

# QUANTIFYING THE IMPACTS OF A SKILL-BASED US IMMIGRATION REFORM

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## Abstract

The United States is under an active policy debate on a skill-based immigration reform which would curtail family-reunification visas, while favoring applicants based on education, occupation specialty, and language ability. This paper develops a multi-country general equilibrium model with endogenous migration modes of entry to quantify the welfare effects of a skill-based US immigration reform. My model relates exogenous changes of visa regime to immigration composition changes, and can be used to evaluate the welfare effects on the US, migration sending countries, and competing destinations. Assembling multiple datasets, I quantify a model of 13 countries/aggregated economies, and consider migrants from 115 origin countries and 2 education and gender groups. I find a skill-based reform would upgrade the skill composition of US immigrants and raise US welfare and productivity. However, the magnitude of the impacts would be mitigated by mode entry adjustments: workers switch from family-visa to other entry options (skill-visa or illegal cross). I also find the welfare impacts are large for Indian and Central American countries, but are small among other countries, including Mexico.

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# 1 INTRODUCTION

Over the past 2 decades, a handful of developed economies have converged to a skill-based immigration system which filters immigrants mostly based on education, occupation specialty, linguistic ability, etc.<sup>1</sup> However, the US system has prioritized applicants who have family ties with US residents or citizens since the 1960s. There has been an active policy debate of curtailing family-preference visas while prioritizing highly educated workers. These debates have resulted in part of the comprehensive immigration act 2007, and recently in President Trump's call on a "Merit-system" reform. Few comparative studies discuss how a skill-based immigration reform might affect US immigration composition (Borjas 1993, Antecol et al. 2003).<sup>2</sup> Unfortunately, we still lack a solid quantitative understanding on the extent to which a skill-based reform could impact the composition of US immigrants, and how the resulting composition changes would impact the economy.

This paper quantifies the aggregate and distribution impacts of a skill-based US immigration system reform both on the US and on foreign countries. I argue that the impact of skill-based reform will not simply lead to the one-to-one swapping of low-skill with high-skill immigrants. Instead, workers endogenously choose from many visas or illegal cross when migrating. When policy environment changes, some immigrants are able to switch to other entry modes of migration, while others switch to alternative destinations or stay in their home country. The economic impacts of immigration reform thus depends on the magnitude of entry mode adjustments, and an unintended consequence is raising US illegal immigration.

Literature has not to date explicit related changes in visa regime to changes of individual's location choice, and hence to the aggregate immigration labor force. This conceptual disjuncture imposes a challenge to analyzing the effects of immigration policy. This paper bridges this gap by modeling workers' choice of entry mode in a multi-country general equilibrium environment. Building upon the highly tractable assignment model (Lagakos & Waugh 2013, Hsieh et al. 2013), I assume that individuals were born at their home country, and optimize their real wages by choosing countries to which they migrate (Borjas 1987) and which occupation to work (Roy 1951), but also choose an entry mode of migrating from many types of visa or illegal cross. Differences in wages create numerous tensions for people to migrate from the poor to the rich countries. However, geographic and policy barriers discourage migration. Policy barriers of migration are characterized by a vector of iceberg migration costs, with each element referring to the cost of migration via each entry mode. I then simulate changes in mode entry by changes in the entry mode costs that are invariant to immigrants' national-origin.<sup>3</sup>

In this environment, data on entry mode distribution among US immigrants summarizes the cost of migrating through one mode relative to other alternative modes, and predicts immigration composition changes in response to policy changes through two channels. First, the share of entry through a given mode determines the extent to which immigrants would switch

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<sup>1</sup>The skill-based immigration system is often referred to point-system. It was first introduced by Canada in 1960s, and was adopted by Australia in 1989, and New Zealand in 1991. Recent adoption of point-based system includes: Sweden in 2003, Singapore in 2004, Hong Kong in 2006, Denmark in 2007 and the UK in 2008.

<sup>2</sup>Borjas (1993) argue a skill-based immigration system work by mainly alter immigration national-origin mix that destination countries would receive. Antecol et al. (2003) argue against that, the difference in geographic and historical ties, not just that in immigration policy would also play a role in examining the differences in immigration national-origin mix received at each country.

<sup>3</sup>The origin-invariant cost changes reflect the feature that US visa has been mostly granted without discriminating immigrants' national-origin.

in response to changes in migration cost of this mode. For example, reducing a number of family visas would be felt more by Mexican immigrants than by Indian immigrants, because the former are more likely to migrate through family mode than the latter. Second, the share of entry through alternative modes determines the magnitude of entry mode adjustments. Returning to the family visa reduction example, among immigrants who no longer find it optimal to migrate through family visa, Mexican immigrants are more likely to switch to illegal cross than Indian immigrants. This is because the former faces low costs of illegal entry relative to other options than the latter, as indicated by the entry share of illegal mode.

The national-origin and skill composition change of US immigrants would affect certain US occupations more while affecting others less.<sup>4</sup> In the model, data on occupation sorting summarizes the market return to skills, labor market frictions and comparative advantages of work in an occupation relative to the others. In line with the intuition discussed in [Costinot & Vogel \(2010\)](#) and [Burstein et al. \(2015\)](#), occupation sorting also determines the differential wage responses across labor groups through two channels. First, occupation sorting governs the direct wage impacts, the extent to which workers are exposed to occupations which now face less immigration competition. For example, reducing labor supply at service occupation benefits less educated US natives more than highly educated ones. Second, occupation sorting determines the magnitude of occupation switching. Among workers who are not work at service occupation, less educated US natives are more likely to switch to service occupations than highly educated natives, because the former have comparative advantage in service occupations relative to other occupations than the latter. Occupation switching intensifies the differential wage impacts.

I validate the model by taking the total number of US green cards, as well as that by each broad class of admission granted since 1990 to the model, and compare the model-generated cross-country visa allocation with that of the data from Department of Homeland Security for each case. I find that simulating changes of entry mode by changes in origin-invariant mode entry cost, can generate the cross-country visa allocation that aligns well with data of employment-based and family-based green card categories. Since, employment-based and family-based green cards account for more than 80% of the total, unsurprisingly, the predicted allocation matches well with the observed allocation on the aggregate level.<sup>5</sup>

With the model validity established, I estimate two elasticity parameters using the Integrated Public Use Micro Samples (IPUMS) combined 2011, 2012, and 2013 American Community Survey samples ([Ruggles et al. 2015](#)). First, I estimate the labor supply elasticity by relating the variation in occupation sorting of US immigrants to countries' education quality that matters in a given occupation.<sup>6</sup> This parameter governs the responsiveness of choosing a country-occupation-mode option when a mode entry cost changes by 1 percent. For the labor demand side, I estimate the occupation elasticity of substitution parameter by relating changes in average occupation wages to that in total occupational labor since 1990. I apply a Card-type

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<sup>4</sup>[Hanson & Liu \(2016\)](#) documents there is substantial difference in occupation sorting of US immigrants across origin country. Thus together with skill composition changes, the model allows changes in national-origin is another source that affect the US occupation structure.

<sup>5</sup>The model prediction matches the data less well at refugee and diversity category, presumably because the national-origin invariant mode entry cost changes abuses how the diversity green cards has been allocated.

<sup>6</sup>Following from [Hanson & Liu \(2017\)](#), I measure country's labor productivity at each occupation by combining country's math score of international student assessment (PISA), linguistic proximity obtained from Automated Similarity Judgment Program (ASJP), and O\*NET occupation task intensity. Differ from [Hanson & Liu \(2017\)](#), I impose a parametric assumption to measure labor productivity at each occupation so that labor supply elasticity is identified.

instrument to predict the endogenous occupational labor hours based on historical occupation specialization of US immigrants.<sup>7</sup>

Applying *the exact hat algebra* (Dekle et al. 2008), I show the model can be solved in proportional changes by knowing these two elasticity parameters estimated above, without knowing information on the large dimension of model primitives. I then use my model to simulate the counterfactual of interest: holding the total number of green cards issued unchanged since 1990, but reallocating green cards to employment-based categories among college educated workers at cognitive-intensive occupations such that the green card distribution matches exactly the Canadian system as in Figure 1 below.

I combine multiple microdata sources to measure their labor market variables, international migration stock, and the distribution of mode migration of US immigrants. I then quantify my model of 13 aggregated regions and multiple occupations. I consider migration from 115 country of origin, 2 education (college and non-college) and gender groups to OECD destinations. I cluster mode of migration to four broad modes including family, employment, other legal (mainly refugee and diversity green card), and illegal modes.<sup>8</sup> I combine three data sources including Current Population Surveys (CPS), Yearbook of Immigration Statistics from Department of Homeland Security (DHS), and New Immigrant Survey (NIS), to estimate the mode distribution of US immigrants by national origin, education and gender at each occupation.

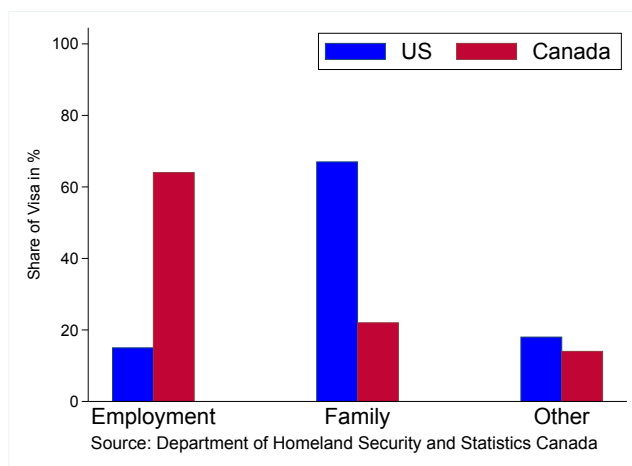


Figure 1: US VS CANADIAN GREEN CARD SHARE BY TYPES SINCE 1990

Notes: The green card distribution for US is calculated based on Yearbook of Immigration Statistics 1996-2015. The data for Canada is obtained from Canadian Statistics.

I find had US adopted a skill-based immigration reform in 1990 would reduce the stock of less educated immigrants from Mexican, and Central American and Caribbean countries, but increase the stock of highly educated immigrants from Indian and East Asian countries. However, the magnitude of the impacts would be mitigated by mode entry adjustments: workers switch from family-visa to other entry options (skill-visa or illegal cross). These results from my model are mainly driven by the data on entry mode distribution of US immigrants. The

<sup>7</sup>The instrument relies on the persistence in occupation specialization of US immigrants by national-origin. This makes the estimation consistent with my model which segments the US labor market by occupations.

<sup>8</sup>The purpose of aggregating to broad mode is to increase the precision when using the NIS sample which has small number of observations.

skill upgrade of US immigrants would raise the overall US output by 2.15%, and narrow US college premium and gender wage gap. However, as an unintended consequence, the number of US illegal immigrants raises by 8%. Further calculation implies the number of border patrol personnel needs to be increased by 10.6% to maintain illegal immigration unchanged.<sup>9</sup>

I also find a skill-based US immigration reform would impact the global economy. On the international labor movement, the US would mostly draw those newly-absorbed global talents from immigrants' home countries. The majority of immigrants who no longer find it optimal to migrate to the US through family entry mode would switch to their home countries. These results from my model are mainly driven by data on the migration rate and home stay rate of each national-origin and demographic group.<sup>10</sup> Moreover, among individual foreign economy which are affected the most, I find high-skill workers become relative more scarce in India and East Asian countries, while become relative more abundant in Central American and Caribbean countries. The relative skill abundance is nearly unchanged in Mexico. As a result, welfare inequality raises in India, but narrows in Central American and Caribbean countries. The welfare impacts are small among other countries, including Mexico.

This paper relates to several strands of literature. Few studies shed light on how a skill-based US immigration reform would affect immigration composition by comparing the observable characteristics of immigrants in the US with Canada or Australia — countries that filter immigrants based on education, occupation specialty, and language ability (Borjas 1993, Antecol et al. 2003). However, we still lack a solid understanding on how a skill-based reform could change immigration composition and the economy. I study this question quantitatively. My approach advances the literature of immigration selection (Borjas 1987, Grogger & Hanson 2011) by building in the mode entry of migration in a multi-country general equilibrium environment, which allows to relate changes in visa regime to immigration composition changes. My results emphasize the importance of incorporating mode entry to analyzing immigration policy reform. That is, if abstracting mode of entry from the model, one would overlook equilibrium adjustment of mode entry and over-predict the economic gain of a skill-based reform.

