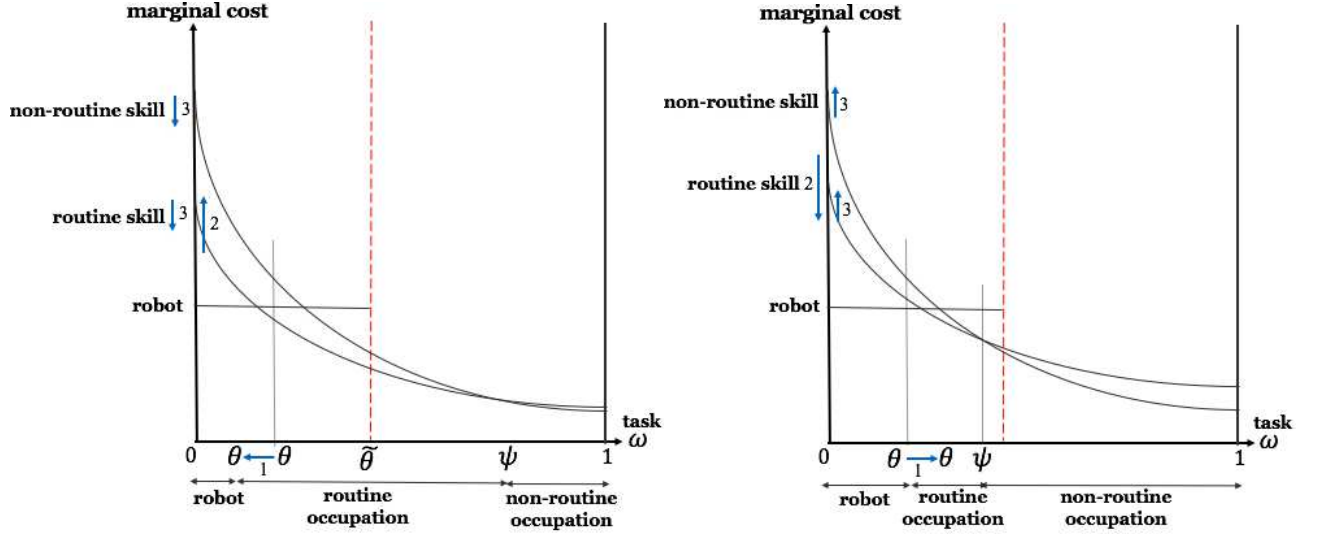


Figure 11: Long run (left: plant, right: office)

Formerly, under the fixed automation adjustment, long-run transition of skill prices is shaped by two effects defined as follows.

Definition 4. [Displacement and Productivity Effect of Automation]

Displacement effect is automation impacts to the routine skill prices, such that $\frac{dq}{d\theta}$. Productivity effect is automation impacts to skill prices from production level change, such that $\frac{dq^{occ}}{dY}(\frac{dY}{dq} \frac{dq}{d\theta} + \frac{dY}{dR} \frac{dR}{d\theta} + \frac{dY}{dS} \frac{dS}{d\theta})$.

Immigration-induced automation The series of equilibrium responses illustrates unintended consequences of immigration via automation adjustment: in plant sector, if low-skilled immigration inflow decreases the short-run routine skill price, and the automation intensity falls. In office sector, high-skilled immigration inflow raises the short-run routine skill price, and the automation intensity rises (Step 1). Suppose θ is adjustable and (15) holds. Then, the automation intensity is adjusted as

$$\left(\frac{d\theta}{d \ln \widehat{S}^F}\right)_{long} = \left(\frac{\partial \theta}{\partial \ln \underline{q}}\right)_{long} \left(\frac{d \ln \underline{q}}{d \ln \widehat{S}^F}\right)_{short} \begin{cases} < 0 & (\text{plant}) \\ > 0 & (\text{office}) \end{cases} \quad (17)$$

This is a key prediction in the benchmark model, distilling a hypothesis of immigration-induced automation; low-skilled immigration inflow downshifts automation, while high-

skilled immigration upshifts automation via the routine skill price change.⁴⁰

Automation and skill prices As a result of automation shifts, routine skill price upshifts *[downshifts]*. (Step 2, *displacement* effect) Then, establishments lower *[raise]* the routine skills due to the upshifted *[downshifted]* routine skill price to shrink *[expand]* the production as counteracting feedback. Moreover, due to the smaller *[wider]* task coverage of automation, the establishments undergo *[achieve]* a productivity loss *[gain]*, benefited from the new technological advance, embodied by a drop of quality-adjusted rental price of robots. As a result, skill prices uniformly downshift *[upshift]* across both occupation workers. (Step 3, *productivity* effect) Combining Step 2 and 3, automation's impact on skill prices are formulated across sectors as⁴¹

$$\frac{d \ln \underline{q}}{d\theta} = \underbrace{\Phi \left(\frac{-1}{\psi - \theta} \right)}_{\text{displacement effect}} + \underbrace{\Phi \alpha}_{\text{productivity effect}}, \quad \frac{d \ln \bar{q}}{d\theta} = \underbrace{\bar{\Phi} \alpha \Phi}_{\text{productivity effect}}.$$

Observe that the impact of induced-automation change to the skill prices are given as follows, using a combination of displacement and productivity effects. Finally, automation adjustment is accompanied by labor adjustment to re-optimize to the updated menu of skill prices. Iterate labor adjustments in Step 3-6 in the short run. The total impact in the long run is an entirely empirical question and will be analyzed in the augmented quantitative model.

3.6.3 Aggregate Impact of Immigration via Automation Adjustment

So far, both drivers and outcomes of short-run and long-run technology adjustments are illustrated from the lens of task allocation. Counteracting these two time-horizons, the net impact of immigration to automation and the economic consequence are characterized by the change of robot adoption and routine skill prices in the regional level.

Proposition 5. [Three Elasticities with respect to Immigration]

Suppose R0-R3 are imposed. Then, the regional elasticity of robot deployment, routine skill prices, and native premium with respect to immigration inflow in each sector is given by

⁴⁰ If $CA^{H,L}(\psi)$ is sufficiently large, $(\frac{d \ln \underline{q}}{d \ln \hat{S}^F})_{short}$ is negative *[positive]* from (15). Since $(\frac{\partial \theta}{\partial \ln \underline{q}})_{long} > 0$ across sectors, the results immediately hold.

⁴¹The formulation does not include effects from further labor adjustments. To avoid complexity, further labor adjustments are excluded here, but included in the simulation of the elasticities below.

$$\left(\frac{d \ln R}{d \ln \widehat{S}^F}\right)_{net} = \underbrace{\alpha \widehat{\chi} \phi \widehat{\Phi}^F}_{\text{scale effect}} + \underbrace{\frac{1}{\theta} \left(\frac{d \theta}{d \ln \widehat{S}^F}\right)_{long}}_{\text{displacement effect}} \quad (18)$$

$$\begin{aligned} \left(\frac{d \ln q}{d \ln \widehat{S}^F}\right)_{net} = & \underbrace{\Phi[\alpha \widehat{\chi} \phi \widehat{\Phi}^F]}_{\text{scale effect}} + \left\{ \underbrace{\alpha \Phi}_{\text{productivity effect}} + \underbrace{\frac{-1}{\psi - \theta}}_{\text{displacement effect}} \right\} \left(\frac{d \theta}{d \ln \widehat{S}^F}\right)_{net} + \underbrace{\frac{1}{\psi - \theta} \left(\frac{d \psi}{d \ln \widehat{S}^F}\right)_{net}}_{\text{occupational substitution effect}} \\ & + \mathbb{I}(G = p) \left\{ \underbrace{-\alpha \phi \widehat{\Phi}^F}_{\text{labor supply effect}} + \underbrace{(\widehat{\Phi}^F - \widehat{\Phi}^D) \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{net}}_{\text{foreign substitution effect}} \right\} \end{aligned} \quad (19)$$

$$\begin{aligned} \left(\frac{d \ln(\widehat{q}^D / \widehat{q}^F)}{d \ln \widehat{S}^F}\right)_{net} = & \underbrace{\alpha \phi \widehat{\Phi}^F}_{\text{labor supply effect}} - (\widehat{\Phi}^F - \widehat{\Phi}^D) \left(\underbrace{\alpha \widehat{\chi} \phi \widehat{\Phi}^F}_{\text{scale effect}} + \underbrace{\alpha \Phi}_{\text{productivity effect}} \right) \left(\frac{d \theta}{d \ln \widehat{S}^F}\right)_{long} \\ & - \underbrace{\left(\frac{\widehat{\Phi}^F}{\phi} + \frac{\widehat{\Phi}^D}{1 - \phi}\right) \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{net}}_{\text{foreign substitution effect}} \mp \underbrace{\left[\frac{\widehat{\Phi}^F - \widehat{\Phi}^D}{\widehat{\chi}} \left\{ \left(\frac{d \psi}{d \ln \widehat{S}^F}\right)_{net} - \mathbb{I}(G = p) \left(\frac{d \theta}{d \ln \widehat{S}^F}\right)_{long} \right\} \right]}_{\text{occupational substitution and displacement effect}} \end{aligned} \quad (20)$$

$\mp$ applies to plant and office, respectively. The first result associated with robot density captures the degree of automation, illustrated by a pair of motivating graphics in Figure 1 and 2. The second result regarding routine-skill price serves both a cause (short-run shift) and consequence (long-run shift) of the automation. The third result of inequality in skill prices across foreign and domestic groups are formulated as a function of task allocations.

4 Data

This section presents the primary data sources, introduces empirical counterparts for model objects and summarizes key features of the data. In particular, a pair of driving forces of automation dynamics is featured: demographic change (Force A, in Figure 12) and technology progress (Force B, in Figure 14). Further details are relegated to Data Appendix.

4.1 Unit of Analysis

The two sectors, plant and office in the conceptual model are represented by a pair of tradable sectors, manufacturing, and information service, respectively, classified according to BEA (Bureau of Economic Analysis) code, generally following NAICS (North American

Industry Classification System). The manufacturing sector consists of three sub-industries (31-33), while the information service sector is comprised of sub-industries of Information (51), Finance and Insurance (52), Professional, Scientific, Technical Services (54), and Management of Companies and Enterprises (55).⁴² Islands (regional labor markets) are proxied by Commuting Zones (CZs), developed by [Tolbert and Sizer \(1996\)](#), best regarded as a semi-independent unit of regional labor markets, shaped by commuting patterns of local workers. In contrast to the traditionally-used Metropolitan Statistical Areas (MSAs), CZs cover the entire U.S. mainland, including less-developed rural areas, and maintain the consistent boundary definitions throughout the periods, 1980-2015. 722 CZs in the U.S. mainland, excluding Hawaii and Alaska, are on board. Urban areas comprise the largest 37 CZs in the labor force out of 722 CZs, accounting for the half the nationwide country labor force in 1980. (See Data Appendix for a map)

4.2 Demography and Labor Markets

Demographic change The analysis draws on repeated cross-section datasets from the Census Integrated Public Use Microdata Samples ([IPUMS \(2019\)](#)) for years 1980, 1990, 2000, and American Commuting Survey (ACS) for 2005 to 2015. The analysis is restricted to working-age individuals from 16 to 64, excluding students.⁴³

The demographic projection draws on 2017 National Population Projections by [Census Bureau \(2017\)](#), offering nationwide projections of population by nativity, sex and single age every future year from 2016 to 2050. The U.S. underwent a remarkable rise in immigration inflow in 1980-2015, and their presence is projected to grow, albeit it is less stark. Net immigration inflow represented 39.5% of growth in the working-age population in 1980-2015. The working-age population is forecast to grow until 2050, and under the status quo immigration policy, 26.1% of future population growth relies on net immigration inflow.

Figure 12 illustrates the demographic change in the target period 1980-2015, and future projections in 2016-2050, of young-aged (16-35), middle-aged (36-50) and old-aged (aged 50-64) domestic labor and foreign labor, separately in two skill groups.⁴⁴

⁴²Non-tradable local service industries including Wholesale Trade (42), Retail Trade (44-45), Real Estate Rental and Leasing (53), Education Services (61), Health Care and Social Assistance (62), and Accommodation and Food Services (72) are excluded due to scarce density of high-skilled immigrants.

⁴³Incorporating investments into education would substantially complicate the analysis, because college enrollment is potentially guided by the future prospects of acquiring high skills. The demographic or technological impact to education attainments is relegated to future work.

⁴⁴As Census does not offer projections of educational attainment, skill level is extrapolated from the trend of 2010-2015, which exhibits stably rising trend in high-skilled ratio (college enrollments) across age groups.

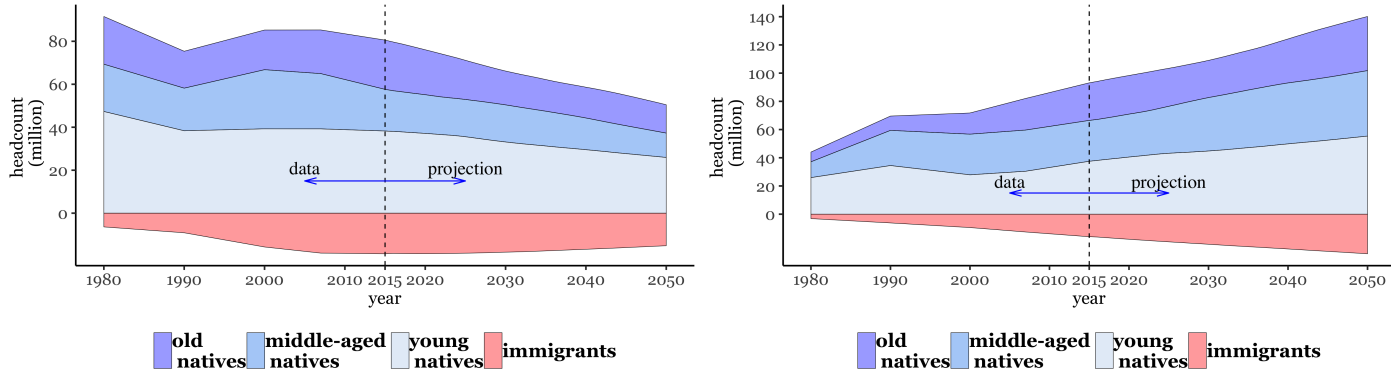


Figure 12: Driving force A: demography transition in the U.S. throughout 1980-2050. (left: low-skilled, right: high-skilled. 1980-2015 is target period, while 2016-2050 is projection period.)

Notes: Data in 1980-2015 from Census and ACS. 2016-2050 are based on 2017 National Population Projections from the Census. Old natives aged from 50 to 64, middle natives: aged from 35 to 49, young natives: aged 16 to 34) For smoother connection of data and projection, the graphics include students, and cover Alaska and Hawaii.

In the low-skilled population, the presence of foreign labor is expected to grow from 19.0% in 2015 to 23.1% in 2050 (6.5% in 1980), while the young group of natives slightly declines from 38.5% in 2015 to 39.5% in 2050 (48.3 % in 1980). In the high-skilled population, the presence of foreign labor is smaller but steadily growing from 14.7% in 2015 to 16.7% in 2050 (6.7 % in 1980). The young group of natives slightly declines from 34.4% in 2015 to 32.9% in 2050 (55.0 % in 1980).

Next, I turn to a regional perspective. To map the CZs onto the geographic units in Census, and ACS, I draw on crosswalks with connection weights from [Dorn \(2009\)](#), respectively bridging 1990 CZs and Census County Groups in 1980, Public Use Micro Areas (PUMAs) in 1990 and after. Immigrants are defined as foreign-born, non-citizen (including naturalized citizen), and natives are the rest of the individuals in the US. ([Borjas \(2003\)](#)) Figure 13 illustrates that immigration inflow is highly dispersed across CZs. Figure 13 illustrates the immigration inflow across skill-levels into CZs from 1980-2015 jointly by graphs and maps. The graphs show remarkably biased inflow of foreign labor, constituting a large variation of immigration-driven demographic change. Measured by absolute headcount terms, only the top 12 and 10 megacity CZs out of 722 accounts for 50% of the net low-skilled and high-skilled immigration inflow in 1980-2015, respectively. Moreover, it is intriguing to observe that high-skilled immigrants are more likely than low-skilled immigrants to be concentrated in urban areas (shown in blue bars).

To construct demography-driven labor supply shocks across CZs from 1980-2015, labor force participation with occupation choice (routine/non-routine across two sectors, plus a

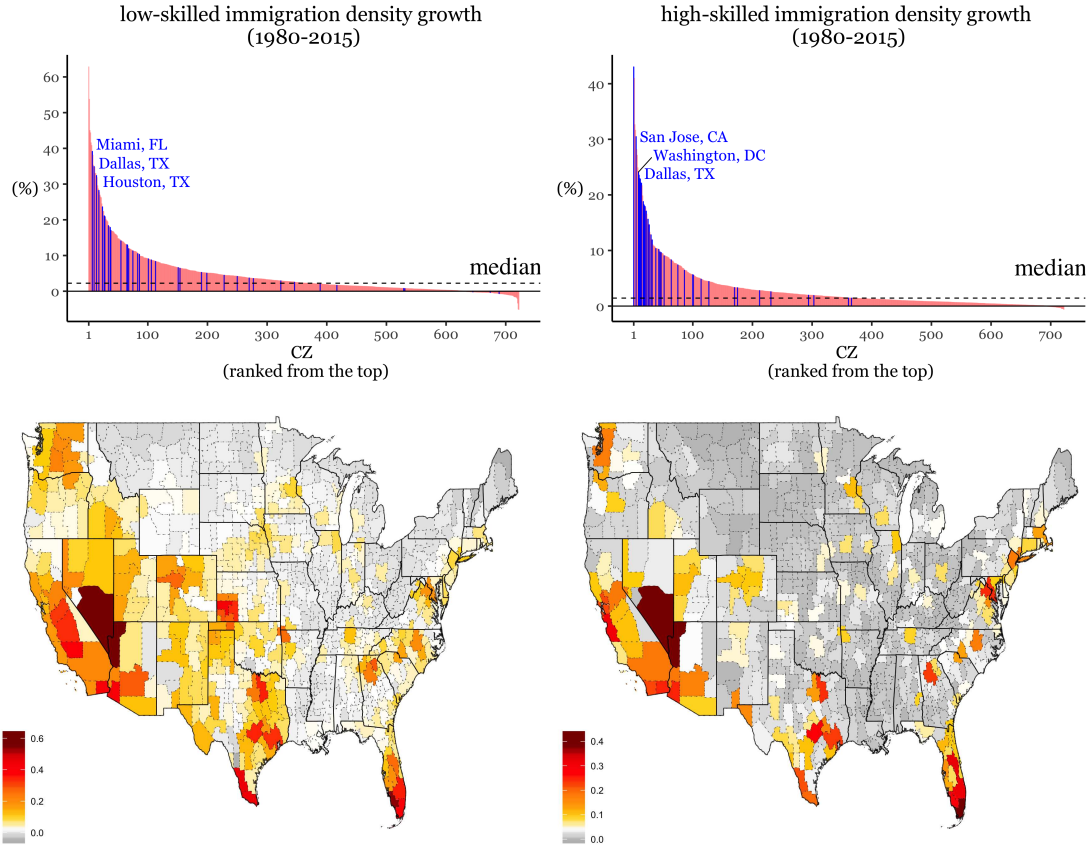


Figure 13: Immigration inflow across CZs in 1980-2015 (left: low-skilled immigration, right: high-skilled immigration)

Notes: The inflow is proxied by net inflow of working-age immigrants between 1980 and 2015 relative to regional total working age populations in 1980, $\frac{\hat{N}_{15}^F - \hat{N}_{80}^F}{\hat{N}_{80} + \hat{N}_{80}}$, computed from Census (1980) and ACS (2015). In graphs: blue bars capture urban areas, and red bars show rural areas.

group of alternative occupations, including service occupations in non-tradable service) by age, sex, nativity, education attainment, non-labor income and other observables (including the number of children) in 2015, are estimated by logit model. Then, this self-selection rule is applied to 1980-2015 data to construct the demography-driven labor supply shocks, serving as inputs to the dynamic full-model.

Labor markets across sectors This paper explicitly distinguishes high-/low-skilled individuals and non-routine-/routine-skills: the former is characterized by education attainment regardless of their labor market status, while the latter is based on occupation class as a result

of self-selection to each occupation class in equilibrium.⁴⁵ Guided by the benchmark model, production workers in the manufacturing sector are classified into *routine* occupations (e.g., laborers) and *non-routine* occupations (e.g., frontline managers and mechanical engineers). Symmetrically, non-production workers in the information service sector are also split into *routine* occupations (e.g., administrative clerks) and *non-routine* occupations (e.g., managers and engineers).⁴⁶ Real wages are computed by annual labor income with top-coding adjustments following the Census and ACS and inflation adjustments by consumer price index from [FRED \(2019b\)](#), divided by working hours.

4.3 Technology and Capitals

As extensively employed in macroeconomics, capital investments and stocks are taken from National Income and Product Accounts (NIPA) from BEA. It covers physical capitals and information capitals, in consistent classification of industries (BEA industries based on NAICS) and capitals throughout the years of interest, from 1980 to 2015.

As automation is unobservable per se, it is measured by automation-embodiment capitals. The model presumes that R is skill-replacing robots, and K is skill-augmenting capitals; however, empirically sorting out the two is a non-trivial task. In the manufacturing sector, industrial robot data from the World Robotics from the International Federation of Robotics ([IFR \(2015\)](#)) is a well-established source for skill-replacing machines.⁴⁷ To connect BEA and IFR datasets, I explore which combination of capital categories in NIPA best correspond with industrial robots from IFR. Through a cross-validation exercise, a pair of *metalworking machines* and *special industry machines* is found to match best the industrial robots from the IFR. (See Data Appendix) In the information service sector, based on definitions of BEA capital classification, I proxy autonomous IT capitals with a set of mainframe computers, system integrators, custom software, and own-account software.⁴⁸ Investment prices are all quality-adjusted, following indices and methods from [Cummins and Violante \(2002\)](#),

⁴⁵Of course, these two measures, however, are strongly correlated; low-skilled individuals enter routine occupations with substantially higher probability than high-skilled ones.

⁴⁶The number of non-production workers in manufacturing are relatively small compared to production workers. The occupation class could be interpreted as managerial capital included in TFP terms. Production workers in information sector is negligible and thus, excluded.

⁴⁷Recent empirical works on robotization (e.g. [Acemoglu and Restrepo \(2017\)](#) and [Graetz and Michaels \(2017\)](#)) uses [IFR \(2015\)](#). Since industrial robots are rigorously defined, the proxies only cover a very tiny fraction (less than 10%) of the total physical capital stocks in BEA, not representative enough to draw aggregate economic implications, sought in this paper.

⁴⁸Unlike industrial robots, to the best of my knowledge, no external dataset is available for capitals, accurately embodying IT automation. The results remain robust to several alternatives of categories.

deflated by the GDP deflator from [FRED \(2019a\)](#), and normalized to 1980 as unity. Figure 14 illustrates investment-specific technical change, sharply contrasting paths of investment prices of physical capitals and information capitals. Quality-adjusted investment prices of physical capital prices are relatively stable, while those of information capitals rapidly drop over time.

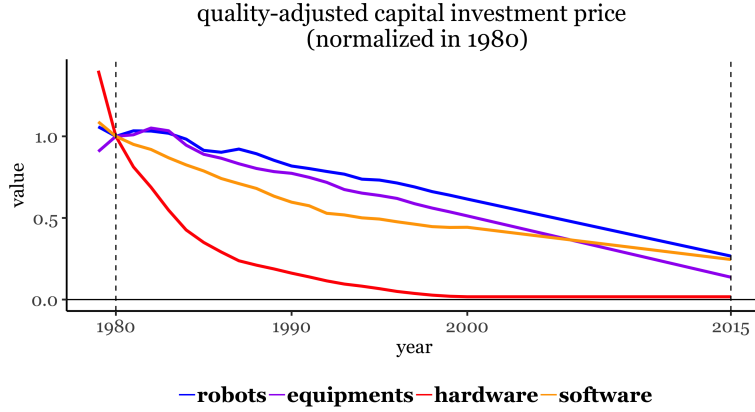


Figure 14: Driving force B: Technological progress: quality-adjusted capital investment price
Notes: Denominated by GDP deflator from [FRED \(2019a\)](#), and normalized to unity in 1980.

The rental price for capital is computed based on the canonical perpetual inventory method.

$$q_t^M = (\delta_t^M + RealInterestRate_t - \mathbb{E}(p_t^M))p_t^M$$

where δ_t^M is a depreciation rate, $\mathbb{E}(p_t^M)$ is expected growth rate of investment price (proxied by a three-year moving average trend of the previous year), and p_t^M is an investment price of capital M , at year t , respectively. Both robots and equipment are treated as quality-controlled capital units, nominal values denominated by the normalized quality-adjusted real investment prices.

Founded by the categorization, regional capital deployments are imputed using the benchmark model. As the benchmark model involves neither automation friction nor labor adjustment frictions, automation intensity and skill thresholds are common within regions at the baseline year such that⁴⁹

$$\theta_{i,t_0} = \theta_{l,t_0} \quad \psi_{i,t_0} = \psi_{l,t_0} \quad \forall i \in l.$$

⁴⁹ [Acemoglu and Restrepo \(2017\)](#) adopts a similar imputation strategy of regional industrial robot deployments in CZ level.

For all regions l, l' in sector G , the following relationships hold:

$$\frac{R_{l',t_0}^G}{R_{l,t_0}^G} \stackrel{(1)}{=} \frac{q_{l',t_0}^R R_{l',t_0}^G}{q_{l,t_0}^R R_{l,t_0}^G} \stackrel{(2)}{=} \frac{W_{l',t_0} + \bar{W}_{l',t_0} + V_{l',t_0}^K}{W_{l,t_0} + \bar{W}_{l,t_0} + V_{l,t_0}^K}, \quad \frac{K_{l',t_0}^G}{K_{l,t_0}^G} \stackrel{(1')}{=} \frac{q_{l',t_0}^K K_{l',t_0}^G}{q_{l,t_0}^K K_{l,t_0}^G} \stackrel{(2')}{=} \frac{W_{l',t_0} + \bar{W}_{l',t_0}}{W_{l,t_0} + \bar{W}_{l,t_0}}$$

(1), (1') comes from the equalized rental prices of the national capital market, $q_{l,t_0}^M = q_{l',t_0}^M$ ($M \in \{R, K\}$). (2), (2') hold from Proposition 3. Thus, the region-level capital in each sector is computed as a sum of industry-level capital stocks, weighted with a factor ratio of each region within industry g in sector G (3 digit and 4 digit BEA codes in manufacturing and in information service, respectively) such that

$$K_{l,t_0}^G = \sum_{g \in G} \frac{W_{l,t_0} + \bar{W}_{l,t_0}}{W_{t_0}^g + \bar{W}_{t_0}^g} K_{g,t_0}, \quad R_{l,t_0}^G = \sum_g \frac{W_{l,t_0} + \bar{W}_{l,t_0} + V_{l,t_0}^K}{W_{t_0}^g + \bar{W}_{t_0}^g + V_{t_0}^{g,K}} R_{g,t_0}.$$

4.4 Establishment Size Distribution

Plant-level literature (e.g. [Dinlersoz, Wolf et al. \(2018\)](#)) documents that remarkable heterogeneity exists for technology adoption. To identify differential propensity for automation adoption, establishment-level robot investments would be the ideal source. However, the dataset with this granularity is unavailable. Instead, I view that evolution of establishment employment size is informative to differential automation adjustments. Specifically, I rely on establishment-level labor size, from County Business Patterns (CBP). CBP covers the semi-universe of the establishments in county $\times$ industry-level (SICs from 1980 to 1997, and NAICS from 1998-2015) throughout the periods of interest. Cross-validating the aggregated labor from CBP and Population Census, establishment i 's recorded employment in CBP, denoted by N_i^{CBP} , is found to include both routine- and non-routine occupations. CBP classifies each establishment by 12 bins, but I approximate N_i^{CBP} by taking middle points of each bin except the largest bin so that $N_{i,l}^{CBP} \in \{3, 7, 15, 35, 75, 175, 375, 750, 1250, 2000, 3750, 5000\}$.⁵⁰ To translate counties in each year into CZs, I connects David Dorn's crosswalk between county in 1990 and 1990 CZs with a series of inter-temporal county crosswalks from the Census Bureau. The sample is narrowed down to include at least 10 establishments across sectors throughout the years, because distributional outcome gets very noisy in very small samples. Three statistical moments of size distribution, mean, standard deviation per mean,

⁵⁰The results are insensitive to alternative methods, such as random sampling. A lower bound 5000 of the largest bin is taken without top-coding adjustments. This is a conservative choice so that the effect of disappearance or emergence of this class of establishments is limited to minimum.

and skewness of employment shares in addition to Herfindahl-Hirschman index (HHI)⁵¹ are featured. Each moment represents magnitude, dispersion, asymmetry and concentration of the size distribution.

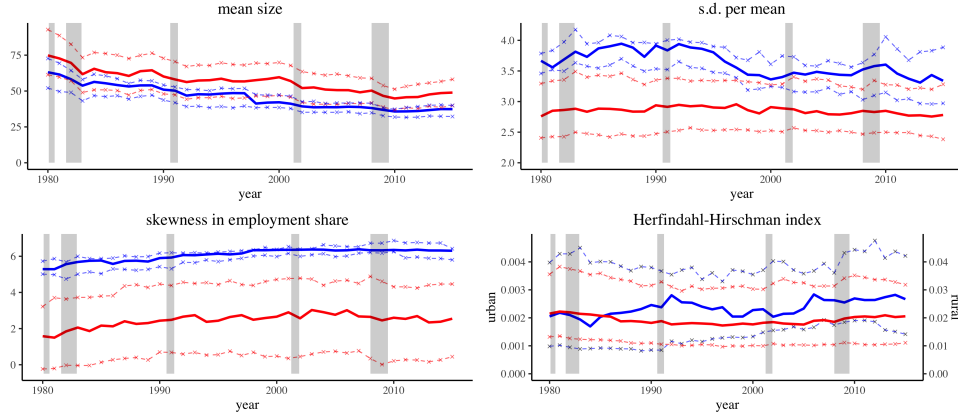


Figure 15: Evolution of size distribution across CZs in 1980-2015 (top: manufacturing, bottom: information service, urban (blue) vs. rural (red) areas)

Notes: Blue lines capture a set of urban regions, while red lines represent a set of rural regions. Dotted lines are 25 and 75 percentiles weighted by establishment size each year, respectively. Shaded areas are NBER recession periods.

5 Identification and Estimation

This section delivers an identification strategy, elaborates estimation procedures, and reports estimation results, separately in two stages. In Stage 1, intensive-margin of technology, namely, continuous productivity functions of $\{\underline{a}(\omega), \bar{a}(\omega), \widehat{a}^F(\omega')\}$ for tasks (and sub-tasks) and regional factor-augmenting productivities of $\{A_l^R, \bar{A}_l, \widehat{A}_l^F\}$ are recovered. In Stage.2, given the flexible productivity pattern of factor assignment over the task spectrum, dynamic parameters of automation adjustment are estimated from cross-sectional variation of size distribution evolutions of establishments.

⁵¹HHI index in region l is defined as $\sum_{i \in l} (\frac{N_i^{CBP}}{\sum_{i \in l} N_i^{CBP}})^2$. HHI index is influenced by the number of establishments in a region. To neutralize the effect of entry-exits, I compute adjusted HHI index by normalizing the size distribution such that for years after $t > 1980$. The number of establishments recorded in M_t^{bin} is adjusted to $M_{l,t}^{bin}$ such that $M_{l,t}^{bin} = M_{l,t}^{bin} \frac{\sum_{bin} M_{l,t}^{bin}}{\sum_{bin} M_{l,80}^{bin}}$. Adjusted HHI index is reported in the main text.

Stage 1: Recover the Intensive-margin Technology

In Stage.1-1, guided by the model, region-specific elasticities of three economic outcomes with respect to immigration inflow are estimated by reduced-form specifications. In Stage 1-2, drawing on the analytical mappings derived in Proposition 5 as moment conditions, I semi-parametrically estimate the continuous productivity functions, consistently generating the reduced-form elasticities by General Method of Moments (GMM).

Stage 1-1 Estimate Reduced-form Region-specific Elasticities with respect to Immigration Inflow

The benchmark model generates CZ-specific elasticities on a trio of outcomes in the production economy, namely, robot deployment, routine skill price and native premium in skill prices. To obtain the empirical counterparts, run the following regression across CZs indexed by l throughout the decade from the baseline year $t = 1980$ to $t = 1990$.⁵² In each sector, for each dependent variable $z_{l,t} \in \{R_{l,t}, \underline{q}_{l,t}, \frac{\hat{q}_{l,t}^D}{\hat{q}_{l,t}^F}\}$, specify

$$\ln z_{l,t} = \beta_0^z + \beta_1^z \ln \hat{S}_{l,t}^F + \beta_{2,l}^z I(l) \ln \hat{S}_{l,t}^F + \varepsilon_{l,t}^z \quad (21)$$

where $I(l)$ is an dummy variable for CZ l .⁵³ Then, region-specific elasticity with respect to immigration is a common shifter plus a CZ-specific coefficient. Formerly, for each $z_{l,t}$, region l^* -specific elasticity with respect to immigration inflow is obtained by

$$\left(\frac{d \ln z_{l,t}}{d \ln \hat{S}_{l,t}^F} \right)_{l=l^*} = \beta_1^z + \beta_{2,l^*}^z.$$

As is often evoked in the literature, the issue of endogeneity of immigration inflow into region l arises; $\ln \hat{S}_{l,t}^F$ and unobservable terms $\varepsilon_{l,t}^z$, which potentially includes regional business climates, could be systematically correlated, plausibly due to immigrants' selection of regions. To address this issue, I exploit historical ethnic settlement patterns in $t_{-1} = 1940$ to construct an instrument for immigration entry in the following periods. Formally, following the immigration literature⁵⁴, the instrument for the immigration inflows into l from the

⁵²I deliberately focus on the decadal change from the baseline year 1980; automation intensities do not coincide with cost shares of robots, because the quantitative simulation presumes frictional automation adjustment in the subsequent years.