This paper also relates to the literature on the labor market impacts of immigration. Literature which is mostly based on the reduce-form approach has highlighted the key facts that determine the effects of immigration. These facts include the substitutability across education groups (Card 2009) and between natives and immigrants (Ottaviano & Peri 2012); the relative skill abundance of natives (Borjas 2003); the geographic and institutional frictions (Angrist & Kugler 2003); and the skill transferability of immigrants (Schoellman & Hendricks 2016). A few others emphasize the importance of equilibrium adjustments using structural approaches (Llull 2013, Colas 2016). My general equilibrium model incorporates the above key facts. My main departure from previous literature is studying immigration in a multi-country setting, and hence can speak to the welfare impacts on multiple countries — analogous to the quantitative general equilibrium analysis which has been widely used in international trade literature.<sup>11</sup> Another distinction is that my model distinguishes immigrants by national-origin.

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<sup>9</sup>I obtain this number to first solve a implied migration costs changes in order to keep the illegal immigration constant. I then relate the costs changes to changes in the number of border patrol policy based on Gathmann (2008).

<sup>10</sup>In my model, migration rate summarizes the wage and migration barrier to a country relative to those in all countries.

<sup>11</sup>Various versions of Eaton & Kortum (2002) include multi-sector extension as in Costinot et al. (2011), multinational production as in Ramondo & Rodríguez-Clare (2013), cross sector inter-dependence of intermediate inputs as in Caliendo & Parro (2015), and multi-sector with Roy selection as in Redding (2016), Galle et al. (2015), Lee

My results suggest immigrant-native substitution varies dramatically across national-origins within the education group.

Finally, this paper relates to the fast-growing literature on the Roy-like model. Building upon [Lagakos & Waugh \(2013\)](#) and [Hsieh et al. \(2013\)](#), multiple extension has been developed to study computerization on wage inequality ([Burstein et al. 2015](#)), as well as the impacts of international trade on between-group inequality ([Adão 2015](#), [Galle et al. 2015](#), [Lee 2016](#)), and immigration on US tradable and non-tradable occupations ([Burstein et al. 2017](#)).<sup>12</sup> My model extends this literature to analyzing immigration policy. In addition, I also provide a new way of estimating labor supply elasticity.

The paper is organized as follows. Section 2 presents the model, and section 3 discusses the data source; section 4 discusses the counterfactual this paper performs, and analyzes two key model predictions which guides the empirical results. Section 5 estimates model parameters and performs validation exercises. Section 6 reports the policy impacts on US economies in terms of composition changes of US immigrants, US wage structure, employment, and productivity efficiency; section 7 discusses the policy impacts on foreign economies; section 8 performs robustness analysis. Section 9 concludes.

## 2 MODEL

This section presents a multi-country, multi-occupation, multi-mode Roy model of international migration in a static environment. Each country is endowed with workers who were born at home country and choose a country to live, an occupation to work, and a mode through which to migrate, by maximizing their perceived income. Empirically, I consider four modes of migration including employment-based green card, family-based green card, refugee and other legal green card, and illegal migration. The current baseline model allows labor movement across countries, but not allowing international trade of goods. The labor markets are segmented by countries and occupations. I index country by  $\kappa$ , occupation by  $\sigma$  and the mode by  $m$ . The model considers many national-origin, education and gender groups, indexed by  $\nu$ .

### 2.1 PRODUCTION

The production unit at each country employs workers both domestically and internationally to work at a finite number of occupations  $\sigma$ . A single final product produced in country  $\kappa$  is combined from various tasks with a CES production function,

$$Y_{\kappa} = \left[ \sum_{\sigma} A_{\kappa,\sigma} L_{\kappa,\sigma}^{\frac{\rho_{\kappa}-1}{\rho_{\kappa}}} \right]^{\frac{\rho_{\kappa}}{\rho_{\kappa}-1}},$$

$\rho_{\kappa}$  denotes the elasticity of substitution across occupations of country  $\kappa$ .  $A_{\kappa,\sigma}$  is total factor productivity at country  $\kappa$  and occupation  $\sigma$ . I assume  $A_{\kappa,\sigma}$  is exogenous in the baseline model, but will endogenize it as a function of the stock of college educated workers in Appendix F.1.

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(2016), among others.

<sup>12</sup>[Lagakos & Waugh \(2013\)](#) first brought *Fréchet* productivity into a 2-sector Roy model to study cross-country differences in agricultural labor productivity. [Hsieh et al. \(2013\)](#) developed this literature to multi-sector Roy model to study the labor-occupation mis-allocation in the US during 1960-2010.

$L_{\kappa,\sigma}$  is the efficiency unit of labor aggregated over all labor groups worked in country  $\kappa$  at occupation  $\sigma$ . In baseline, I assume that workers from different countries of origin and education-gender groups are perfect substitutes within each occupation.<sup>13</sup> I present various models extension to consider illegal immigrants are imperfect substitutes with natives and legal immigrants in Appendix F.2, and native and immigrants are imperfect substitute in Appendix F.3. The model treats labor as the only inputs in production.<sup>14</sup> The model remains tractable by considering international trade in occupation as presented in Appendix F.4.

## 2.2 LABOR SUPPLY

I group workers based on their country of origin, education and gender, indexed by  $\nu$ .  $m$  denotes the mode of migration.  $\sigma$  contains all actual occupations, plus two options of unemployment or not in the labor force.<sup>15</sup> It is important to consider immigrants who are not in the labor force, since they account for over 10% of the overall immigrants.

Each worker  $i$  from group  $\nu$  draw a vector of efficiency units if working at country  $\kappa$ , occupation  $\sigma$  and mode status  $m$ , denoted as  $\{\eta_{\nu,\kappa,\sigma,m}(i)\}$ . Each element of the vector is draw independently from a marginal *Fréchet* productivity distribution that has the cumulative distribution function below

$$P(\eta_{\nu,\kappa,\sigma,m} < z) = \exp \left\{ -T_{\nu,\kappa,\sigma}^\vartheta z^{-\vartheta} \right\}.$$

Every marginal distribution is characterized by two parameters: the scale parameter of productivity  $T_{\nu,\kappa,\sigma}$ , and the shape parameter  $\vartheta$ . A larger  $T_{\nu,\kappa,\sigma}$  corresponds to a higher average level and also a fat upper tail of group productivity at country and occupation. I also assume that the distribution is invariant across mode  $m$ . This means some workers can be more productive if working at family green card than at illegal status, but the group productivity distribution are the same irrespective of their mode status.

It is also worth emphasizing that  $T_{\nu,\kappa,\sigma}$  reflects the mixture of innate occupational talents and the skill transfer-ability. Both innate talents and the extent to which skill can be transferred can vary by groups, host countries and by occupations.  $\vartheta$  governs the shape of the productivity distribution, and a larger  $\vartheta$  corresponds a less within-group dispersion conditional on  $T_{\nu,\kappa,\sigma}$ . I assume  $\vartheta$  be the same across labor groups. When referring to unemployment or not in labor force, the *Fréchet* distribution denotes that of the reservation wage.

## 2.3 LOCATION AND OCCUPATION CHOICES

Workers choose  $\kappa$ - $\sigma$ - $m$  by maximizing their net perceived earnings. I use  $\Omega_{\kappa,\sigma}$  to denote the wage efficiency unit per labor at country  $\kappa$  and occupation  $\sigma$ , then a worker who draws  $\eta_{\nu,\kappa,\sigma,m}(i)$  efficiency unit of labor productivity, the wage she would earn if choose to live in country  $\kappa$ , occupation  $\sigma$  and at mode status  $m$  equals  $\tau_{\nu,\kappa,\sigma,m} \times \Omega_{\kappa,\sigma} \times \eta_{\nu,\kappa,\sigma,m}(i)$ .

<sup>13</sup>As mentioned in Card (2001), the assumption of perfect substitutes between natives and immigrants at occupation level can be justified by US immigration law, which requires legal immigrants are not undercut wages by their employers in the same occupation.

<sup>14</sup>The model also remains analytically tractable by incorporating multiple production factors such as land, capital. Alternatively, the model is isomorphic with a model with capital and labor as two input factors combined through a Cobb-Douglas technology, and capital is frictionless. In that case, firms' optimal choice on capital (as a function of labor) will yield the production function as constant return to scale to labor.

<sup>15</sup>In the case where  $\sigma$  corresponds to unemployment or not in the labor force,  $A_{\kappa,\sigma} = 0$  in production function.

Where  $\tau_{\nu,\kappa,\sigma,m}$  is iceberg migration costs, interpreted as the take-home wage rate net out migration costs, and hence takes value between 0 and 1. The variation in  $\tau_{\nu,\kappa,\sigma,m}$  reflects differences in destination's immigration policy, in bilateral gravity forces and the interaction between them. The multiplicative form of migration frictions aims to keep the model tractable, and has been widely adopted in the literature of immigration self-selection, for example see [Borjas \(1987\)](#), [Chiquiar & Hanson \(2005\)](#).<sup>16</sup>

Given the *Fréchet* distribution assumption, the fraction of group  $\nu$  work in country  $\kappa$ , occupation  $\sigma$ , and migrate through mode  $m$  has closed form as follows

$$P_{\kappa,\sigma,m|\nu} = \frac{T_{\nu,\kappa,\sigma}^{\vartheta} \Omega_{\kappa,\sigma}^{\vartheta} \tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\sigma'} \sum_{m'} T_{\nu,\kappa',\sigma'}^{\vartheta} \Omega_{\kappa',\sigma'}^{\vartheta} \tau_{\nu,\kappa',\sigma',m'}^{\vartheta}}.$$

where  $\vartheta$  is *Fréchet* dispersion parameter and also captures labor supply elasticity with respect to a given  $\kappa$ - $\sigma$  market and through a given mode  $m$ . Throughout this paper, I use the notation  $P_{\cdot|\cdot}$  to note for conditional probability. Summing over options within a country to obtain the bilateral migration rate for group  $\nu$

$$P_{\kappa|\nu} = \frac{\sum_{\sigma} \sum_{m} T_{\nu,\kappa,\sigma}^{\vartheta} \Omega_{\kappa,\sigma}^{\vartheta} \tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\sigma'} \sum_{m'} T_{\nu,\kappa',\sigma'}^{\vartheta} \Omega_{\kappa',\sigma'}^{\vartheta} \tau_{\nu,\kappa',\sigma',m'}^{\vartheta}}.$$

The functional form of the migration flow is consistent with the reduce-form immigration literature, see [Grogger & Hanson \(2011\)](#), [Kennan & Walker \(2011\)](#), [Monte, Redding & Rossi-Hansberg \(2015\)](#). I next present expression for three conditional probability which will be extensively analyzed in section 4. The fraction of immigrants in country  $\kappa$  who work at occupation  $\sigma$  has the form

$$P_{\sigma|\nu,\kappa} = \frac{\sum_m T_{\nu,\kappa,\sigma}^{\vartheta} \Omega_{\kappa,\sigma}^{\vartheta} \tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{\sigma'} \sum_{m'} T_{\nu,\kappa,\sigma'}^{\vartheta} \Omega_{\kappa,\sigma'}^{\vartheta} \tau_{\nu,\kappa,\sigma',m'}^{\vartheta}}. \quad (1)$$

The fraction of immigrants in country  $\kappa$  who entered through mode  $m$  has the form

$$P_{m|\nu,\kappa} = \frac{\sum_{\sigma} T_{\nu,\kappa,\sigma}^{\vartheta} \Omega_{\kappa,\sigma}^{\vartheta} \tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{\sigma'} \sum_{m'} T_{\nu,\kappa,\sigma'}^{\vartheta} \Omega_{\kappa,\sigma'}^{\vartheta} \tau_{\nu,\kappa,\sigma',m'}^{\vartheta}} \quad (2)$$

In addition, among  $\nu$  immigrants who work at occupation  $\sigma$ , the mode through which migrants in a given occupation that entered the US, depends on the frictions of entering through that mode relative to the sum of any other mode frictions

$$P_{m|\nu,\kappa,\sigma} = \frac{\tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{m'} \tau_{\nu,\kappa,\sigma,m'}^{\vartheta}}. \quad (3)$$

In the model, each conditional probability  $P_{\cdot|\cdot}$  is explained by the average benefits of being in one cell relative to the sum of benefits over all cells. In appendix [G.1](#), I also show the close-form expression of conditional probability including  $P_{\kappa,\sigma|\nu}$ ,  $P_{\kappa,m|\nu}$ ,  $P_{\sigma|\nu,\kappa}$ ,  $P_{m|\nu,\kappa}$ ,  $P_{m|\nu,\kappa,\sigma}$  and

<sup>16</sup>Literature in immigration selection assumes a additive migration cost on log perceive wage. For example, recall the seminal paper by [Borjas \(1987\)](#), the take-home wage net migratory costs at destination is written as  $\log w_1 - c = \mu_1 + \varepsilon_1 - c$ , where  $c$  is assumed to be a constant across workers. [Chiquiar & Hanson \(2005\)](#) also assumes log additive migration costs, but increase with respect to education. In my model, taking the logarithm of  $\tau_{\nu,\kappa,\sigma,m} \times \Omega_{\kappa,\sigma} \times \eta_{\nu,\kappa,\sigma,m}(i)$  will result in the same function form as in those papers. However, my model is more flexible by allowing migration costs to be specific to each origin, education and gender group, host country, occupation and mode of migration.



$P_{\sigma,m|\nu,\kappa}$ .

The *Fréchet* distribution implies the average group efficiency units of labor that works in country  $\kappa$ , occupation  $\sigma$  and migrate through mode  $m$  equals,

$$E[\eta_{\nu,\kappa,\sigma,m}|\kappa, \sigma, m] = \Gamma(1 - \frac{1}{\vartheta}) \cdot T_{\nu,\kappa,\sigma} [P_{\kappa|\nu} \cdot P_{\sigma,m|\nu,\kappa}]^{-\frac{1}{\vartheta}}.$$

where  $\Gamma(\cdot)$  denotes gamma function. Differ from log normal distribution (Heckman 1979, Borjas 1987), *Fréchet* distribution generates selection bias in a simple manner, captured by term  $[P_{\kappa|\nu} \cdot P_{\sigma,m|\nu,\kappa}]^{-\frac{1}{\vartheta}}$ . It says, first, the smaller fraction of workers who are selected into a cell, the more positive selection bias there would be. The intuition is that when the barrier to enter a given labor market is high or its return is low, only the most productive workers find optimal to work in the market; while as barrier falls or the return rises, the market would absorb less productive workers as well, and hence lowering the degree of positive selection. This prediction is line with the recent facts documented in Lazear (2017). Second, as the fraction of workers who work in a given cell increases, the skill-selectivity bias falls faster when productivity is highly dispersed, i.e.,  $\vartheta$  is small.

Multiplying occupation wage unit, the average wage of workers work in occupation  $\sigma$  under mode  $m$  at country  $\kappa$  can be expressed as

$$W_{\sigma,m|\nu,\kappa} = \Gamma(1 - \frac{1}{\vartheta}) \cdot T_{\nu,\kappa,\sigma} \cdot \Omega_{\kappa,\sigma} \cdot [P_{\kappa|\nu} \cdot P_{\sigma,m|\nu,\kappa}]^{-\frac{1}{\vartheta}}.^{17}$$

## 2.4 GENERAL EQUILIBRIUM

The primitives of the global economy are given by  $\Lambda = \{A, \tau, L, T, \rho, \vartheta\}$ , including country-occupation specific total factor productivity  $A_{\kappa,\sigma}$ , bilateral and mode specific migratory costs  $\tau_{\nu,\kappa,\omega,m}$ , the stock of labor force at each origin-education group  $L_{\nu}$ , *Fréchet* productivity location parameter  $T_{\nu,\kappa,\sigma}$ , *Fréchet* shape parameter  $\vartheta$ , and the elasticity of substitution across occupation at each country,  $\rho_{\kappa}$ .

The CES production function implies the labor demand at each country  $\kappa$  and occupation  $\sigma$  is

$$L_{\kappa,\sigma}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}}$$

The total efficiency unit of labor supplied at each market equals

$$L_{\kappa,\sigma}^{\text{supply}} = \sum_{\nu} \sum_{m} E[\eta_{\nu,\kappa,\sigma,m}|\kappa, \sigma, m] \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu} = \frac{1}{\Omega_{\kappa,\sigma}} \sum_{\nu} \sum_{m} W_{\sigma,m|\nu,\kappa} \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu}^{18}$$

<sup>17</sup>An alternative expression for  $W_{\sigma,m|\nu,\kappa}$  is

$$W_{\sigma,m|\nu,\kappa} = \frac{1}{\tau_{\nu,\kappa,\sigma,m}} \cdot \Gamma(1 - \frac{1}{\vartheta}) \cdot \left[ \sum_{\sigma'} \sum_m T_{\nu,\kappa,\sigma'}^{\vartheta} \tau_{\nu,\kappa,\sigma',m}^{\vartheta} \Omega_{\kappa,\sigma'}^{\vartheta} \right]^{\frac{1}{\vartheta}} \cdot P_{\kappa|\nu}^{-\frac{1}{\vartheta}}.$$

The above expression explains that the wage gaps across occupations earned by a given group is formed by variation in occupation barriers, differing from the prediction that the wage earned by a given group is a constant across occupations as in studies by Hsieh et al. (2013), Burstein et al. (2015), Galle et al. (2015).

<sup>18</sup>The second equality holds because the total expenditure on labor equals the products of wage efficiency per unit and the overall efficiency units of labor.

where  $L_\nu$  is the total labor stock of  $\nu$  workers. Given the primitives  $\Lambda$ , a competitive equilibrium in global economy consists the location-occupation-mode sorting of  $\nu$  workers,  $P_{\kappa,\sigma,m|\nu}$ , bilateral migration rate  $P_{\kappa|\nu}$ , the average wages earned by  $\nu$  workers at country  $\kappa$ , occupation  $\sigma$  and mode  $m$ ,  $W_{\sigma,m|\nu,\kappa}$ . The wage efficiency unit of labor at each  $\kappa$ - $\sigma$  market  $\Omega_{\kappa,\sigma}$  equalizes the labor demand with labor supply such that  $L_{\kappa,\sigma}^{\text{supply}} = L_{\kappa,\sigma}^{\text{demand}}$ .

## 2.5 Solving Equilibrium in Proportional Changes

I solve model by applying *the exact hat algebra* first recognized by Dekle et al. (2008) in a gravity trade context and being adopted to the case of elastic labor supply by Burstein et al. (2015), Redding (2016). Its great advantage is to solve the model in proportional changes without knowing the level of many model primitives. In my case, solving the model would only require two elasticity that carries the general equilibrium structure, namely the demand elasticity,  $\rho_{us}$  and labor supply elasticity,  $\vartheta$ .

Define proportional changes  $\hat{X} = \frac{X_1}{X_0}$ , where the  $X_1$  denotes the counterfactual equilibrium variables, and  $X_0$  denotes the equilibrium variables of the initially observed economy in year 2010. I then express equilibrium labor flow in terms of proportional changes as follows

$$\hat{P}_{\kappa,\sigma,m|\nu} = \frac{\hat{T}_{\nu,\kappa,\sigma}^\vartheta \hat{\Omega}_{\kappa,\sigma}^\vartheta \hat{\tau}_{\nu,\kappa,\sigma,m}^\vartheta}{\sum_{\kappa'} \sum_{\sigma'} \sum_{m'} \hat{T}_{\nu,\kappa',\sigma'}^\vartheta \hat{\Omega}_{\kappa',\sigma'}^\vartheta \hat{\tau}_{\nu,\kappa',\sigma',m'}^\vartheta P_{0,\kappa,\sigma,m'|\nu}} \quad (4)$$

Subscript 0 denotes variables observed in year 2010. It is important to notice from equation (4) that  $\hat{P}_{\kappa,\sigma,m|\nu}$  is a function of  $\hat{T}_{\nu,\kappa,\sigma}$ ,  $\hat{\Omega}_{\kappa,\sigma}$ ,  $\hat{\tau}_{\nu,\kappa,\sigma,m}$ ,  $\vartheta$  and the data  $P_{0,\kappa,\sigma,m|\nu}$ , while the level of model primitives such as  $T_{\nu,\kappa,\sigma}$ ,  $\tau_{\nu,\kappa,\sigma,m}$  enter only in terms of  $P_{0,\kappa,\sigma,m|\nu}$ . This implies that information of  $P_{\kappa,\sigma,m|\nu}$  is sufficient to capture information on these model primitives. Analogously, proportional changes for migration rate, average wages and the labor market clear conditions can be obtained as follows

$$\hat{P}_{\kappa|\nu} = \frac{\sum_{\sigma'} \hat{T}_{\nu,\kappa,\sigma'}^\vartheta \hat{\Omega}_{\kappa,\sigma'}^\vartheta P_{0,\sigma'|\nu,\kappa} B_{\nu,\kappa,\sigma'}}{\sum_{\kappa'} \sum_{\sigma'} \hat{T}_{\nu,\kappa',\sigma'}^\vartheta \hat{\Omega}_{\kappa',\sigma'}^\vartheta P_{0,\kappa',\sigma'|\nu} B_{\nu,\kappa,\sigma'}} \quad (5)$$

where  $B_{\nu,\kappa,\sigma} = \sum_m [\hat{\tau}_{\nu,\kappa,\sigma,m}^\vartheta P_{0,m|\nu,\kappa,\sigma}]$ , and one also has the proportional changes in wage has the form

$$\hat{W}_{\sigma,m|\nu,\kappa} = \frac{1}{\hat{\tau}_{\nu,\kappa,\sigma,m}^\vartheta} \left\{ \sum_{\sigma'} \hat{T}_{\nu,\kappa,\sigma'}^\vartheta \hat{\Omega}_{\kappa,\sigma'}^\vartheta P_{0,\sigma'|\nu,\kappa} B_{\nu,\kappa,\sigma'} \right\}^{\frac{1}{\vartheta}} \hat{P}_{\kappa|\nu}^{-\frac{1}{\vartheta}} \quad (6)$$

$$\hat{A}_{\kappa,\sigma}^{\rho_\kappa} \hat{\Omega}_{\kappa,\sigma}^{1-\rho_\kappa} \cdot \hat{Y}_\kappa = \frac{\sum_\nu \sum_m W_{0,\sigma,m|\nu,\kappa} L_{0,\nu} P_{0,\kappa,\sigma,m|\nu} \hat{W}_{\sigma,m|\nu,\kappa} \hat{L}_\nu \hat{P}_{\kappa,\sigma,m|\nu}}{\sum_\nu \sum_m W_{0,\sigma,m|\nu,\kappa} L_{0,\nu} P_{0,\kappa,\sigma,m|\nu}} \quad 19, \quad \forall \kappa, \sigma. \quad (7)$$

The expression for  $\hat{P}_{\sigma|\nu,\kappa}$ ,  $\hat{P}_{\kappa,\sigma|\nu}$ ,  $\hat{P}_{\sigma,m|\nu,\kappa}$  can also be obtained analogously, and the detailed derivation is provided in appendix G.2.

For a counterfactual which only deviates from the data by changes in immigration frictions captured by  $\hat{\tau}_{\nu,\kappa,\sigma,m}$ , while other primitives are unchanged in counterfactual such that  $\hat{A}_{\kappa,\sigma} = \hat{T}_{\nu,\kappa,\sigma} = 1$ . Then given parameter values on  $\vartheta$  and  $\rho_\kappa$ , and data on sets of moment  $\{W_{\sigma,m|\nu,\kappa}\}$ ,  $\{P_{\kappa|\nu}\}$ ,  $\{P_{\sigma|\nu,\kappa}\}$ ,  $\{P_{m|\nu,\kappa,\sigma}\}$  observed in year 2010, one can solve  $\hat{\Omega}_{\kappa,\sigma}$  from systems of equation

<sup>19</sup>where

$$\hat{Y}_\kappa = \frac{\sum_{\nu,\sigma,m} W_{0,\sigma,m|\nu,\kappa} L_{0,\nu} P_{0,\kappa,\sigma,m|\nu} \hat{W}_{\sigma,m|\nu,\kappa} \hat{L}_\nu \hat{P}_{\kappa,\sigma,m|\nu}}{\sum_{\nu,\sigma,m} W_{0,\sigma,m|\nu,\kappa} L_{0,\nu} P_{0,\kappa,\sigma,m|\nu}},$$

(4) – (7). Other endogenous variables on changes in equilibrium labor allocation and wages can be then solved using  $\widehat{\Omega}_{\kappa,\sigma}$ .<sup>20</sup>

Section 4.1 discusses how I define and measure the counterfactual policy shocks in details. I show that using *the exact hat algebra* in my situation has two additional advantages. First, it allows me measure the counterfactual policy experiment without knowing the level of friction  $\tau_{\nu,\kappa,\sigma,m}$ . Second, the counterfactual policy experiment which changes US migration frictions does not need any information on the number of mode types, or the mode distribution of migration at any other countries.