⁵³A decent part of CZs in these years have no immigrants recorded in the Census. In that case, I set $\hat{S}_{l,t}^F = 1$ to include all regions. The magnitude of this value is not sensitive to the results.

⁵⁴See Jaeger, Ruist and Stuhler (2018) for a review and an extensive list of literature, using this strategy.

dependent variable	manufacturing			information service		
	routine skill price	robot	native premium	routine skill price	robot	native premium
common effect of foreign skill	-0.0487 (.010)***	-0.769 (.052)***	0.123 (.0051)***	-0.0124 (.0022)***	-0.410 (.017)***	0.0172 (.0022)***
summary of regional elasticities						
median	-0.0065	-0.0050	0.0124	0.0044	0.0287	0.0094
sd	0.0018	0.2022	0.0389	0.0096	0.1772	0.0576
max	0.0445	0.350	0.4227	0.0298	0.4360	0.4410
min	-0.0487	-0.880	-0.0964	-0.0244	-0.5647	-0.2407
sample size	703	703	703	689	689	689

Table 2: Quasi-experiment results

Notes: The common effect captures β_1^z in the specification above. A bracket is a standard error. (***) $p < 0.1\%$) State fixed effects are included in all specifications. Sample attrition occurs due to degeneration of dummy coefficients or lack of valid instruments.

reference year t_{-1} to year t is given by

$$IV_{l,t} = \sum_{e'} \underbrace{\frac{N_{l,t-1}^{e'}}{N_{t-1}^{e'}}}_{\text{settlement share of } e' \text{ in } l} \underbrace{\Delta N_t^{e'}}_{\text{a new immigration wave of } e'}$$

where e' is an ethnic group in the reference year $t_{-1} = 1940$ and Δ captures the change from the reference year $t_{-1} = 1940$ to year t of interest.⁵⁵ $\frac{N_{l,t-1}^{e'}}{N_{t-1}^{e'}}$ captures the settlement ratio of a region l of ethnic group e' population in 1940. The instrument is a weighted sum of allocation of a new wave of immigrants in each ethnic group, following the historical distribution of the same group.

As is common in the instrumental variable strategy, the two identification conditions, exogeneity and exclusion restriction are imposed. The exogeneity necessitates that the unobserved factors attracting immigrants to region l in t_{-1} are orthogonal to changes in the relative economic incentives offered by the two zones in the following periods. Exclusion restriction requires that the only channel through which immigrant distribution in t_{-1} affects robot adoption after t_0 is its effect on the actual distribution of immigrants across regions.

Reassuringly, median values of reduced-form estimates of routine skill prices and robots

More generally, background of Bartik-type shift-share instruments is discussed in [Borusyak, Hull and Jaravel \(2018\)](#).

⁵⁵Ethnic groups in the 1970 Census are: Mexico, Central America, Central Europe, South America, Caribbean, India, China, Philippines, Africa, Vietnam, Japan and East Asia, Canada and Other North America, the 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)

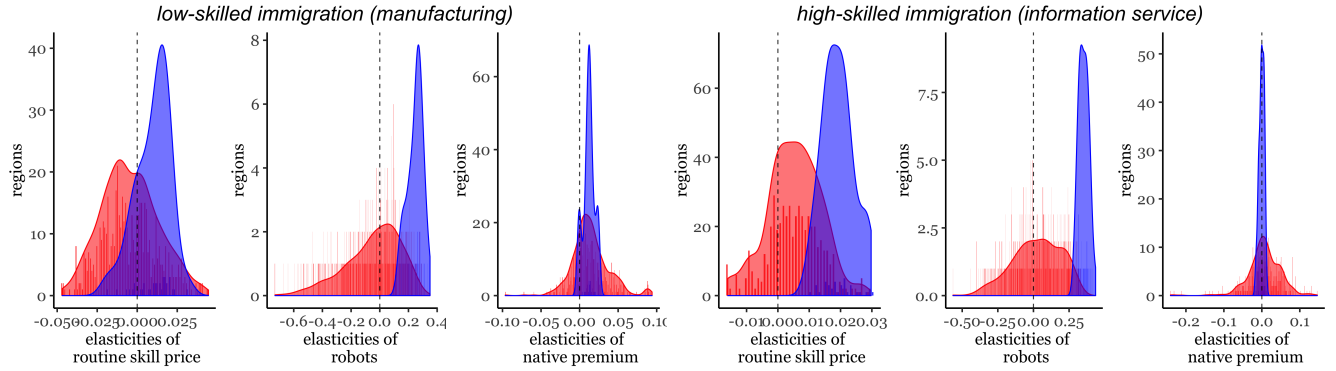


Figure 16: Histograms of a trio of region-specific elasticities with respect to immigration across CZs (left three: low-skilled immigrants, manufacturing (599 CZs), right three: high-skilled immigrants, information service (552 CZs), blue: urban areas, red: rural areas)

Notes: To exclude outliers, samples are restricted to CZs with foreign income share with 0.5% and above in respective occupation class.

are negative in manufacturing and positive in information service, consistent with the working hypothesis. It is not surprising that immigration inflow augments the native premium by labor supply effect, measured by a ratio of domestic and foreign skill prices.

One could find remarkable regional heterogeneity of elasticities with respect to immigration inflows. To highlight the geographical divergence, the regions are split into urban and rural areas, where urban areas are defined as a group of largest CZs, accounting for the top half of the labor force in 1980. The rest of the area outside the urban CZ is classified as *rural*. (See Data Appendix for the map) Strikingly, a pair of elasticities of routine skill price and robot deployments are systematically right skewed in urban areas relative to rural areas across sectors. In particular, across sectors, immigration inflow upshifted routine skill prices and robot deployments in urban areas but downshifted both in rural areas.⁵⁶

Stage 1-2: Semi-parametrically Identify and Estimate a Set of Comparative Advantage Schedules from Region-specific Elasticities

The discrepancies of regional reduced-form estimates are exploited as a source of identification by the task-based framework with flexible substitution patterns. In each region, given a threshold-specific CA of foreign skills to domestic skills, a pair of threshold-specific CAs of routine skills to robots and of routine skills to non-routine skills, are just-identified from elasticities of robots and of routine skill price with respect to immigration inflow under some

⁵⁶In Miami, FL, the elasticity of routine skill price is weakly negative (-0.013), which is more consistent with recent reappraisal of Borjas (2017) than the classical no significant negative results in Card (1990).

regularities of elasticities.

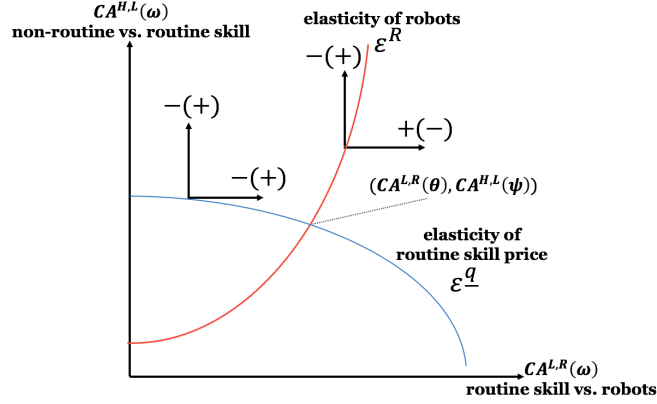


Figure 17: Identify a pair of CAs of routine skill vs. robots, non-routine skills vs. routine skills

Notes: A red curve is an iso-quant of elasticity of robots, and a blue curve is an iso-quant of elasticity of routine skill price. Signs outside of brackets are for plant sector, those inside brackets are for office sector. Suppose that $CA^{F,D}(\phi)$ is given and $CA^{H,L}(\psi)$ is sufficiently large as Proposition 7 presumes.

Figure 17 best summarizes an idea for identification of CAs of routine skills vs. robots and between non-routine vs. routine- skills. Using the equations derived from the model, given a CA of foreign skills to domestic skills at the immigration threshold, a pair of elasticities is characterized by a pair of iso-quants of CAs, and for some regularities of elasticities, a single-crossing point is shown to exist. The impact of routine skill price on automation, embodied by robot adoption. and the impact of automation on routine skill price hinges on a pair of CAs, $\{CA^{L,R}(\theta), CA^{H,L}(\psi)\}$, where $CA^{H,L}(\psi)$ regulates labor adjustment of immigrants, while $CA^{L,R}(\theta)$ governs the automation adjustment. The intuition of the proposition directly stems from comparative statics of elasticities in Proposition 5. Next, the following procedure is designed to recover task productivities.

Semi-parametric identification and estimation

Each region l is characterized by a tuple of $(\theta_l, \psi_l, \phi_l)$ and the number of regions is N . $6N$ moment conditions (1)-(6) are set up as sufficient conditions for identifying the parameter set $\Theta = \{CA_l^{L,R}(\omega), CA_l^{H,L}(\omega), CA_l^{F,D}(\omega')\}$,

$A_l^R, \bar{A}_l, \hat{A}_l^F\}^{57}$

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

where m_l^1, m_l^2, m_l^3 are analytical mappings from Proposition 5. (See Model Appendix for explicit function forms.) Rewriting single-crossing conditions of marginal costs in Proposition 1 yields

$$\begin{cases} \underline{a}^{-1}(\frac{q_l}{q^R/A_l^R} \mid CA_l^{L,R}(\omega)) = \theta = \frac{x_{l,t_0}^R}{1 - x_{l,t_0}^K} & (4) \\ \bar{a}^{-1}(\frac{\bar{q}_l/\bar{A}_l}{\bar{q}_l/\bar{A}_l} \mid CA_l^{H,L}(\omega)) = \psi = 1 - \frac{x_{l,t_0}^H}{1 - x_{l,t_0}^K} & (5) \\ \widehat{a}^F^{-1}(\frac{\widehat{q}_l^F/\widehat{A}_l^F}{\widehat{q}_l^D} \mid CA_l^{F,D}(\omega')) = \phi = \widehat{x}_{l,t_0}^F & (6) \end{cases}$$

where $x_{l,t_0}^R, x_{l,t_0}^H, x_{l,t_0}^K$ is a factor share of robots, non-routine skills and capital equipment, respectively, and $\widehat{x}_{l,t_0}^F$ is a factor share of foreign skills within the immigration-intensive skills in region l in year t_0 ; formerly, they are defined by

$$x_l^R \equiv \frac{q^R R_l}{W^{total}}, \quad x_l^L \equiv \frac{q_l \underline{S}_l}{W_l^{total}}, \quad x_l^H \equiv \frac{\bar{q}_l \bar{S}_l}{W_l^{total}}, \quad x_l^K \equiv \frac{q^K K_l^K}{W_l^{total}}, \quad \widehat{x}_l^F \equiv \frac{\widehat{q}_l^F \widehat{S}_l^F}{\widehat{q}_l \widehat{S}_l}$$

where the total factor cost, $W^{total} \equiv q^R R_l + q_l \underline{S}_l + \bar{q}_l \bar{S}_l + q^K K_l^K$.

The second equality in (4)-(6) comes straightforward from the links between factor share and task thresholds from Proposition 2 such that

$$\underline{q}_l \underline{S}_l = \alpha(\psi_l - \theta_l)Y_l, \quad \bar{q}_l \bar{S}_l = \alpha(1 - \psi_l)Y_l, \quad \widehat{q}_l^F \widehat{S}_l^F = \phi_l \widehat{W}_l, \quad V_l^R = \alpha\theta_l Y_l, \quad V_l^K = (1 - \alpha)Y_l.$$

⁵⁸Without task productivities specified, iso-elastic task aggregation to produce the final good yields that task thresholds (extensive margin technology) are mapped with labor/capital incomes and foreign/domestic labor incomes.

⁵⁷ Observe that moment conditions exceed the number of parameters: $3M < 3N$ ($N = 721$ in manufacturing, $N = 720$ in information service). Thus, the parameters are generically identifiable.

⁵⁸This system of equations belongs to Seemingly Unrelated Regression Equations (SURE) in that $\{A_l^R, \bar{A}_l, \hat{A}_l^F\}$ does not enter in (1)-(3). (4)-(6) are jointly included as moment conditions, because standard errors of $\{A_l^R, \bar{A}_l, \hat{A}_l^F\}$ systematically affect the estimates of $\{CA_l^{L,R}(\omega), CA_l^{H,L}(\omega), CA_l^{F,D}(\omega')\}$ derived from the information in (1)-(3).

To facilitate the estimation, task productivity functions (and their differentiated CA functions) are common across regions inside a sector. (thus, a subscript l is dropped hereafter)⁵⁹ In addition, CA functions are polynomially parameterized by a trio of M dimensional vectors $\beta = \{\underline{\beta}, \bar{\beta}, \widehat{\beta}^F\}$ such that

$$CA^{L,R}(\omega) = \sum_{m=0}^M \underline{\beta}_m (\ln \omega)^m, \quad CA^{H,L}(\omega) = \sum_{m=0}^M \bar{\beta}_m (\ln \omega)^m, \quad CA^{F,D}(\omega') = \sum_{m=0}^M \beta_m^F (\ln \omega')^m \quad (22)$$

where M is a large positive integer. The estimator $\widehat{\Theta}$ minimizes the weighted distance of violations of moment conditions:

$$\min_{\Theta} \bar{g}_N(\Theta)' \mathbf{W} \bar{g}_N(\Theta) \quad s.t. \quad \bar{g}_N(\Theta) = \frac{1}{N} \sum_{l=1}^N g_l(\Theta)$$

where $\mathbf{W}$ is a weight matrix and $g_l(\Theta)$ is $6N$ vector-valued function of $3(M+N)$ vector of Θ such that $g_l(\Theta) = [g^1 \ g^2 \ g^3 \ g^4 \ g^5 \ g^6]$ and

$$\begin{cases} g_l^1 = \epsilon_l^R - m_l^1(\beta \mid \theta_l, \psi_l, \phi_l) \\ g_l^2 = \epsilon_l^q - m_l^2(\beta \mid \theta_l, \psi_l, \phi_l) \\ g_l^3 = \epsilon_l^{\widehat{q}^F/\widehat{q}^D} - m_l^3(\beta \mid \theta_l, \psi_l, \phi_l) \end{cases} \quad \begin{cases} g_l^4 = \ln(\frac{q_l}{q_l^R/A_l^R}) - \sum_{m=0}^M \underline{\beta}_m (\ln \omega)^m \\ g_l^5 = \ln(\frac{\bar{q}_l}{\bar{q}_l/A_l}) - \sum_{m=0}^M \bar{\beta}_m (\ln \omega)^m \\ g_l^6 = \ln(\frac{q_l^F/\widehat{A}_l^F}{q_l^D}) - \sum_{m=0}^M \beta_m^F (\ln \omega')^m \end{cases}$$

Θ is jointly estimated by two-step GMM. On the first stage, set $\mathbf{W} = \mathbf{I}$ and estimate the consistent $\widehat{\Theta}_1$. On the second stage, using $\widehat{\Theta}_1$, update the weight as inverse of covariance of the moment conditions $\mathbf{W} = \mathbf{S}^{-1} = (\frac{1}{N} \sum_{l=1}^N (g_l(\widehat{\Theta}_1) - \bar{g}_N(\widehat{\Theta}_1))(g_l(\widehat{\Theta}_1) - \bar{g}_N(\widehat{\Theta}_1))')^{-1}$ and reestimate the efficient $\widehat{\Theta}_2$.⁶⁰ The set of CA patterns across factors is consistently recovered to generate the distribution of regional elasticities with respect to immigration.

⁵⁹Note that *realized* CA s differ across regions due to heterogeneous task thresholds.

⁶⁰Estimation was implemented by simulated annealing algorithm. Only non-zero coefficients in M dimensional vector, β , is used for computation. GMM estimator converges in distribution as $\sqrt{N}(\widehat{\Theta} - \Theta_0) \xrightarrow{d} \mathcal{N}(0, (\mathbf{G}' \mathbf{S}^{-1} \mathbf{G})^{-1})$, and a variance-covariance matrix is estimated as

$$\widehat{\mathbf{V}}_{\Theta} = (\widehat{\mathbf{G}}' \widehat{\mathbf{S}}^{-1} \widehat{\mathbf{G}})^{-1}/N \quad \text{where} \quad \widehat{\mathbf{S}} = \frac{1}{N} \sum_{l=1}^N (g_l(\widehat{\Theta}_1) - \bar{g}_N(\widehat{\Theta}_1))(g_l(\widehat{\Theta}_1) - \bar{g}_N(\widehat{\Theta}_1))', \quad \widehat{\mathbf{G}} = \frac{1}{N} \sum_{l=1}^N \frac{\partial}{\partial \Theta} g_l(\widehat{\Theta}_1)$$

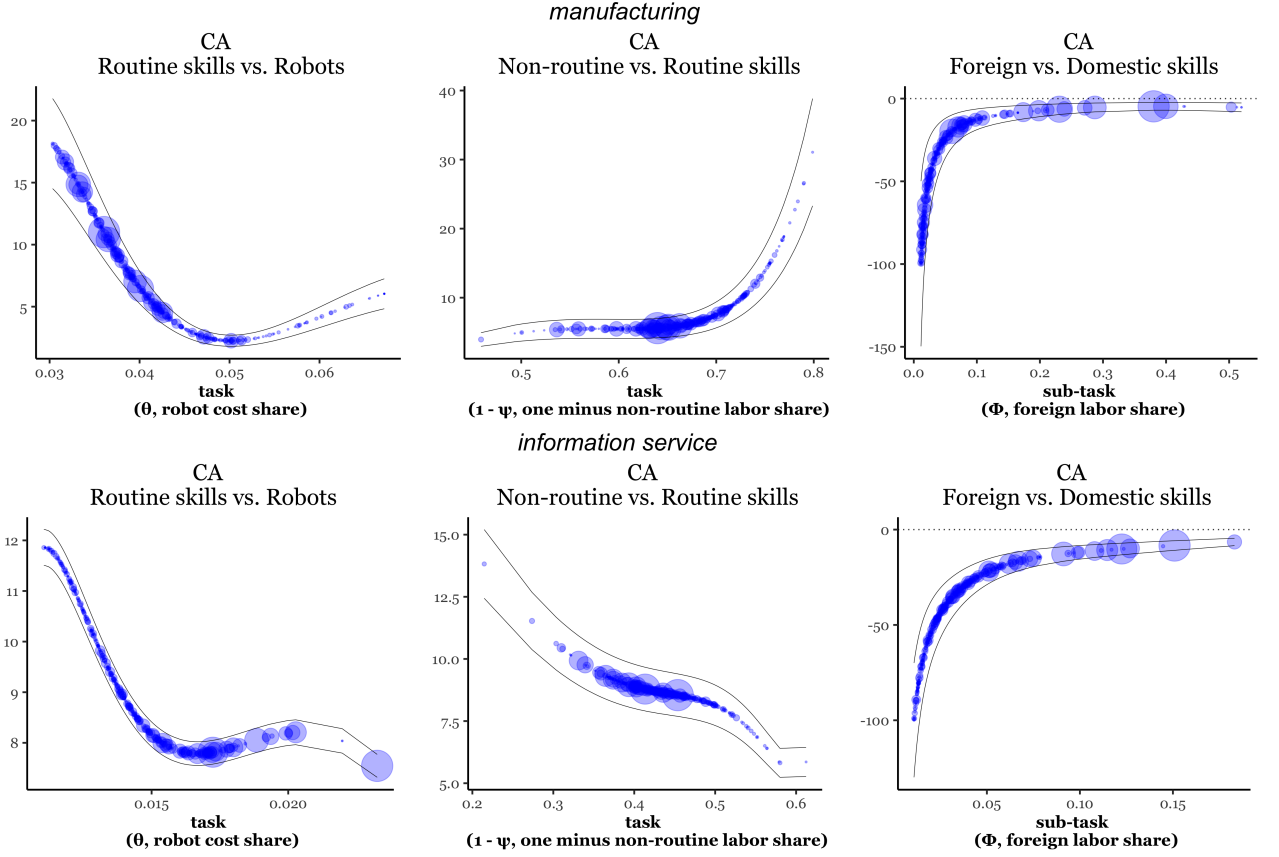


Figure 18: Estimated comparative advantage schedules (top: manufacturing, bottom: information service)

Notes: A band bounded by solid gray curves is bootstrapped standard errors, computed from the estimated CA functions based on standard errors of non-zero estimates of $\beta = \{\underline{\beta}, \bar{\beta}, \widehat{\beta}^F\}$. Each bubble represents CZ used for the semi-parametric estimation of the CA's task position. The size of the bubbles is within-sector employment share in 1980. Outliers of too small or large shares are excluded from the figure, but included in estimation. Four cities with largest industry employment in each sector is depicted in the figures.

The next graphics show the fit of elasticities with respect to immigration, simulation versus reduced-form estimates. The CZs are dispersed along the 45-degree line, which indicates a good fit.

Once β is estimated, using polynomial parameterization of (22), the three CA curves within each task (and sub-task) domain in 1980 are recovered. Then, each CA curve is parametrically extrapolated outside each task domain to cover the entire task (or sub-task) spectrum.⁶¹ Using the entire CA curve and the definition of CAs (Definition.2), one could

⁶¹This is not so restrictive for the ensuing analysis because the most of factor shares in later periods overlap with the factor share coverage in 1980. Linear approximation is used for the extrapolation of the curves.

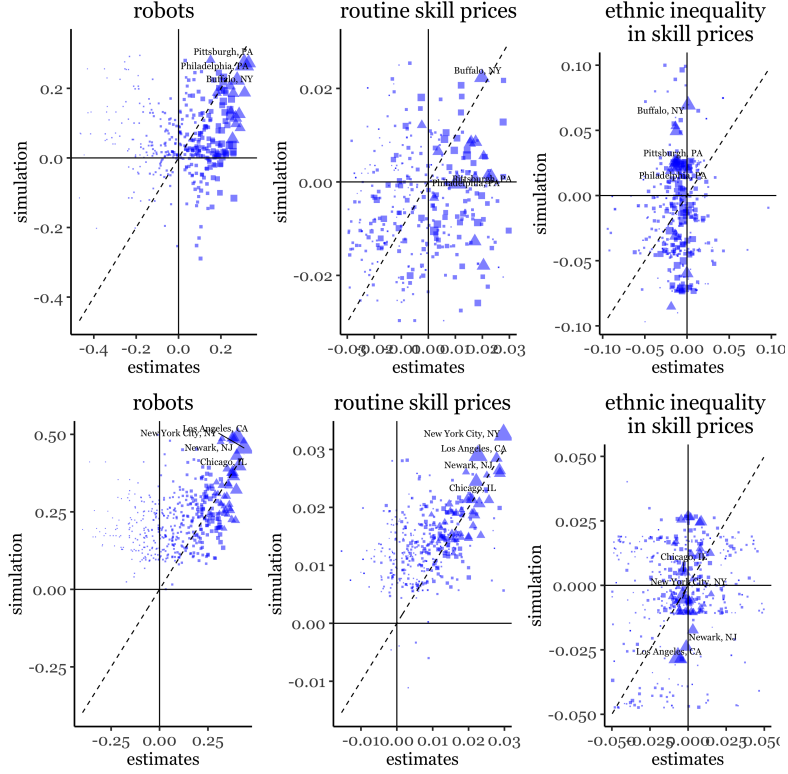


Figure 19: Simulated elasticities from estimated CAs vs. reduced-form estimates (top: manufacturing, bottom: information service)

Notes: A dashed 45 degree line shows a perfect fit. The size of the bubbles is within-sector employment share in 1980. Triangles capture urban areas as defined above.

recover the entire series of task productivities $\{\underline{a}(\omega), \bar{a}(\omega), \widehat{a^F}(\omega')\}$, serving as critical inputs to shape the dynamic analysis in Stage 2.

This proposed semi-parametric estimation procedure could make a methodologically contribution to the long-lasting controversies, occurring in nearly separate communities, about the elasticity of substitutions of foreign vs. domestic labor ([Ottaviano and Peri \(2012\)](#)), and of labor vs. capital ([Raval and Oberfield \(2017\)](#)). By applying this task-based model with its non-linear cross-factor substitution patterns into more than 700 regional and 35 years of rich variation of immigration inflows, could serve as a potential remedy by integrating a series of reduced-form estimates to empirically recover the entire comparative advantage schedule. The ensuing quantitative analysis is tightly disciplined by cross-factor substitutions.

Stage 2: Recover the Adjustment Costs of Automation

Four parameters, dynamic parameters of adjustment costs (non-convex and convex costs), market competition parameter, stationarity of TFP shocks $\Theta = \{\zeta, \tau, \sigma, \rho\}$ are identified

and estimated by $4N$ (N is a number of available CZs) regional variation of size distribution evolution of establishments and volatility of sectoral robot investment series moments. The moments of size distribution are mean, standard deviation per mean, skewness, and Herfindahl index. The idea of identification follows the sensitivity of moments to the parameters, summarized in Section 5.2. The sectoral shifter ξ_t is calibrated to match the sectoral production trend.

Simulate method of moments (SMM) For an arbitrary set of parameters, $\Theta = \{\zeta, \tau, \sigma, \rho\}$, the discrete-continuous dynamic choice dynamic programming problem is solved and a policy function is generated. Using the policy function, generate the model-simulated data. Using the model-simulated data, compute simulated moments $\Psi^s(\Theta)$, as opposed to data moments, Ψ^d . All model and data moments are constructed equivalently; given size distribution in 1980 as a starting point, the model generates outputs in 140 quarter data points in 35 years. Outputs in the end quarter of the year are used as the annual moments, since the earlier quarters involve an adjustment process initiated from the demographic and technology shocks at the first quarter. Regional data moments are weighted median with the number of establishments across CAs in 1980.⁶² To capture dynamic variation of moments, mean is denominated by the 1980 mean size, and other three unit-free moments are differenced from 1980. For each distributional moment, squared distances between model moments and data moments are summed up across 35 years, crafting a degree of deviation in CZ-level.

The estimate $\hat{\Theta}$ minimizes the weighted distance between the data moments $\Psi^d(\Theta)$ and the simulated moments $\Psi^s(\Theta)$. Formally, I solve

$$\min_{\Theta} [\Psi^d - \frac{1}{R} \sum_{r=1}^R \Psi^s(\Theta)]' \mathbf{W} [\Psi^d - \frac{1}{R} \sum_{r=1}^R \Psi^s(\Theta)].$$

The number of simulations is set to $R = 100$. The optimal weight matrix $\mathbf{W}$ is set as inverse of variance-covariance matrix of the data moments, weighted with the initial establishment number.⁶³

⁶²The model abstracts from entries and exits of establishments, so that every model-implied moment is constructed weighted with the number of regional establishments in 1980.

⁶³In general, the variance-covariance matrix of the SMM estimator is given by

$$[\mathbf{G}^T \mathbf{W} \mathbf{G}]^{-1} \mathbf{G}^T \mathbf{W} \Sigma \mathbf{W}^T \mathbf{G} [\mathbf{G}^T \mathbf{W} \mathbf{G}]^{-1}$$

where

$$\mathbf{G} = \frac{\partial g_n(\Theta)}{\partial \Theta}, \quad g_n(\Theta) = \Psi^d - \frac{1}{R} \sum_{r=1}^R \Psi^s(\Theta)$$

If I choose $\Sigma = \mathbf{W}^{-1}$, a variance-covariance matrix is collapsed to $(\mathbf{G}^T \mathbf{W} \mathbf{G})^{-1}$. Therefore, the asymptotic

Estimation results

The estimated parameters across sectors are summarized as follows.

Table 3: Estimates of the parameters

	Simulated Method of Moments Estimates	
	manufacturing	information service
non-convex costs (ζ)	3.51 (.95)	1.43 (.26)
convex costs (τ)	2.33 (.93)	2.81 (.53)
competition (σ)	1.24 (.52)	1.82 (0.61)
stationarity of productivity (ρ)	1.15 (.38)	1.23 (.52)

Notes: The brackets are bootstrapping standard errors with 1000 iterations.

To illustrate the workings of the model and understand the intuition behind the estimates across sectors, the simulated upgrading policy given the parameter estimates is depicted across the initial productivity class A_0 as follows. In manufacturing, upgrading frequency is relatively unsynchronized compared to information service so that intervals of less productive plants are much longer than productive plants (*larger* non-convex costs ζ), generating dispersion of vintages of robots. However, each upgrading is relatively more drastic in larger extended intensity (*smaller* convex costs τ). Information service exhibits a contrasting behavior in that upgrading frequency is synchronized, but wider gap in intensities, resulting in more equalized access to the latest vintage.

External validity

To ensure the external validity of the model, I compare the model's predictions of nationwide labor share and labor productivity against the data. I stress that neither of these two are targeted in the estimation. Nationwide labor share is labor income of both routine and non-routine occupations divided by real GDP, denominated by GDP deflator normalized in 2015, formerly $\frac{\sum_i W_{i,t} + \bar{W}_{i,t}}{\sum_i P_{i,t} Y_{i,t}}$. Labor productivities are GDP per labor hours across occupations,

distribution of Θ is given by

$$\sqrt{n}(\hat{\Theta} - \Theta) \xrightarrow{d} \mathcal{N}(0, (\mathbf{G}^T \mathbf{W} \mathbf{G})^{-1})$$

See McFadden (1989) and Pakes and Pollard (1989) for the statistical properties of the SMM estimator.

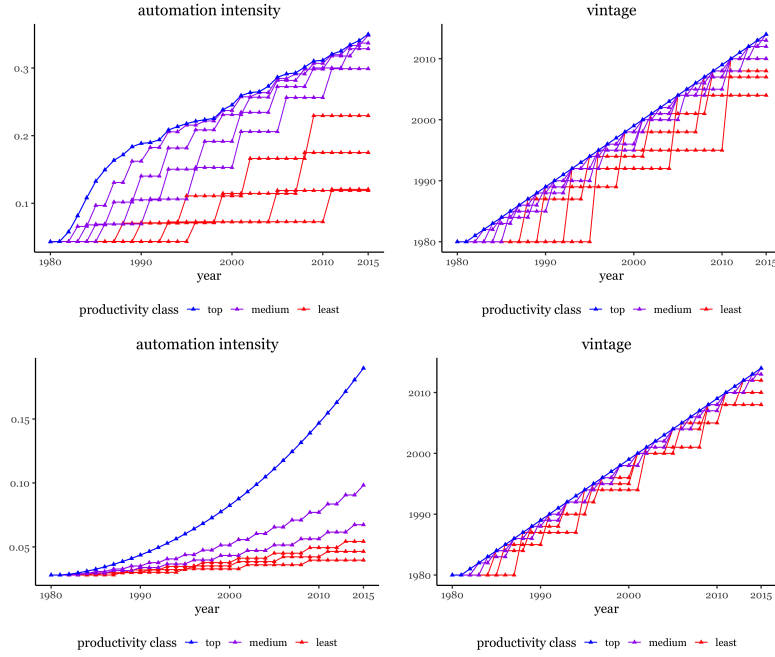


Figure 20: Simulated automation upgrading in equilibrium (top: manufacturing, bottom: information service)

Notes: The blue lines indicate the top 4 productive bins, green ones show the middle 4, and the red ones represent the 4 least productive bins. Average across 100 simulations, given parameter estimates $\Theta^* = \{\zeta, \tau, \sigma, \rho\}$.

$\frac{\sum_i P_{i,t} Y_{i,t}}{\sum_i \underline{L}_{i,t} + \bar{L}_{i,t}}$. Across sectors, labor share is steadily declining, while labor productivity is rising, less stark after the Great Recession. Figure 21 shows the model reproduces this pattern well, assuring the quantitative assessments in the next section.

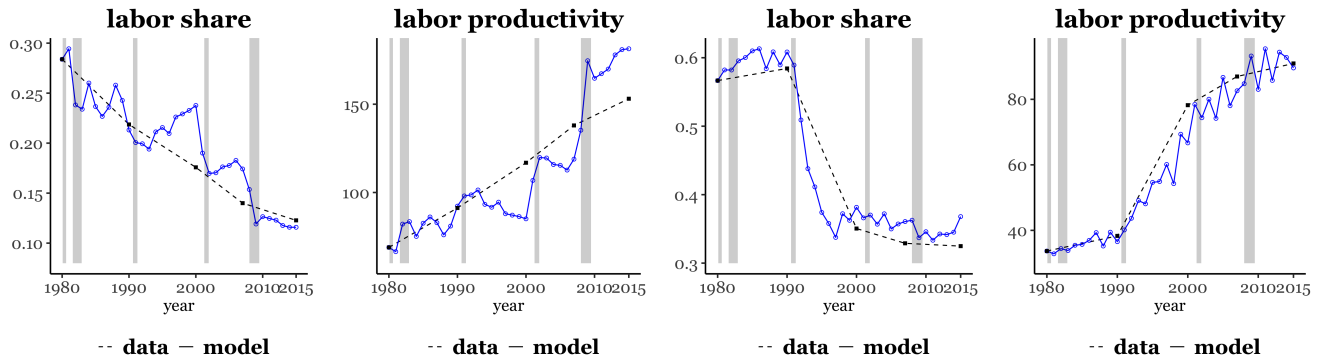


Figure 21: Non-targeted economic aggregates: model: solid line vs. data: dotted line (left two: manufacturing, right two: information service)

Notes: Shaded years are NBER recession periods.