### 3 DATA

The empirical exercise of this paper requires measurement on three sets of variables. I combine multiple country census and micro survey to measure occupation share, average wages at each country. I also use brain-drain dataset from Institute for Employment Research (IAB) to measure bilateral migration stock. Finally, I combine Current Population Surveys (CPS), Yearbook of Immigration Statistics at Department of Homeland Security, and New Immigrant Survey (NIS), to estimate the conditional mode distribution of US immigrants.

#### 3.1 Labor market and migration data

I consider workers from 115 national-origin, 2 education (college and non-college) and 2 gender groups, leaving a total of 460 labor groups in the analysis. I consider US, Canada, Oceania, and OECD Europe as both source and destination countries of migration, while the other countries are treated as source country of migration only.<sup>21</sup> I solve the general equilibrium of a world economy with  $\dim(\kappa) = 13$  countries/regions including 4 individual countries, namely, US, Canada, India, and Mexico, and 9 regions including Africa, Central America, East Asia, East Europe, Middle east and south Asia, Oceania, OECD Europe, Southeast Asia, and South America.

The empirical exercise of this paper requires the following three sets of labor market variables at each country/region and occupation. (1) The bilateral migration rate to US, Canada, OECD Europe and Oceania for each group  $\nu$  observed in year 2010,  $\{P_{\kappa|\nu}\}$ ; (2) The occupation share supplied by each labor group at each country observed in year 2010,  $\{P_{\sigma|\nu,\kappa}\}$ ; (3) The average wages earned at each occupation and country by labor groups observed in year 2010,  $\{W_{\sigma,m|\nu,\kappa}\}$ .

**US LABOR MARKET:** I measure the average wage and employment of US labor market for each origin, education and gender group based on American Community Survey (ACS) 5-year sample 2009-2013 drawn from Integrated Public Use Microdata Series USA (Ruggles et al. 2015). I

<sup>20</sup>To solving equilibrium efficiently, I notice that equilibrium changes in labor allocation and wages (4) – (6) are functions of changes in wage efficiency unit of labor  $\widehat{\Omega}_{\kappa,\sigma}$ . This allows us to express  $\widehat{P}_{\sigma|\nu,\kappa}$ ,  $\widehat{P}_{\kappa|\nu}$  and  $\widehat{W}_{\sigma|\nu,\kappa}$  in terms of  $\widehat{\Omega}_{\kappa,\sigma}$  and solve the equilibrium in changes  $\widehat{\Omega}_{\kappa,\sigma}$  using systems of equation (7), for each country and occupation labor market.

<sup>21</sup>Omitting south-to-south migration is not a limitation of the model, but due to the data challenge on the measurement of south-to-south migration. To the best of my knowledge, data on south-to-south migration in 2010 has been collected.

restrict the sample to individuals who are 18-64 years old. Variables of weeks worked of IPUMS Census is reported in interval. I thus take the middle point of each interval to approximate the number of weeks worked last year.

I aggregate the ACS education categories into 2 broad groups including non-college educated, and college educated and above. I aggregate the detailed ACS occupations which are similar in the nature of task contents, into 28 aggregated categories, following closely to the categories based on IPUMS variable OCC1990. Table 4 at appendix A provides transformed percentile values of widely used 5 tasks intensity measurement obtained from Direction of Occupational Titles, to show the 28 aggregate occupations used in this paper are distinct in their task contents. I also has two options for unemployment and not in labor force.

I measure the occupation share in terms of total hours worked by each labor group at US. I also calculate the weighted average of occupation wage, while adjust the weight by hours worked to take into account the variation in labor hours across occupations and labor groups.<sup>22</sup> This gives the average occupation wage by groups,  $W_{\sigma|\nu,\kappa}$ . I calculate  $W_{\sigma,m|\nu,\kappa}$  for legal mode at each occupation for each group as the product of  $W_{\sigma|\nu,\kappa}$  and the ratio of average occupation wage earned by legal immigrants to that earned by all immigrants base on CPS (Borjas 2017). I assume  $W_{\sigma,m|\nu,\kappa}$  is constant across all legal modes. I calculate  $W_{\sigma,m|\nu,\kappa}$  for illegal mode analogously.

**Foreign labor market:** I draw data during year 2000-2010 from Integrated Public Use Microdata Series (IPUMS) International to obtain labor market information for the other 12 economies. For the 3 individual foreign countries including Canada, Mexico and India, I obtain information using the most recent data population Census available at IPUMS for Mexico, Canada and India.

For each of the 9 regions, I measure occupation share and average wages for each country whenever its information is available. After that, I calculate population weighted average among all countries within each region. For countries whose data are not available at IPUMS International, I extract information from Luxembourg income study (LIS). In addition, for countries which data are unavailable in neither source, I use Database on Immigrants in OECD countries (DIOC) to measure occupation share, and combine DIOC with Occupational Wages around the World (OWW) Database to impute average group wage at each country. Details of data source that this paper used are provided in table 3 at Appendix A.

Among the 12 foreign economies, the education categories are also divided into college and non-college. The occupation is grouped to 20 categories for Mexico and India. For the other economies, their occupational categories are aggregated according to 1-digit International Standard Classification of Occupations (ISCO88) to have 9 broad occupation categories.<sup>23</sup>

<sup>22</sup>I weight each observation using the following weights adjusted by hours worked as

$$\text{ADJUSTED WEIGHTS} = \frac{\text{CENSUS WEIGHT} \times \text{WEEKS WORKED} \times \text{USUAL HOURS PER WEEK}}{2000}$$

<sup>23</sup>The Freeman and Oostendorp dataset have collected information on earnings by occupation from the International Labor Organization's October Inquiry Survey. Freeman and Oostendorp standardizes the ILO data to correct for differences in how countries report earnings. The resulting data contain observations on earnings in up to 163 occupations per country in each year.

**Migration data:** I measure migration rate to each destination by group in year 2010, using the brain-drain dataset collected by Institute for Employment Research (IAB). Assuming US, OECD, Oceania countries and Canada are the only migration receiving countries, I compute the fraction of workers who stay at home country by labor groups.

Second, I use Database on Immigrants in OECD countries (DIOC) to measure the occupation share of immigrants by national-origin, education and sex group at each destination. DIOC databases is jointly collected by OECD and the World Bank from census data of year round 2010. It is publicly available at OECD website in the form of cross-tabulation on the characteristics of the migrant populations by country of birth in 33 OECD countries. The various cross-tabulation table contains migrant populations by country of birth, age, sex, gender, education, occupation, citizenship, duration of stay, etc.

## 3.2 Mode distribution of US immigrants

I combining three data sources to estimate the mode distribution of US immigrants including Current Population Surveys (CPS), Yearbook of Immigration Statistics at Department of Homeland Security, and New Immigrant Survey (NIS). I aggregate the modes of migration into four broad types, the purpose of which is to increase the precision when estimating conditional mode distribution for US immigrants of using the small sample of NIS data. I have three broad green card categories including family, denoted as  $m_f$ , employment, denoted as  $m_e$ , any other legal channels which aggregates refugee, diversity and others, denoted as  $m_o$ , and an illegal mode, denoted as  $m_i$ . I estimate mode distribution of US immigrants in 3 steps.

First, I first adopt the algorithm developed in [Borjas \(2017\)](#) to create a dummy variable of illegal identifier based on the sample Current Population Surveys (CPS) in 2010. Borjas simplifies the complex probabilistic method from [Passel & Cohn \(2016\)](#), to define a worker is a legal immigrants if he/she satisfies at least one conditions from many. The residual group of all other foreign-born is classified as undocumented. Since Borjas' algorithm tends to make high-skill immigrants over-represented among illegal immigration population, I further filter legal immigrants by assuming an immigrant is legal if one has a masters', professional or Doctoral degree, or work in skill-intensive occupations. The detailed conditions used to filter legal migrants is presented in appendix [A](#). From then, I obtain estimates on the share of legal immigrants from each national-origin, and the condition share of illegal US immigrants of each group who working at each occupation.

Second, I draw data from yearbook of immigration statistics from year 1996-2015 and cluster green card to three categories include family, employment and any others. Based on the share of green card at each category, I divide the share of legal immigrants of each national-origin obtained at step 1, into each of these three green card categories.

Third, I use data from the New Immigrant Survey (NIS) to divide the share of each type of green card immigrants obtained at step 2, into each education, gender and occupation cell. NIS is a survey based on a sample of 8573 immigrants granted lawful permanent residence in 2003. It has information on individual record of education, age, gender, occupation background, and the class of green card admission. I apply the conditional mode distribution estimated from a sample of immigrants entered in 2003 to the entire stock US immigrants, while assuming occupation and education selectivity of each visa mode does not since 2003 for each national-origin.

I aggregate the NIS class of admission as three broad modes, consistent with those used at step 2. To improve estimation precision, I aggregate NIS occupation to three widely used broad categories including cognitive, routine and manual occupations following Autor, Levy & Murnane (2003), cluster national-origin into 12 countries/regions, and pool male and female within each national-origin and education group.<sup>24</sup> Appendix A.3 provides details of how I aggregate NIS occupations to cognitive, routine and manual occupations. Education attainment are grouped to college (CL) and non-college (NCL), consistent with the dis-aggregation used later. I also pool male and female within each national-origin and education group. I then count the number of workers at each occupation and education as a share among the total number of workers of each national-origin by each green card category.  $P_{m|\nu,\kappa,\sigma}$  is estimated for 12 national-origin, 2 education groups, 3 occupations and 4 modes. Clustering American Community Survey (ACS) occupations as cognitive, routine or manual occupations (see appendix A.3 for details), I assign  $P_{m|\nu,\kappa,\sigma}$  obtained by broader cells in to finer cells of 460 labor groups and 28 occupations.

Overall, the share for illegal immigrants of each origin is implied from CPS, and the share for each green card category matches data from Yearbook of Immigration Statistics. While the NIS sample divides the green card share of each national-origin to education and occupation cells. This makes the estimate on  $P_{m|\nu,\kappa,\sigma}$  less sensitive to the problem of the under-representative small NIS sample.<sup>25</sup>

I close this subsection by discussing the estimated mode distribution of each major origin and education groups. I display the data in a bar chart on figure 2. Unsurprisingly, family green card account for a predominate share of immigrants entry from most country of origin and education groups, except for college educated workers from India and China. Also notice that college educated groups have higher propensity to enter through employment-mode, while non-college migrants have higher propensity to enter illegally.

Another evident feature is that, within each education category, there is a large degree of heterogeneity in mode distribution across origin countries. Among college workers, those from 61.4% Indian, 48% Chinese and 45% European migrate through employment-mode, in contrast to 8.6% Mexican and 3.4% Central American counterparts. Among non-college workers, over 56% of Mexican non-college, 33% of Central American have illegal status, comparing to less than 5% of European, Chinese and Indian counterparts.

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<sup>24</sup>The 12 countries/regions include Canada, China, India, Korea, Mexico, Central America & Caribbean, East Europe, Europe, Mideast & Africa, Oceania, Southeast Asia and South America.

<sup>25</sup>Hendricks & Schoellman (2016) show that NIS sample of US immigrants tend to be younger, better educated, lower paid, under-represent Mexican-born immigrants.

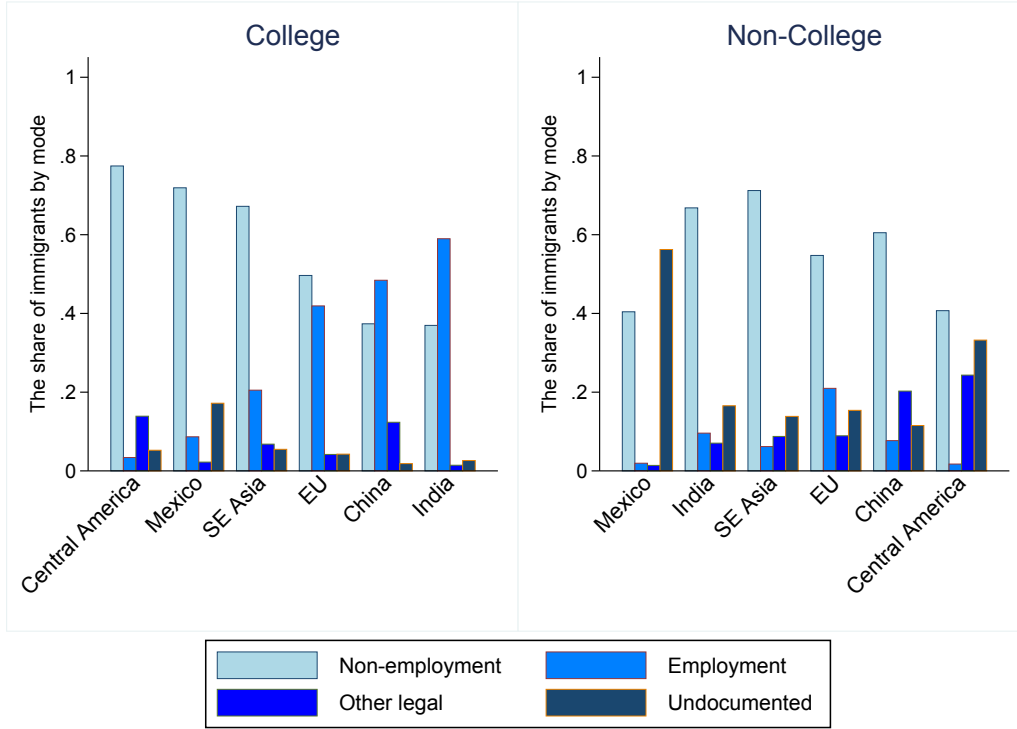


Figure 2: MODE DISTRIBUTION BY ORIGIN AND EDUCATION GROUPS

## 4 COUNTERFACTUAL REGIME AND MODEL FEATURES

This section formally introduces the counterfactual of interest and discusses the two key model predictions associated with the counterfactual. In section 4.1, I define the counterfactual policy in terms of  $\hat{\tau}_{\nu,\kappa,\sigma,m}$  and show that my model can map any exogenous changes in green card number or distribution by categories, to endogenous changes in labor forces both at US and at foreign countries without knowing the level of  $\tau_{\nu,\kappa,\sigma,m}$ .

Section 4.2 provides analytically the partial equilibrium migration elasticity, to illustrate how changes in terms of  $\hat{\tau}_{\nu,\kappa,\sigma,m}$  cause differential changes in migration rate across national-origin and demographic groups, and hence the labor composition changes at US and at foreign countries. To relating composition changes of US immigrants to changes in wages, section 4.3 then shows a the partial equilibrium immigrant-native wage elasticity. Although both elasticity analyzes partial equilibrium responses, they capture the first order and the direct effect of changes in policy or economic environment, and also guide the quantitative results of this paper.

Section 4.4 conducts 50 counterfactuals to show the degree of heterogeneity to native substitution across immigrants' national-origin using the general equilibrium model. Each counterfactual simulates the general equilibrium impacts of natives' average wage response to an exogenous increase of 0.1 million immigration inflow from one of the 25 major sending countries of either non-college or college educated labor groups. The simulation results confirm that, natives wage elasticity varies substantially across origin-education groups even if taking into account equilibrium adjustment of occupation switching.

## 4.1 COUNTERFACTUAL POLICY REGIME

I define a hypothetical counterfactual which only differs from the data by shifting US green card distribution to follow that used in Canadian system, and prioritizing employment-based among college educated workers at high-skill occupations. In addition, the total number of green card US has issued since 1990 is unchanged, so is the border protection and illegal regulation that US has enforced since 1990.

To implement, let  $\bar{Q}$  denote the total number of green card granted since 1990.  $\Phi_m^{CAN}$  and  $\Phi_m^{US}$  are green card distribution displayed in Figure 1 for Canada and for US, respectively. I then calculate  $Q_m$ , the difference in the number of green card issued between counterfactual and the realized economy in year 2010 as

$$Q_m = \bar{Q} \times (\Phi_m^{CAN} - \Phi_m^{US}), \quad m \in \{m_f, m_e, m_o\}.$$

I next relate the exogenous policy shock in terms of  $Q_{m_f}$ ,  $Q_{m_o}$  and  $Q_{m_e}$  to  $\tau_{\nu, \kappa, \sigma, m}$ .

1. For family, and other legal types modes of green card, indexed as  $m_f$  and  $m_o$ , respectively, migration friction increases without discriminating country of origin, education, gender and occupation, such that  $\hat{\tau}_{\nu, \kappa, \sigma, m} = \hat{\tau}_m$ . This implies the following two equality restrictions

$$\sum_{\nu} \sum_{\omega} L_{\nu} \cdot P_{\kappa, \sigma, m_f | \nu} \cdot (\hat{P}_{\kappa, \sigma, m_f | \nu} - 1) = Q_{m_f}, \quad \nu \in \text{foreign-born} \quad (8)$$

$$\sum_{\nu} \sum_{\omega} L_{\nu} \cdot P_{\kappa, \sigma, m_o | \nu} \cdot (\hat{P}_{\kappa, \sigma, m_o | \nu} - 1) = Q_{m_o}, \quad \nu \in \text{foreign-born} \quad (9)$$

for each restriction,  $\hat{\tau}_m$  enters equation through  $\hat{P}_{\kappa, \sigma, m | \nu}$ . In partial equilibrium when  $\hat{\Omega}_{\kappa, \sigma}$  are given,  $\hat{\tau}_{m_f}$  and  $\hat{\tau}_{m_o}$  each is uniquely determined.

2. For employment-based green card, indexed by  $m_e$ , migration friction is relaxed to prioritize college educated workers who work at skill intensive occupations, while without discriminating country of origin.<sup>26</sup> Formally, I capture this as

$$\hat{\tau}_{\nu, \kappa, \sigma, m_e} = \begin{cases} \hat{\tau}_{m_e} > 1, & \text{if college educated at skill-intensive occupations,} \\ 1, & \text{otherwise.} \end{cases}$$

Analogously  $\hat{\tau}_{m_e}$  is determined to match the following equality

$$\sum_{\nu} \sum_{\omega} L_{\nu} \cdot P_{\kappa, \sigma, m_e | \nu} \cdot (\hat{P}_{\kappa, \sigma, m_e | \nu} - 1) = Q_{m_e}, \quad \nu \in \text{foreign-born} \quad (10)$$

3. Illegal migration friction is unchanged such that  $\hat{\tau}_{\nu, \kappa, \sigma, m_i} = 1$ <sup>27</sup>

Other than the US, I assume immigration policy at foreign countries is unchanged between counterfactual and the reality. It is important to emphasize that assuming no country of origin

<sup>26</sup>I include skill-intensive occupations as executive management, health professional, social scientists, lawyers and judges, engineers, computer system analysts, math & science occupation, computer software developers.

<sup>27</sup>I am aware that shut-down family visa would increase the number of attempt of illegal border crossing, and hence the ratio of border patrols per illegal attempt falls. Here I assume that  $\tau_{\nu, \kappa, \sigma, m_i}$  is a function of the number of border patrols, instead of border patrols per illegal attempt.



discrimination is crucial in establishing the unique mapping from policy shock in terms of  $Q_{m_f}, Q_{m_o}, Q_{m_e}$  to those in  $\hat{\tau}_{m_f}, \hat{\tau}_{m_o}, \hat{\tau}_{m_e}$ , respectively, since it introduces the same number of restrictions and unknowns.

Assuming no country of origin discrimination is consistent with US green card selection mechanism of both family-based and employment-based which do not preferentially select applicants by country of origin. Regarding the other green card mode, the assumptions tends to hold to refugee and asylum type of admission, but abuses the way how diversity green card are issued. In validation exercise performed in section 5, I find the model generated data match observations reasonably well, presumably because refugee and asylum type of green card account from a large share of  $m_o$  entry.

Thus, given  $Q_{m_f}, Q_{m_e}$  and  $Q_{m_o}$ , and values on  $\rho_\kappa$  and  $\vartheta$ , one can solve the global general equilibrium in terms of changes in wage units  $\hat{\Omega}_{\kappa,\sigma}$ , in migration frictions  $\hat{\tau}_{m_f}, \hat{\tau}_{m_e}, \hat{\tau}_{m_o}$  from system of equation (4) - (10). The changes of migration flow is then determined in  $\hat{P}_{\sigma|\nu,\kappa,m}$ . To close this section, I show the following proposition which implies the counterfactual exercise requires mode distribution of migration only for US immigrants, but free for immigrants to other destinations.

### Proposition 1. MODE INDEPENDENCE

*If  $\hat{\tau}_{\nu,\kappa,\sigma,m} = 1$ , then neither  $\hat{P}_{\kappa,\sigma,m|\nu}$  nor  $\hat{W}_{\sigma,m|\nu,\kappa}$  are functions of  $P_{m|\nu,\kappa,\sigma}$ .*

The proof is straightforward according to equation (4) and (5), but the implication is useful. It implies that for countries other than US, solving counterfactual policy changes do not require information on the mode distribution of foreign countries.

## 4.2 THE DIRECT MIGRATION ELASTICITY

This section shows the close-form expression of direct migration elasticity in response to the policy shocks studied in counterfactual experiment. Fix US destination, and consider a change of US immigration policy on mode  $m$  modeled in terms of  $\Delta\tau_{\kappa,m}$ . In my counterfactual exercise, defined in section 4.1, this would be restricting family green card or other legal type of green card. One can show that the direct elasticity has the following form

$$\frac{\partial P_{\kappa|\nu}}{P_{\kappa|\nu}} \bigg/ \frac{\partial \tau_{\kappa,m}}{\tau_{\kappa,m}} = \vartheta \cdot (1 - P_{\kappa|\nu}) \cdot P_{m|\nu,\kappa}, \quad m \in \{m_f, m_o\}.$$

Appendix G.3 provides a detailed derivation and also analyze the migration elasticity to an infinitesimal change of occupational biased demand changes.<sup>28</sup> The above expression says for example, when reducing the number of family green card issued, it will (1) disproportionately reduce immigrants from  $\nu$  who has strong  $m_f$  mode linkage to migrate, i.e.,  $P_{m|\nu,\kappa}$  is larger, (2) disproportionately reduce immigrants from  $\nu$  who have sent a small fraction of workers to US, i.e.,  $P_{\kappa|\nu}$  is smaller, (3) is less responsive if productivity is highly dispersed and hence the infra-marginal density is small, i.e.,  $\vartheta$  is small.

<sup>28</sup>This is of particular interest as the US has experienced increasing demand of cognitive tasks over the last three decades (Autor, Levy & Murnane 2003).

Next, consider an expansion of employment-based green card at occupation  $\sigma$ , captured by  $\Delta\tau_{\kappa,\sigma,m_e}$ . The direct elasticity has expression below

$$\frac{\partial P_{\kappa|\nu}}{P_{\kappa|\nu}} \bigg/ \frac{\partial \tau_{\kappa,\sigma,m_e}}{\tau_{\kappa,\sigma,m_e}} = \vartheta \cdot (1 - P_{\kappa|\nu}) \cdot P_{\sigma|\nu,\kappa} \cdot P_{m_e|\nu,\kappa,\sigma}$$

Notice that two variables which differ from the previous expression. It says, for example increase the number of employment green card among cognitive occupations will (1) disproportionately increase immigrants who are specialized at cognitive occupations, i.e.,  $P_{\sigma|\nu,\kappa}$  is larger, and (2) disproportionately increase immigrants whose workers at cognitive occupations have strong  $m_e$  mode linkage, i.e.,  $P_{m_e|\nu,\kappa,\sigma}$  is larger. To consistent with my counterfactual, this argument only applies among college educated workers.

The discussion so far has emphasized the cross country differences in mode-linkage of migration. However, the intuition applies analogously to analyze the differences of mode-linkage of migration across skill groups, to answer how skill composition of US immigrants would change in response to policy shock.

My analysis in this section advances the previous work which qualitatively discuss the effects of a skill-based immigration policy on the composition of US immigrants. Borjas (1993) argue that a skill-based policy reform would improve immigration skill composition mainly by altering the national-origin mix of migration, while not work in a way as one may expect. Antecol et al. (2003) point out that Borjas' analysis overlook the differences in wage structure and geography between US and Canada.<sup>29</sup> My model takes into account factors such as geographic forces, immigration policy and wage structure in shaping the composition of US immigrants, and delineates that the mode-linkages of migration drives migration skill-composition change in response to a skill-based system reform.

### 4.3 THE DIRECT CROSS WAGE ELASTICITY

Next, I provide the close form expression of immigrant-native substitution, measured as cross-wage elasticity normalized by group size. The normalization makes a 1% increase of Mexican immigrants comparable to 1% increase of migrants from Tonga. Again, it is important to emphasize that the expression captures the first order effects of native wage response, without taking into account equilibrium reallocation of workers across occupations.