6 Quantitative Assessments

Armed with the dynamic model with non-linear comparative advantage (CA) schedules, it is now ready to assess quantitatively the economic consequences of immigration. The analysis follows along with the flow chart in Figure 3. To start, Section 6.1 evaluates the aggregate outcomes of immigration on wages and welfare (defined below). Then, Section 6.2 investigates the aggregate effect on wages by three channels, and decomposes each channel by competing forces shaping the task reallocation mechanics, formulated in Section 3.6.

6.1 Aggregate Economic Outcomes of Immigration

Aggregate labor market outcomes

First, I explore the aggregate effect of immigration inflow on wages. To see this, I suppose the U.S. underwent no net immigration growth since 1980. I assess the contribution of immigration by comparing the wage shifts during 1980-2015 in the counterfactual case with the baseline.⁶⁴ Figure 22 shows the simulated wage of the no immigration growth case.

The top two graphs show the simulated routine native wages and non-routine wages in manufacturing, relative to the baseline. The discrepancies from the baseline indicate that low-skilled immigration exhibits an aggregate *positive* role on routine native wages and a *negative* role on non-routine wages. The bottom two graphs show the simulated counterfactual routine native wages and non-routine wages in information service, relative to the baseline. They show that high-skilled immigration has *positive* effects in both routine wages and non-routine native wages. Across sectors, I narrow down the simulation within the top 30 CZs with highest rise in immigration density in the proxy of Figure 13, as depicted in dashed curves. The top 30 CZs absorbed 46% and 68% of low-skilled, and high-skilled immigration inflow. Reassuringly, the top 30 CZs exhibit steeper curves than all the CZs with positive immigration inflow.

As simulation algorithm closely follows the timeline in Section 3.6, it allows for isolating the direct impact of immigration separately and the indirect effect via automation adjustment. To exclude the contribution of automation adjustment, I measure the shifts of wages exclusively from immigration in the simulation algorithm and analogously take a difference between no immigration case and the baseline.

Figure 23 shows the immigration's impacts on wages of different occupation classes with

⁶⁴In no immigration growth case, both baseline and counterfactual cases are limited to the CZs receiving positive immigration inflow.

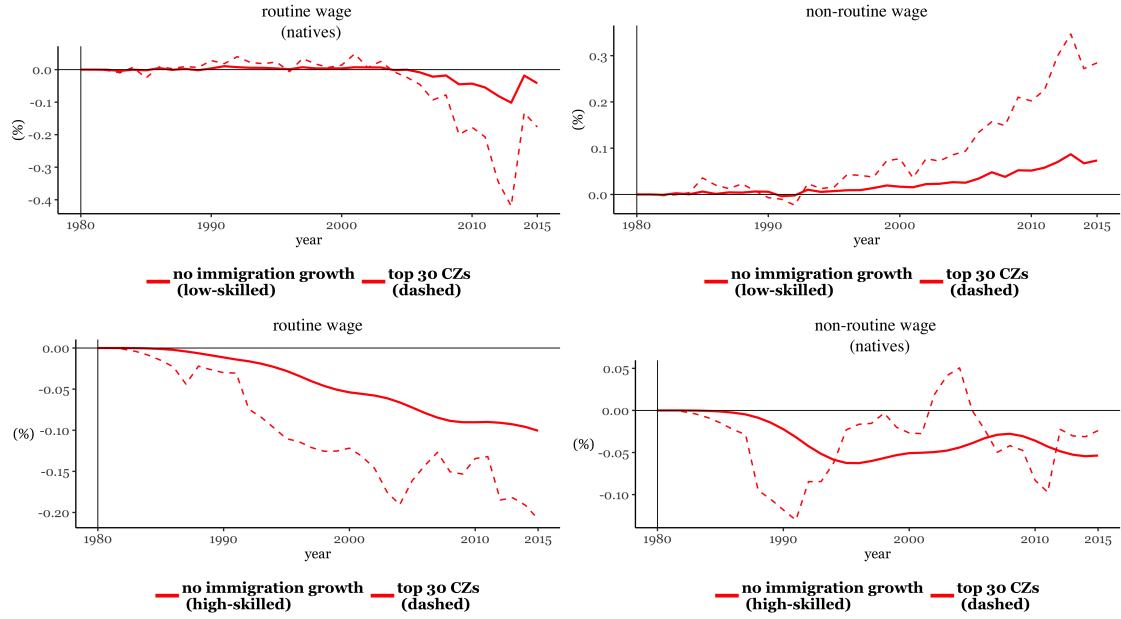


Figure 22: Simulated wage paths compared to the baseline by occupation class (top two: manufacturing, bottom two: information service)

Notes: The mean value across CZs of interest, weighted with labor hours of each occupation class. The value is the detrended average of 100 simulations.

and without automation adjustment across sectors. Without automation adjustment, low-skilled immigration has negative impacts on routine wages, implying that low-skilled immigration stifled the automation; the gap between with and without automation adjustment implies that weakened adoption of automation augments the routine native wages and harms non-routine wages in manufacturing via automation adjustment. In contrast, high-skilled immigration alone has positive impacts on routine wages, implying that high-skilled immigration heightens the adoption of automation; the gap between with and without automation adjustment is negligible in the impact on routine wages, but sizable in non-routine wages. This implies that increased automation upshifts the non-routine native wages in information service via automation adjustment.

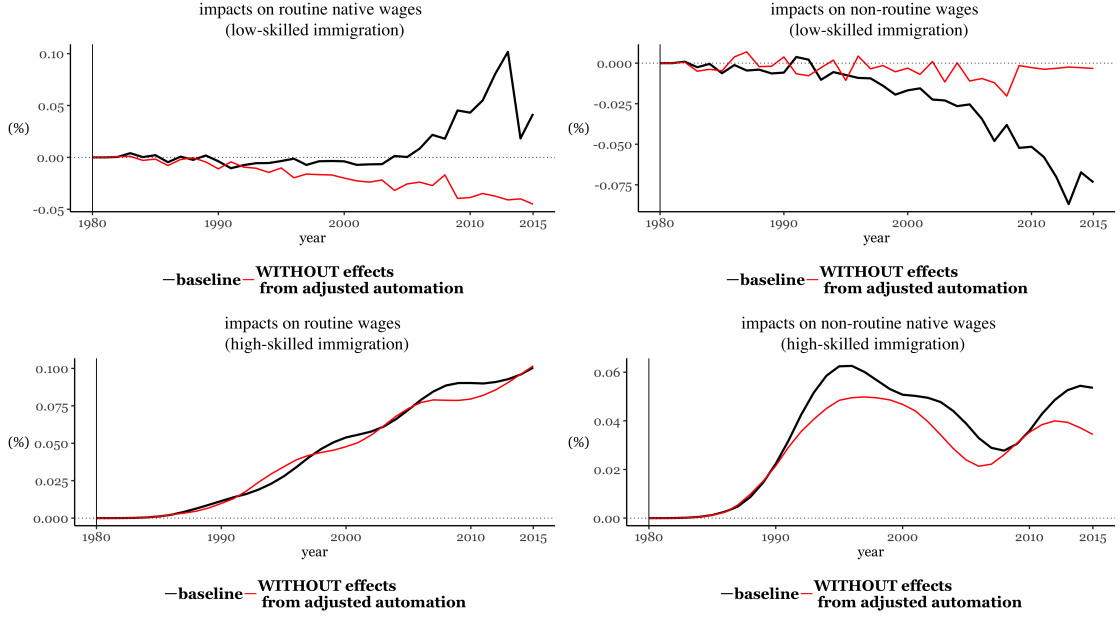


Figure 23: Immigration's impacts on wages: with vs. without adjustments of automation (top two: manufacturing, bottom two: information service)

Notes: The mean value across CZs, weighted with labor hours in each occupational class. The value is a detrended average of 100 simulations.

Welfare assessments

To systematically evaluate previous and future immigration policies, I introduce social welfare as a weighted sum of consumption utilities of all *native* citizens.⁶⁵⁶⁶

Definition 5. [Social Welfare]

The social welfare function (SWF) in year t is a weighted average of curved utilities across citizens such that

$$SWF(t) \equiv \sum_j \xi_{j,t} \Upsilon(U(C_{j,t}); v) \quad (e_j = D)$$

⁶⁵Only the utilities of U.S. citizens are incorporated to avoid an ideological issue on how much utilities of immigrants should be evaluated.

⁶⁶The social welfare is more comprehensive proxy to capture national benefit than wages on three points. First, the social welfare discounts inequality under distributional preference. Second, the welfare covers non-working individuals as well as labor force. Third, consumption utility depends on total earning, including non-labor income.

where an individual utility is curved as

$$\Upsilon(U(C_{j,t}); v) \equiv \frac{\{exp U(C_{j,t})\}^v - 1}{v}.$$

$v \leq 0$ captures inequality preference, and $C_{j,t} = W_{j,t} + NLI_{j,t}$, where $W_{j,t}$ and $NLI_{j,t}$ is labor income and non-labor income, respectively, for all j at t , excluding the students and other occupations outside the model economy. $\xi_{j,t}$ is a welfare weight of the planner such that $\sum_j \xi_{j,t} = 1$, proxied either by identical weights or by marginal utilities of consumption. Parameterize a utility function by $U(C_{j,t}) = \frac{C_{j,t}^\gamma - 1}{\gamma}$ with a CRRA parameter $\gamma = 0.1$ is externally calibrated. I try $\nu \in \{-0.03, -0.01, 0\}$ in utility transformation by the planner. $\nu = 0$ corresponds with the linear case without any utility transformation. Figure 24 shows

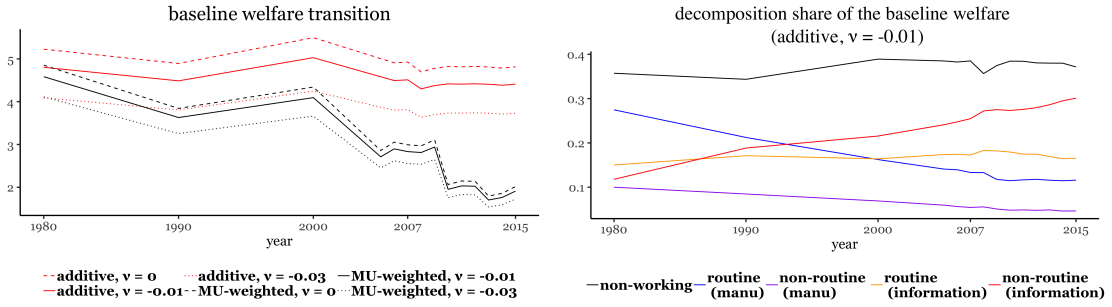


Figure 24: Baseline welfare transition (computed from the data)

a data-based welfare path in 35 years across 6 (3×2) parameter specifications. The marginal utility weights punish inequality more severely than identical weights with more progressive preference, as does negatively larger γ . In every welfare protocol, the overall welfare trend is declining after 2000, mirrored by exacerbating total earning inequality, as shown in occupational decomposition of welfare in the right graph in Figure 24. In both sectors, non-routine occupations exhibit rising welfare shares, and routine occupations display declining shares.

Founded by the baseline welfare, I examine immigration's impacts on the aggregate domestic welfare. By interacting implied regional change of labor incomes across occupation classes by labor income data, I compute model-implied labor incomes, serving as inputs to the welfare for 1980-2015.

Then, I assess the welfare contribution of immigration by comparing the baseline with non-immigration growth case. Both low-skilled and high-skilled immigration during 1980-2015 played a welfare-enhancing role in 2015. I examine the sensitivity of the welfare impacts with respect to substitution between foreign and domestic skills, $CA^{F,D}(\phi)$. To see this, I consider counterfactual simulations where the substitutions are set to be uniformly minimum

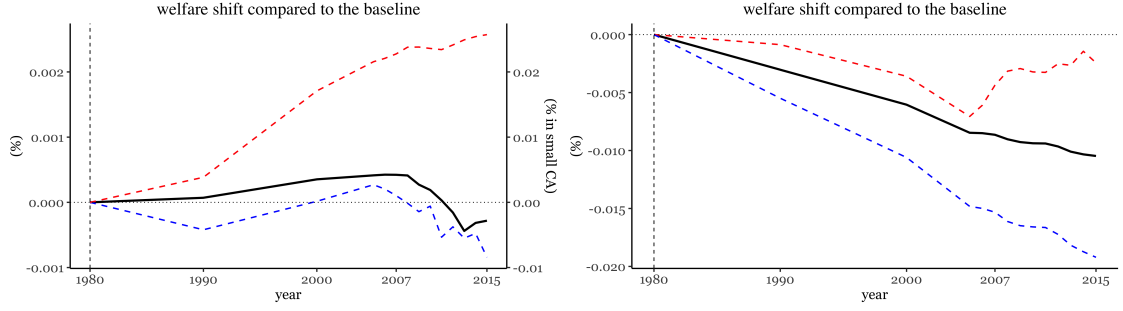


Figure 25: Simulated welfare transition (additive weight case with $\gamma = -0.01$. left: low-skilled immigration, right: high-skilled immigration)

Note: red (or blue) dashed line is smallest (or largest, respectively) differentiation between foreign and domestic skills among CZs. The value is a detrended average of 100 simulations.

(red dashed line) and maximum (blue dashed line) across regions. The ethnic substitution pattern is more sensitive to substitution estimates in manufacturing; in the CZ with largest substitution⁶⁷, low-skilled immigration is welfare-harming. In the information service sector, the welfare implication is relatively stable with respect to substitution estimates.

6.2 Understanding the Task-based Mechanics

To diagnose the aggregate simulation results in Section 6.1, I decompose the aggregate effect into three channels. Each channel is formulated by competing forces, coursing the task reallocation mechanics (Definition 3 and 4).

Channel 1: The Impact of Immigration without Automation Adjustment

Firstly, I decompose the direct impact on skill prices *without* automation adjustment, shown in Figure 23, into the four forces, formerly defined in Definition 3. Namely, the impact of immigration shocks $d\widehat{S}^F$ on the skill price in each occupation class is split by as follows. Recall that $\widehat{q}^e$ is ethnic skill price of $e \in \{F, D\}$ and $\widetilde{q}$ is non-immigration intensive skill price in each sector.

$$\left. \frac{d\widehat{q}^e}{d\widehat{S}^F} \right|_{\theta} = \underbrace{\frac{d\widehat{q}^e}{d\widehat{S}^F}}_{\text{labor supply effect}} + \underbrace{\frac{d\widehat{q}^e}{dY_l} \Sigma_{i \in l} \frac{dY_i}{d\widehat{S}^F}}_{\text{scale effect}} + \underbrace{\frac{d\widehat{q}^e}{dW_l^e} \Sigma_{i \in l} \frac{dW_i^e}{d\psi} \left(\frac{d\psi}{d\widehat{S}^F} \right)_{\text{short}}}_{\text{occupational substitution effect}} + \underbrace{\frac{d\widehat{q}^e}{dW_l^e} \Sigma_{i \in l} \frac{dW_i^e}{d\phi} \left(\frac{d\phi}{d\widehat{S}^F} \right)_{\text{short}}}_{\text{foreign substitution effect}}$$

⁶⁷This turns out to be the highest ϕ , inferred by foreign income shares. See the CA curves in Figure 18.

$$\left. \frac{d\tilde{q}}{d\widehat{S^F}} \right|_{\theta} = \underbrace{\frac{d\tilde{q}}{dY_l} \sum_{i \in l} \frac{dY_i}{d\widehat{S^F}}}_{\text{scale effect}} + \underbrace{\frac{d\tilde{q}}{d\widehat{W}_l} \sum_{i \in l} \frac{d\widehat{W}_i}{d\psi} \left(\frac{d\psi}{d\widehat{S^F}} \right)_{short}}_{\text{occupational substitution effect}}$$

As defined in Definition 3, *labor supply effect* is a mechanical impact of immigration shocks on immigration-intensive skill prices. *Scale effect* is immigration's impacts on skill prices induced from production gains via more affordable skill prices. Immigration inflow would lower the foreign skill prices, and producers produce goods affordably and expand sales in the product market. This production expansion augments skill prices across occupations. *Substitution effect* is immigration's impacts on skill prices induced from reallocating the tasks across factors. In each layer of the task spectrum, this effect is two-fold: between routine- and non-routine skills and between foreign and domestic skills. Low-skilled (or high-skilled) immigration inflow would partially substitute both non-routine (or routine) skills in a higher layer and routine (or non-routine) domestic skills in a lower layer, lowering their skill prices.

Recall that all three forces are defined excluding the indirect effects from induced automation adjustment. I record the effect from each force in simulation algorithm, all of which are immune from the impacts of automation upgrading. Figure 26 shows decomposition by each force. Across sectors, labor supply effect dominates scale effect and substitution effect within impacts on similarly-skilled wages of immigration inflow. Regarding the impacts on less immigration-intensive occupation wages ($\tilde{q}$), scale effects and substitution effects approximately cancel each other.

Channel 2: Immigration-induced Automation

Why does automation occur? In the quantitative model, automation is adjusted in the following accounting formula from mutually exclusive drivers.⁶⁸

$$d\theta = \underbrace{\left(\frac{d\theta}{d\tilde{q}} \right) \left(\frac{d\tilde{q}}{d\widehat{S^F}} \right) d\widehat{S^F}}_{\text{immigration}} + \underbrace{\left(\frac{d\theta}{d\tilde{q}} \right) \left(\frac{d\tilde{q}}{d\widehat{S^D}} \right) d\widehat{S^D}}_{\text{domestic demography}} + \underbrace{\left(\frac{d\theta}{dp^R} \right) dp^R}_{\text{technological progress } (> 0)} + \underbrace{(d\theta)^{fric}}_{\text{adjustment friction } (< 0)}$$

Using the estimated full-model, I assess the role of each driver for automation upgrading, by turning off each driver compared to the baseline, as depicted in Figure 27. To turn off technological progress, the quality-adjusted investment price is assumed to be stable in 1980;

⁶⁸However, these are not exhaustive; extra factors outside the paper's focus including rental price of capitals, TFP growth, and other equilibrium interactions affect automation upgrading.

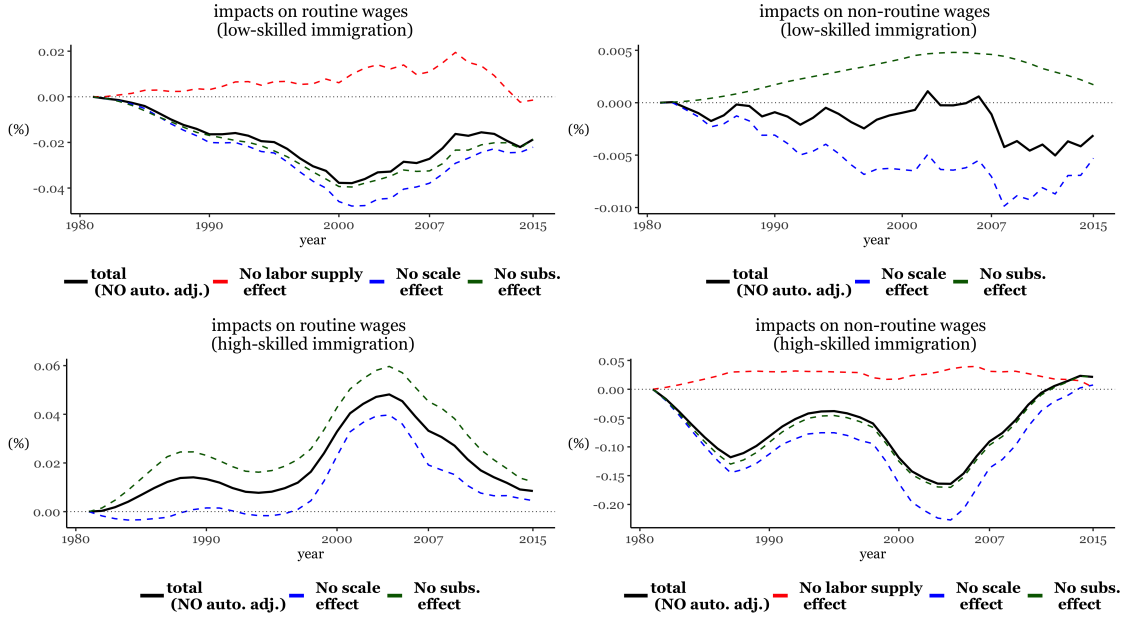


Figure 26: The direct effect of immigration on wages *without* automation adjustment (top two: low-skilled immigration, bottom two: high-skilled immigration)

Notes: The value is an average of 100 simulations, of mean across CZs weighted with labor hours across each occupation class. Other effects from equilibrium interaction are excluded from the graphs.

$p_t^R = p_0^R$. To eliminate the friction for automation, all adjustment cost parameters are set to zero; $\zeta = 0$ and $\tau = 0$.⁶⁹ To exclude the circular impacts from automation on wages, affecting future automation, I exclude the labor market impacts of the automation from the simulation.⁷⁰

Perhaps unsurprisingly, technological progress is the prime driver for automation upgrading. The top two graphs in Figure 27 depict simulated paths of the nationwide automation intensity across sectors from 1980-2015 under two counterfactual scenarios compared to the baseline. In the stationary fertility case, I suppose that fertility rate has been hypothetically stationary so that age composition of working-age natives remains fixed at the level of 1980 until 2015, with the total working-age population unchanged. Both low- and high- skilled immigration plays an outsized role in the labor-driven automation upgrading across sectors. In manufacturing, low-skilled immigration's impact on automation is larger than age composition change on average. The effect is much larger when regions are limited to the top 30

⁶⁹Without adjustment friction, every productivity class of establishments run the automation adjustment, exclusively driven by annual factor price changes.

⁷⁰Automation typically lower routine wages, serving as a counterbalancing force to deter the further automation upgrading.

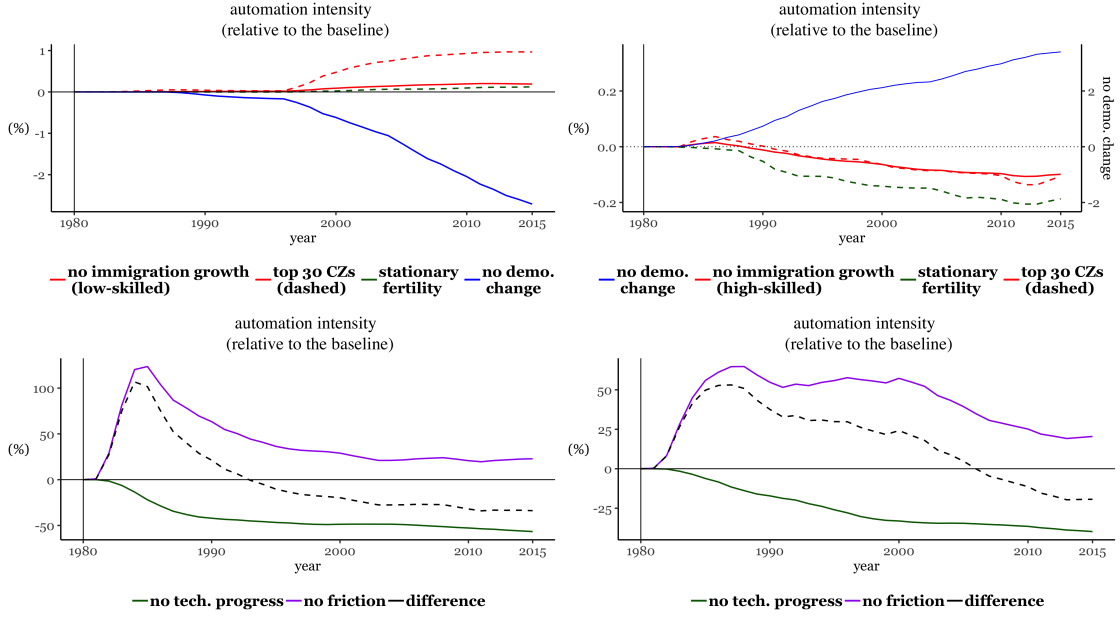


Figure 27: The role of immigration for adjustments of automation (left: manufacturing, right: information service)

Notes: Automation intensity is nation-wide weighted average of establishment-level θ , weighted by real production value. The value is the average of 100 simulations.

CZs with the highest low-skilled immigration inflow. In information service, the labor supply into routine occupation due to the age composition change is larger than immigration's impact, but immigration still played a sizable role relative to their headcount share.

Channel 3: Automation's Impacts on Wages

Finally, I examine the labor market outcome of automation. The impact of automation adjustment $d\theta$ on the skill price in each occupation class is given by the forces defined in Definition 4 such that

$$\begin{aligned} \left(\frac{d\hat{q}^e}{d\theta} \right)_{long} &= \underbrace{\mathbb{I}(G=p) \frac{dq_l^e}{dW_l^e} \Sigma_{i \in l} \frac{dW_i^e}{d\theta}}_{\text{displacement effect} < 0 \text{ (only plant)}} + \underbrace{\frac{d\hat{q}^e}{dY_l} \Sigma_{i \in l} \frac{dY_i}{d\theta}}_{\text{productivity effect} > 0} \\ \left(\frac{d\tilde{q}}{d\theta} \right)_{long} &= \underbrace{\mathbb{I}(G=o) \frac{dq_i}{dW_l} \Sigma_{i \in l} \frac{dW_i}{d\theta}}_{\text{displacement effect} < 0 \text{ (only office)}} + \underbrace{\frac{d\tilde{q}}{dY_l} \Sigma_{i \in l} \frac{dY_i}{d\theta}}_{\text{productivity effect} > 0} \end{aligned}$$

where $\mathbb{I}(G = g)$ is an indicator function of the sector $g \in \{p, o\}$. Recall that *displacement effect* is automation's impacts on routine skill prices, induced by routine skill demand shifts

from reallocating tasks from routine skills to robots. Automation upgrading would slash routine skill demands, thus, reduce the routine skill prices. *Productivity effect* is automation’s impacts on skill prices induced from production gains. In the heterogeneous establishment model, this effect takes place in two-fold: if a part of establishments upgrade automation, the new technology allows for producing goods with lower marginal costs. Moreover, automation upgrading would suppress routine skill prices by displacement effect, and this would allow for cost-effective production for all producers, including non-upgraders.⁷¹ Consequently, both upgraders and non-upgraders expand sales, augmenting the skill demands and their skill prices.

Then, what is the effect of automation upgrading on wages? To see this, I assess the contribution of automation upgrading by comparing the baseline case relative to the non-automation case, where automation upgrading is mechanically halted. Then, I isolate the wage shifts exclusively from automation upgrading in the simulation algorithm and decompose the effect into each force, recorded in the simulation algorithm. Figure 28 shows the effect of automation on wages; automation reduces routine wages and augments non-routine wages, expanding the wage inequality in both sectors. As displacement effect dominates productivity effect, the effect on routine wages is negative. In contrast, positive productivity effect drives the growth of non-routine wages. The automation’s impact on wages are larger in manufacturing than in information service.

7 Counterfactuals and Policy Experiments

This section extends the simulation to the future period 2016-2050 and reports the policy experiments. Section 7.1 and 7.2 explores the effect of restricting future immigration of each skill level. Section 7.3 explores the economic consequence of a universal basic income policy to native citizens across sectors, fixing the current immigration policy.

7.1 Baseline Prediction from 2016-2050

To extend the simulation toward the future period, demographic transition in CZ-level in 2016-2050 is needed as a future baseline, in which demography transition proceeds as predicted in the Census projection (baseline case, hereafter). To obtain this, I draw on state-level decomposition projections by [Weldon Cooper Center \(2018\)](#). It provides a projection

⁷¹The model predicts that non-upgraders with more labor-intensive technology would typically absorb the displaced labor with lower wages, and thus, turn larger.

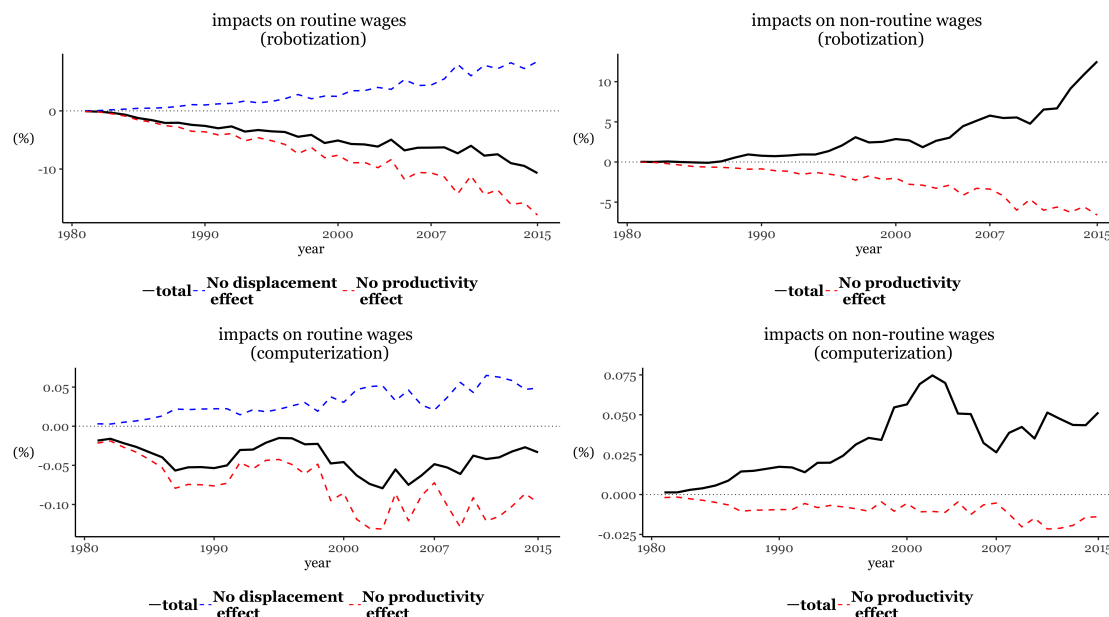


Figure 28: The effect of automation on wages (top: manufacturing, bottom: information service)
Notes: Percentage change of wages from 1980. The value is a detrended average of 100 simulations, of mean across CZs weighted with labor hours across occupation classes.

of state-level working-age population by ten age groups (15 to 19, 20 to 24, 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 59, 60 to 64) $\times$ sex cells in three decadal snapshots of 2020, 2030, and 2040. To construct CZ-level demography-driven labor supply shocks, datasets in the future periods are needed. Of course, nobody has future population datasets, and I construct the hypothetical datasets in 2020, 2030, 2040 and 2050 as follows. In the following, all the extrapolations are run under linear and spline approximation, chosen based on the internal validity of the target period.

To begin, I construct a table of shifts of statistical population sample weights across CZs in 2020, 2030, 2040 and 2050 relative to 2015 by demographic bins: age group, sex, nativity and five education attainment groups⁷². The state-level demographic decadal trend from the projections by [Weldon Cooper Center \(2018\)](#) in 2030-40 is extrapolated to the final decade of 2040-50 by 10 age groups $\times$ sex cells. This state-level demographic trend is applied to all CZs belonging to each state. Immigration inflow to each CZ is extrapolated based on immigration inflow trends across CZs from 2008 to 2015, scaled by the nationwide projection of immigration growth from the nationwide projection from [Census Bureau \(2017\)](#). A trend

⁷²Education attainments are classified into five groups: below high-school degrees, high-school degrees, some college years, four-year college degrees, and above four-year college.

of education attainments conditional on the demographic characters is also extrapolated from the data across CZs from 2000 to 2015. By tweaking statistical population sample weights of the 2015 ACS data by the future population weight shifts across demographic bins, the hypothetical population datasets in 2020, 2030, 2040, and 2050 are constructed.

After compiling the future datasets, the remaining is analogous to 1980-2015. I recover the self-selection rule of labor force participation and occupation choice from 2008-2015, estimating a logit model in the stacked 2010-2015 ACS repeated cross sectional datasets. Then, this self-selection rule is applied to the hypothetical population datasets obtained in the first step to construct a projection of demography-driven labor supply shocks across CZs in 2016-2050.⁷³

7.2 Welfare Implication of Restricting Immigration

Suppose that the U.S. government restricts the net future immigration inflow at the beginning of 2020 to keep the foreign labor mix in each skill class at the level of 2020. Presume that the immigration policy only covers foreign-born individuals without citizenship and naturalized citizens, excluding descendants of immigrants with citizenship. Other protocol follows the future baseline as stated in 7.1. Also, recall that the welfare incorporates only utilities of the native individuals.