Be specific to my context, considering  $\nu_1$  as US natives and  $\nu_2$  as immigrants from a arbitrary origin and demographic group. I use  $\sigma$  and  $\omega$  to denote occupations. The goal is to obtain the wage elasticity earned by natives in response to changes in immigration labor supply of type  $\nu_2$ . In the rest of this section, I focus on the US and abstract country subscript  $\kappa$  to ease notation. The derivation of cross-group wage elasticity relies on the following equality

$$\frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{L_{\nu_2}} = \sum_{\sigma} \left[ \frac{\partial W_{\nu_1}}{\partial L_{\sigma}} \frac{L_{\sigma}}{W_{\nu_1}} \times \frac{\partial L_{\sigma}}{\partial L_{\nu_2}} \frac{L_{\nu_2}}{L_{\sigma}} \right] = \sum_{\sigma} \left[ \left( \sum_{\omega} \frac{\partial W_{\nu_1}}{\partial \Omega_{\omega}} \frac{\Omega_{\omega}}{W_{\nu_1}} \times \frac{\partial \Omega_{\omega}}{\partial L_{\sigma}} \frac{L_{\sigma}}{\Omega_{\omega}} \right) \times \frac{\partial L_{\sigma}}{\partial L_{\nu_2}} \frac{L_{\nu_2}}{L_{\sigma}} \right] \quad (11)$$

where  $W_{\nu_1}$  is the average group wage earned by natives,  $L_{\nu_2}$  is the current stock of type- $\nu_2$  immigration workers,  $L_{\sigma}$  is the stock of labor at occupation  $\sigma$ , and  $\Omega_{\omega}$  is wage unit at occupation

<sup>29</sup>The analysis of Borjas (1993), Antecol et al. (2003) are qualitative, and based on the comparison of the skill composition and national-origin mix of immigrants in the US with that in Canada and Australia which are operating point system.

$\omega$ . The two equal sign in equation (11) holds by chain rule. The first equality states that the wage earned by natives in response to changes in immigration labor supply equals the sum product of natives wage elasticity in response to changes in occupation labor supply, and the occupational labor elasticity to changes in type- $\nu_2$  immigration workers. The second equality holds by re-expressing natives wage elasticity to occupation labor as the sum product of natives wage elasticity to occupation wage unit, and the elasticity of occupation wage unit to occupation labor supply induced by immigrants.

Appendix G.4 provides detailed steps of deriving each elasticity appeared in equation (11). Armed with expression of each direct elasticity, I obtain the close-form expression of normalized cross-group wage elasticity as follows

$$\frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{1} = \frac{1}{\rho} \sum_{\sigma} \left[ \underbrace{(R_{\sigma} - P_{\sigma|\nu_1, \kappa})}_{\text{substitution dominates if } < 0} \times \underbrace{\frac{P_{\sigma|\nu_2, \kappa}}{L_{\sigma}}}_{\text{percentage changes in occupation employment}} \right] \quad (12)$$

where  $R_{\sigma}$  denotes the occupational wage bills as a share of the total wage bills, and captures the occupation size of the entire economy. As in equation (12), the normalized cross wage elasticity is the sum product of two terms, scaled by the inverse of occupation elasticity of substitution,  $\frac{1}{\rho}$ . Intuitively, when immigrants cause  $\frac{P_{\sigma|\nu_2, \kappa}}{L_{\sigma}}$  percentage change in occupation labor supply, complementary effects dominates if native workers underrepresented in this occupation, such that  $R_{\sigma} - P_{\sigma|\nu_1, \kappa} > 0$ . Conversely, substitution effect dominates if  $R_{\sigma} - P_{\sigma|\nu_1, \kappa} < 0$ . The overall native wage response is aggregated over all occupations and is re-scaled by  $\frac{1}{\rho}$ . Appendix G.4 also shows details that the micro-foundation are from the occupation CES production function.

Equation (12) can be used to analyze an important question of immigration from which country and demographic group benefit natives the most.<sup>30</sup> A general message is that US natives benefit more from immigrants who would cause a larger proportional employment change at occupation that natives are under-represented, and vice versa.

Finally, I use a simple case that one can relate the immigrant-native elasticity to comparative advantages. Consider an illustrative case of two occupations, denoting as  $\sigma_1$  and  $\sigma_2$ . Still use  $\nu_1$  to denote US natives, while let  $\nu_2$  and  $\nu_3$  denote immigrants of two distinct groups. For example,  $\nu_2$  and  $\nu_3$  can differ either by national-origin or by demographic groups.

## Proposition 2. COMPARATIVE ADVANTAGE AND DIRECT WAGE ELASTICITY

Consider two occupations  $\sigma_1$  and  $\sigma_2$  and suppose  $\tau_{\nu, \kappa, \sigma, m} = \tau_{\nu, \kappa, m} \times \tau_{\kappa, \sigma, m}$ , then

$$\left| \frac{T_{\nu_1, \kappa, \sigma_1}}{T_{\nu_1, \kappa, \sigma_2}} - \frac{T_{\nu_2, \kappa, \sigma_1}}{T_{\nu_2, \kappa, \sigma_2}} \right| > \left| \frac{T_{\nu_1, \kappa, \sigma_1}}{T_{\nu_1, \kappa, \sigma_2}} - \frac{T_{\nu_3, \kappa, \sigma_1}}{T_{\nu_3, \kappa, \sigma_2}} \right| \iff \frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{1} > \frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_3}}{1}.$$

Proposition 2 says, suppose  $\tau_{\nu, \kappa, \sigma, m}$  is separable, meaning the labor market friction (or migration friction to the US) does not discriminate a labor group to work in a given occupation,

<sup>30</sup>This can be mapped into a linear optimization problem such that pick vector values of  $P_{\sigma|\nu_2, \kappa}$  such that  $\frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{1}$  is maximized or minimized. One will end up with corner solution

$$P_{\sigma|\nu_2, \kappa} = \begin{cases} 1, & \text{if } \sigma = \operatorname{argmax}_{\omega} \left\{ \frac{R_{\omega} - P_{\omega|\nu, \kappa}}{L_{\omega}} \right\}, \\ 0, & \text{other } \sigma. \end{cases}$$

and hence implying the differences in the occupation specialization across migration groups are due to their differences in occupation comparative advantage, then immigrants would lead to a larger wage gain of US natives if and only if their occupation comparative advantage are more distant from that of US natives. Appendix G.5 provides the proof. The analysis abstracts education and gender groups, but extension is straightforward.

#### 4.4 SIMULATING IMMIGRANT-NATIVE SUBSTITUTION

To provide evidence of how immigrant-native substitution differ across immigrants' national-origin and education groups in general equilibrium, I use the model to compute 50 counterfactual exercises. Each counterfactual simulates the average wage impacts for natives in response to an increase of 0.1 million migration inflow from one of the 25 major sending countries, either non-college or college labor group, holding constant the stock of US immigrants from other countries and education groups. On each simulation, I introduce changes in occupation and mode neutral policy shock  $\hat{\tau}_{\nu, \kappa_{us}}$  for each group to absorb 0.1 million additional  $\nu$  immigrants.

Figure 3 plots the simulated changes on non-college US native wages to non-college immigrants on the left panel, and for college US native wages to college immigrants on the right panel, against the immigration share among US immigrants for each national-origin and education group. The value in each panel averages over gender groups.

Two things are worth noting from Figure 3. First, within each education groups, native and immigrants are generally substitutes, as natives' wage impacts are negative in all simulations. Comparing across two panels, immigrant-native substitution is stronger within non-college groups than college. Second, the left panel shows that immigrant-native substitution among non-college group is stronger for countries which have sent more non-college immigrants, e.g., Mexico, EL Salvador. The opposite pattern is displayed from the right panel, as it shows that immigrant-native substitution among college group is weaker for countries which have sent more college immigrants, e.g., India, Philippines.

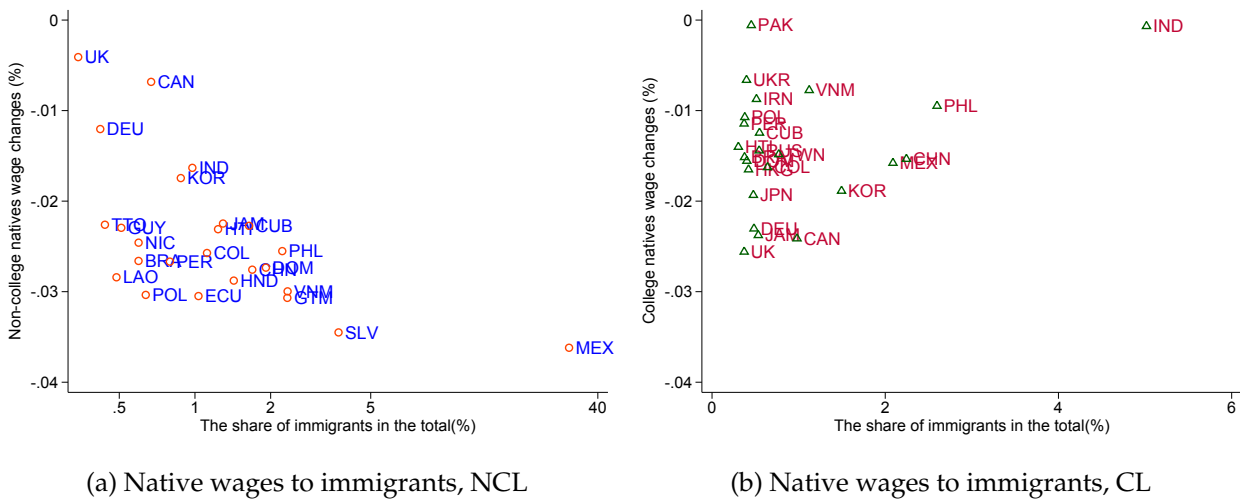


Figure 3: IMMIGRANT-NATIVE SUBSTITUTION, WITHIN EACH EDUCATION GROUP

Figure 4 plots the simulated changes on US native wages to immigrants across education groups. Another two new features are worth noting. First, cross education groups, native and

immigrants are generally complements, as natives' wage impacts are positive in all simulations. Comparing across two panels, the complementarity of college immigrant to non-college natives is stronger than that of non-college immigrants to college natives. Second, the left panel shows that the complementarity of non-college immigrants to college natives is more clustered, the orange circle are more concentrated vertically; while the complementarity of college immigrants to non-college natives is more scattered, since the green triangle are more dispersed vertically on the left panel. In appendix C, I also plot the average natives wage responses over non-college and college education group to immigrants of different national-origin and education group in Figure 6.

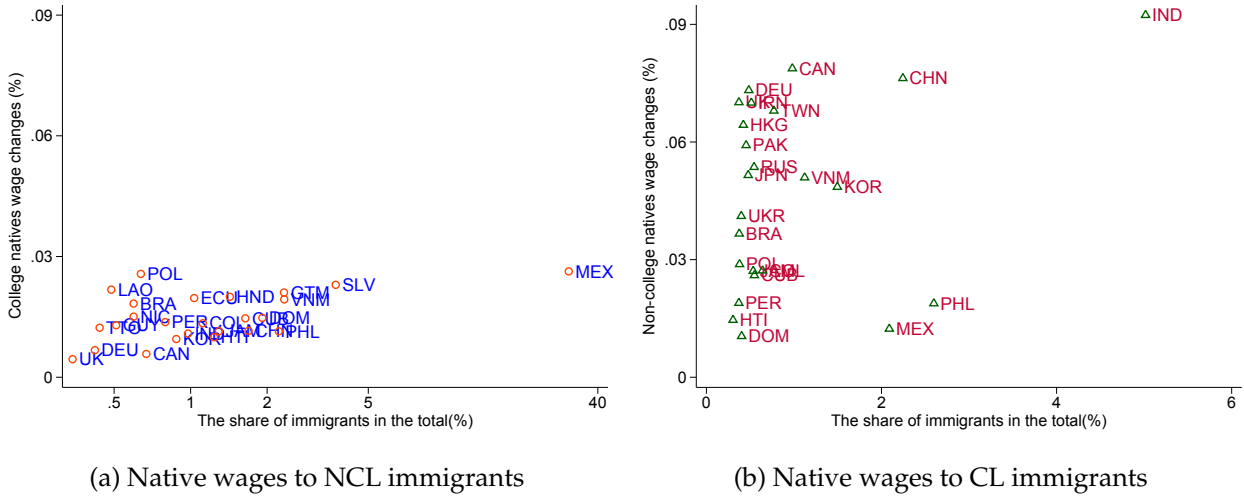


Figure 4: IMMIGRANT-NATIVE SUBSTITUTION, WITHIN EACH EDUCATION GROUP

## 5 PARAMETER VALUES AND VALIDATION

This section first estimate demand elasticity  $\rho$  for US by associating changes in relative occupation wages to changes in relative occupation labor supply, while instrumenting labor supply using a Card-type instrument. I also estimate labor supply elasticity  $\vartheta$ , using revealed comparative advantage approach extended from Hanson & Liu (2016). The estimation of  $\vartheta$  also serves as a validation testing of origin-occupation comparative advantage. I close this section by validating model properties of mode-linkage of migration, to show model generated green card allocation across countries similar to data observed from DHS.<sup>31</sup>