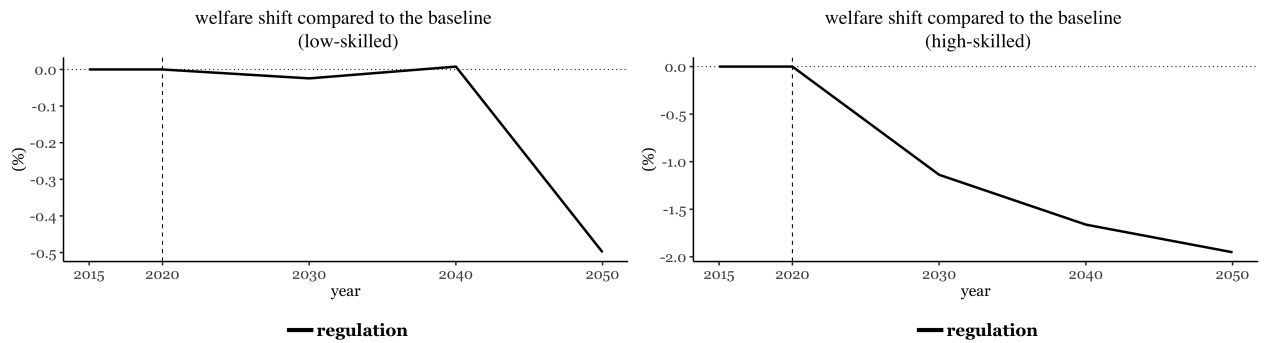


Figure 29: Simulated welfare transition by immigration regulation after 2020 (left: low-skilled, right: high-skilled)

Notes: Use additive weights and $\nu = -0.01$. The value is the average of 100 simulations in 2015, 2020, 2030, 2040, and 2050.

Then, the counterfactual simulation shows that this regulation policy of low-skilled and high-skilled immigration would deteriorate the welfare across sectors in the long run in 2050

⁷³The quality-adjusted capital investment price is extrapolated from the trends in 2008-2015 after the Great Recession.

by 0.5% and 2.0%, respectively, relative to the future baseline immigration policy projected by the Census. (See Figure 29) The result mirrors the welfare analysis during the baseline period, 1980-2015. As low-skilled immigration weakens the adoption of automation in the long run, alleviating the inequality and enhancing the domestic welfare. As high-skilled immigration benefits the non-routine native workers without harming the routine occupations, inclusive of the adjusted technology, the restriction in the future would more unambiguously diminish the domestic welfare, compared to restricting low-skilled immigration.

7.3 Economic Consequences of a Universal Basic Income (UBI)

Suppose the U.S. government launches a universal basic income (UBI) policy in the beginning of the year 2025, granting an unconditional stipend to every U.S. citizen above 25 years old. Overlooking the recent policy debates, two plausible plans of unconditional granting (A) 1,200 USD per month and (B) 800 USD per month are on board.⁷⁴ I suppose that immigration policies are fixed to the baseline.⁷⁵

Granting the unconditional non-labor income floor to U.S. citizens is predicted to alter substantially the self-selection of natives in each occupation class, including non-working.⁷⁶ I compute the UBI-induced labor supply shocks for 2025 to 2050 from the estimated 2010-2015 self-selection rule. Within-CZ estimation shows sensitivity of labor force participation with respect to non-labor income is systematically negative; UBI typically drives a regional shrinkage of domestic labor force by inducing voluntary quasi-retirements.

Rising automation and wage response As automation and wages mutually serve as causes and consequences of each other, I explore how a UBI reshapes the automation adjustment in parallel to wages in each occupation class. The counterfactual simulation predicts that a UBI substantially boosts automation, especially by raising routine occupation wages (shown below). Plan A (or B) would raise automation intensity by 0.62% (or 0.45%). Observe that the automation upgrading is projected to take a decade to reach a ceiling, since automation upgrading is frictional and less productive establishments delays upgrading au-

⁷⁴From the administration viewpoint, a long political process is required until it is implemented. In that case, the early announcement of UBI might form the expectation, which might induce wage rises and generate the similar results. The current simulation should be viewed as an extreme exercise.

⁷⁵The primary obstacle to implement a UBI is its massive expenditure, and I suppose that this would be compensated by heavier income tax. It might be worth considering to adjust immigration policies to compensate for the necessary expenditure.

⁷⁶To simplify the simulation, I abstract from labor supply response of high-income earners to heavier income tax.

tomation. Furthermore, as shown later, the routine wage would be harmed by the surging automation, serving as a counteracting force to further automation. This would generate further lags of the adoption of automation for less productive establishments.

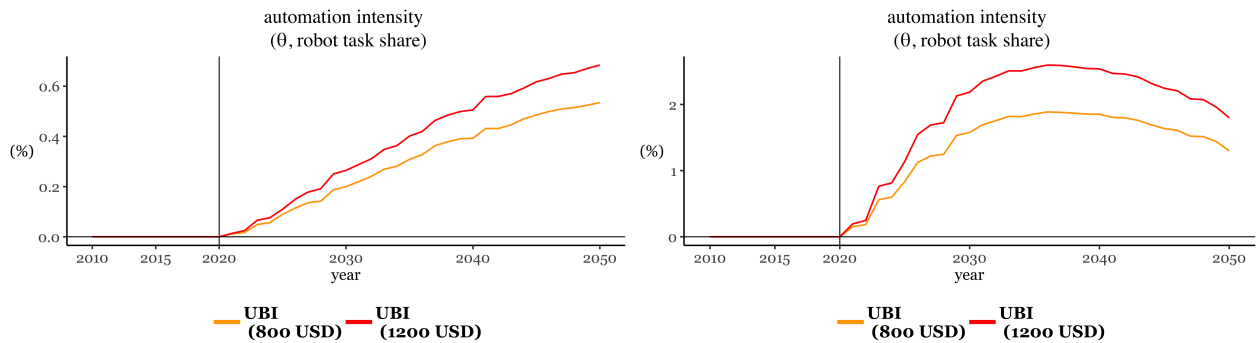


Figure 30: Nationwide dynamics of automation (left: manufacturing, right: information service)

Notes: The value is the average of 100 simulations.

Next, I simulate changes in wages in response to a UBI policy. Right after the announcement of the UBI, both routine and non-routine wages start to elevate because some individuals exit from the labor force. This effect is more distinct in low-skilled individuals (typically engaged in routine occupations) whose exit sensitivity to non-labor income is larger than high-skilled individuals (typically engaged in non-routine occupations). Thus, non-routine wages also rise from their skill demand rise by partially substituting tasks previously done by routine workers. Routine immigrant wages are relatively immune from the initial labor supply shock.

Due to delayed automation upgrading, routine native wages are gradually harmed, but after automation reaches a ceiling, routine native wages are on the constant rise, consistent with non-routine wages, benefitting from aging demography and technological progress. However, routine immigrant wages are on the constant decline due to immigration inflow and rising automation. The egalitarian-oriented UBI has the potential to exacerbate the wage inequality by substantially accelerating automation.

A natural corollary of a UBI is a widening gap between native and immigrant wages. As a UBI provides an unconditional stipend exclusively to native citizens, the policy shock primarily hits domestic labor. As a result, establishments expand their use of foreign labor. Fixing the national immigration policy, nationwide foreign dependency, proxied by employment share across sectors, would consistently rise. The provision of a UBI not only raises reliance on automation, but heightens economic dependency on foreign labor in parallel to shrinking domestic labor force.

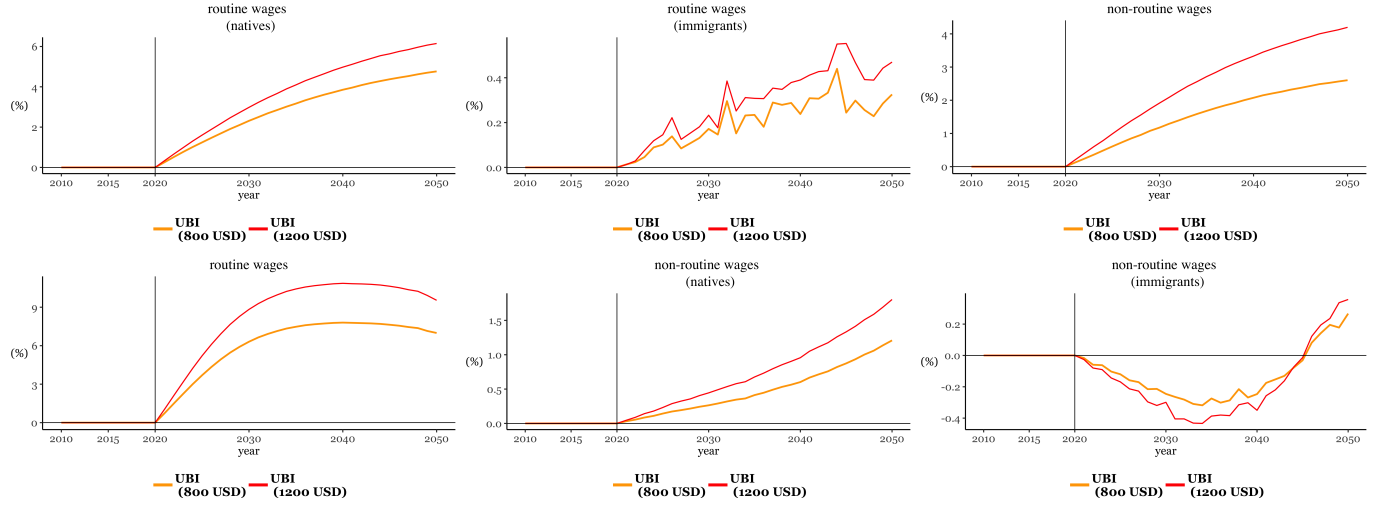


Figure 31: Simulated wage paths relative to the baseline by UBI regimes

Notes: Top three: manufacturing. Bottom three: information service. The value is the average of 100 simulations.

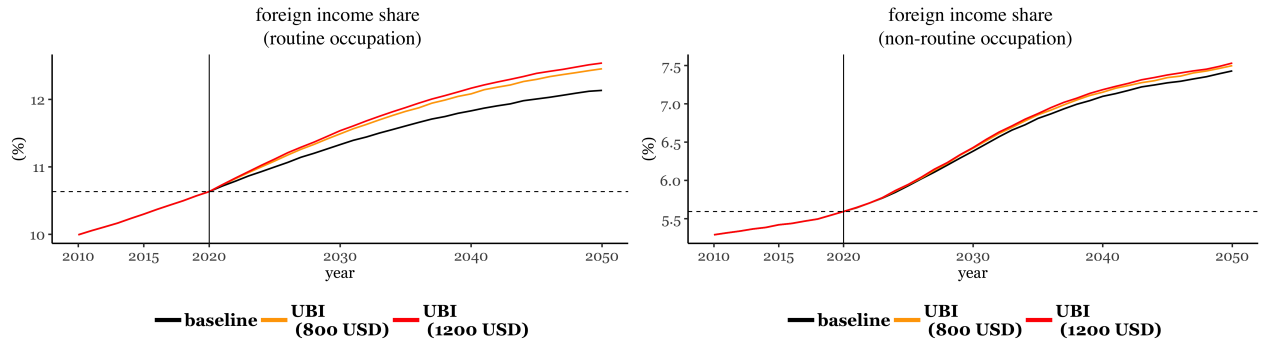


Figure 32: Dependency on foreign labor by UBI regimes (left: manufacturing, right: information service)

Notes: The value is the average of 100 simulations.

8 Concluding Remarks

This paper explores the impact of immigration inflow on automation adoption by establishments across various regions, and their labor market consequences. The dynamic model predicts that immigration's impact on native wages during 1980-2015 could vary and even be reversed by including automation adjustments and their indirect effects on native wages. I find that low-skilled immigration stifled robotization in manufacturing, and thus, augmented routine native wages in the long run. In contrast, strong use of computerization driven by high-skilled immigration in information service sector further upshifted non-routine native

wages. Consequently, I find there is a long-run welfare-enhancing role for both skill types of immigration.

Methodologically, to the best of my knowledge, this paper is the first to empirically estimate the cross-factor substitution schedule, and task-specific productivities despite the sizable body of literature employing a task-based approach, which is prominently used in labor economics and macro economics. By analyzing more than 700 geographical units and 35 year inter-temporal variations, I exploit consistently asymmetric inflows of ethnically-driven immigration inflow into U.S. regional labor markets as instruments used to infer the substitution patterns of routine skills vs. robots, non-routine skills vs. routine skills and foreign vs. domestic skills, under the perspective of optimal task allocation. As stressed in this paper, the substitution schedule dictates the ensuing quantitative simulation. The joint investigation of foreign labor and automation at the regional level is shown to be helpful for understanding the labor market consequences of immigration and constructing a theory-grounded, more nuanced policy prescriptions.

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Appendices

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Contents

A	Model Appendix	2
A.1	Equilibrium	2
A.1.1	Optimal task allocation	2
A.1.2	Dynamic task allocation equilibrium	4
A.2	Dynamic Task-Based Model with Heterogeneity	6
A.3	Proof of Proposition 3 [Automation Upgrading Policy]	8
A.4	Equilibrium Shifts	10
A.5	Comparative Statics	15
A.6	Analytical Formula of Elasticities with Respect to Immigration	24
B	Simulation Appendix	27
B.1	Preparation at the Baseline Year	27
B.2	Computation Steps	28
C	Data Appendix	34
C.1	Labor	34
C.1.1	Foreign labor distribution across sectors	34
C.1.2	Marshallian labor supply elasticity	37
C.1.3	Welfare	37
C.2	Capital	38
C.2.1	Classification	38
C.2.2	Robots vs. equipment	38
C.2.3	Investment price	39
C.3	Establishment	40
C.3.1	Urban and rural areas	40
C.3.2	Size distribution	41
C.4	Corroborating Reduced-Form Results	42

A Model Appendix

A.1 Equilibrium

A.1.1 Optimal task allocation

Proposition 1 [Optimal Task Allocation over Production Factors]

I show that regularity conditions in the main paper yields corner conditions, ensuring single-crossing of marginal cost curves. The proof largely follows [Acemoglu and Restrepo \(2018\)](#), and common in the literature of task-based approach.

R1 [Routine skills vs. Robots]

$$\frac{\psi - \theta}{\theta} \frac{A^R}{\underline{a}(1)} < \frac{\underline{S}}{R} < (1 - \psi)A^R$$

If $\frac{\psi - \theta}{\theta} \frac{A^R}{\underline{a}(1)} < \frac{\underline{S}}{R} < (1 - \psi) \frac{A^R}{\underline{a}(0)}$ holds, then

$$\frac{\underline{q}}{\underline{a}(1)} < \frac{q^R}{A^R} < \frac{\underline{q}}{\underline{a}(0)} \quad (\text{A.1})$$

holds. Given factor demand functions $\underline{S} = \frac{(\psi - \theta)\alpha Y}{\underline{q}}$ and $R = \frac{\theta\alpha Y}{q^R}$, $\frac{\underline{S}}{R} = \frac{(\psi - \theta)/\underline{q}}{\theta/q^R} = \frac{\psi - \theta}{\theta} \frac{q^R}{\underline{q}}$ holds. Then, one gets

$$\begin{cases} \frac{\psi - \theta}{\theta} \frac{A^R}{\underline{a}(1)} < \frac{\psi - \theta}{\theta} \frac{q^R}{\underline{q}} \Rightarrow \frac{\underline{q}}{\underline{a}(1)} < \frac{q^R}{A^R} \\ \frac{\psi - \theta}{\theta} \frac{q^R}{\underline{q}} < (1 - \psi) \frac{A^R}{\underline{a}(0)} \Rightarrow \frac{q^R}{A^R} < (1 - \psi) \frac{\theta}{\psi - \theta} \frac{\underline{q}}{\underline{a}(0)} < \frac{\underline{q}}{\underline{a}(0)}. \end{cases}$$

The two equations yield (A.1). Together with R0, it assures single-crossing of the two marginal costs: there exists $\theta \in (0, 1)$ equalizing the task price such that $\underline{p}(\theta) = \frac{q^R}{A^R}$.

R2 [Non-routine skills vs. Routine skills]

$$\frac{(\psi - \theta)\bar{A}\bar{a}(\theta)}{(1 - \psi)\underline{a}(\theta)} < \frac{\underline{S}}{\bar{S}} < \frac{(\psi - \theta)\bar{A}\bar{a}(1)}{(1 - \psi)\underline{a}(1)}$$

If $\frac{\psi - \theta}{1 - \psi} \frac{\bar{A}\bar{a}(\theta)}{\underline{a}(\theta)} < \frac{\underline{S}}{\bar{S}} < \frac{\psi - \theta}{1 - \psi} \frac{\bar{A}\bar{a}(1)}{\underline{a}(1)}$ holds, then

$$\frac{\underline{q}}{\underline{a}(\theta)} < \frac{\bar{q}}{\bar{A}\bar{a}(\theta)}, \quad \frac{\underline{q}}{\underline{a}(1)} > \frac{\bar{q}}{\bar{A}\bar{a}(1)} \quad (\text{A.2})$$

holds. Given factor demand functions $\underline{S} = \frac{(\psi - \theta)\alpha Y}{\underline{q}}$ and $\bar{S} = \frac{(1 - \psi)\alpha Y}{\bar{q}}$, $\frac{\underline{S}}{\bar{S}} = \frac{(\psi - \theta)/\underline{q}}{(1 - \psi)/\bar{q}} = \frac{\psi - \theta}{1 - \psi} \frac{\bar{q}}{\underline{q}}$ holds. Then, one gets

$$\begin{cases} \frac{\psi - \theta}{1 - \psi} \frac{\bar{A}\bar{a}(\theta)}{\underline{a}(\theta)} > \frac{\psi - \theta}{1 - \psi} \frac{\bar{q}}{\underline{q}} \Rightarrow \frac{\bar{A}\bar{a}(\theta)}{\underline{a}(\theta)} > \frac{\bar{q}}{\underline{q}} \Rightarrow \frac{\underline{q}}{\underline{a}(\theta)} < \frac{\bar{q}}{\bar{A}\bar{a}(\theta)} \\ \frac{\psi - \theta}{1 - \psi} \frac{\bar{q}}{\underline{q}} < \frac{\psi - \theta}{1 - \psi} \frac{\bar{A}\bar{a}(1)}{\underline{a}(1)} \Rightarrow \frac{\bar{q}}{\underline{q}} < \frac{\bar{A}\bar{a}(1)}{\underline{a}(1)} \Rightarrow \frac{\underline{q}}{\underline{a}(1)} > \frac{\bar{q}}{\bar{A}\bar{a}(1)}. \end{cases}$$

The two equations yield (A.2). Together with R0, it assures single-crossing of the two marginal costs: there exists ψ with $\theta < \psi < 1$ equalizing the task price such that $\underline{p}(\psi) = \bar{p}(\psi)$.

R3 [Foreign skills vs. Domestic skills]

$$\frac{\phi}{(1 - \phi)\widehat{A^F}} < \frac{\widehat{S^F}}{\widehat{S^D}} < \frac{\phi}{(1 - \phi)\widehat{A^F a^F}(1)}$$

If $\frac{\phi}{(1 - \phi)\widehat{A^F a^F}(0)} < \frac{\widehat{S^F}}{\widehat{S^D}} < \frac{\phi}{(1 - \phi)\widehat{A^F a^F}(1)}$ holds, then

$$\frac{\widehat{q^F}}{\widehat{A^F a^F}(0)} < \widehat{q^D}, \quad \frac{\widehat{q^F}}{\widehat{A^F a^F}(1)} > \widehat{q^D} \quad (\text{A.3})$$

holds. Given factor demand function $\widehat{S^F} = \frac{\phi \widehat{S}}{\widehat{q^F}}$ and $\widehat{S^D} = \frac{(1 - \phi)\widehat{S}}{\widehat{q^D}}$, $\frac{\widehat{S^F}}{\widehat{S^D}} = \frac{\phi \widehat{S}/\widehat{q^F}}{(1 - \phi)\widehat{S}/\widehat{q^D}} = \frac{\phi}{1 - \phi} \frac{\widehat{q^D}}{\widehat{q^F}}$ holds. One gets

$$\begin{cases} \frac{\phi}{(1 - \phi)\widehat{A^F a^F}(0)} < \frac{\phi}{1 - \phi} \frac{\widehat{q^D}}{\widehat{q^F}} \Rightarrow \frac{1}{\widehat{A^F a^F}(0)} < \frac{\widehat{q^D}}{\widehat{q^F}} \Rightarrow \frac{\widehat{q^F}}{\widehat{A^F a^F}(0)} < \widehat{q^D} \\ \frac{\phi}{1 - \phi} \frac{\widehat{q^D}}{\widehat{q^F}} < \frac{\phi}{(1 - \phi)\widehat{A^F a^F}(1)} \Rightarrow \frac{\widehat{q^D}}{\widehat{q^F}} < \frac{1}{\widehat{A^F a^F}(1)} \Rightarrow \frac{\widehat{q^F}}{\widehat{A^F a^F}(1)} > \widehat{q^D}. \end{cases}$$

The two equations yield (A.3). Together with R0, it assures single-crossing of the two marginal costs: this assures that there exists $\omega' = \phi$ with $\theta < \phi < 1$ such that $\widehat{p^F}(\phi) = \widehat{p^D}(\phi)$.

In sum, the regularities of R0-R3 assures single-crossing of marginal cost curves; each task is implemented by robots, routine-skills, or non-routine skills, and each sub-task is run

by domestic skills or foreign skills. ■

A.1.2 Dynamic task allocation equilibrium

Proposition 2 [Equilibrium Outcomes]

Proof.

Impose the regularities R0-R3. Then, the perfect specialization equilibrium emerges from Proposition 1. The task-level technology is reduced to

$$y(\omega) = \begin{cases} \{A^R r(\omega)\}^\alpha k(\omega)^{1-\alpha} & (\omega \in [0, \theta), \text{ low-end tasks}) \\ \{\underline{A}\underline{a}(\omega)\underline{s}(\omega)\}^\alpha k(\omega)^{1-\alpha} & (\omega \in [\theta, \psi]), \text{ medium tasks}) \\ \{\bar{A}\bar{a}(\omega)\bar{s}(\omega)\}^\alpha k(\omega)^{1-\alpha} & (\omega \in [\psi, 1]), \text{ high-end tasks}). \end{cases}$$

By Cobb-Douglas property of task-level technology,

$$q^R r(\omega) = \underline{q}\underline{s}(\omega) = \bar{q}\bar{s}(\omega) = \alpha p(\omega)y(\omega), \quad q^K k(\omega) = (1 - \alpha)p(\omega)y(\omega)$$

By the unit-elastic task aggregation of tasks, the manager spends equalized expenditure to each task such that

$$p(\omega)y(\omega) = PY \quad \forall \omega \in [0, 1].$$

Then, factor demand functions are

$$r(\omega) = \frac{\alpha p(\omega)y(\omega)}{q^R} = \frac{\alpha PY}{q^R}, \quad \underline{s}(\omega) = \frac{\alpha p(\omega)y(\omega)}{\underline{q}} = \frac{\alpha PY}{\underline{q}}, \quad \bar{s}(\omega) = \frac{\alpha p(\omega)y(\omega)}{\bar{q}} = \frac{\alpha PY}{\bar{q}}$$

and

$$k(\omega) = \frac{(1 - \alpha)p(\omega)y(\omega)}{q^K} = \frac{(1 - \alpha)PY}{q^K}.$$

Task price is equalized to factor price in efficiency unit such that

$$p(\omega) = \begin{cases} \left(\frac{q^R}{A^R \alpha}\right)^\alpha \left(\frac{q^K}{1 - \alpha}\right)^{1-\alpha} & (\omega \in [0, \theta)) \\ \left(\frac{\underline{q}}{\underline{A}\underline{a}(\omega)\alpha}\right)^\alpha \left(\frac{q^K}{1 - \alpha}\right)^{1-\alpha} & (\omega \in [\theta, \psi)) \\ \left(\frac{\bar{q}}{\bar{A}\bar{a}(\omega)\alpha}\right)^\alpha \left(\frac{q^K}{1 - \alpha}\right)^{1-\alpha} & (\omega \in [\psi, 1]). \end{cases}$$

Then, task demand for ω is given by

$$y(\omega) = \frac{PY}{p(\omega)} = \begin{cases} (\frac{A^R \alpha}{q^R})^\alpha (\frac{1-\alpha}{q^K})^{1-\alpha} PY & (\omega \in [0, \theta]) \\ (\frac{\underline{A}a(\omega) \alpha}{\underline{q}})^\alpha (\frac{1-\alpha}{q^K})^{1-\alpha} PY & (\omega \in (\theta, \psi]) \\ (\frac{\bar{A}\bar{a}(\omega) \alpha}{\bar{q}})^\alpha (\frac{1-\alpha}{q^K})^{1-\alpha} PY & (\omega \in (\psi, 1]). \end{cases}$$

Thus, factor demand is given by

$$r(\omega) = \begin{cases} \frac{\theta \alpha PY}{q^R} & (\omega \in [0, \theta]) \\ 0 & (\omega \in (\theta, 1]) \end{cases} \quad \underline{s}(\omega) = \begin{cases} 0 & (\omega \in [0, \theta]) \\ \frac{(\psi - \theta) \alpha PY}{\underline{q}} & (\omega \in (\theta, \psi]) \\ 0 & (\omega \in (\psi, 1]) \end{cases} \quad \bar{s}(\omega) = \begin{cases} 0 & (\omega \in [0, \theta]) \\ 0 & (\omega \in (\theta, \psi]) \\ \frac{(1 - \psi) \alpha PY}{\bar{q}} & (\omega \in (\psi, 1]) \end{cases}$$

and

$$k(\omega) = \frac{(1 - \alpha) PY}{q^K} (\omega \in [0, 1]).$$

Since each skill follows a law of one price, factor demand is equal within task intervals such that

$$\underline{s}(\omega) = \frac{\underline{S}}{\psi - \theta}, \quad \bar{s}(\omega) = \frac{\bar{S}}{1 - \psi}, \quad r(\omega) = \frac{R}{\theta}, \quad k(\omega) = K.$$

Plugging these back into the technology, the aggregate production is formulated as

$$\begin{aligned} Y &= \exp \left[\int_0^\theta [\alpha (\ln r(\omega) + \ln A^R) + (1 - \alpha) \ln k(\omega)] d\omega + \int_\theta^\psi [\alpha \{ \ln \underline{s}(\omega) + \ln \underline{A}a(\omega) \} + (1 - \alpha) \ln k(\omega)] d\omega \right. \\ &\quad \left. + \int_\psi^1 [\alpha \{ \ln \bar{s}(\omega) + \ln \bar{A}\bar{a}(\omega) \} + (1 - \alpha) \ln k(\omega)] d\omega \right] \\ &= B(\theta, \psi, \alpha) \left\{ \left(\frac{R}{\theta} \right)^\theta \left(\frac{\underline{S}}{\psi - \theta} \right)^{\psi - \theta} \left(\frac{\bar{S}}{1 - \psi} \right)^{(1 - \psi)} \right\}^\alpha K^{1 - \alpha} \end{aligned}$$

where

$$B(\theta, \psi, \alpha) = \{ (A^R)^\theta (\bar{A})^{1 - \psi} \}^\alpha \exp \left[\alpha \left\{ \int_\theta^\psi \ln \underline{a}(\omega) d\omega + \int_\psi^1 \ln \bar{a}(\omega) d\omega \right\} \right].$$

Nested sub-task allocation between domestic and foreign groups is analogous to the upper level. Given the skill demand $\widehat{S}$ in each sector, the occupation manager further allocates domestic and foreign skills to the sub-task spectrum to produce the aggregate upper level skill demand. R3 and Proposition.1 implies that there exists $\phi \in (0, 1)$ in ω' spectrum such that

$$\frac{\widehat{q^F}}{\widehat{A^F a^F}(\phi)} = \frac{\widehat{q^D}}{\widehat{A^D a^D}(\phi)}$$

By iso-elastic task aggregation, the aggregate price is given by

$$\ln \widehat{q} = \int_0^1 \ln \widehat{p}(\omega') d\omega'.$$

The skill production function is reduced to

$$\widehat{s}(\omega') = \begin{cases} \widehat{A}^F \widehat{a}^F(\omega') \widehat{s}^F(\omega') & (0 \leq \omega' < \phi) \\ \widehat{A}^D \widehat{a}^D(\omega') \widehat{s}^D(\omega') & (\phi \leq \omega' \leq 1). \end{cases}$$

Then, domestic and foreign skill demand is given by

$$\widehat{s}^F(\omega') = \begin{cases} \frac{\widehat{q} \widehat{S}}{\widehat{q}^F} & (0 \leq \omega' < \phi) \\ 0 & (\phi \leq \omega' \leq 1) \end{cases} \quad \widehat{s}^D(\omega') = \begin{cases} 0 & (0 \leq \omega' < \phi) \\ \frac{\widehat{q} \widehat{S}}{\widehat{q}^D} & (\phi \leq \omega' \leq 1). \end{cases}$$

Plugging this into the aggregation of prices, one obtains $\widehat{q} = \frac{(\widehat{q}^F)^\phi (\widehat{q}^D)^{1-\phi}}{B'(\phi)}$ where $B'(\phi) = (\widehat{A}^F)^\phi \exp[\int_0^\phi \ln \widehat{a}^F(\omega') d\omega]$.¹ Analogous to the upper level tasks, the equilibrium splits the aggregate factor income by a ratio of sub-task interval of domestic and foreign groups such that $\widehat{W}^F = \phi \widehat{W}$, $\widehat{W}^D = (1 - \phi) \widehat{W}$. ■

A.2 Dynamic Task-Based Model with Heterogeneity

Dynamics and heterogeneity of unobservable productivities are added to the benchmark model. In each sector G , the aggregate final good is differentiated by $\sigma^G > 0$, elasticity of substitution in the global tradable market in sector G . (G is dropped in σ below)

$$\widehat{C}_t = \{\Sigma_{i \in G} (\widehat{C}_{i,t})^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1}}, \widehat{P}_t = \{\Sigma_{i \in G} (P_i)^{1-\sigma}\}^{\frac{1}{1-\sigma}}.$$

A baseline production $X_{i,t}$ is augmented by unobservable stochastic productivity shock $A_{i,t}$ such that

$$\widehat{Y}_{i,t} = (A_{i,t})^\eta (Y_{i,t})^{1-\eta} \tag{A.4}$$

where $A_{i,t}$ is a serially correlated unobservable productivity in the AR1 process:

$$\ln A_{i,t} = \xi + \rho \ln A_{i,t-1} + \epsilon_t$$

where $\rho \in (-1, 1)$ and ϵ_t is i.i.d. standard normal productivity shock. A baseline production is non-stochastically governed in market competition,

¹Recall the normalization $\widehat{A}^D = 1$, $\widehat{a}^D(\omega') \quad \forall \omega' \in [0, 1]$.

$$Y_{i,t} = \left(\frac{P_{i,t}}{\widehat{P}_t}\right)^{-\sigma} \widehat{Y}_t^G$$

Thus, the transition of production in response to price change follows a relative price shift and sector-level growth such that

$$\underbrace{\frac{Y_{i,t}}{Y_{i,t-1}}}_{\text{individual growth}} = \underbrace{\left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{-\sigma}}_{\text{relative price change}} \underbrace{\frac{\widehat{Y}_t^G}{\widehat{Y}_{t-1}^G}}_{\text{sectoral growth}}$$

where $P'_{i,t} \equiv \frac{P_{i,t}}{\widehat{P}_t}$ is relative price in the sector. Rewriting this, one gets²

$$P'_{i,t} Y_{i,t} = \left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{1-\sigma} P'_{i,t-1} Y_{i,t-1} \frac{\widehat{Y}_t^G}{\widehat{Y}_{t-1}^G}. \quad (\text{A.5})$$

³⁴To produce the baseline production X_i^G , an establishment solves a Hicksian problem of cost minimization such that

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

$$s.t. \quad \exp\left(\int_0^1 \ln y_i(\omega) d\omega\right) \geq Y_i, \text{ where } y_i(\omega) = \{A^R r(\omega) + \underline{A} \underline{a}(\omega) \underline{s}(\omega) + \bar{A} \bar{a}(\omega) \bar{s}(\omega)\}^\alpha k(\omega)^{1-\alpha}$$

$$\int_0^1 \underline{s}(\omega) d\omega = \underline{S}_i, \quad \int_0^1 \bar{s}(\omega) d\omega = \bar{S}_i, \quad \int_0^1 r(\omega) d\omega = R_i, \quad \int_0^1 k(\omega) d\omega = K_i$$

Lower-level immigration-intensive occupation manager's cost minimization problem is analogous to the benchmark model. Impose the R0-R3 and Proposition 1 (task specialization of each factor) holds. The task price is equalized to factor price in efficiency unit as in Proposition 2. Plugging the marginal cost functions for each task into the aggregated price

2

$$Y_{i,t} = \left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{-\sigma} Y_{i,t-1} \frac{\widehat{Y}_t^G}{\widehat{Y}_{t-1}^G} \implies \frac{P'_{i,t}}{P'_{i,t-1}} Y_{i,t} = \frac{P'_{i,t}}{P'_{i,t-1}} \left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{-\sigma} Y_{i,t-1} \frac{\widehat{Y}_t^G}{\widehat{Y}_{t-1}^G}$$

³When $\sigma > 1$, $P'_{i,t-1} > P'_{i,t}$ implies $\left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{1-\sigma} > 1$ so that baseline production value increases with respect to quality-adjusted price advantage.

⁴Each establishment is small enough so that their automation choice does not affect the global industry price.

equation, the final price good for i is given by

$$\begin{aligned}
P_i &= \exp\left[\int_0^1 \ln p_i(\omega) d\omega\right] \\
&= \exp[\alpha\{\ln(q_i^R)^{\theta_i} + \ln(\underline{q})^{\psi-\theta_i} + \ln(\bar{q})^{1-\psi}\} + (1-\alpha)\ln q^K - \ln B(\theta_i, \psi, \alpha) - \ln \alpha^\alpha(1-\alpha)^{1-\alpha}] \\
&= \frac{\{(q_i^R)^{\theta_i} \underline{q}^{\psi-\theta_i} \bar{q}^{1-\psi}\}^\alpha (q^K)^{1-\alpha}}{\alpha^\alpha(1-\alpha)^{1-\alpha} B(\theta_i, \psi, \alpha)} \tag{A.6}
\end{aligned}$$

A.3 Proof of Proposition 3 [Automation Upgrading Policy]

As the form of threshold rule is common in investment literature (e.g. [Adda and Cooper \(2000\)](#)), this section clarifies the sufficient state variables for automation upgrading policy, featuring the analytical form of a periodic profit function. A periodic profit function is

$$\begin{aligned}
\Pi_i(\mathbf{X}_t, A_{i,t}, \theta_i \mid \Theta) &= \underbrace{\alpha\theta_{i,t}A_{i,t}\left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{1-\sigma}P_{i,t-1}Y_{i,t-1}\Delta_{t-1}^G}_{\text{gross profit}} - \underbrace{p_{i,t}^R I_{i,t}^R(\theta_{i,t} \mid \theta_{i,t-1})}_{\text{investment}} \\
&\quad - \underbrace{\mathbb{I}(\theta_{i,t} > \theta_{i,t-1})c(\mathbf{X}, A, \theta' \mid \Theta^A)P_{i,t-1}\hat{Y}_{i,t-1}}_{\text{adjustment cost}}
\end{aligned}$$

⁵Standardized by the previous production value, the periodic profit function is reduced to

$$\begin{aligned}
\pi_i(\mathbf{X}_t, A_{i,t}, \theta_i \mid \Theta) &\equiv \frac{\Pi_i(\mathbf{X}_t, A_{i,t}, \theta_i \mid \Theta)}{P_{i,t-1}Y_{i,t-1}} \\
&= \alpha\theta_{i,t}A_{i,t}\left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{1-\sigma}\Delta_{t-1}^G - \frac{p_{i,t}^R I_{i,t}^R(\theta_{i,t} \mid \theta_{i,t-1})}{P_{i,t-1}Y_{i,t-1}} - \mathbb{I}(\theta_{i,t} > \theta_{i,t-1})c(\mathbf{X}_t, A_{i,t}, \theta_i \mid \Theta^A).
\end{aligned}$$

The optimal automation θ_i is chosen to maximize π_i .

The relative price index is

⁵Gross profit excluding investment and adjustment cost is

$$P_{i,t}Y_{i,t} - \underbrace{V_{l,t}^K}_{\text{rental price for equipments}} - \underbrace{(\underline{W}_{l,t} + \bar{W}_{l,t})}_{\text{labor compensation}} = \alpha\theta_{i,t}P_{i,t}\hat{Y}_{i,t} = \alpha\theta_{i,t}A_{i,t}P_{i,t}Y_{i,t}$$

Arranging (A.5), one gets

$$P_{i,t}Y_{i,t} = \left(\frac{P'_{i,t}}{P'_{i,t-1}}\right)^{1-\sigma}P_{i,t-1}Y_{i,t-1}\underbrace{\frac{P_t^G Y_t^G}{P_{t-1}^G Y_{t-1}^G}}_{\equiv \Delta_{t-1}^G}.$$

Substituting this into the equation above yields the gross profit function.

$$P'_{i,t} = \frac{\{(q_{i,t}^R)^{\theta_{i,t}}(\underline{q}_t)^{\psi_0 - \theta_{i,t}}(\bar{q}_t)^{1 - \psi_t}\}^\alpha (q^K)^{1 - \alpha}}{P_t^G \alpha^\alpha (1 - \alpha)^{1 - \alpha} B(\theta_{i,t}, \psi_t, \alpha)} = \underbrace{\left(\frac{q_{i,t}^R / A^R}{\underline{q}_t}\right)^{\alpha \theta_{i,t}} \exp\left(\alpha \int_0^{\theta_{i,t}} \ln \underline{a}(\omega) d\omega\right)}_{\text{depend on } \theta_{i,t}} Q_{i,t}$$

where automation-independent price bundle is

$$Q_{i,t} \equiv \frac{(\underline{q}_t)^{\alpha \psi_t} (\bar{q}_t / \bar{A})^{\alpha(1 - \psi_t)} (q^K)^{1 - \alpha}}{P_t^G \alpha^\alpha (1 - \alpha)^{1 - \alpha} \exp\{\alpha(\int_0^{\psi_t} \ln \underline{a}(\omega) d\omega + \int_{\psi_t}^1 \ln \bar{a}(\omega) d\omega)\}}$$

Recall that labor adjustment, implemented by task allocation between routine skills and non-routine skills and sub-task allocation between foreign-domestic skills is set frictionless. Thus, the thresholds ψ, ϕ is set every period to reflect the skill price inequality to satisfy the single crossing conditions. Since regional skill prices are equalized as a law of one price, $\psi_{i,n} = \psi_{l,n}, \phi_{i,n} = \phi_{l,n}$ for every $i \in l$. Taking a ratio change of price index,

$$\begin{aligned} \frac{P'_{i,t}}{P'_{i,t-1}} &= f(\theta_{i,t-1}, \frac{q_{i,t}^R}{\underline{q}_t}, \Delta Q_{i,t-1}, \theta_{i,t}) = \frac{\left(\frac{q_{i,t}^R / A^R}{\underline{q}_t}\right)^{\alpha \theta_{i,t}} \exp(\alpha \int_0^{\theta_{i,t}} \ln \underline{a}(\omega) d\omega)}{\left(\frac{q_{i,t-1}^R / A^R}{\underline{q}_{t-1}}\right)^{\alpha \theta_{i,t-1}} \exp(\alpha \int_0^{\theta_{i,t-1}} \ln \underline{a}(\omega) d\omega)} \frac{Q_{i,t}}{\underbrace{Q_{i,t-1}}_{\equiv \Delta Q_{i,t-1}}} \\ &= \underbrace{\left(\frac{\left(\frac{q_{i,t}^R}{\underline{q}_t}\right)^{\theta_{i,t}}}{\left(\frac{q_{i,t-1}^R}{\underline{q}_{t-1}}\right)^{\theta_{i,t-1}}}\right)^\alpha (A^R)^{\theta_{i,t-1} - \theta_{i,t}} \frac{\exp(\alpha \int_0^{\theta_{i,t}} \ln \underline{a}(\omega) d\omega)}{\exp(\alpha \int_0^{\theta_{i,t-1}} \ln \underline{a}(\omega) d\omega)} \Delta Q_{i,t-1}}_{\text{automation-dependent}} \end{aligned}$$

⁶Thus, observable state variables sufficient to characterize the automation policy at t are reduced to

$$\mathbf{X}_t = \left\{ \underbrace{\theta_{i,t-1}}_{\text{automation intensity}}, \underbrace{\frac{q_{i,t-1}^R}{\underline{q}_{t-1}}}_{\text{current vintage}}, \underbrace{\Delta Q_{i,t-1}}_{\text{growth of price aggregates}} \right\}$$

⁶ If not upgrading, the automation-dependent term is reduced to $(\frac{\underline{q}_t}{\underline{q}_{t-1}})^{-\theta_{i,t-1}}$.

A.4 Equilibrium Shifts

This section delivers building blocks of equilibrium shifts, applied in comparative statics in Section A.5. The impact of demographic changes, including immigration, on automation adoption or their joint impact to the labor market is formulated by combination of the following analytical linkages.

A.1.2.1 Drivers of Factor demand curve shift

In response to task reallocation, the aggregate factor demand curve shifts. As shown in equilibrium above, a factor demand curve is characterized by an iso-quant of its factor income. For notational convenience, regional factor incomes are proxied by the following notations.

Definition A.1. [Factor Incomes]

Define the labor income $\underline{W}_l, \bar{W}_l, \widehat{W}_l^e$ and the capital income V_l^R, V_l^K in region l as

$$\underline{W}_l \equiv q_l S_l, \quad \bar{W}_l \equiv \bar{q}_l \bar{S}_l, \quad \widehat{W}_l^e \equiv \widehat{q}^e \widehat{S}^e, \quad V_l^R \equiv q^R R_l, \quad V_l^K \equiv q^K K_l$$

$V_l^R, \underline{W}_l, \bar{W}_l, V_l^K, \widehat{W}_l^F$ are factor incomes for robots, routine skills, non-routine skills, equipment and foreign skills in region l , respectively. As shown in Proposition 1, demand curves are proxied by factor incomes. Factor income is changed either by extensive-margin technology adjustments or production shifts. The factor demand curve shifts from task reallocation are formulated as

$$\frac{d \ln \underline{W}}{d \theta} = -\frac{d \ln \bar{W}}{d \psi} = \frac{d \ln(\psi - \theta)}{d \theta} = \frac{-1}{\psi - \theta}, \quad \frac{d \ln \bar{W}}{d \psi} = \frac{d \ln(1 - \psi)}{d \psi} = \frac{-1}{1 - \psi}, \quad \frac{d \ln V^R}{d \theta} = \frac{d \ln \theta^R}{d \theta} = \frac{1}{\theta^R}$$

and

$$\frac{d \ln \underline{W}^F}{d \phi} = \frac{1}{\phi}, \quad \frac{d \ln \underline{W}^D}{d \theta} = \frac{-1}{1 - \phi}.$$

The elasticity of factor income with respect to production is unity such that

$$\frac{\partial \ln V^R}{\partial \ln Y} = \frac{\partial \ln \underline{W}}{\partial \ln Y} = \frac{\partial \ln Y}{\partial \ln \bar{S}} = 1.$$

A.1.2.2 Consequences of Factor demand curve shift

The factor demand shifts, in turn, alter the equilibrium factor prices and allocations. The elasticity of factor prices and allocations with respect to factor incomes are given by

$$\frac{d \ln \tilde{q}}{d \ln \tilde{W}} = \Phi, \quad \frac{d \ln \tilde{S}}{d \ln \tilde{W}} = 1 - \Phi$$

where Φ is a function of uncompensated labor supply elasticity, ϵ_U , such that $\Phi = (\epsilon_U + 1)^{-1}$ for corresponding skills. The skill demand curve shift is split to changes in skill price and allocation by Φ . I show this statement below.

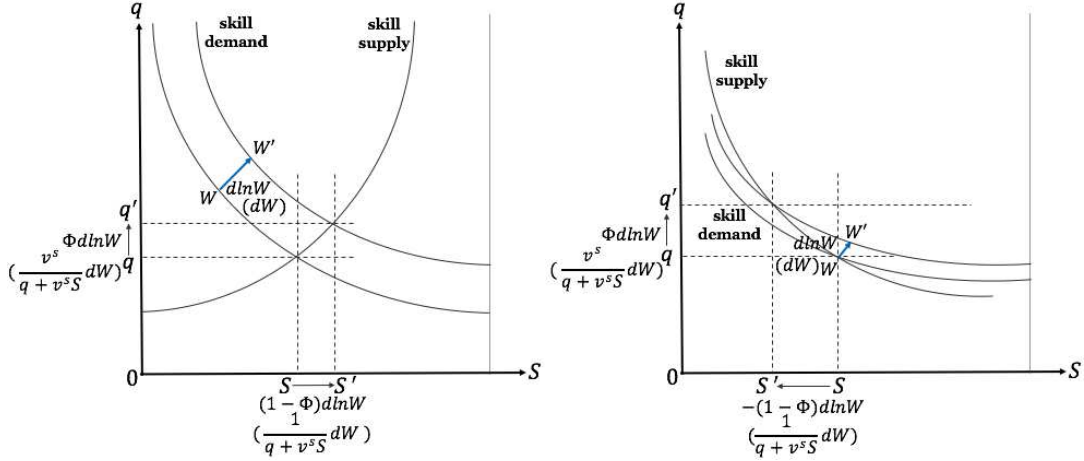


Figure A.1: Aggregate skill demand curve shifts, skills (left) / capital (right)

As a result of task reallocation, demand curve shifts from W to W' such that $qS = W$ and $(q + dq)(S + dS) = W'$. Thus, dropping the second-order term,

$$qdS + Sdq = dW \quad (\text{A.7})$$

holds. Define the slopes of labor demand, labor supply curves, as v^d, v^s , respectively as

$$v^d \equiv \frac{dq}{dS^d} = -\frac{q}{S}, \quad v^s \equiv \frac{dq}{dS^s} = \epsilon_U^{-1} \frac{q}{S}$$

where S^d, S^s are skill demand, and supply, respectively. Introduce Φ as a function of uncompensated labor-supply elasticity, ϵ_U .

$$\Phi \equiv \frac{v^s}{v^s - v^d} = (\epsilon_U + 1)^{-1} \quad (\text{A.8})$$

⁷Therefore, under the demand system, the elasticity of skill prices or allocations with

⁷Eliminate the knife-edge case such that $v^s = -\frac{q}{S} = v^d$.

respect to skill demand is reduced to Φ and $1 - \Phi$, respectively.

$$\begin{cases} \frac{d \ln q}{\frac{d \ln W}{\frac{d \ln S}{d \ln W}}} = \frac{v^s}{q + v^s S} \frac{W}{q} = \frac{v^s S}{q + v^s S} \stackrel{\text{A.8}}{=} \Phi \\ \frac{d \ln S}{\frac{d \ln W}{\frac{d \ln S}{d \ln W}}} = \frac{1}{q + v^s S} \frac{W}{S} = \frac{q}{q + v^s S} \stackrel{\text{A.8}}{=} 1 - \Phi \end{cases}$$

The first equality comes from by plugging $dS = \frac{dq}{v^s}$ into [A.7](#).⁸

Domestic and foreign skill demand shifts are analogously formulated. If the immigration-intensive skill demand rises given any domestic and foreign skill supply curve, domestic and foreign skill demand shifts change the domestic skill price and allocation as

$$\begin{cases} \frac{d \ln \widehat{q}^e}{\frac{d \ln \widehat{W}^e}{\frac{d \ln \widehat{S}^e}{d \ln \widehat{W}^e}}} = \frac{v^s}{\widehat{q}^e + v^s \widehat{S}^e} \frac{\widehat{W}^e}{\widehat{q}^e} = \frac{v^s \widehat{S}^e}{\widehat{q}^e + v^s \widehat{S}^e} \stackrel{\text{A.8}}{=} \widehat{\Phi}^e \\ \frac{d \ln \widehat{S}^e}{\frac{d \ln \widehat{W}^e}{\frac{d \ln \widehat{S}^e}{d \ln \widehat{W}^e}}} = \frac{1}{\widehat{q}^e + v^s \widehat{S}^e} \frac{\widehat{W}^e}{\widehat{S}^e} = \frac{\widehat{q}^e}{\widehat{q}^e + v^s \widehat{S}^e} \stackrel{\text{A.8}}{=} 1 - \widehat{\Phi}^e. \end{cases}$$

The following corollary is used in simulation algorithm in Simulation Appendix [B.2](#).

Corollary A.1. [Demand-driven Equilibrium Shifts]

The response of q and S to q' and S' from the factor income shift from W to W' is given by

$$q' = q + \frac{(W' - W)\Phi}{S}, \quad S' = S + \frac{(W' - W)\epsilon_U \Phi}{q}$$

Proof.

$$\begin{cases} \frac{dq}{q} = \frac{1}{q} \frac{dq}{dW} dW = \frac{1}{q} \frac{v^s}{q + v^s S} dW = \frac{1}{q} \frac{\Phi}{S} dW = \Phi \frac{dW}{W} \\ \frac{dS}{S} = \frac{1}{S} \frac{dS}{dW} dW = \frac{1}{S} \frac{1}{q + v^s S} dW = \frac{1}{S} \frac{\epsilon_U \Phi}{q} dW = \epsilon_U \Phi \frac{dW}{W} \end{cases} \quad (\text{A.9})$$

Observe that the increase of factor demand ($\frac{dW}{W} > 0$) unambiguously raises q , but moves S conditional on the sign of ϵ_U . Each third equality holds because

$$\begin{cases} \frac{v^s}{q + v^s S} = S^{-1}(\epsilon_U + 1)^{-1} = \frac{\Phi}{S} \\ \frac{1}{q + v^s S} = q^{-1} \frac{\epsilon_U}{\epsilon_U + 1} = \frac{\epsilon_U \Phi}{q}. \end{cases}$$

⁸To write concretely, one gets $(\frac{q}{v^s} + S)dq = dW$ and $(q + v^s S)dS = dW$. Manipulating these, $\frac{dq}{dW} = \frac{v^s}{q + v^s S}$ and $\frac{dS}{dW} = \frac{1}{q + v^s S}$ holds.

Rewriting A.9 yields

$$\begin{cases} \frac{q'}{q} = \frac{dq}{q} + 1 = \Phi \frac{dW}{W} + 1 = \left(\frac{W'}{W} - 1\right)\Phi + 1 \\ \frac{S'}{S} = \frac{dS}{S} + 1 = \epsilon_U \Phi \frac{dW}{W} + 1 = \left(\frac{W'}{W} - 1\right)\epsilon_U \Phi + 1. \end{cases}$$

Therefore, one gets

$$\begin{cases} q' = q + \frac{(W' - W)\Phi}{S} \\ S' = S + \frac{(W' - W)\epsilon_U \Phi}{q}. \end{cases}$$

■

Due to perfect elasticity of capital supply, the capital demand curve shift on capital allocation is unity. Since the equilibrium capital deployment is $M = \frac{V^M}{q^M}$, one gets $\frac{d \ln M}{d \ln V^M} = 1$ for $M \in \{R, K\}$.

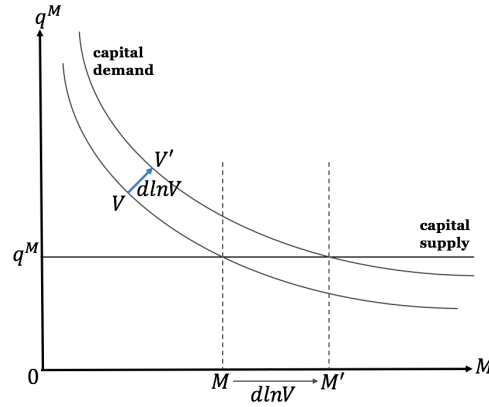


Figure A.2: Aggregate factor demand curve shifts, skills (left) / capital (right)

Note: $M \in \{R, K\}$.

A.1.2.4 Consequences of Factor supply curve shifts

Equilibrium shift from skill supply curve shifts are characterized by labor supply propensity. Formerly, regardless of the slopes of the labor supply curve,

$$\frac{d \ln q}{d \ln S^s} = -\Phi < 0, \quad \frac{d \ln S}{d \ln S^s} = \Phi > 0$$

holds.

Consider that the skill supply shifts rightward by dS^s . Recall that v^d, v^s are slopes of demand and supply curves, respectively.

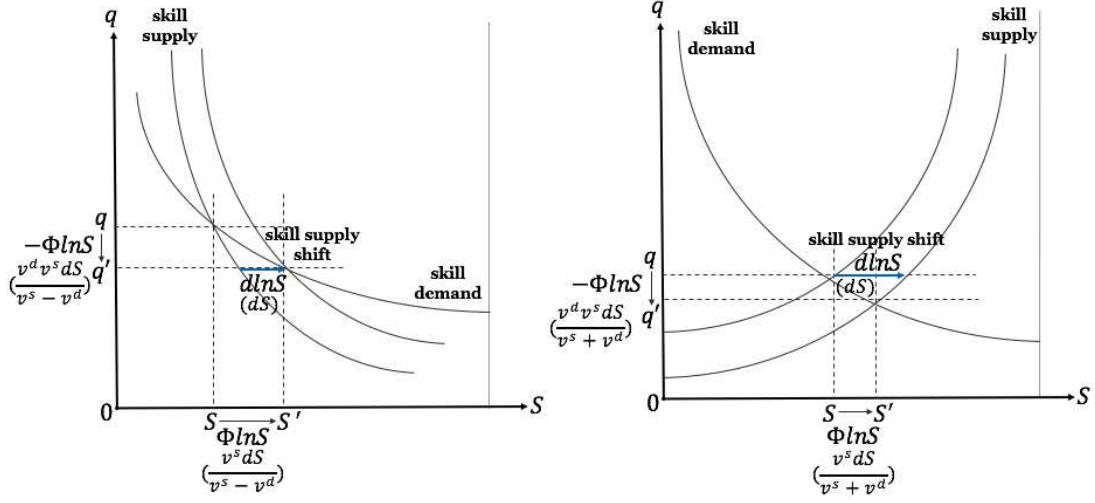


Figure A.3: Aggregate skill supply curve shifts (Case.1, left, Case.2, right)

- Case.1: $v^d < 0 < v^s$ (skill supply curve is *upward*-sloping)

$$dq\left(\frac{1}{|v^s|} + \frac{1}{|v^d|}\right) = dq\left(\frac{1}{v^s} - \frac{1}{v^d}\right) = dS^s > 0$$

- Case.2: $v^s < v^d < 0$ (skill supply curve is *downward*-sloping)

$$\frac{-dq}{|v^s|} - \frac{-dq}{|v^d|} = dq\left(\frac{1}{v^s} - \frac{1}{v^d}\right) = dS^s > 0$$

In both cases, skill supply upshifts lower the skill price, and raise the allocation such that

$$\begin{cases} \frac{dq}{dS^s} = \frac{v^d v^s}{v^d - v^s} < 0 \\ \frac{dS}{dS^s} = \frac{-v^s}{v^d - v^s} > 0. \end{cases}$$

Therefore,

$$\begin{cases} \frac{dq}{dS^s} = \frac{v^d v^s}{v^d - v^s} = -\frac{q}{S} \frac{1}{\epsilon_U + 1} = -\frac{q}{S} \Phi \\ \frac{dS}{dS^s} = \frac{-v^s}{v^d - v^s} = \frac{1}{\epsilon_U + 1} = \Phi \end{cases}$$

holds. Thus, one gets

$$\begin{cases} \frac{d \ln q}{d \ln S^s} = -\Phi < 0 \\ \frac{d \ln S}{d \ln S^s} = \Phi > 0. \end{cases}$$

Given the fixed demand curves, the skill price and allocation changes from supply curve shifts are characterized by Φ . In both cases, upshifts of skill supply curves decrease skill

prices.

Perfect elastic factors

Under imposed perfect elasticity of immigration-intensive aggregate skills and capital supply, supply curve shifts are characterized by changes in foreign-intensive skill price and capital rental price. The elasticities of aggregate factor allocations with respect to the rental prices are negative unity such that $\frac{d \ln \hat{S}}{d \ln \hat{q}} = \frac{d \ln M}{d \ln q^M} = -1$. With production PY kept, log-differentiate each factor demand function, $\hat{S} = \frac{\alpha \hat{\chi} PY}{\hat{q}}$, $R = \frac{\theta \alpha PY}{q^R}$ and $K = \frac{(1 - \alpha) PY}{q^K}$ immediately yields the results.

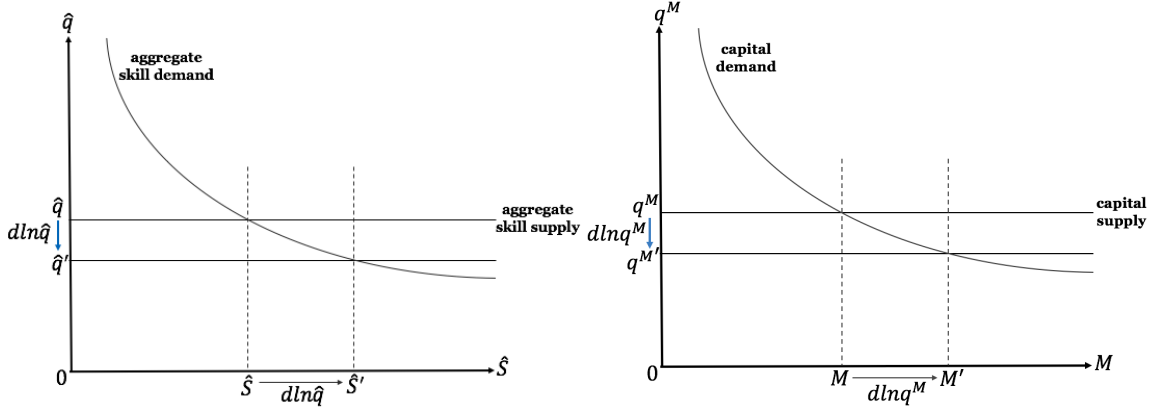


Figure A.4: The effect of downshifts in immigration-intensive aggregate skill supply curve (left) and aggregate capital supply curve (right)

A.5 Comparative Statics

The equilibrium response in response to immigration inflow is mostly symmetric across the sectors, but distinct in treatment of domestic and foreign skills.

Short run

Stage 1: immigration shock

The order of events is indexed by 10 and 11.

- As immigration flows in, an aggregate skill price drops. (*labor supply effect* of immigration)

$$\left(\frac{d \ln \hat{q}}{d \ln \hat{S}^F} \right)_{10} = \phi \left(\frac{d \ln \hat{q}^F}{d \ln \hat{S}^F} \right)_{10} = -\phi \hat{\Phi}^F < 0$$

- As the aggregate skill price decreases, a manager demands more skills, and the allocation rises.

$$\left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{10} = -\left(\frac{d \ln \widehat{q}}{d \ln \widehat{S}^F}\right)_{10}$$

- Production shifts.

$$\left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11} = \alpha \widehat{\chi} \left(\frac{d \ln S}{d \ln \widehat{S}^F}\right)_{10}$$

- Factor demand curve shifts from the production change.

$$\left(\frac{d \ln W}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln W}{d \ln Y}\right)}_{=1} \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11} = \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11}, \quad \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln \overline{W}}{d \ln Y}\right)}_{=1} \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11} = \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11}$$

$$\left(\frac{d \ln V^M}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln V^M}{d \ln Y}\right)}_{=1} \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11} = \left(\frac{d \ln Y}{d \ln \widehat{S}^F}\right)_{11} \quad (M \in \{R, K\})$$

- A factor demand shifts change the equilibrium, interacted with skill supply curve with a rate of $\underline{\Phi}, \overline{\Phi}$. (*scale effect* of immigration)

$$\left(\frac{d \ln q}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln q}{d \ln \underline{W}}\right)}_{=\underline{\Phi}} \left(\frac{d \ln \underline{W}}{d \ln \widehat{S}^F}\right)_{11} = \mathbb{I}(G=o) \underline{\Phi} \left(\frac{d \ln \underline{W}}{d \ln \widehat{S}^F}\right)_{11} \left(\frac{d \ln \underline{S}}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln \underline{S}}{d \ln \underline{W}}\right)}_{=1-\underline{\Phi}} \left(\frac{d \ln \underline{W}}{d \ln \widehat{S}^F}\right)_{11} = \begin{cases} = (1-\underline{\Phi}) \left(\frac{d \ln \underline{W}}{d \ln \widehat{S}^F}\right)_{11} & \text{(plant)} \\ = \left(\frac{d \ln \underline{W}}{d \ln \widehat{S}^F}\right)_{11} & \text{(office)} \end{cases}$$

$$\left(\frac{d \ln \overline{q}}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln \overline{q}}{d \ln \overline{W}}\right)}_{=\overline{\Phi}} \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} = \mathbb{I}(G=p) \overline{\Phi} \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} \left(\frac{d \ln \overline{S}}{d \ln \widehat{S}^F}\right)_{11} = \underbrace{\left(\frac{d \ln \overline{S}}{d \ln \overline{W}}\right)}_{=1-\overline{\Phi}} \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} = \begin{cases} = (1-\overline{\Phi}) \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} & \text{(plant)} \\ = \left(\frac{d \ln \overline{W}}{d \ln \widehat{S}^F}\right)_{11} & \text{(office)} \end{cases}$$

$$\left(\frac{d \ln M}{d \ln \widehat{S}^F}\right)_{11} = \left(\frac{d \ln V^M}{d \ln \widehat{S}^F}\right)_{11} \quad (M \in \{R, K\})$$

where $\mathbb{I}(G=g)$ is an indicator function of sector $g \in \{p, o\}$.

Stage 2 Labor adjustment

The order of events is indexed by 20, 21, 22 and 23.

- In the response of factor price changes, the task reallocation between routine- and non-routine skill occurs.

$$\left(\frac{d \psi}{d \ln \underline{S}^F}\right)_{20} = \left(\frac{d \psi}{d \ln \underline{q}}\right) \left\{ \underbrace{\left(\frac{d \ln \underline{q}}{d \ln \underline{S}^F}\right)_{10} + \left(\frac{d \ln \underline{q}}{d \ln \underline{S}^F}\right)_{11}}_{=0} \right\} + \left(\frac{d \psi}{d \ln \overline{q}}\right) \left(\frac{d \ln \overline{q}}{d \ln \underline{S}^F}\right)_{11} = C A^{H,L}(\psi)^{-1} \left\{ -\left(\frac{d \ln \underline{q}}{d \ln \underline{S}^F}\right)_{10} + \left(\frac{d \ln \overline{q}}{d \ln \underline{S}^F}\right)_{11} \right\}$$

$$(\frac{d\psi}{d\ln \widehat{S^F}})_{20} = (\frac{d\psi}{d\ln \underline{q}})(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}})_{11} + (\frac{d\psi}{d\ln \bar{q}})\underbrace{\{(\frac{d\ln \bar{q}}{d\ln \widehat{S^F}})_{10} + (\frac{d\ln \bar{q}}{d\ln \widehat{S^F}})_{11}\}}_{=0} = CA^{H,L}(\psi)^{-1}\{(\frac{d\ln \bar{q}}{d\ln \widehat{S^F}})_{10} - (\frac{d\ln \underline{q}}{d\ln \widehat{S^F}})_{11}\}$$

- As a result of task reallocation, skill demand curve shifts.

$$(\frac{d\ln W}{d\ln \widehat{S^F}})_{20} = (\frac{d\ln(\psi - \theta)}{d\ln \widehat{S^F}})_{20} = \frac{1}{\underline{\chi}}(\frac{d\psi}{d\ln \widehat{S^F}})_{20}, \quad (\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} = (\frac{d\ln(1 - \psi)}{d\ln \widehat{S^F}})_{20} = \frac{-1}{\bar{\chi}}(\frac{d\psi}{d\ln \widehat{S^F}})_{20}$$

- The skill price and allocation shifts. Also, the capital allocation shifts. (*occupational substitution effect* of immigration)

$$(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}})_{20} = (\underbrace{\frac{d\ln \underline{S}}{d\ln \widehat{W}}}_{\Phi})(\frac{d\ln \underline{W}}{d\ln \widehat{S^F}})_{20} = \mathbb{I}(G = o) \Phi (\frac{d\ln \underline{W}}{d\ln \widehat{S^F}})_{20} \quad (\frac{d\ln \underline{S}}{d\ln \widehat{S^F}})_{20} = (\underbrace{\frac{d\ln \underline{S}}{d\ln \bar{W}}}_{=1-\Phi})(\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} \begin{cases} = (\frac{d\ln \underline{W}}{d\ln \widehat{S^F}})_{20} & \text{(plant)} \\ = (1 - \Phi)(\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} & \text{(office)} \end{cases}$$

$$(\frac{d\ln \bar{q}}{d\ln \widehat{S^F}})_{20} = (\underbrace{\frac{d\ln \bar{q}}{d\ln \bar{W}}}_{=\bar{\Phi}})(\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} = \mathbb{I}(G = p) \bar{\Phi} (\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} \quad (\frac{d\ln \bar{S}}{d\ln \widehat{S^F}})_{20} = (\underbrace{\frac{d\ln \bar{S}}{d\ln \bar{W}}}_{=1-\bar{\Phi}})(\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} \begin{cases} = (1 - \bar{\Phi})(\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} & \text{(plant)} \\ = (\frac{d\ln \bar{W}}{d\ln \widehat{S^F}})_{20} & \text{(office)} \end{cases}$$

- Production changes from factor employment changes due to task reallocation.

$$(\frac{d\ln Y}{d\ln \widehat{S^F}})_{20} = (\frac{d\ln Y}{d\ln \underline{S}})_{20}(\frac{d\ln \underline{S}}{d\ln \widehat{S^F}})_{20} + (\frac{d\ln Y}{d\ln \bar{S}})_{20}(\frac{d\ln \bar{S}}{d\ln \widehat{S^F}})_{20} = \alpha\{(\psi - \theta)(\frac{d\ln \underline{S}}{d\ln \widehat{S^F}})_{20} + (1 - \psi)(\frac{d\ln \bar{S}}{d\ln \widehat{S^F}})_{20}\} = 0$$

- Equipment shifts as

$$(\frac{d\ln K}{d\ln \widehat{S^F}})_{20} = (\underbrace{\frac{d\ln K}{d\ln \bar{V}}}_{=1})(\frac{d\ln \bar{V}^K}{d\ln \widehat{S^F}})_{20} = (\frac{d\ln Y}{d\ln \widehat{S^F}})_{20}$$

Domestic and foreign skill adjustment

- The domestic and foreign skill demand curve shifts, because the demand of aggregate routine (non-routine) skills changes.

$$(\frac{d\ln \widehat{W^e}}{d\ln \widehat{S^F}})_{21} = (\frac{d\ln \widehat{S}}{d\ln \widehat{S^F}})_{11} + (\frac{d\ln \widehat{S}}{d\ln \widehat{S^F}})_{20} > 0$$

- The domestic and foreign skill prices and allocations shift.

$$(\frac{d\ln \widehat{q^e}}{d\ln \widehat{S^F}})_{21} = \widehat{\Phi^e}(\frac{d\ln \widehat{W^e}}{d\ln \widehat{S^F}})_{21}, \quad (\frac{d\ln \widehat{S^e}}{d\ln \widehat{S^F}})_{21} = (1 - \widehat{\Phi^e})(\frac{d\ln \widehat{W^e}}{d\ln \widehat{S^F}})_{21}$$

$$\begin{aligned}
\left(\frac{d \ln \widehat{q}}{d \ln \widehat{S}^F}\right)_{21} &= \phi \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{21} + (1 - \phi) \left(\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F}\right)_{21} = \underbrace{\{\phi \widehat{\Phi}^F + (1 - \phi) \widehat{\Phi}^D\}}_{= \widehat{\Phi}} \left\{ \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{11} + \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{20} \right\} \\
&= \widehat{\Phi} \{ \alpha \widehat{\chi} \phi \widehat{\Phi}^F \pm \frac{1}{\widehat{\chi}} \left(\frac{d \psi}{d \ln \widehat{S}^F}\right)_{20} \}
\end{aligned}$$

$\pm$ applies to plant and office sector, respectively.