### (A) Estimating $\rho_{us}$ for US

I turn to estimate  $\rho$ , the elasticity of substitution across occupations for US labor market. I obtain the estimating equation from the model by taking first order condition on CES production function with respect to  $L_\sigma$ , which gives

$$\Omega_\sigma = A_\sigma \cdot Y^{\frac{1}{\rho}} \cdot L_\sigma^{-\frac{1}{\rho}}$$

<sup>31</sup>It is important to emphasize that since my model is solved in proportional changes without imposing point values for many model primitives, this hence leaves a great degree of freedom for these primitives to match the model implied moment with the data.

where  $L_\sigma$  is the aggregate occupation efficiency unit of labor, and  $\Omega_\sigma$  is wage efficiency units per labor. Since neither  $\Omega_\sigma$  nor  $L_\sigma$  is observed, I re-express  $\Omega_\sigma = \frac{W_\sigma}{E_\sigma}$ , and  $L_\sigma = \frac{H_\sigma}{E_\sigma}$ .  $W_\sigma$  denotes the average hourly occupation wage,  $E_\sigma$  denotes the average occupation efficiency unit per hour, and  $H_\sigma$  denotes the aggregate occupation labor hours. Re-arrange to have

$$W_\sigma = A_\sigma \cdot Y^{\frac{1}{\rho}} \cdot H_\sigma^{-\frac{1}{\rho}} \cdot E_\sigma^{1-\frac{1}{\rho}}$$

normalize by a baseline occupation  $\sigma'$  and take logarithm to have

$$\log \frac{W_\sigma}{W_{\sigma'}} = -\frac{1}{\rho} \log \frac{H_\sigma}{H_{\sigma'}} + \log \frac{A_\sigma}{A_{\sigma'}} + \left(1 - \frac{1}{\rho}\right) \log \frac{E_\sigma}{E_{\sigma'}}$$

I explore time variation during year 1990-2015 to obtain the following estimating equation

$$\log \frac{W_{\sigma,t}}{W_{\sigma',t}} = -\frac{1}{\rho} \log \frac{H_{\sigma,t}}{H_{\sigma',t}} + \varepsilon_{\sigma,t} \quad (13)$$

the term  $\varepsilon_{\sigma,t} = \log \frac{A_{\sigma,t}}{A_{\sigma',t}} + \left(1 - \frac{1}{\rho}\right) \log \frac{E_{\sigma,t}}{E_{\sigma',t}}$  captures the unobserved changes in the mixture of occupational demand shifter and in aggregate occupation labor productivity. To estimate equation (13), I take data from census for every 5 year from 1990, 2000, 2005, 2010 and 2015, restrict sample to 18-65 year old. I measure  $W_{\sigma,t}$  using average occupation hourly wage, and measure  $H_{\sigma,t}$  as the overall occupational labor hours.

It is well-known from the *Skill-biased technological changes* literature that  $\varepsilon_{\sigma,t}$  and  $\log \frac{H_{\sigma,t}}{H_{\sigma',t}}$  are positively correlated, as both have grown faster at cognitive intensive occupation, but have either grown slower or declined at manual and routine intensive occupations. OLS estimates on  $\rho$  thus leads to bias. To address the endogeneity issue, I construct an instrumental variable relying on the fact that there is a persistent origin-occupation sorting of US immigrants over time [Hanson & Liu \(2016\)](#). The instrument share the same spirit as [Card \(2001\)](#) and captures the captures the logarithm of relative occupational labor hours expected to be, in the absence of any changes in distortions caused by occupation demand or changes in origin-country specific occupation labor productivity. I denote the instrumental variable as  $\log \frac{\tilde{H}_{\sigma,t}}{\tilde{H}_{\sigma',t}}$ , where

$$\tilde{H}_{\sigma,t} = H_{\sigma,1990} + \sum_{\nu} \left[ P_{\sigma,1990|\kappa,\nu} \times \Delta H_{\nu,\sigma^-,t} \right], \quad t \in \{2000, 2005, 2010, 2015\}.$$

$P_{\sigma,1990|\kappa,\nu}$  is the share of  $\nu$  workers who work at occupation  $\sigma$ , conditional among those who work in US.  $\Delta H_{\nu,\sigma^-,t}$  is the net inflow of immigrants of group  $\nu$  from 1990 to year  $t$ , excluding those who work at occupation  $\sigma$ .

Table 5 of appendix B shows the results estimated using OLS and 2 stage-least square (2SLS). Unsurprising, the OLS regression leads to an upward bias of  $-\frac{1}{\rho}$ . The first stage has  $R^2$  achieves 0.62, with a coefficient of 0.523 which is statistically significant at 1% confidence level. The 2SLS regression implies a value of  $\rho$  equal to 2.188, with a standard error equal to 0.162.<sup>32</sup> I choose  $\rho = 2.18$  as the preferred value in baseline for US, and  $\rho_o = 0.9$  for other foreign countries following [Goos, Manning & Salomons \(2014\)](#).

<sup>32</sup>The implied standard error is derived according to *Delta method*, given the negative inverse function is a continuous mapping. The first is calculated as  $0.026 * \frac{1}{0.403^2} = 0.160$ , while the second is calculated as  $0.034 * \frac{1}{0.457^2} = 0.162$ .

**(B) Estimating  $\vartheta$  — validating origin-occupation comparative advantage**

I next estimate labor supply elasticity  $\vartheta$ . I use a revealed comparative approach extended from recent work in Hanson & Liu (2017) who pursue a more flexible functional form specification to test the hypothesis of labor market comparative advantages, but leaving the parameter  $\vartheta$  unidentified. The current approach identifies  $\vartheta$  by imposing stronger parameter assumption on  $T_{\nu,\kappa,\sigma}$ . The revealed comparative advantage approach is analogous to that used to estimate trade elasticity by Costinot, Donaldson & Komunjer (2011).<sup>33</sup>

The reduce-form specification is derived consistently from equation (1) by taking difference-in-difference of  $P_{\sigma|\nu,\kappa}$  between two groups and two occupations to have

$$\frac{P_{\sigma|\nu,\kappa}}{P_{\sigma|\nu',\kappa}} \bigg/ \frac{P_{\sigma'|\nu,\kappa}}{P_{\sigma'|\nu',\kappa}} = \left( \frac{T_{\nu,\kappa,\sigma}}{T_{\nu',\kappa,\sigma}} \bigg/ \frac{T_{\nu,\kappa,\sigma'}}{T_{\nu',\kappa,\sigma'}} \right)^\vartheta \times \left( \frac{\sum_m \tau_{\nu,\kappa,\sigma,m}}{\sum_m \tau_{\nu',\kappa,\sigma,m}} \bigg/ \frac{\sum_m \tau_{\nu,\kappa,\sigma',m}}{\sum_m \tau_{\nu',\kappa,\sigma',m}} \right)^\vartheta$$

taking logarithm and restrict to US labor market and to have

$$\log \frac{P_{\sigma|\nu,\kappa_{us}}}{P_{\sigma|\nu',\kappa_{us}}} \bigg/ \frac{P_{\sigma'|\nu,\kappa_{us}}}{P_{\sigma'|\nu',\kappa_{us}}} = \vartheta \cdot \log \frac{T_{\nu,\kappa_{us},\sigma}}{T_{\nu',\kappa_{us},\sigma}} \bigg/ \frac{T_{\nu,\kappa_{us},\sigma'}}{T_{\nu',\kappa_{us},\sigma'}} + \varepsilon_{\nu,\kappa_{us},\sigma}$$

where the term  $\varepsilon_{\nu,\kappa_{us},\sigma}$  captures the unobserved friction component. The base group is chosen as US native counterpart.

Following Hanson & Liu (2017), it is easier and econometrically equivalent to estimate  $\vartheta$  use the following estimating equation

$$\log P_{\sigma|\nu,\kappa_{us}} = \vartheta \log T_{\nu,\kappa_{us},\sigma} + \alpha_{\nu,\kappa_{us}} + \alpha_{\kappa_{us},\sigma} + \log \varepsilon_{\nu,\kappa_{us},\sigma} \quad (14)$$

$P_{\sigma|\nu,\kappa}$  is estimated using total hours at US occupation labor market for each national-origin group. Differing from Hanson & Liu (2017), I impose a stronger parameteric assumption on  $T_{\nu,\kappa_{us},\sigma}$  as follows,

$$T_{\nu,\kappa_{us},\sigma} = \alpha_{m,\sigma} \cdot \text{math} + \alpha_{s,\sigma} \cdot \text{science} + \alpha_{l,\sigma} \cdot \text{linguistic proximity}$$

it assumes that labor productivity is fully determined by three dimensional abilities (quantitative ability, scientific ability and language ability), the importance of each type of ability vary across occupations and are weighted by  $\alpha_{m,\sigma}$ ,  $\alpha_{s,\sigma}$ , and  $\alpha_{l,\sigma}$ . I transform these as percentile O\*NET tasks intensity at each occupation.<sup>34</sup>

Where math and science capture origin country average math and science ability measurement, respectively. I obtain the measurement from Program for International Student Assessment. Linguistic proximity measures the similarity of the two most spoken language between origin country and US, and it is obtained from Automated Similarity Judgment Program (ASJP). I scale all these three variables to take value from 0-1, with a value closer to 1 corresponds to a higher math or science ability for variables math and science, and a closer linguistic proximity to the language spoken in US.

I restrict sample to 18-65 years old to run Ordinary Least Square (OLS) regression to estimate  $\vartheta$ . Panel A1) of table 6 in appendix B report results using the average, 75th, and 90th

<sup>33</sup>The author links the log difference in trade share to that in technologies.

<sup>34</sup>The baseline results are estimated using transformed percentile O\*NET tasks intensity. The results are similar if use the raw O\*NET standardized score measurement.

percentile PISA score to measure  $T_{\nu, \kappa_{us}, \sigma}$ , respectively. OLS estimate produces a value of  $\vartheta$  equal to 3.103 when measuring  $T_{\nu, \kappa, \sigma}$  using the average PISA in math and science. The results are similar with alternative measurement based on 75th and 90th percentile PISA math and science score. Panel A2) also report results which group small countries into regions, and I find the estimate are consistent, but slightly smaller ranging from 2.85-2.94.<sup>35</sup>

In my setting, running log-linear regression has two important limitations analogous to the 'log gravity' problem recognized in international trade literature. First, the sample selection problem of "zero", that is the log regression would omit country-occupation observation pairs whenever the group to occupation matching is not observed in the data. As pointed out in [Silva & Tenreyro \(2006\)](#), the consistency of log regression also requires assumption on higher-order conditional moments, for example, the parameters of log regression estimated by OLS lead to biased estimates under conditional heteroskedasticity.<sup>36</sup> I run pseudo-maximum-likelihood (PML) estimator developed in [Silva & Tenreyro \(2006\)](#) based on a sample formed by pairwise combination of country and occupation, irrespective of whether the country-to-occupation labor match is not observed in US labor market. As reported in Panel B1) of table 6, the estimates range from 3.65 to 3.89 and are larger in comparing to the log regression. This indicates that the sample selection problem of OLS regression underestimate  $\vartheta$ , since it omits "zeros" which are the country-occupation pairs have the least comparative advantage such that labor-occupation sorting are not realized in the data. Panel B2) of table 6 also reports that PML estimates are similar when use region-occupation as observation units. I set  $\vartheta = 3.66$  as the preferred value obtained from PML estimator on PISA average score.

Also notice that estimation of  $\vartheta$  serves as a validation of origin-occupation comparative advantage in line with the test performed by [Hanson & Liu \(2017\)](#). My approach of estimating  $\vartheta$  also differ from those used in previous literature, which obtain  $\vartheta$  by matching the empirical wage distribution and tend to overlook the specific context of Roy selection.<sup>37</sup>

### (C) Validating mode-linkage of migration

This section performs validation exercise to examine if the model can predict green card allocation across countries that is consistent with DHS data. I set  $\rho_{us} = 2.18$ ,  $\vartheta = 3.66$  and  $\rho_o = 0.9$  to perform counterfactual exercises including (a) the total number of  $m_f$  green card had not been issued since 1990, absorbed by changes in  $\hat{\tau}_{m_f}$ ; (b) the total number of  $m_e$  green card had not been issued since 1990, absorbed by changes in  $\hat{\tau}_{m_e}$ ; (c) the total number of  $m_o$  green card had not been issued since 1990, absorbed by changes in  $\hat{\tau}_{m_o}$ ; (d) none of these green visa had been issued since 1990, absorbed by changes in  $\hat{\tau}_m$  for all three modes.