- The occupation manager reallocates the tasks between domestic and foreign groups in response to the current skill prices.

$$\begin{aligned}
\left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{21} &= \underbrace{\frac{d \phi}{d \ln \widehat{S}^F}}_{<0} \left\{ \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{10} + \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{21} \right\} + \underbrace{\frac{d \phi}{d \ln \widehat{q}^D}}_{>0} \left(\frac{d \widehat{q}^D}{d \ln \widehat{S}^F}\right)_{21} \\
&= C A^{F,D} (\phi)^{-1} \left[\left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{10} + (\widehat{\Phi}^F - \widehat{\Phi}^D) \left\{ \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{11} + \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{20} \right\} \right]
\end{aligned}$$

- The domestic and foreign skill demand curve shifts, because of the task reallocation.

$$\left(\frac{d \ln \widehat{W}^F}{d \ln \widehat{S}^F}\right)_{22} = \frac{1}{\phi} \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{21} > 0, \quad \left(\frac{d \ln \widehat{W}^D}{d \ln \widehat{S}^F}\right)_{22} = \frac{-1}{1 - \phi} \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{21} < 0$$

- The equilibrium skill prices and employments change. (*foreign substitution effect* of immigration)

$$\begin{aligned}
\left(\frac{d \ln \widehat{q}^e}{d \ln \widehat{S}^F}\right)_{22} &= \underbrace{\frac{d \ln \widehat{q}^e}{d \ln \widehat{W}^e}}_{= \widehat{\Phi}^e} \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{22}, \quad \left(\frac{d \ln \widehat{S}^e}{d \ln \widehat{S}^F}\right)_{22} = \underbrace{\frac{d \ln \widehat{S}^e}{d \ln \widehat{W}^e}}_{= 1 - \widehat{\Phi}^e} \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{22} \\
\left(\frac{d \ln \widehat{q}}{d \ln \widehat{S}^F}\right)_{22} &= \phi \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{22} + (1 - \phi) \left(\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F}\right)_{22} = (\widehat{\Phi}^F - \widehat{\Phi}^D) \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{21}
\end{aligned}$$

Immigration and Labor adjustments

Following the analytical steps so far, the intermediate results in the short run are derived. Task reallocation in the short run is given as follows:

$$\begin{aligned}
\left(\frac{d \psi}{d \ln \widehat{S}^F}\right)_{short} &= \left(\frac{d \psi}{d \ln \widehat{S}^F}\right)_{20} = \pm \alpha C A^{H,L} (\psi)^{-1} \left\{ - \left(\frac{d \ln \widehat{q}}{d \ln \widehat{S}^F}\right)_{10} + \left(\frac{d \ln \widehat{q}}{d \ln \widehat{S}^F}\right)_{11} \right\} = \alpha C A^{H,L} (\psi)^{-1} \{ \phi \widehat{\Phi}^F + \widetilde{\Phi} \alpha \widehat{\chi} \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{10} \} \\
&= \pm \alpha C A^{H,L} (\psi)^{-1} \{ \widetilde{\Phi} \alpha \widehat{\chi} + 1 \} \phi \widehat{\Phi}^F = \begin{cases} \alpha C A^{H,L} (\psi)^{-1} \{ \widetilde{\Phi} \alpha (\psi - \theta) + 1 \} \phi \widehat{\Phi}^F & \text{(plant)} \\ -\alpha C A^{H,L} (\psi)^{-1} \{ \widetilde{\Phi} \alpha (1 - \psi) + 1 \} \phi \widehat{\Phi}^F & \text{(office)} \end{cases}
\end{aligned}$$

$$\begin{aligned}
\left(\frac{d\phi}{d\ln \widehat{S^F}}\right)_{short} &= \left(\frac{d\phi}{d\ln \widehat{S^F}}\right)_{21} = CA^{F,D}(\phi)^{-1} \left[-\left(\frac{d\ln \widehat{q^F}}{d\ln \widehat{S^F}}\right)_{10} + (\widehat{\Phi^F} - \widehat{\Phi^D}) \left\{ \left(\frac{d\ln \widehat{S}}{d\ln \widehat{S^F}}\right)_{11} + \left(\frac{d\ln \widehat{S}}{d\ln \widehat{S^F}}\right)_{20} \right\} \right] \\
&= CA^{F,D}(\phi)^{-1} \left[\underbrace{\phi \widehat{\Phi^F}}_{\text{labor supply effect}} + (\widehat{\Phi^F} - \widehat{\Phi^D}) \left\{ \underbrace{\alpha \widehat{\chi} \widehat{\Phi^F}}_{\text{scale effect}} \pm \underbrace{\frac{1}{\widehat{\chi}} \left(\frac{d\psi}{d\ln \widehat{S^F}}\right)_{short}}_{\text{occupational substitution effect}} \right\} \right] \\
&= \begin{cases} CA^{F,D}(\phi)^{-1} [\phi \underline{\Phi^F} + (\underline{\Phi^F} - \underline{\Phi^D}) \{ \alpha(\psi - \theta) \phi \underline{\Phi^F} + \frac{1}{\psi - \theta} \left(\frac{d\psi}{d\ln \underline{S^F}}\right)_{20} \}] & \text{(plant)} \\ CA^{F,D}(\phi)^{-1} [\phi \overline{\Phi^F} + (\overline{\Phi^F} - \overline{\Phi^D}) \{ \alpha(1 - \psi) \phi \overline{\Phi^F} + \frac{-1}{1 - \psi} \left(\frac{d\psi}{d\ln \overline{S^F}}\right)_{20} \}] & \text{(office)} \end{cases}
\end{aligned}$$

$\pm$ applies to plant and office sector, respectively.

Immigration and Routine skill price

The impact of immigration to routine skill price without automation adjustment is given as follows:

$$\begin{aligned}
\left(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}}\right)_{short} &= \begin{cases} \left(\frac{d\ln \underline{q}}{d\ln \underline{S^F}}\right)_{10} + \left(\frac{d\ln \underline{q}}{d\ln \underline{S^F}}\right)_{21} + \left(\frac{d\ln \underline{q}}{d\ln \underline{S^F}}\right)_{22} & \text{(plant)} \\ \left(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}}\right)_{11} + \left(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}}\right)_{20} & \text{(office)} \end{cases} \\
&= \begin{cases} \underbrace{-\phi \underline{\Phi^F}}_{\text{labor supply effect}} + \underbrace{\underline{\Phi} \{ \alpha(\psi - \theta) \phi \underline{\Phi^F} + \frac{1}{\psi - \theta} \left(\frac{d\psi}{d\ln \underline{S^F}}\right)_{20} \}}_{\text{scale effect}} + \underbrace{\frac{1}{\psi - \theta} \left(\frac{d\psi}{d\ln \underline{S^F}}\right)_{20}}_{\text{occupational substitution effect}} + \underbrace{(\underline{\Phi^F} - \underline{\Phi^D}) \left(\frac{d\phi}{d\ln \underline{S^F}}\right)_{21}}_{\text{foreign substitution effect}} & \text{(plant)} \\ \underbrace{\underline{\Phi} \alpha(1 - \psi) \phi \overline{\Phi^F}}_{\text{scale effect}} + \underbrace{\underline{\Phi} \frac{1}{\psi - \theta} \left(\frac{d\psi}{d\ln \underline{S^F}}\right)_{20}}_{\text{occupational substitution effect}} & \text{(office)} \end{cases} \\
&= \underline{\Phi} \{ \underbrace{\alpha \widehat{\chi} \phi \widehat{\Phi^F}}_{\text{scale effect}} + \underbrace{\frac{1}{\widehat{\chi}} \left(\frac{d\psi}{d\ln \widehat{S^F}}\right)_{20}}_{\text{occupational substitution effect}} \} \\
&\quad + \mathbb{I}(G = p) \left\{ \underbrace{-\phi \underline{\Phi^F}}_{\text{labor supply effect}} + \underbrace{(\underline{\Phi^F} - \underline{\Phi^D}) \left(\frac{d\phi}{d\ln \underline{S^F}}\right)_{short}}_{\text{foreign substitution effect}} \right\}
\end{aligned}$$

Long run

Stage 3: Automation adjustment

The order of events is indexed by 30 and 31.

- The task reallocation between routine-skill and robots occurs.

$$\begin{aligned}
\left(\frac{d\theta}{d\ln \widehat{S^F}}\right)_{30} &= \underbrace{\left(\frac{d\theta}{d\ln \underline{q}}\right)}_{= CA^{L,R}(\theta)^{-1}} \left(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}}\right)_{short} \\
&= CA^{L,R}(\theta)^{-1} \left(\frac{d\ln \underline{q}}{d\ln \widehat{S^F}}\right)_{short}
\end{aligned}$$

- The skill/robot demand curve, characterized by factor income, shifts.

$$\left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} = \left(\frac{d \ln(\psi - \theta)}{d \ln \widehat{S^F}}\right)_{30} = \frac{-1}{\psi - \theta} \left(\frac{d \theta}{d \ln \widehat{S^F}}\right)_{30}, \quad \left(\frac{d \ln V^R}{d \ln \widehat{S^F}}\right)_{30} = \left(\frac{d \ln \theta}{d \ln \widehat{S^F}}\right)_{30} = \frac{1}{\theta} \left(\frac{d \theta}{d \ln \widehat{S^F}}\right)_{30}$$

- The skill price, allocation and capital allocation shifts. (*displacement effect* of automation)

$$\begin{aligned} \left(\frac{d \ln q}{d \ln \widehat{S^F}}\right)_{30} &= \underbrace{\left(\frac{d \ln S}{d \ln \widehat{S^F}}\right)}_{\Phi} \left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} = \mathbb{I}(G = o) \Phi \left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} \left(\frac{d \ln S}{d \ln \widehat{S^F}}\right)_{30} = \underbrace{\left(\frac{d \ln S}{d \ln \widehat{S^F}}\right)}_{=1-\Phi} \left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} = \begin{cases} \left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} & \text{(plant)} \\ (1 - \Phi) \left(\frac{d \ln W}{d \ln \widehat{S^F}}\right)_{30} & \text{(office)} \end{cases} \\ \left(\frac{d \ln R}{d \ln \widehat{S^F}}\right)_{30} &= \underbrace{\left(\frac{d \ln R}{d \ln \widehat{S^F}}\right)}_{=1} \left(\frac{d \ln V^R}{d \ln \widehat{S^F}}\right)_{30} \end{aligned}$$

- Production changes from factor employment changes via task reallocation. (*productivity effect* of automation)

$$\begin{aligned} \left(\frac{d \ln Y}{d \ln \widehat{S^F}}\right)_{30} &= \left(\frac{d \ln Y}{d \ln \underline{S}}\right)_{30} \left(\frac{d \ln \underline{S}}{d \ln \widehat{S^F}}\right)_{30} + \left(\frac{d \ln Y}{d \ln R}\right)_{30} \left(\frac{d \ln R}{d \ln \widehat{S^F}}\right)_{30} = \alpha \left\{ (\psi - \theta) \left(\frac{d \ln S}{d \ln \widehat{S^F}}\right)_{30} + \theta \left(\frac{d \ln R}{d \ln \widehat{S^F}}\right)_{30} \right\} \\ &= \alpha \left\{ (\psi - \theta) \frac{-1}{\psi - \theta} \left(\frac{d \theta}{d \ln \widehat{S^F}}\right)_{30} + \theta \frac{1}{\theta} \left(\frac{d \theta}{d \ln \widehat{S^F}}\right)_{30} \right\} = 0 \end{aligned}$$

Due to interior optimality of task reallocation, this effect is set to 0 in analytical formula by the envelope theorem.

Domestic and foreign skill adjustment

- In plant sector, the domestic and foreign skill demand curve shifts, because the demand of aggregate routine skills changes. In office sector, automation does not directly affect the non-routine skill demands.

$$\left(\frac{d \ln \underline{W}^e}{d \ln \underline{S}^F}\right)_{31} = \left(\frac{d \ln \underline{S}}{d \ln \underline{S}^F}\right)_{30} > 0 \text{ (plant)} \quad \left(\frac{d \ln \overline{W}^e}{d \ln \overline{S}^F}\right)_{31} = \left(\frac{d \ln \overline{S}}{d \ln \overline{S}^F}\right)_{30} = 0 \text{ (office)}$$

- The domestic and foreign skill prices and allocations shift.

$$\left(\frac{d \ln \widehat{q}^e}{d \ln \widehat{S^F}}\right)_{31} = \widehat{\Phi}^e \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S^F}}\right)_{31}, \quad \left(\frac{d \ln \widehat{S}^e}{d \ln \widehat{S^F}}\right)_{31} = (1 - \widehat{\Phi}^e) \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S^F}}\right)_{31}$$

$$\left(\frac{d \ln \widehat{q}}{d \ln \widehat{S^F}}\right)_{31} = \phi \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S^F}}\right)_{31} + (1 - \phi) \left(\frac{d \ln \widehat{q}^D}{d \ln \widehat{S^F}}\right)_{31} = \underbrace{\{\phi \widehat{\Phi}^F + (1 - \phi) \widehat{\Phi}^D\}}_{=\widehat{\Phi}} \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S^F}}\right)_{30} = \mathbb{I}(G = p) \frac{-\Phi}{\psi - \theta} \left(\frac{d \theta}{d \ln \widehat{S^F}}\right)_{30}$$

- As routine skill price drops, a manager demands more routine (or non-routine) skills, and the equilibrium skill allocation rises and production shifts.

$$\begin{cases} (\frac{d \ln \underline{S}}{d \ln \underline{S}^F})_{31} = -(\frac{d \ln \underline{q}}{d \ln \underline{S}^F})_{31} & \text{(plant)} \\ (\frac{d \ln \underline{S}}{d \ln \underline{S}^F})_{32} = -(\frac{d \ln \underline{q}}{d \ln \underline{S}^F})_{30} & \text{(office)} \end{cases} \quad (\frac{d \ln Y}{d \ln \underline{S}^F})_{32} = \begin{cases} \alpha \underline{\chi} (\frac{d \ln \underline{S}}{d \ln \underline{S}^F})_{31} & \text{(plant)} \\ \alpha \underline{\chi} (\frac{d \ln \underline{S}}{d \ln \underline{S}^F})_{32} & \text{(office)} \end{cases}$$

- Demand curve shifts from the production change.

$$(\frac{d \ln W}{d \ln \underline{S}^F})_{32} = (\frac{d \ln W}{d \ln Y}) \underbrace{(\frac{d \ln Y}{d \ln \underline{S}^F})_{32}}_{=1} = (\frac{d \ln Y}{d \ln \underline{S}^F})_{32}, \quad (\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32} = (\frac{d \ln \bar{W}}{d \ln Y}) \underbrace{(\frac{d \ln Y}{d \ln \underline{S}^F})_{32}}_{=1} = (\frac{d \ln Y}{d \ln \underline{S}^F})_{32}$$

$$(\frac{d \ln V^M}{d \ln \underline{S}^F})_{32} = (\frac{d \ln V^M}{d \ln Y}) \underbrace{(\frac{d \ln Y}{d \ln \underline{S}^F})_{32}}_{=1} = (\frac{d \ln Y}{d \ln \underline{S}^F})_{32} \quad (M \in \{R, K\})$$

- A rising demand of routine or non-routine skills changes the equilibrium, interacted with skill supply curve with a ratio of $\underline{\Phi}, \bar{\Phi}$. (*productivity effect* of automation)

$$(\frac{d \ln \underline{q}}{d \ln \underline{S}^F})_{32} = (\frac{d \ln \underline{q}}{d \ln \underline{W}}) \underbrace{(\frac{d \ln \underline{W}}{d \ln \underline{S}^F})_{32}}_{=\underline{\Phi}} = \mathbb{I}(G=o) \underline{\Phi} (\frac{d \ln \underline{W}}{d \ln \underline{S}^F})_{32} (\frac{d \ln \underline{S}}{d \ln \underline{S}^F})_{32} = (\frac{d \ln \underline{S}}{d \ln \underline{W}}) \underbrace{(\frac{d \ln \underline{W}}{d \ln \underline{S}^F})_{32}}_{=1-\underline{\Phi}} \begin{cases} = (\frac{d \ln \underline{W}}{d \ln \underline{S}^F})_{32} & \text{(plant)} \\ = (1-\underline{\Phi}) (\frac{d \ln \underline{W}}{d \ln \underline{S}^F})_{32} & \text{(office)} \end{cases}$$

$$(\frac{d \ln \bar{q}}{d \ln \underline{S}^F})_{32} = (\frac{d \ln \bar{q}}{d \ln \bar{W}}) \underbrace{(\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32}}_{=\bar{\Phi}} = \mathbb{I}(G=p) \bar{\Phi} (\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32} (\frac{d \ln \bar{S}}{d \ln \underline{S}^F})_{32} = (\frac{d \ln \bar{S}}{d \ln \bar{W}}) \underbrace{(\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32}}_{=1-\bar{\Phi}} \begin{cases} = (1-\bar{\Phi}) (\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32} & \text{(plant)} \\ = (\frac{d \ln \bar{W}}{d \ln \underline{S}^F})_{32} & \text{(office)} \end{cases}$$

$$(\frac{d \ln M}{d \ln \underline{S}^F})_{32} = (\frac{d \ln V^M}{d \ln \underline{S}^F})_{32} \quad (M \in \{R, K\})$$

Foreign skill adjustment

- In both sector, the foreign and domestic skill demand curve shifts, due to the changing demand of aggregate routine skills.

$$(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F})_{33} = (\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F})_{32}$$

- The foreign and domestic skill prices and employments are adjusted.

$$(\frac{d \ln \widehat{q}^e}{d \ln \widehat{S}^F})_{33} = \widehat{\Phi}^e (\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F})_{33}, \quad (\frac{d \ln \widehat{S}^e}{d \ln \widehat{S}^F})_{33} = (1 - \widehat{\Phi}^e) (\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F})_{33}$$

$$\begin{aligned} (\frac{d \ln \widehat{q}}{d \ln \underline{S}^F})_{33} &= \phi (\frac{d \ln \widehat{q}^F}{d \ln \underline{S}^F})_{33} + (1 - \phi) (\frac{d \ln \widehat{q}^D}{d \ln \underline{S}^F})_{33} = \underbrace{\{\phi \widehat{\Phi}^F + (1 - \phi) \widehat{\Phi}^D\}}_{=\widehat{\Phi}} (\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F})_{33} \\ &= \widehat{\Phi} \alpha (\psi - \theta) \frac{\Phi}{\psi - \theta} (\frac{d \theta}{d \ln \underline{S}^F})_{30} = \widehat{\Phi} \alpha \Phi (\frac{d \theta}{d \ln \underline{S}^F})_{30} \end{aligned}$$

Following the analytical steps so far, the intermediate results in the long run are derived as follows.

Automation and skill prices

Proof.

Though the formulation of the process is asymmetric across sectors, the final consequences are same. In plant, the effect to the routine foreign and domestic skill price is given by

$$\begin{aligned}\frac{d \ln q^e}{d\theta} &= \underbrace{\left(\frac{d \ln q^e}{d\theta}\right)_{31}}_{\text{displacement effect}} + \underbrace{\left(\frac{d \ln q^e}{d\theta}\right)_{33}}_{\text{productivity effect}} = \underline{\Phi}^e \left(\frac{d \ln S}{d\theta}\right)_{30} + \underline{\Phi}^e \alpha \underline{\chi} \left(\frac{d \ln S}{d\theta}\right)_{31} \\ &= \underline{\Phi}^e \left\{ \frac{-1}{\psi - \theta} + \alpha(\psi - \theta) \underline{\Phi} \frac{1}{\psi - \theta} \right\} = \underline{\Phi}^e \left\{ \frac{-1}{\psi - \theta} + \alpha \underline{\Phi} \right\}.\end{aligned}$$

Thus, the effect to the aggregate routine skill price is given by

$$\frac{d \ln q}{d\theta} = \phi \frac{d \ln q^F}{d\theta} + (1 - \phi) \frac{d \ln q^D}{d\theta} = \underbrace{(\phi \underline{\Phi}^F + (1 - \phi) \underline{\Phi}^D)}_{=\underline{\Phi}} \left\{ \frac{-1}{\psi - \theta} + \alpha \underline{\Phi} \right\}. \quad (\text{A.10})$$

The effect to the non-routine skill price is given by

$$\begin{aligned}\frac{d \ln \bar{q}}{d\theta} &= \underbrace{\left(\frac{d \ln \bar{q}}{d\theta}\right)_{32}}_{\text{productivity effect}} = \bar{\Phi} \left(\frac{d \ln \bar{W}}{d\theta}\right)_{32} = \bar{\Phi} \left(\frac{d \ln Y}{d\theta}\right)_{32} = \bar{\Phi} \alpha (\psi - \theta) \left(\frac{d \ln S}{d\theta}\right)_{31} \\ &= \bar{\Phi} \alpha (\psi - \theta) \left(-\left(\frac{d \ln q}{d\theta}\right)_{31}\right) = \bar{\Phi} \alpha (\psi - \theta) \underline{\Phi} \frac{1}{\psi - \theta} = \bar{\Phi} \alpha \underline{\Phi}.\end{aligned} \quad (\text{A.11})$$

In office, the effect to the aggregate routine skill price is given by

$$\begin{aligned}\frac{d \ln q}{d\theta} &= \underbrace{\left(\frac{d \ln q}{d\theta}\right)_{31}}_{\text{displacement effect}} + \underbrace{\left(\frac{d \ln q}{d\theta}\right)_{32}}_{\text{productivity effect}} = \underline{\Phi} \left(\frac{d \ln S}{d\theta}\right)_{30} + \underline{\Phi} \left(\frac{d \ln W}{d\theta}\right)_{32} = \underline{\Phi} \left(\frac{d \ln S}{d\theta}\right)_{30} + \underline{\Phi} \alpha \underline{\chi} \left(\frac{d \ln S}{d\theta}\right)_{30} \\ &= \underline{\Phi} \frac{-1}{\psi - \theta} + \underline{\Phi} \alpha (\psi - \theta) \underbrace{\left\{ -\left(\frac{d \ln q}{d\theta}\right)_{30} \right\}}_{\substack{1 \\ = \frac{1}{\psi - \theta}}} = \underline{\Phi} \left(\frac{-1}{\psi - \theta} + \underline{\Phi} \alpha \right).\end{aligned} \quad (\text{A.12})$$

The effect to the non-routine foreign and domestic skill price is given by

$$\frac{d \ln \bar{q}^e}{d\theta} = \underbrace{\left(\frac{d \ln \bar{q}^e}{d\theta}\right)_{33}}_{\text{productivity effect}} = \bar{\Phi}^e \left(\frac{d \ln \bar{S}}{d\theta}\right)_{32} = \bar{\Phi}^e \alpha (\psi - \theta) \left(\frac{d \ln S}{d\theta}\right)_{32} = \bar{\Phi}^e \alpha (\psi - \theta) \underline{\Phi} \frac{1}{\psi - \theta} = \bar{\Phi}^e \alpha \underline{\Phi}.$$

Thus, the effect to the aggregate non-routine skill price is given by

$$\frac{d \ln \bar{q}}{d \theta} = \phi \frac{d \ln \bar{q}^F}{d \theta} + (1 - \phi) \frac{d \ln \bar{q}^D}{d \theta} = \bar{\Phi} \alpha \underline{\Phi}. \quad (\text{A.13})$$

(A.10), (A.11), (A.12) and (A.13) yield the results in the main text.

Stage 4: Labor adjustment

- The task reallocation between routine- and non-routine skill occurs.

$$\left(\frac{d \psi}{d \ln \underline{S}^F} \right)_{40} = C A^{H,L}(\psi)^{-1} \left\{ \underbrace{- \left(\frac{d \ln q}{d \ln \underline{S}^F} \right)_{31}}_{\text{displacement effect}} - \underbrace{\left(\frac{d \ln q}{d \ln \underline{S}^F} \right)_{32}}_{\text{productivity effect}} + \underbrace{\left(\frac{d \ln q}{d \ln \underline{S}^F} \right)_{22}}_{\text{foreign substitution effect}} \right\} \text{ (plant)}$$

$$\left(\frac{d \psi}{d \ln \bar{S}^F} \right)_{40} = C A^{H,L}(\psi)^{-1} \left\{ - \underbrace{\left(\frac{d \ln q}{d \ln \bar{S}^F} \right)_{30}}_{\text{displacement effect}} - \underbrace{\left(\frac{d \ln q}{d \ln \bar{S}^F} \right)_{32}}_{\text{productivity effect}} + \underbrace{\left(\frac{d \ln \bar{q}}{d \ln \bar{S}^F} \right)_{22}}_{\text{foreign substitution effect}} \right\} \text{ (office)}$$

- As a result of task reallocation, skill demand curve, characterized by labor income, shifts.

$$\left(\frac{d \ln W}{d \ln \underline{S}^F} \right)_{40} = \left(\frac{d \ln(\psi - \theta)}{d \ln \underline{S}^F} \right)_{40} = \frac{1}{\psi - \theta} \left(\frac{d \psi}{d \ln \underline{S}^F} \right)_{40}, \quad \left(\frac{d \ln \bar{W}}{d \ln \bar{S}^F} \right)_{40} = \left(\frac{d \ln(1 - \psi)}{d \ln \bar{S}^F} \right)_{40} = \frac{-1}{1 - \psi} \left(\frac{d \psi}{d \ln \bar{S}^F} \right)_{40}, \quad \left(\frac{d \ln V^R}{d \ln \bar{S}^F} \right)_{40} = 0$$

- The equilibrium skill price and employment shifts. Also, the equilibrium capital level shifts.

$$\left(\frac{d \ln q}{d \ln \underline{S}^F} \right)_{40} = \underbrace{\left(\frac{d \ln \underline{S}}{d \ln \underline{W}} \right)}_{\underline{\Phi}} \left(\frac{d \ln W}{d \ln \underline{S}^F} \right)_{40} = \mathbb{I}(G = o) \underline{\Phi} \left(\frac{d \ln W}{d \ln \bar{S}^F} \right)_{40} \left(\frac{d \ln \underline{S}}{d \ln \bar{S}^F} \right)_{40} = \underbrace{\left(\frac{d \ln \underline{S}}{d \ln \bar{W}} \right)}_{= 1 - \underline{\Phi}} \left(\frac{d \ln W}{d \ln \bar{S}^F} \right)_{40} \begin{cases} = \left(\frac{d \ln W}{d \ln \underline{S}^F} \right)_{40} & \text{(plant)} \\ = (1 - \underline{\Phi}) \left(\frac{d \ln W}{d \ln \bar{S}^F} \right)_{40} & \text{(office)} \end{cases}$$

$$\left(\frac{d \ln \bar{q}}{d \ln \bar{S}^F} \right)_{40} = \underbrace{\left(\frac{d \ln \bar{q}}{d \ln \bar{W}} \right)}_{=\bar{\Phi}} \left(\frac{d \ln \bar{W}}{d \ln \bar{S}^F} \right)_{40} = \mathbb{I}(G = o) \bar{\Phi} \left(\frac{d \ln \bar{W}}{d \ln \underline{S}^F} \right)_{40} \left(\frac{d \ln \bar{S}}{d \ln \underline{S}^F} \right)_{40} = \underbrace{\left(\frac{d \ln \bar{S}}{d \ln \bar{W}} \right)}_{= 1 - \bar{\Phi}} \left(\frac{d \ln \bar{W}}{d \ln \underline{S}^F} \right)_{40} \begin{cases} = (1 - \bar{\Phi}) \left(\frac{d \ln \bar{W}}{d \ln \underline{S}^F} \right)_{40} & \text{(plant)} \\ = \left(\frac{d \ln \bar{W}}{d \ln \bar{S}^F} \right)_{40} & \text{(office)} \end{cases}$$

- Production changes from factor allocation changes from task reallocation.

$$\left(\frac{d \ln Y}{d \ln \bar{S}^F} \right)_{40} = \left(\frac{d \ln Y}{d \ln \underline{S}} \right) \left(\frac{d \ln \underline{S}}{d \ln \bar{S}^F} \right)_{40} + \left(\frac{d \ln Y}{d \ln \bar{S}} \right) \left(\frac{d \ln \bar{S}}{d \ln \bar{S}^F} \right)_{40} = \alpha \{ (\psi - \theta) \left(\frac{d \ln \underline{S}}{d \ln \bar{S}^F} \right)_{40} + (1 - \psi) \left(\frac{d \ln \bar{S}}{d \ln \bar{S}^F} \right)_{40} \} = 0$$

- Equipment shifts.

$$\left(\frac{d \ln K}{d \ln \bar{S}^F} \right)_{40} = \underbrace{\left(\frac{d \ln K}{d \ln \bar{V}} \right)}_{= 1} \left(\frac{d \ln \bar{V}}{d \ln \bar{S}^F} \right)_{40} = \left(\frac{d \ln Y}{d \ln \bar{S}^F} \right)_{40}$$

Foreign skill adjustment

- The domestic and foreign skill demand curve shifts, because the aggregate routine skill demand gets smaller as a feedback.

$$\left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{41} = \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{40} < 0$$

- The domestic and foreign skill prices and allocations upshift.

$$\left(\frac{d \ln \widehat{q}^e}{d \ln \widehat{S}^F}\right)_{41} = \widehat{\Phi}^e \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{41}, \quad \left(\frac{d \ln \widehat{S}^e}{d \ln \widehat{S}^F}\right)_{41} = (1 - \widehat{\Phi}^e) \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{41}$$

- The occupation manager reallocates the sub-tasks in response to skill prices.

$$\begin{aligned} \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{41} &= \underbrace{\frac{d \phi}{d \ln q^F}}_{<0} \left\{ \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{31} + \left(\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F}\right)_{41} \right\} + \underbrace{\frac{d \phi}{d \ln q^D}}_{>0} \left\{ \left(\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F}\right)_{31} + \left(\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F}\right)_{41} \right\} \\ &= -CA^{F,D}(\phi)^{-1} \left[-\widehat{\Phi}^F \left\{ \left(\frac{d \ln \widehat{W}^F}{d \ln \widehat{S}^F}\right)_{31} + \left(\frac{d \ln \widehat{W}^F}{d \ln \widehat{S}^F}\right)_{41} \right\} + \widehat{\Phi}^D \left\{ \left(\frac{d \ln \widehat{W}^D}{d \ln \widehat{S}^F}\right)_{31} + \left(\frac{d \ln \widehat{W}^D}{d \ln \widehat{S}^F}\right)_{41} \right\} \right] \\ &= -CA^{F,D}(\phi)^{-1} (\widehat{\Phi}^D - \widehat{\Phi}^F) \left\{ \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{30} + \left(\frac{d \ln \widehat{S}}{d \ln \widehat{S}^F}\right)_{40} \right\} \end{aligned}$$

- The domestic and foreign skill demand curve shifts by sub-task reallocation.

$$\left(\frac{d \ln \widehat{W}^F}{d \ln \widehat{S}^F}\right)_{42} = \frac{1}{\phi} \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{41} > 0, \quad \left(\frac{d \ln \widehat{W}^D}{d \ln \widehat{S}^F}\right)_{42} = \frac{-1}{1 - \phi} \left(\frac{d \phi}{d \ln \widehat{S}^F}\right)_{41}$$

- The skill prices and allocations change.

$$\left(\frac{d \ln \widehat{q}^e}{d \ln \widehat{S}^F}\right)_{42} = \underbrace{\frac{d \ln \widehat{q}^e}{d \ln \widehat{W}^e}}_{=\widehat{\Phi}^e} \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{42}, \quad \left(\frac{d \ln \widehat{S}^e}{d \ln \widehat{S}^F}\right)_{42} = \underbrace{\frac{d \ln \widehat{S}^e}{d \ln \widehat{W}^e}}_{=1-\widehat{\Phi}^e} \left(\frac{d \ln \widehat{W}^e}{d \ln \widehat{S}^F}\right)_{42}$$

A.6 Analytical Formula of Elasticities with Respect to Immigration

Proposition 4 [Three Elasticities with respect to Immigration]

Proof.

- elasticity of robots

$$(\frac{d \ln R}{d \ln \widehat{S}^F})_{short} = (\frac{d \ln R}{d \ln \widehat{S}^F})_{11} = \alpha \widehat{\chi} \phi \widehat{\Phi}^F = \begin{cases} \alpha(\psi - \theta) \phi \widehat{\Phi}^F & \text{(plant)} \\ \alpha(1 - \psi) \phi \widehat{\Phi}^F & \text{(office)} \end{cases} \quad (\frac{d \ln R}{d \ln \widehat{S}^F})_{long} = \frac{1}{\theta} (\frac{d \theta}{d \ln \underline{S}_F})_{30} = \frac{1}{\theta} (\frac{d \theta}{d \ln \underline{S}_F})_{long}$$

Summing up the pair above, one gets

$$(\frac{d \ln R}{d \ln \widehat{S}^F})_{net} = (\frac{d \ln R}{d \ln \widehat{S}^F})_{short} + (\frac{d \ln R}{d \ln \widehat{S}^F})_{long} = \underbrace{\alpha \widehat{\chi} \phi \widehat{\Phi}^F}_{\text{scale effect}} + \underbrace{\frac{1}{\theta} (\frac{d \theta}{d \ln \widehat{S}^F})_{long}}_{\text{displacement effect}}$$

• elasticity of routine skill prices

$$(\frac{d \ln q}{d \ln \underline{S}^F})_{short} = \Phi \{ \underbrace{\alpha \widehat{\chi} \Phi^F}_{\text{scale effect}} + \underbrace{\frac{1}{\psi - \theta} (\frac{d \psi}{d \ln \underline{S}^F})_{short}}_{\text{occupational substitution effect}} \} + \mathbb{I}(G = p) \{ \underbrace{-\alpha \phi \widehat{\Phi}^F}_{\text{labor supply effect}} + \underbrace{(\widehat{\Phi}^F - \widehat{\Phi}^D) (\frac{d \phi}{d \ln \widehat{S}^F})_{short}}_{\text{foreign substitution effect}} \}$$

$$\begin{aligned} (\frac{d \ln q}{d \ln \underline{S}^F})_{long} &= \Phi \{ \underbrace{\alpha \Phi}_{\text{productivity effect}} + \underbrace{\frac{-1}{\psi - \theta}}_{\text{displacement effect}} \} (\frac{d \theta}{d \ln \underline{S}^F})_{long} + \underbrace{\frac{1}{\psi - \theta} (\frac{d \psi}{d \ln \underline{S}^F})_{long}}_{\text{occupational substitution effect}} \\ &\quad + \mathbb{I}(G = p) \underbrace{(\widehat{\Phi}^F - \widehat{\Phi}^D) (\frac{d \phi}{d \ln \widehat{S}^F})_{long}}_{\text{foreign substitution effect}} \end{aligned}$$

Summing up the pair above, one gets

$$\begin{aligned} (\frac{d \ln q}{d \ln \widehat{S}^F})_{net} &= \Phi [\underbrace{\alpha \widehat{\chi} \phi \widehat{\Phi}^F}_{\text{scale effect}} + \{ \underbrace{\alpha \Phi}_{\text{productivity effect}} + \underbrace{\frac{-1}{\psi - \theta}}_{\text{displacement effect}} \} (\frac{d \theta}{d \ln \widehat{S}^F})_{long} + \underbrace{\frac{1}{\psi - \theta} (\frac{d \psi}{d \ln \widehat{S}^F})_{net}}_{\text{occupational substitution effect}}] \\ &\quad + \mathbb{I}(G = p) (\underbrace{-\alpha \phi \widehat{\Phi}^F}_{\text{labor supply effect}} + \underbrace{(\widehat{\Phi}^F - \widehat{\Phi}^D) (\frac{d \phi}{d \ln \widehat{S}^F})_{net}}_{\text{foreign substitution effect}}). \end{aligned}$$

• elasticity of native premium

$$\begin{aligned} (\frac{d \ln(\widehat{q}^F / \widehat{q}^D)}{d \ln \widehat{S}^F})_{short} &= (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{short} - (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{short} \\ &= (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{10} + \{ (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{21} + (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{22} \} - \{ (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{21} + (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{22} \} \\ &= -\alpha \phi \widehat{\Phi}^F + (\widehat{\Phi}^F - \widehat{\Phi}^D) \{ \alpha \widehat{\chi} \phi \widehat{\Phi}^F \pm \frac{1}{\widehat{\chi}} (\frac{d \psi}{d \ln \widehat{S}^F})_{short} \} + (\frac{\widehat{\Phi}^F}{\phi} + \frac{\widehat{\Phi}^D}{1 - \phi}) (\frac{d \phi}{d \ln \widehat{S}^F})_{short} \end{aligned}$$

$$\begin{aligned} (\frac{d \ln(\widehat{q}^F / \widehat{q}^D)}{d \ln \widehat{S}^F})_{long} &= (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{long} - (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{long} = \{ (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{31} + (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{33} + (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{41} + (\frac{d \ln \widehat{q}^F}{d \ln \widehat{S}^F})_{42} \} \\ &\quad - \{ (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{31} + (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{33} + (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{41} + (\frac{d \ln \widehat{q}^D}{d \ln \widehat{S}^F})_{42} \} \\ &= -(\widehat{\Phi}^F - \widehat{\Phi}^D) \mathbb{I}(G = p) \frac{1}{\widehat{\chi}} (\frac{d \theta}{d \ln \widehat{S}^F})_{long} - \alpha \phi \widehat{\Phi}^F \end{aligned}$$

Summing up the pair above, one gets

$$\begin{aligned}
\left(\frac{d \ln(\hat{q}^F/\hat{q}^D)}{d \ln \hat{S}^F}\right)_{net} = & \underbrace{-\alpha\phi\hat{\Phi}^F}_{\text{labor supply effect}} + (\hat{\Phi}^F - \hat{\Phi}^D) \underbrace{(\alpha\hat{\chi}\phi\hat{\Phi}^F + \alpha\Phi)}_{\text{scale effect}} \left(\frac{d\theta}{d \ln \hat{S}^F}\right)_{long} \\
& + \underbrace{\left(\frac{\hat{\Phi}^F}{\phi} + \frac{\hat{\Phi}^D}{1-\phi}\right)\left(\frac{d\phi}{d \ln \hat{S}^F}\right)_{net}}_{\text{foreign substitution effect}} \pm \underbrace{\left[\frac{\hat{\Phi}^F - \hat{\Phi}^D}{\hat{\chi}} \left\{ \left(\frac{d\psi}{d \ln \hat{S}^F}\right)_{net} - \mathbb{I}(G=p) \left(\frac{d\theta}{d \ln \hat{S}^F}\right)_{long} \right\} \right]}_{\text{occupational substitution and displacement effect}}
\end{aligned}$$

■

Moment conditions

Plugging the elasticities of technology adjustment in Proposition 3 into the results in Proposition 4 yields the following closed-form analytical formulas in each sector.

Plant sector

$$\left\{ \begin{aligned} \left(\frac{d \ln R}{d \ln \underline{S}^F}\right)_{net} &= \alpha(\psi - \theta)\phi\Phi^F + \frac{1}{\theta}CA^{L,R}(\theta)^{-1}\epsilon_{short}^q \\ \left(\frac{d \ln \underline{q}}{d \ln \underline{S}^F}\right)_{net} &= \epsilon_{short}^q + \frac{1}{\psi - \theta} \{ \Phi + CA^{F,D}(\phi)^{-1}(\Phi^F - \Phi^D)^2 \} [(CA^{H,L}(\psi)^{-1} \frac{\Phi}{\psi - \theta} - 1) CA^{L,R}(\theta)^{-1} \epsilon_{short}^q \\ &\quad - CA^{H,L}(\psi)^{-1}(\Phi^F - \Phi^D)\epsilon_{short}^\phi] \\ \left(\frac{d \ln(\underline{q}^D/\underline{q}^F)}{d \ln \underline{S}^F}\right)_{net} &= \Phi^F - (\Phi^F - \Phi^D) \{ \alpha(\psi - \theta)\phi\Phi^F + \frac{1}{\psi - \theta} \frac{(\bar{\Phi}\alpha(\psi - \theta) + 1)\phi\Phi^F}{CA^{H,L}(\psi)} \} - \left(\frac{\Phi^F}{\phi} + \frac{\Phi^D}{1-\phi}\right)\epsilon_{short}^\phi \\ &\quad - \left\{ 1 + \left(\frac{\Phi^F}{\phi} + \frac{\Phi^D}{1-\phi}\right) \frac{1}{CA^{F,D}(\phi)} \right\} \frac{\Phi^F - \Phi^D}{\psi - \theta} \left[\left\{ \frac{\Phi}{(\psi - \theta)CA^{H,L}(\psi)} - 1 \right\} \frac{\epsilon_{short}^q}{CA^{L,R}(\theta)} - \frac{(\Phi^F - \Phi^D)\epsilon_{short}^\phi}{CA^{H,L}(\psi)} \right] \end{aligned} \right.$$

where a trio of short-run elasticities are defined as

$$\left\{ \begin{aligned} \epsilon_{short}^q \equiv \left(\frac{d \underline{q}}{d \ln \underline{S}^F}\right)_{short} &= [-\phi + \Phi(\psi - \theta)\phi + \frac{(\Phi^F - \Phi^D)\{(\Phi^F - \Phi^D)(\psi - \theta)\phi - 1\}}{CA^{F,D}(\phi)}]\Phi^F + \frac{1}{\psi - \theta} \left\{ \Phi + \frac{(\Phi^F - \Phi^D)^2}{CA^{F,D}(\phi)} \right\} \epsilon_{short}^\psi \\ \epsilon_{short}^\phi \equiv \left(\frac{d \phi}{d \ln \underline{S}^F}\right)_{short} &= CA^{F,D}(\phi)^{-1} [(\Phi^F - \Phi^D) \{ (\psi - \theta)\phi\Phi^F + \frac{1}{\psi - \theta} \epsilon_{short}^\psi \} - \Phi^F] \\ \epsilon_{short}^\psi \equiv \left(\frac{d \psi}{d \ln \underline{S}^F}\right)_{short} &= -CA^{H,L}(\psi)^{-1} (\bar{\Phi}(\psi - \theta) - 1)\phi\Phi^F. \end{aligned} \right.$$

Office sector

$$\left\{ \begin{aligned} \left(\frac{d \ln R}{d \ln \bar{S}^F}\right)_{net} &= (1 - \psi)\bar{\Phi}^F + \frac{1}{\theta}CA^{L,R}(\theta)^{-1}\epsilon_{short}^q \\ \left(\frac{d \ln \bar{q}}{d \ln \bar{S}^F}\right)_{net} &= \left\{ \frac{\Phi}{\psi - \theta} (-1 + CA^{H,L}(\psi)^{-1} \frac{\Phi}{\psi - \theta}) CA^{L,R}(\theta)^{-1} + 1 \right\} \epsilon_{short}^q + \frac{\Phi}{\psi - \theta} CA^{H,L}(\psi)^{-1} (\bar{\Phi}^D - \bar{\Phi}^F) \epsilon_{short}^\phi \\ \left(\frac{d \ln(\bar{q}^D/\bar{q}^F)}{d \ln \bar{S}^F}\right)_{net} &= \bar{\Phi}^F - (\bar{\Phi}^F - \bar{\Phi}^D) \{ (1 - \psi)\phi\bar{\Phi}^F + \frac{\{\Phi(1 - \psi) + 1\}\phi\bar{\Phi}^F}{(1 - \psi)CA^{H,L}(\psi)} \} + \left(\frac{\bar{\Phi}^F}{\phi} + \frac{\bar{\Phi}^D}{1-\phi}\right)\epsilon_{short}^\phi \\ &\quad + \left\{ 1 - \left(\frac{\bar{\Phi}^F}{\phi} + \frac{\bar{\Phi}^D}{1-\phi}\right) \frac{1}{CA^{F,D}(\phi)} \right\} \frac{\bar{\Phi}^F - \bar{\Phi}^D}{1 - \psi} \left\{ \frac{\Phi}{(\psi - \theta)CA^{H,L}(\psi)} \frac{\epsilon_{short}^q}{CA^{L,R}(\theta)} - \frac{(\bar{\Phi}^F - \bar{\Phi}^D)\epsilon_{short}^\phi}{CA^{H,L}(\psi)} \right\} \end{aligned} \right.$$

where a trio of short-run elasticities are defined as

$$\begin{cases} \epsilon_{short}^q \equiv \left(\frac{dq}{d \ln \bar{S}^F}\right)_{short} = \underline{\Phi} \{ (1 - \psi) \phi \bar{\Phi}^F + \frac{\epsilon_{short}^\psi}{\psi - \theta} \} \\ \epsilon_{short}^\phi \equiv \left(\frac{d\phi}{d \ln \bar{S}^F}\right)_{short} = CA^{F,D}(\phi)^{-1} [-\bar{\Phi}^F + (\bar{\Phi}^F - \bar{\Phi}^D) \{ (1 - \psi) \phi \bar{\Phi}^F - \frac{\epsilon_{short}^\psi}{1 - \psi} \}] \\ \epsilon_{short}^\psi \equiv \left(\frac{d\psi}{d \ln \bar{S}^F}\right)_{short} = CA^{H,L}(\psi)^{-1} \{ \underline{\Phi} (1 - \psi) - 1 \} \phi \bar{\Phi}^F. \end{cases}$$

B Simulation Appendix

This problem is solved by the value function iteration approach. One period is set to a quarter in 1980-2015. Demographic change (including immigration inflow, reallocation, retirement) and technology changes (changes of quality-adjusted investment price of robots and rental price for equipment) are given in the first quarter. Labor force participation rate is computed in each decade by each demographic class, and interacted by the demographic change, the demography-driven labor supply shocks are computed every year.

As is shown in Rust (1987) and the ensuing literature, a discount factor β is hard to identify, thus, is exogenously set as $\beta = 0.98$. Assume Markov transition of the state matrix and a transition matrix is computed as follows. The evolution of θ is straightforward from the upgrading policy. Evolution of the relative vintage, $\frac{q_{i,t}^R}{\underline{q}_t}$, comes from (B.3) and rational expectation of routine prices. After discretizing A into 100 grids, AR (1) evolution is incorporated into a transition matrix. An initial TFP, A_0 is inferred after allocating aggregate production and factor inputs into each establishment in the ratio of the twelve size bin in CBP under the isomorphic technology. $\Delta Q_{i,t-1}$ is computed from rational expectation of a price taker, specified at each region, given intensive-margin of production $\{\underline{a}(\omega), \bar{a}(\omega), \widehat{a}^F(\omega')\}$ and $\{A_l^R, \bar{A}_l, \widehat{A}_l^F\}$, estimated in Section 6, Stage 1. The simulation algorithm closely follows the adjustment process delineated in Section 3.

B.1 Preparation at the Baseline Year

This section recovers initial factor levels $\widehat{S}_i^e$, $\widetilde{S}_i$, R_i , K_i and initial unobservable productivity A_{i,t_0} , using employment size N_{i,t_0}^{CBP} from CBP as an informative allocation weight.

Initial factor allocation at the baseline year At the baseline year, every establishment has no friction for automation and skill prices are homogeneous within regions due to the law of one price, technology is isomorphic across establishments: $\theta_{i,t_0} = \theta_{l,t_0}$, $\psi_{i,t_0} = \psi_{l,t_0}$, $\phi_{i,t_0} = \phi_{l,t_0}$ for all $i \in l$. Then, introducing the scaling ratio for establishment i in region l at the

baseline year, $\tau_{i,l} \equiv \frac{N_{i,l}^{CBP}}{N_l^{CBP}}$, every factor allocation to establishment is scaled by $\tau_{i,l}$.

Given the regional-level skill employments $\widehat{S}_l^e$, $\widetilde{S}_i$, and capital allocations R_{l,t_0} , K_{l,t_0} (computed in Section 4.3), the individual establishment i 's factor allocation is computed by $\widehat{S}_i^e = \tau_{i,l} \widehat{S}_l^e$, $\widetilde{S}_i = \tau_{i,l} \widetilde{S}_l^e$, $R_i = \tau_{i,l} R_l$, $K_i = \tau_{i,l} K_l$. Individual working hour for one employment from CBP is computed as $h_{i,l}^{CBP} = \frac{\widehat{S}_i^D + \widehat{S}_i^F + \widetilde{S}_i}{N_{i,l}^{CBP}}$. $h_{i,l}^{CBP}$ is only used to translate model-implied factor skill hours into CBP-based employment head counts to get comparable moments of size distributions to data moments from CBP.

Recover the baseline establishment TFP By Proposition.3, labor incomes are

$$\underline{W}_{i,t_0} = \alpha_l(\psi_{l,t_0} - \theta_{i,t_0})P_{i,t_0}\widehat{Y}_{i,t_0}, \quad \overline{W}_{i,t_0} = \alpha_l(1 - \psi_{l,t_0})P_{i,t_0}\widehat{Y}_{i,t_0}$$

At the baseline year, no friction across establishments is imposed as $\theta_{i,t_0} = \theta_{l,t_0}$ ($\forall i \in l$), $\underline{W}_{i,t_0} + \overline{W}_{i,t_0} = \alpha_l(1 - \theta_{l,t_0})P_{i,t_0}\widehat{Y}_{i,t_0}$ holds. Plugging $P_{i,t_0} = P_{l,t_0}$ ($\forall i \in l$) computed by (A.6), individual-level production is inferred by

$$\widehat{Y}_{i,t_0} = \frac{\underline{W}_{i,t_0} + \overline{W}_{i,t_0}}{P_{i,0}(1 - \theta_{l,t_0})\alpha_l} \quad (\text{B.1})$$

The initial TFP of the establishments are recovered by $A_{i,t_0} = \frac{\widehat{Y}_{i,t_0}}{Y_{i,t_0}}$, where

$$\begin{aligned} Y_{i,t_0} &= B(\theta_{i,t_0}, \psi_{l,t_0}, \alpha_l \mid A_i^R, \overline{A}_i, \{\underline{a}(\omega), \overline{a}(\omega), \widehat{a}^F(\omega')\}) \\ &\times \left\{ \left(\frac{R_{i,t_0}}{\theta_{i,t_0}} \right)^{\theta_{i,t_0}} \left(\frac{\underline{S}_{i,t_0}}{\psi_{l,t_0} - \theta_{i,t_0}} \right)^{\psi_{l,t_0} - \theta_{i,t_0}} \left(\frac{\overline{S}_{i,t_0}}{1 - \psi_{l,t_0}} \right)^{1 - \psi_{l,t_0}} \right\}^\alpha K_{i,t_0}^{1-\alpha} \end{aligned} \quad (\text{B.2})$$

The following figure summarizes $\ln(A_{i,t_0})$ across the twelve size bins in CBP. Reassuringly, the recovered A_{i,t_0} is positively associated with the establishment size, N_{i,t_0}^{CBP} from CBP, indicating an empirical regularity that large establishments exhibit larger unobservable TFPs.

B.2 Computation Steps

Period t starts with initial thresholds, $\{\theta_{i,0}, \psi_0, \phi_0\}$, robot deployment $R_{i,0}$, vintage $q_{i,0}^R = \widetilde{q}_{i,s}^R$, where $s < t$ is the last time for upgrading, production $Y_{i,0}$, factor demand $\{\widehat{W}_{i,0}^e, \widetilde{W}_{i,0}, V_{i,0}^K\}$, and aggregated factor demand functions proxied by $\{\widehat{W}_0^e, \widetilde{W}_0, V_0^K\}$, which are inherited from the previous period. If no immigrants are observed, I set $\widehat{q}^F = \widehat{q}^D$.

The one iteration consists of Stage 1-4, crafted as a simulated version in the comparative

statics in Section 3. Stage 1, 2 corresponds with short-run responses from immigration inflow, and Stage 3, 4 does with long-run responses from induced automation adjustment in the timeline of events.

Stage 1 Immigration inflow The order of events is indexed by 10 and 11.

- Suppose the skill equilibrium shifts to $\{\widehat{S}_{10}^e, \widetilde{S}_{10}\}$ by immigration inflow (and/or demographic change).
- Supply-side shocks shift prices from $\{\widehat{q}_0^e, \widetilde{q}_0\}$, with the initial demand curve, characterized by $\{\widehat{W}_0^e, \widetilde{W}_0\}$, fixed. $\widehat{q}_{10}^e - \widehat{q}_0^e$ and $\widetilde{q}_{10} - \widetilde{q}_0$ are demography (mechanical) effects.

$$\widehat{q}_{10}^e = \frac{\widehat{W}_0^e}{\widehat{S}_{10}^e}, \quad \widehat{q}_{10} = \frac{(\widehat{q}_{10}^F)^{\phi_0} (\widehat{q}_{10}^D)^{1-\phi_0}}{B'(\phi_0)}, \quad \widetilde{q}_{10} = \frac{\widetilde{W}_0}{\widetilde{S}_{10}}$$

- The individual-level skill allocation shifts as

$$\widehat{S}_{i,10}^e = \frac{\widehat{W}_{i,0}^e}{\widehat{q}_{i,10}^e}, \quad \widetilde{S}_{i,10} = \frac{\widetilde{W}_{i,0}}{\widetilde{q}_{10}}, \quad K_{i,10} = \frac{V_{i,0}^K}{q^K}, \quad \widehat{S}_{10}^e = \Sigma_i \widehat{S}_{i,10}^e, \quad \widetilde{S}_{10} = \Sigma_i \widetilde{S}_{i,10}, \quad K_{10} = \Sigma_i K_{i,10}$$

- The price is updated as

$$P_{i,10} = \frac{\{(q_{i,0}^R)^{\theta_{i,0}} (\underline{q}_{10})^{\psi_0 - \theta_{i,0}} (\bar{q}_{10})^{1-\psi_0}\}^\alpha (q^K)^{1-\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha} B(\theta_{i,0}, \psi_0, \alpha)}, \quad P_{i,10} X_{i,10} = \left(\frac{P_{i,10}}{P_{i,0}}\right)^{1-\sigma} P_{i,0} Y_{i,0} \underbrace{\frac{Y_{G,10}}{Y_{G,0}}}_{\Delta_{G,0}}$$

- The factor demand is updated, given the initial task thresholds

$$\underline{W}_{i,10} = (\psi_0 - \theta_{i,0}) \alpha P_{X,i,10} X_{i,10}, \quad \bar{W}_{i,10} = (1 - \psi_0) \alpha P_{X,i,10} X_{i,10}, \quad V_{i,10}^K = (1 - \alpha) P_{X,i,10} X_{i,10}$$

$$\widehat{W}_{i,10}^F = \phi_0 \widehat{W}_{i,10}, \quad \widehat{W}_{i,10}^D = (1 - \phi_0) \widehat{W}_{i,10}, \quad \widehat{W}_{10}^e = \Sigma_i \widehat{W}_{i,10}^e, \quad \widetilde{W}_{10} = \Sigma_i \widetilde{W}_{i,10}, \quad V_{10}^K = \Sigma_i V_{i,10}^K$$

- The skill price shifts from scale effect (Corollary.A.1)

$$\widehat{q}_{11}^e = \widehat{q}_{10}^e + \underbrace{\frac{(\widehat{W}_{10}^e - \widehat{W}_0^e) \widehat{\Phi}^e}{\widehat{S}_{10}^e}}_{\text{scale effect}}, \quad \widehat{q}_{11} = \frac{(\widehat{q}_{11}^F)^{\phi_0} (\widehat{q}_{11}^D)^{1-\phi_0}}{B'(\phi_0)}, \quad \widetilde{q}_{11} = \widetilde{q}_{10} + \underbrace{\frac{(\widetilde{W}_{10} - \widetilde{W}_0) \widetilde{\Phi}}{\widetilde{S}_{10}}}_{\text{scale effect}}$$

- The establishment-level skill allocation shifts under the factor demand curves

$$\widehat{S}_{i,11}^e = \frac{\widehat{W}_{i,10}^e}{\widehat{q}_{11}^e}, \quad \widetilde{S}_{i,11} = \frac{\widetilde{W}_{10}}{\widetilde{q}_{11}}, \quad K_{i,11} = \frac{V_{i,10}^K}{q^K}, \quad \widehat{S}_{11}^e = \Sigma_i \widehat{S}_{i,11}^e, \quad \widetilde{S}_{11} = \Sigma_i \widetilde{S}_{i,11}, \quad K_{11} = \Sigma_i K_{i,11}$$

Stage 2 Labor adjustment

Stage 2-1 Occupational adjustment

- ψ is adjusted from ψ_0 to ψ_{20} (Proposition 1)

$$\frac{\bar{a}(\psi_{20})}{\underline{a}(\psi_{20})} = \frac{\underline{q}_{11}}{\bar{q}_{11}/\bar{A}}$$

- Factor demand curve shift

$$\underline{W}_{i,20} = (\psi_{20} - \theta_{i,0})\alpha P_{i,10}Y_{i,10}, \quad \bar{W}_{i,20} = (1 - \psi_{20})\alpha P_{i,10}Y_{i,10}, \quad V_{i,20}^K = (1 - \alpha)P_{i,10}Y_{i,10}$$

$$\widehat{W}_{i,20}^F = \phi_0 \widehat{W}_{i,20}, \quad \widehat{W}_{i,20}^D = (1 - \phi_0) \widehat{W}_{i,20}, \quad \widehat{W}_{20}^e = \Sigma_i \widehat{W}_{i,20}^e, \quad \widetilde{W}_{20} = \Sigma \widetilde{W}_{i,20}, \quad V_{20}^K = \Sigma V_{i,20}^K$$

- The factor prices shift as skill substitution effect (Corollary A.1)

$$\widehat{q}_{20}^e = \widehat{q}_{11}^e + \underbrace{\frac{(\widehat{W}_{20}^e - \widehat{W}_{10}^e)\widehat{\Phi}^e}{\widehat{S}_{11}^e}}_{\text{occupational substitution effect}}, \quad \widetilde{q}_{20} = \frac{(\widehat{q}_{20}^F)^{\phi_0}(\widehat{q}_{20}^D)^{1-\phi_0}}{B'(\phi_0)}, \quad \widetilde{q}_{20} = \widetilde{q}_{11} + \underbrace{\frac{(\widetilde{W}_{20} - \widetilde{W}_{10})\widetilde{\Phi}}{\widetilde{S}_{11}}}_{\text{occupational substitution effect}}$$

- The establishment-level skill allocation shifts under the factor demand curves

$$\widehat{S}_{i,20}^e = \frac{\widehat{W}_{i,20}^e}{\widehat{q}_{i,20}^e}, \quad \widetilde{S}_{i,20} = \frac{\widetilde{W}_{i,20}}{\widetilde{q}_{20}}, \quad K_{i,20} = \frac{V_{i,20}^K}{q^K}, \quad \widehat{S}_{20}^e = \Sigma_i \widehat{S}_{i,20}^e, \quad \widetilde{S}_{20} = \Sigma_i \widetilde{S}_{i,20}, \quad K_{20} = \Sigma_i K_{i,20}$$

- The establishment-level final good price is updated to

$$P_{i,20} = \frac{\{(q_{i,0}^R)^{\theta_{i,0}}(\underline{q}_{20})^{\psi_{20}-\theta_{i,0}}(\bar{q}_{20})^{1-\psi_{20}}\}^\alpha (q^K)^{1-\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha} B(\theta_{i,0}, \psi_0, \alpha)}, \quad P_{i,20}Y_{i,20} = \left(\frac{P_{i,20}}{P_{i,10}}\right)^{1-\sigma} P_{i,10}Y_{i,10} \underbrace{\frac{Y_{G,20}}{Y_{G,10}}}_{\Delta_{G,10}}$$

Stage 2-2 Foreign/Domestic adjustment

- Skill demand shifts

$$\widehat{W}_{i,21}^D = (\psi_{20} - \theta_{i,0})(1 - \phi_{20})\alpha P_{i,20}Y_{i,20}, \quad \widehat{W}_{i,21}^F = (\psi_{20} - \theta_{i,0})\phi_{20}\alpha P_{i,20}Y_{i,20}$$

$$\widehat{W}_{21}^e = \Sigma_i \widehat{W}_{i,21}^e, \quad \widetilde{W}_{21} = (1 - \psi_{20})\alpha P_{i,20}Y_{i,20}$$

- Skill prices/allocations shift from factor demand shifts in foreign substitution effect (Corollary A.1)

$$\widehat{q}_{21}^e = \widehat{q}_{20}^e + \underbrace{\left(\frac{\widehat{W}_{21}^e - \widehat{W}_{20}^e}{\widehat{S}_{20}^e} \right) \widehat{\Phi}^e}_{\text{scale effect from skill allocation}}, \quad \widehat{q}_{21} = \frac{(\widehat{q}_{21}^F)^{\phi_0} (\widehat{q}_{21}^D)^{1-\phi_0}}{B'(\phi_{21})}, \quad \widetilde{q}_{21} = \widetilde{q}_{20} + \underbrace{\frac{(\widetilde{W}_{21} - \widetilde{W}_{20}) \widetilde{\Phi}}{\widetilde{S}_{20}}}_{\text{scale effect from skill allocation}}$$

- ϕ is adjusted from ϕ_0 to ϕ_{22} to satisfy (Proposition 1)

$$\widehat{a}^F(\phi_{22}) = \frac{\widehat{q}_{21}^F / \widehat{A}^F}{\widehat{q}_{21}^D}.$$

- Skill demand shifts

$$\widehat{W}_{i,22}^D = \frac{1 - \phi_{22}}{1 - \phi_0} \widehat{W}_{i,21}^D, \quad \widehat{W}_{i,22}^F = \frac{\phi_{22}}{\phi_0} \widehat{W}_{i,21}^F, \quad \widehat{W}_{22}^e = \Sigma_i \widehat{W}_{i,22}^e, \quad \widetilde{W}_{22} = \widetilde{W}_{21}$$

- Skill prices/allocations shift from factor demand shifts in foreign substitution effect (Corollary A.1)

$$\widehat{q}_{22}^e = \widehat{q}_{21}^e + \underbrace{\left(\frac{\widehat{W}_{22}^e - \widehat{W}_{21}^e}{\widehat{S}_{21}^e} \right) \widehat{\Phi}^e}_{\text{foreign substitution effect}}, \quad \widehat{q}_{22} = \frac{(\widehat{q}_{22}^F)^{\phi_{22}} (\widehat{q}_{22}^D)^{1-\phi_{22}}}{B'(\phi_{22})}, \quad \widetilde{q}_{22} = \widetilde{q}_{21}$$

- The establishment-level skill allocation shifts under the factor demand curves

$$\widehat{S}_{i,22}^e = \frac{\widehat{W}_{i,22}^e}{\widehat{q}_{22}^e}, \quad \widetilde{S}_{i,22} = \frac{\widetilde{W}_{i,22}}{\widetilde{q}_{22}}, \quad K_{i,22} = \frac{V_{i,22}^K}{q^K}, \quad \widehat{S}_{22}^e = \Sigma_i \widehat{S}_{i,22}^e, \quad \widetilde{S}_{22} = \Sigma_i \widetilde{S}_{i,22}, \quad K_{22} = \Sigma_i K_{i,22}$$

Stage 3 Automation adjustment The equipment rental price changes to q'^K at the beginning of the period.

- $\widetilde{q}_{t-1}^R = q_0^R$ drops to $\widetilde{q}_t^R = q_{30}^R$. θ is adjusted as

$$\theta_{i,30} = d(\theta_{i,0}, \frac{q_{i,0}^R}{\underline{q}_{30}}, \Delta Q_{i,0}, A_{i,0})$$

where $d(\cdot)$ is a automation policy function. The vintage evolution is

$$q_{i,30}^R = \begin{cases} \widetilde{q}_t^R & (i \text{ upgrades}) \\ \widetilde{q}_s^R & (i \text{ does not upgrade, } s < t) \end{cases}$$

- Factor demand curves shift

$$\underline{W}_{i,30} = (\psi_{20} - \theta_{i,30})\alpha P_{X,i,20}X_{i,20}, \quad V_{i,30}^R = \theta_{i,30}\alpha P_{X,i,20}X_{i,20}, \quad \underline{W}_{30} = \Sigma \underline{W}_{i,30}$$

- The factor prices shift by displacement effect as (Corollary A.1)

$$\left\{ \begin{array}{l} \widehat{q}_{30}^e = \widehat{q}_{22}^e + \underbrace{\left(\frac{\widehat{W}_{30}^e - \widehat{W}_{22}^e}{\widehat{S}_{22}^e} \right) \widehat{\Phi}^e}_{\text{displacement effect}}, \quad \widehat{q}_{30} = \frac{(\widehat{q}_{30}^F)^{\phi_{22}} (\widehat{q}_{30}^D)^{1-\phi_{22}}}{B'(\phi_0)}, \quad \widetilde{q}_{30} = \widetilde{q}_{21} \quad (\text{plant}) \\ \widehat{q}_{30}^e = \widehat{q}_{21}^e, \quad \widehat{q}_{30} = \widehat{q}_{21}, \quad \widetilde{q}_{30} = \widetilde{q}_{21} + \underbrace{\left(\frac{\widetilde{W}_{30} - \widetilde{W}_{22}}{\widetilde{S}_{22}} \right) \widetilde{\Phi}}_{\text{displacement effect}} \quad (\text{office}) \end{array} \right.$$

- Robot and routine skill allocations shift from factor demand shifts

$$R_{30} = \frac{V_{i,30}^R}{q_{i,30}^R}, \quad \widehat{S}_{i,30}^e = \frac{\widehat{W}_{i,30}^e}{\widehat{q}_{30}^e}, \quad \widetilde{S}_{i,30} = \frac{\widetilde{W}_{i,30}}{\widetilde{q}_{30}}, \quad K_{i,30} = \frac{V_{i,30}^K}{q'^K}$$

Investment occurs according to laws of motion:

$$I_{i,30}^R = R_{i,30} - (1 - \delta^R)R_{i,0}$$

- The establishment-level final good price is updated to

$$P_{i,30} = \frac{\{(q_{i,0}^R)^{\theta_{i,30}} (\underline{q}_{30})^{\psi_{20}-\theta_{i,30}} (\bar{q}_{30})^{1-\psi_{20}}\}^\alpha (q^K)^{1-\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha} B(\theta_{i,30}, \psi_{20}, \alpha)}, \quad P_{i,30}Y_{i,30} = \left(\frac{P_{i,30}}{P_{i,20}} \right)^{1-\sigma} P_{i,20}Y_{i,20} \underbrace{\frac{Y_{G,30}}{Y_{G,20}}}_{\Delta_{G,20}}$$

- A profit is collected with production after the shock is realized, and a new automation intensity is chosen with updated investment price of robots.

$$\pi_{i,30} = \alpha \theta_{i,30} P_{i,30} \widehat{Y}_{i,30} - p_{i,t}^R I_{i,30}^R - 1(\theta_{i,30} > \theta_{i,0}) c(\mathbf{X}, A_{i,30}, \theta_{i,30} \mid \Theta^A) P_{i,t-1} Y_{i,t-1}$$

$$p_{i,t}^R = \begin{cases} \widetilde{p}_t^R & (i \text{ upgrades}) \\ \widetilde{p}_s^R & (i \text{ does not upgrade}) \end{cases} \quad (\text{B.3})$$

Stage 4 Labor adjustment Stage 4 Labor adjustment is analogous as Stage 2.

- ψ is adjusted from ψ_{20} to ψ_{40} satisfying

$$\frac{\bar{a}(\psi_{40})}{\underline{a}(\psi_{40})} = \frac{q_{30}}{\bar{q}_{30}/\bar{A}}.$$

- Factor demand curve shifts.

$$\underline{W}_{i,40} = (\psi_{40} - \theta_{i,30})\alpha P_{i,30} Y_{i,30}, \quad \bar{W}_{i,40} = (1 - \psi_{40})\alpha P_{i,30} Y_{i,30}, \quad V_{i,40}^K = (1 - \alpha)P_{i,30} Y_{i,30}$$

$$\widehat{W}_{i,40}^F = \phi_{21} \widehat{W}_{i,40}, \quad \widehat{W}_{i,40}^D = (1 - \phi_{21}) \widehat{W}_{i,40}, \quad \widehat{W}_{40}^e = \Sigma_i \widehat{W}_{i,40}^e, \quad \widetilde{W}_{40} = \Sigma \widetilde{W}_{i,40}, \quad V_{40}^K = \Sigma V_{i,40}^e$$

- The factor prices shifts. (Corollary A.1)

$$\widehat{q}_{40}^e = \widehat{q}_{30}^e + \underbrace{\left(\frac{\widehat{W}_{40}^e - \widehat{W}_{30}^e}{\Sigma \widehat{S}_{i,30}^e} \right) \widehat{\Phi}^e}_{\text{occupational substitution effect}}, \quad \widehat{q}_{40} = \frac{(\widehat{q}_{40}^F)^{\phi_{21}} (\widehat{q}_{40}^D)^{1-\phi_{21}}}{B'(\phi_{21})}, \quad \widetilde{q}_{40} = \widetilde{q}_{30} + \underbrace{\frac{(\widetilde{W}_{40} - \widetilde{W}_{30}) \widetilde{\Phi}}{\Sigma_i \widetilde{S}_{i,30}}}_{\text{occupational substitution effect}}$$

- The establishment-level skill allocation shifts under the factor demand curves.

$$\widehat{S}_{i,40}^e = \frac{\widehat{W}_{i,40}^e}{\widehat{q}_{40}^e}, \quad \widetilde{S}_{i,40} = \frac{\widetilde{W}_{i,40}}{\widetilde{q}_{40}}, \quad K_{i,40} = \frac{V_{i,40}^K}{q'^K}$$

- The establishment-level final good price is updated to

$$P_{X,i,40} = \frac{\{(q_{i,30}^R)^{\theta_{i,30}} (\underline{q}_{40})^{\psi_{i,40} - \theta_{i,30}} (\bar{q}_{40})^{1-\psi_{i,40}}\}^\alpha (q'^K)^{1-\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha} B(\theta_{i,30}, \psi_{i,40}, \alpha)}, \quad P_{i,40} = \left(\frac{1}{1-\eta}\right)^{1-\eta} \left(\frac{1}{\eta}\right)^\eta P_{Y,i,40}^\eta$$

and the market competition governs the corresponding production as

$$Y_{i,40} = \left(\frac{P_{i,40}}{P_{i,30}}\right)^{-\sigma} Y_{i,30}, \quad X_{i,40} = \left(\frac{Y_{i,40}}{A^{1-\eta}}\right)^\frac{1}{\eta}$$

Domestic (Foreign) skill adjustment

- Skill demand shifts

$$\widehat{W}_{i,41}^D = (\psi_{40} - \theta_{i,30})(1 - \phi_{21})\alpha P_{i,40} Y_{i,40}, \quad \widehat{W}_{i,21}^F = (\psi_{20} - \theta_{i,0})\phi_{21}\alpha P_{i,40} Y_{i,40}$$

$$\widehat{W}_{41}^e = \Sigma_i \widehat{W}_{i,41}^e, \quad \widetilde{W}_{41} = (1 - \psi_{40})\alpha P_{i,40} Y_{i,40}$$

- Skill prices/allocation shifts from factor demand shifts in foreign substitution effect (Corollary A.1)

$$\widehat{q}_{41}^e = \widehat{q}_{40}^e + \underbrace{\left(\frac{\widehat{W}_{41}^e - \widehat{W}_{40}^e}{\widehat{S}_{40}^e} \right) \widehat{\Phi}^e}_{\text{scale effect from skill allocation}}, \quad \widehat{q}_{41} = \frac{(\widehat{q}_{41}^F)^{\phi_0} (\widehat{q}_{41}^D)^{1-\phi_0}}{B'(\phi_{41})}, \quad \widetilde{q}_{41} = \widetilde{q}_{40} + \underbrace{\frac{(\widetilde{W}_{41} - \widetilde{W}_{40}) \widetilde{\Phi}}{\widetilde{S}_{40}}}_{\text{scale effect from skill allocation}}$$

- ϕ is adjusted from ϕ_{21} to ϕ_{41} to satisfy

$$\tilde{a}^F(\phi_{41}) = \frac{\widetilde{q}_{40}^F / \widetilde{A}^F}{\widetilde{q}_{40}^D}$$

- Skill demand shifts.

$$\widehat{W}_{i,42}^D = \frac{1 - \phi_{41}}{1 - \phi_{21}} \widehat{W}_{i,42}^D, \quad \widehat{W}_{i,42}^F = \frac{\phi_{41}}{\phi_{21}} \widehat{W}_{i,42}^F, \quad \widehat{W}_{42}^e = \Sigma_i \widehat{W}_{i,42}^e, \quad \widetilde{W}_{42} = \widetilde{W}_{41}$$

- Skill prices shift from factor demand shifts in foreign substitution effect. (Corollary A.1)

$$\widehat{q}_{42}^e = \widehat{q}_{41}^e + \underbrace{\left(\frac{\widehat{W}_{42}^e - \widehat{W}_{41}^e}{\widehat{S}_{41}^e} \right) \widehat{\Phi}^e}_{\text{foreign substitution effect}}, \quad \widehat{q}_{42} = \frac{(\widehat{q}_{42}^F)^{\phi_{42}} (\widehat{q}_{42}^D)^{1-\phi_{42}}}{B'(\phi_{42})}, \quad \widetilde{q}_{42} = \widetilde{q}_{41}$$

- The establishment-level skill allocation shifts under the factor demand curves.

$$\widehat{S}_{i,42}^e = \frac{\widehat{W}_{i,42}^e}{\widehat{q}_{42}^e}, \quad \widetilde{S}_{i,42} = \frac{\widetilde{W}_{i,42}}{\widetilde{q}_{42}}, \quad K_{i,42} = \frac{V_{i,42}^K}{q'^K}, \quad \widehat{S}_{42}^e = \Sigma_i \widehat{S}_{i,42}^e, \quad \widetilde{S}_{42} = \Sigma_i \widetilde{S}_{i,42}, \quad K_{42} = \Sigma_i K_{i,42}$$

C Data Appendix

C.1 Labor

C.1.1 Foreign labor distribution across sectors

The model features the roles of low-skilled immigration in manufacturing, and high-skilled immigration in information service. This section provides evidences to support this focus.

Foreign-domestic educational attainment Figure C.1 shows immigrants with with 12 year or less education (high-schools graduates and below) are over-represented in manufacturing, while immigrants with 17 year and more education (above bachelors) are over-represented in in information service.

Immigration density across the occupational spectrum Immigration presence across the spectrum of occupations along the non-routineness in 2015 for production and non-production workers in each sector is presented. Figure C.2 illustrates sharply contrasting presence of foreign labor in the occupational spectrum across production and non-production workers. To appropriately map the model into empirics, non-routineness in occupation is proxied by one minus computerizable probability crafted in Frey and Osborne (2017). (used in Figure C.2, C.1, C.2)⁹ Foreign labor is characterized by contrasting concentration along

⁹Frey and Osborne (2017) cover both production workers and non-production workers across sectors. A purely technical feasibility for automation is systematically codified in a form of numeric index, based on interviews to technology experts. Peri and Sparber (2009) document immigration presence across occupational spectrum along task routineness, crafted from characteristics codified in ONET. They show that immigrants

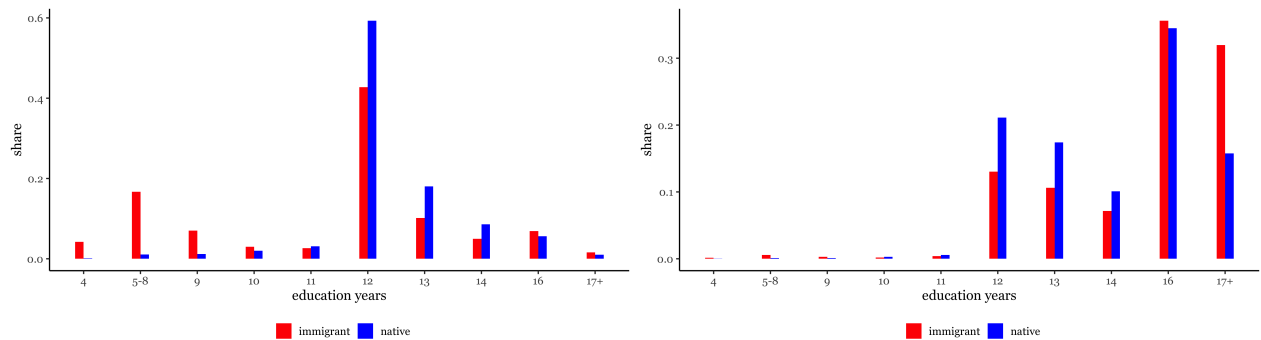


Figure C.1: Educational attainment distribution: immigrants vs. natives (2015)
(left: production workers in manufacturing, right: non-production workers in information service)
Notes: Share of head counts within domestic and foreign group in each sector.

the occupational spectrum across sectors; among the production occupations, routine class of occupations are, on average, immigration-intensive. Among non-production occupations, non-routine class of occupations are on average, immigration-intensive relative to more routine class of workers.

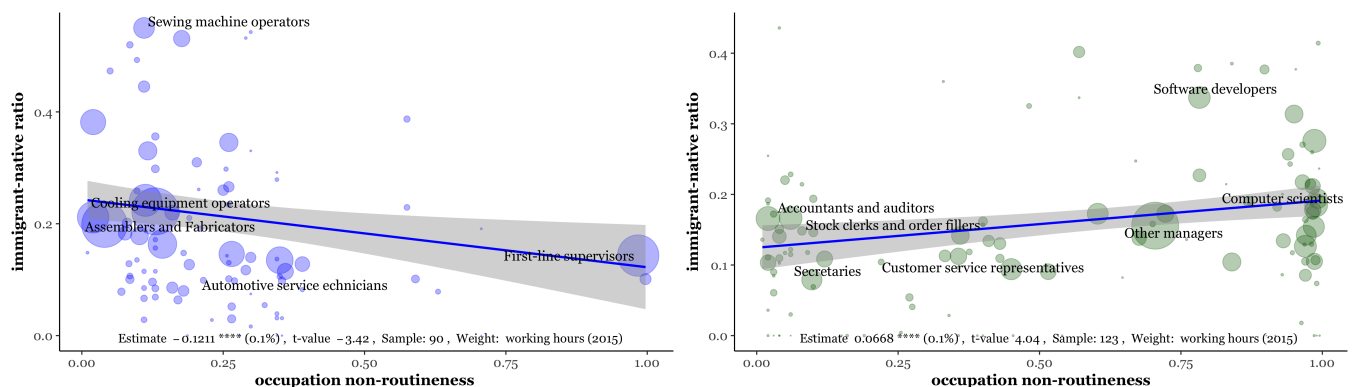


Figure C.2: Occupational non-routineness and immigrant-native ratio (2015)
(left: production workers in manufacturing sector, right: non-production workers in information service sector)
Note: Production workers, non-production workers are classified from occ2010 in ACS, 2015. The size of the bubble shows working hours in 2015. Shaded areas are 99% confidence intervals.

The following pair of tables list up the most and least non-routine occupations, and record immigrant-native ratio, computed by working hours. In 92 production occupations, the average foreign-domestic ratio is 0.123 (top 10) vs. 0.211 (bottom 10). In 136 non-production occupations, the average foreign-domestic ratio is 0.144 (top 10) vs. 0.120 (bottom 10).

agglomerate relatively in manual and analytically intensive occupations. Automation probability from Frey and Osborne (2017) and the task characteristics from ONET are found to be strongly correlated.

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

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

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

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

Table C.2: Top/Bottom 10 non-routine occupations and foreign-domestic ratio (2015, non-production workers)

non-routine ranking	non-routineness	occ2010	employment (2015)	immigration ranking	foreign-domestic ratio
1	0.995	Social and Community Service Managers	390,702	137	0.075
2	0.994	Psychologists	163,502	118	0.096
3	0.993	Medical and Health Services Managers	741,114	79	0.119
4	0.992	Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers	1,809,169	20	0.204
5	0.990	Education Administrators	972,477	130	0.085
6	0.990	Marine Engineers and Naval Architects	13,901	124	0.090
7	0.989	Mechanical Engineers	299,238	25	0.187
8	0.988	Logisticians	177,750	61	0.136
9	0.986	Engineers, nec	689,601	11	0.249
10	0.986	First-Line Supervisors of Office and Administrative Support Workers	1,585,838	97	0.108

routine ranking	non-routineness	occ2010	employment (2015)	immigration ranking	foreign-domestic ratio
1	0.010	New Account Clerks	18,031	98	0.107
2	0.010	Cargo and Freight Agents	28,231	18	0.208
3	0.020	Bookkeeping, Accounting, and Auditing Clerks	1,319,239	84	0.114
4	0.020	Insurance Claims and Policy Processing Clerks	452,927	134	0.079
5	0.020	Claims Adjusters, Appraisers, Examiners, and Investigators	325,751	131	0.081
6	0.020	Shipping, Receiving, and Traffic Clerks	795,044	35	0.165
7	0.020	Brokerage Clerks	6,766	91	0.111
8	0.020	Bank Tellers	440,746	73	0.126
9	0.020	Procurement Clerks	38,550	64	0.135
10	0.020	Credit Analysts	33,304	67	0.131

Notes: Ranking is made based on 136 non-production occupations. (5 occupations are excluded due to lack of Frey-Osborne index) Employment and working hours are taken and foreign-domestic ratio are computed from ACS, 2015.

C.1.2 Marshallian labor supply elasticity

To get the uncompensated (or Marshallian) labor supply elasticity, regress working hours by real wages, controlling for non-labor incomes. Using the cross-section individual datasets (Census/ACS), regress

$$\ln L_{j,l,t} = \gamma_0 + \gamma_1 \ln w_{j,l,t} + \gamma_1' \ln w_{j,l,t} \times I(e_j = F) + \gamma_2 \ln NLI_{j,t} + \gamma_3 \mathbf{X}_{j,t} + \epsilon_{j,t}$$

where $\mathbf{X}_j$ is a vector of observable attributes of individual j , including age, gender, marital status and number of children and NLI_i is non-labor income. Years are taken from $t \in \{1980, 1990, 2000, 2007, 2015\}$. $I(e_j = F)$ is a immigrant dummy for j . Then, uncompensated labor supply elasticity of natives and immigrants are obtained by using a common shifter γ_1 and immigrant dummy coefficient γ_1' such that

$$\epsilon_U^D = \gamma_1, \quad \epsilon_U^F = \gamma_1 + \gamma_1'$$

To control for endogeneity of the log real wage, it is instrumented by Bartik-type labor demand shocks. Following [Diamond \(2016\)](#), I define Bartik shock for each class of workers from year t to t' as

$$\Delta B_{l,t} = \sum_{g \in G} (\ln w_{g,t'} - \ln w_{g,t}) \frac{L_{l,g,t}}{L_{l,t}}$$

Changes in the productivity levels of the industries located within each city contribute to the city's productivity change. Variation in productivity changes across industries will differentially impact cities' local skill productivity levels based on the industrial composition of the city's workforce. ([Bartik \(1991\)](#))

C.1.3 Welfare

Some samples record very low total earning, the lower bound is set as 9600 USD (800 USD per month) for every individual to ensure the finite marginal utility. No inflation is assumed so that every earning is measured by CPI in 2015.

The realized welfare in 1980-2015 is directly computed from the dataset. The counterfactual welfare in 2016-2050 is computed based on the hypothetical datasets. Following predictions from the model, average CZ-level labor income (*incwage* in ACS) in each occupation class is adjusted from the level in 2015. The self-selection rule in 2008-2015, 2020, 2030, 2040, 2050 delivers expected probability of entry of each individual into each occupation class. Interacting these two, the expected labor income of each sample is computed as an ex-ante expected labor income every year. Non-labor income follows the time trend, extrapolated from the one in 2008-2015. In UBI scenario, the social security payment is

removed from non-labor income, and real wages are adjusted including income tax.

C.2 Capital

C.2.1 Classification

Guided by the model, physical capitals in manufacturing are classified into robots and equipment, while information capitals are split into autonomous IT capital, and IT equipment as follows.

Table C.3: BEA capital classification
BEA capital classification

code (BEA)	name	category	code (BEA)	name	category
EP1A	Mainframes	Autonomous (IT)	ET11	Light trucks (including utility vehicles)	Transportation
EP1B	PCs	Equipment (IT)	ET12	Other trucks, buses and truck trailers	Transportation
EP1C	DASDs	Equipment (IT)	ET20	Autos	Transportation
EP1D	Printers	Equipment (IT)	ET30	Aircraft	Transportation
EP1E	Terminals	Equipment (IT)	ET40	Ships and boats	Transportation
EP1F	Tape drives	Equipment (IT)	ET50	Railroad equipment	Transportation
EP1G	Storage devices	Equipment (IT)	EO11	Household furniture	Other equipment
EP1H	System integrators	Autonomous (IT)	EO12	Other furniture	Other equipment
EP20	Communications	Equipment (IT)	EO30	Other agricultural machinery	Equipment
EP34	Nonelectro medical instruments	Equipment	EO21	Farm tractors	Equipment
EP35	Electro medical instruments	Equipment	EO40	Other construction machinery	Equipment
EP36	Nonmedical instruments	Equipment	EO22	Construction tractors	Equipment
EP31	Photocopy and related equipment	Equipment	EO50	Mining and oilfield machinery	Equipment
EP12	Office and accounting equipment	Equipment	EO60	Service industry machinery	Equipment
EI11	Nuclear fuel	Equipment	EO71	Household appliances	Other equipment
EI12	Other fabricated metals	Equipment	EO72	Other electrical	Other equipment
EI21	Steam engines	Equipment	EO80	Other	Other equipment
EI22	Internal combustion engines	Equipment	ENS1	Prepackaged software	Equipment (IT)
EI30	Metalworking machinery	Robot	ENS2	Custom software	Autonomous (IT)
EI40	Special industrial machinery	Robot	ENS3	Own account software	Autonomous (IT)
EI50	General industrial equipment	Equipment			
EI60	Electric transmission and distribution	Equipment			

Notes: Categories in 3rd and 6th columns are my capital classification of the model, except *Transportation* and *Other equipment*. Structure and IPP (intellectual property products) except software are excluded.

C.2.2 Robots vs. equipment

To connect the BEA and IFR datasets, I explore which combination of capital categories in NIPA best correspond with industrial robots from the IFR. By a series of machine learning prediction algorithms (including random forest, SVMs), this combination of *metal working machinery* and *special industry machinery* from NIPA, best minimizes the mean squared prediction errors between these two.¹⁰ This chart indicates a correlation between the pair of proxies in the datasets in 2015, indicating a very good fit.

¹⁰The procedure is available on request.

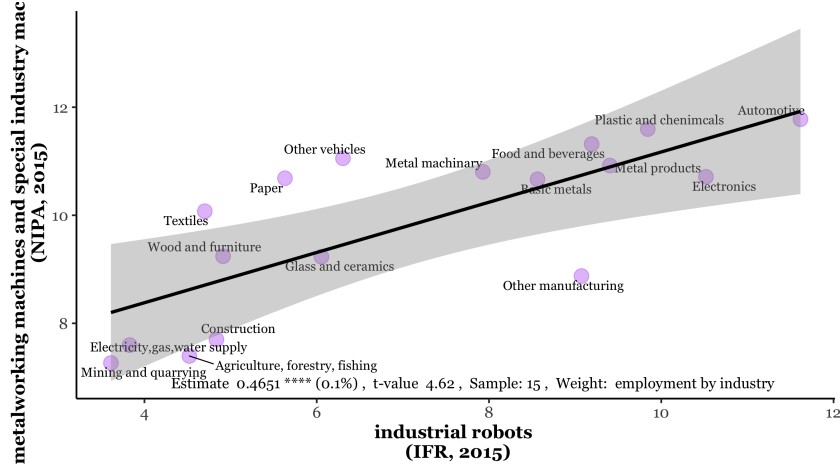


Figure C.3: Cross-validating industrial robot data: the IFR vs. the BEA (2015)

Notes: Industries are from the IFR, connected to the BEA industries by an author. Shaded areas are 99% confidence interval.

C.2.3 Investment price

Investment prices of both robot and equipment in physical capitals and information capitals from 1980 to 2015 are taken from taken from the BEA via [FRED](#), deflated by GDP implicit price deflator from [FRED](#) and they are normalized to one in 2000. All the prices are quality-adjusted, following indices and methods of [Cummins and Violante \(2002\)](#). The capital investment price for robot is defined as the aggregate investment divided by aggregate capital units of metal working machinery and special industry machinery such that

$$p^{robot} \equiv \frac{I^{metal} + I^{special}}{(I^{metal}/p^{metal}) + (I^{spe}/p^{special})}$$

where I is investment values and p is investment prices. Capital equipment price is industrial equipment price from [FRED](#). Superscripts indicate capital categories.

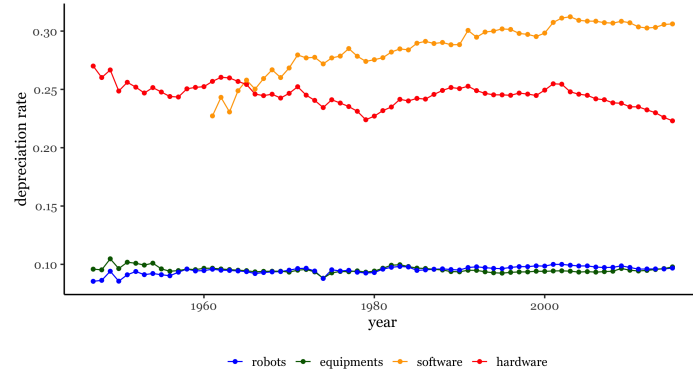


Figure C.4: Depreciation rate by capital category

Notes: Rental prices are imputed from investment prices, denominated by GDP deflator, and normalized to one in 2000. (as computed in Section 4.3)

C.3 Establishment

C.3.1 Urban and rural areas

Urban areas are comprised of the largest CZs in the labor force, accounting for the half of the country labor force in 1980.

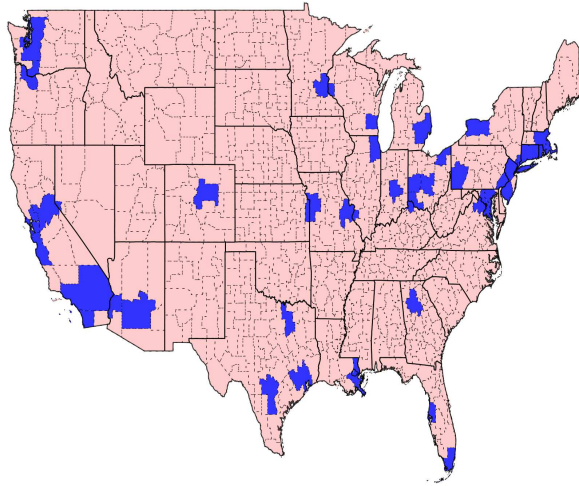


Figure C.5: Urban (blue zones) vs. rural (red zones)

C.3.2 Size distribution

Industry categories in the County business patterns are SICs from 1980 to 1997, and NAICS from 1998-2015. To connect the two sub-industries, use David Dorn's crosswalk from his webpage. Manufacturing sector is SIC 19 (for 1980-86), 20 (for 1987-1997).

Two distributional moments, skewness and HHI, capture the feature of employment share distributions, depicted as follows.

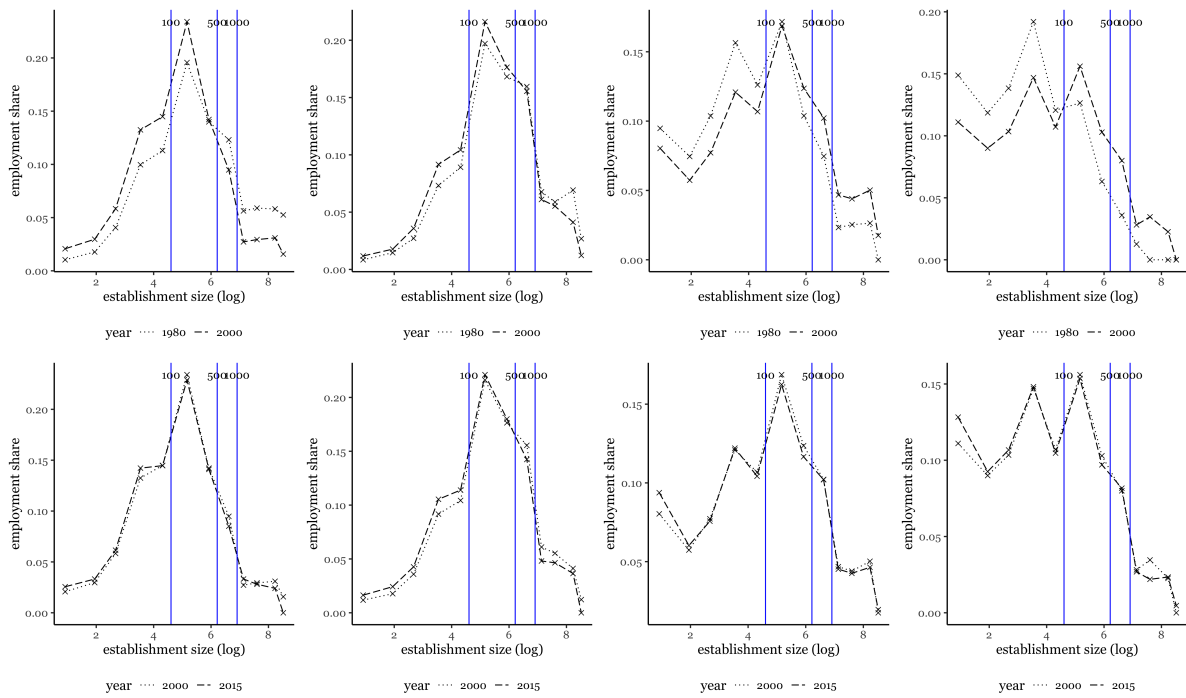


Figure C.6: Employment share by sector(top: 1980 vs. 2000, bottom: 2000 vs. 2015)

Figure C.7 shows the share of employments of establishments in four size class: establishments with 1000 employments and over is classified as mega size, ones with 250 to 1000 is called large, ones with 100 to 250 is called middle, and ones with employments below 100 is called small.

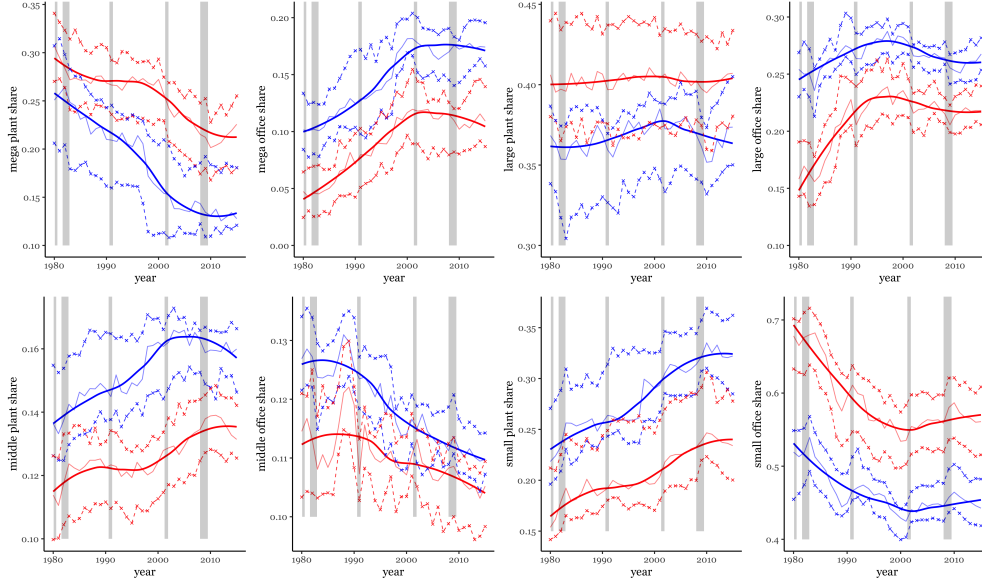


Figure C.7: Employment share by class size (1980-2015)

Notes: Mega size: 1000 and over. Large size: 250 to 1000. Middle size: 100 to 250. Small size: below 100. Blue lines are urban, red lines are rural.

C.4 Corroborating Reduced-Form Results

The goal of this section is to test an immigration-induced automation hypothesis, graphically suggested in Figure 1. The robots in manufacturing (or autonomous IT capitals in information service) per routine working hours is regressed with respect to immigration inflow across commuting zones in each sector. Formerly, for each sector G , run the following regression across commuting zones l , stacked across years $t \in \{1980, 1990, 2000, 2004 - 2015\}$ such that

$$\ln\left(\frac{R_{l,t}}{L_{l,t}}\right) = \alpha^G \ln\left(\frac{\widehat{N_{l,t}^F}}{N_{l,t}}\right) + \epsilon_{l,t}.$$

State-level and time fixed effects are included. Identification conditions and instrument construction is stated in Section 6. A pair of predictions, $\alpha^p < 0$ in manufacturing and $\alpha^o > 0$ in information service empirically backs up the hypothesis of immigration-induced automation. For analysis featuring narrower industrial robots from the IFR, covering construction and agriculture in addition to manufacturing, see a companion paper of [Yoshida \(2019\)](#).

Table C.4: Immigration inflow and automation adoption (1980-2015)

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

Notes: years (1980,1990, 2000, 2004-2015) × 721 commuting zones. All models include an intercept and are weighted by employment hours in each period. Standard errors clustered at the state × year level are reported in parentheses.

*** p<1 %; ** p<5 %; * p<10 %

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