Figure 5 plots for each counterfactual, the predicted visa allocation across countries against the actual observation for the 114 sending countries (excluding US natives) considered in this

<sup>35</sup>Regions in the analysis include large sending countries Brazil, Canada, China, Colombia, France, Germany, Hongkong, Japan, Korea, Mexico, Peru, Poland, Russia, Spain, Taiwan, UK, US, Venezuela; aggregate regions include Central America, East Europe, Middle-east and North Africa, Oceania countries, South America, South Europe, Southeast Asia, Sub-Saharan Africa, West Europe.

<sup>36</sup>The consistency of PML estimator requires  $E[e_{\nu, \kappa, \sigma} | \frac{T_{\nu, \kappa_{us}, \sigma}}{T_{\nu, \kappa_{us}, \sigma'}} / \frac{T_{\nu', \kappa_{us}, \sigma}}{T_{\nu', \kappa_{us}, \sigma'}}] = 1$ ; while to establish consistency of log regression, one also has to assume any high-order conditional moment equals 0. The consistency of PML estimator requires assumption on the first conditional moment of  $e_{\nu, \kappa, \sigma}$ .

<sup>37</sup>See [Lagakos & Waugh \(2013\)](#), [Hsieh et al. \(2013\)](#), [Tombe & Zhu \(2015\)](#), [Fan \(2015\)](#), [Lee \(2016\)](#). As several papers tends to interpret  $\vartheta$  as labor supply elasticity specific to the context of Roy model, the empirical wage distribution would produce a similar  $\vartheta$  estimates, irrespective of the specific context of sectoral, occupational, or geographical Roy selection.



paper. The blue dash line plots the 45 degree line. It is important to notice that although the log scale are used for both the horizontal and vertical, and observations align well along the blue line.

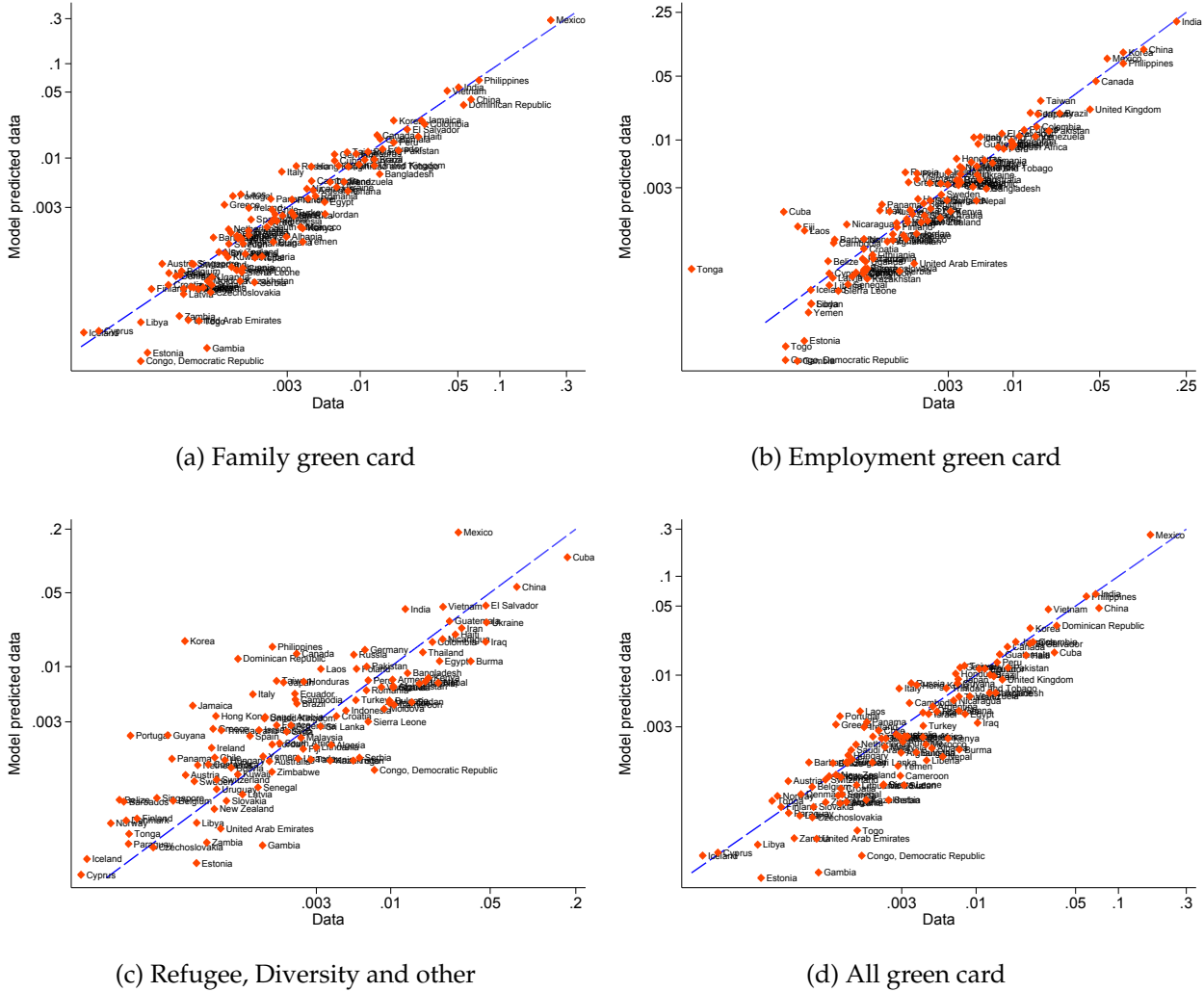


Figure 5: MODEL PREDICTED VS THE ACTUAL GREEN CARD ALLOCATION ACROSS COUNTRIES BY TYPES

The correlation coefficient equals 0.984 in plot (a), 0.987 in plot (b), 0.644 in plot (c) and equals 0.956 in plot (d). It is important to notice that even the assumption of group and occupation invariant friction changes,  $\hat{\tau}_{m_o}$ , is likely to violate for the case of diversity green card, plot (c) predicts visa allocation reasonably well with the data. Because the small fraction of mode  $m_o$ , the correlation coefficient in the overall changes in visa allocation reaches 0.956. In appendix D, I reproduce the plot which based on sample that excludes outliers in Figure 7, to check whether the correlation is sensitive to outliers. It turns out that the correlation remains high. I also present an additional validation exercise which jointly validate mode-linkage of migration and origin-occupation comparative advantage using H-1B visa program. I show the model generated visa allocation aligns with data on H-1B petition drawn from US Citizenship and Immigration Services (USCIS).

## 6 IMPACTS ON THE US

This section focuses on the impacts of policy reform on US. Section 6.1 analyzes the national-origin and skill composition change of US immigrants. I then show that equilibrium adjustments that workers substitute towards employment green card or illegal immigrants mitigate the composition changes. I also analyzes the impacts on the number of illegal immigrants received by US. Section 6.2 relates the composition changes of US immigrants to impacts on wages, occupation structure and aggregate productivity gain.

I set  $\rho_{us} = 2.18$ ,  $\vartheta = 3.66$  and  $\rho_o = 0.9$  to evaluate the counterfactual policy of interest defined previously. The result shows  $\hat{\tau}_f = 0.84$ ,  $\hat{\tau}_e = 1.89$  and  $\hat{\tau}_o = 0.95$ , meaning the counterfactual take-home wage rate for family, employment and other legal mode of migration has to be 84%, 189% and 95% of that in the initial equilibrium, respectively.

### 6.1 THE COMPOSITION CHANGES OF US IMMIGRANTS

#### (A) *On National-origin and skill composition of US immigrants*

Guided by the expression of direct elasticity obtained in section 4, table 7 compares immigration composition both in the observed and counterfactual economy, in terms of foreign-born US workers of each national-origin and education groups as a share of the total US foreign-born labor forces. The empirical exercise includes 115 migration sending countries, while the countries listed are the major sending countries within each continent.

A few things are worth-noting. First and unsurprisingly, the counterfactual policy reform improves the skill composition of US immigrants, the migration share of college educated workers increase from 28.1% to 44.8% as shown in the last row. Second, there are worth-noting changes on the national-origin mix of US immigrants. On one hand, the largest decline is Mexican immigrants, whose share in US immigration falls from 32.1% to 25.9%. The immigration share of Central American and Caribbean born workers also falls from 17.7% to 13.7%. The share declines slightly for immigrants from Southeast Asia, South America, East Europe, Africa, Mid-east and southwest Asia countries. On the other hand, immigration share of Indian-born increase the most, from 5.5% to 12.6%. East Asian countries also experience a significant increase of US foreign-born workers from 9.3% to 13.9%. There are modest increase of labor force from OECD Europe and Canada. While the size of Oceania US immigrants are almost unchanged.

Third, the changes in the share of foreign-born US workers follow the same sign among countries within most countries of each continent. Specifically, the share falls among all Central American and Caribbean, south American, southeast Asia, east Europe, Mid-east and African countries, while rises among all east Asia, OECD Europe countries. This great similarity among countries within each continent reflects the similarity in their mode-linkage of migration.

#### (B) *Substitution to employment-based entry or illegal immigrants*

The impacts on the composition changes of US immigrants reported at table 7 might not as much as one may expect. Now I show evidence that equilibrium adjustment to employment-based or to illegal status plays an important role in mitigating this impact. Column 2 and 3 of table 10 show the size of net inflow to each mode as a share of the total number of US family

and other legal green card reduced by each of major national-origin and education groups. Results after column 4 reports the share the substitute to other countries, and will be discussed in later section. The table considers immigrants from origin including Mexico, Central American & Caribbean, and South America. Since the general equilibrium wage impacts at sending countries are small, the figures reported in table 10 is close to the following interpretation: among those who no longer have access to US family or refugee green card, the fraction that substitutes to employment-based green card or illegal crossing by groups.

Among non-college workers, substituting to illegal status is the primary channel to remain in US. The degree of substitution to illegal crossing are the most notable among immigrants from El Salvador, 21% of those choose to remain in US as illegal status. There are also 17.3% of Mexican, 15.6% of Honduran, 13.2% of Guatemalan and 12.7% of South American choose to substitute to illegal migrants. In contrast, college educated counterparts primarily substitute to employment-based green card, 46.6%, 45.6% of those from Mexico and Central America & Caribbean do so. 14% of those of South American origin manage to access employment-based green card.

What drive the pattern of workers reallocation? To illustrate intuition, let each value of table 10 be  $\Upsilon_{\mu|\nu}$ , where  $\mu$  denote the alternative options including employment-based green card, illegal migration, other destinations and home country.  $\Upsilon_{\mu|\nu}$  can be expressed and simplified as

$$\Upsilon_{\mu|\nu} = \frac{L_{\nu} \cdot P_{\mu|\nu} \cdot \hat{P}_{\mu|\nu}}{\sum_{\mu'} L_{\nu} \cdot P_{\mu'|\nu} \cdot \hat{P}_{\mu'|\nu}} \approx \frac{P_{\mu|\nu}}{\sum_{\mu} P_{\mu|\nu}}. \quad (15)$$

where  $P_{\mu|\nu}$  is the fraction of  $\nu$  workers who choose option  $\mu$  observed in the data. Equation (15) says the share of family and other legal types of green card rejectors that substitute to each alternatives options is approximately shaped by the share of workers in each option observed from the data. The intuition is that the observed data on  $P_{\mu|\nu}$ , restores information on how appealing of option  $\mu$  in terms of the market return to skill, migration barriers, and group productivity relative to other options. A simple derivation is provided in appendix G.6.<sup>38</sup>

### (C) On US illegal immigrants

I then examine the extent to which the number of US illegal migrants would increase for each national-origin and demographic groups. I mainly focus on four major source countries of illegal immigrants including Mexico, Central America & Caribbean, South America and Southeast Asia. Table 8 displays the results. Overall, it increases US illegal immigrants by 7.6%, about 862k. 570k of this increase are contributed by those from Mexico, accounting for 66% of the overall increase. 186k of those are from Central America & Caribbean. Illegal immigrants from South America and Southeast Asia increase slightly, by 36k and 25k, respectively.

## 6.2 WAGE, EMPLOYMENT AND PRODUCTIVITY

### (A) On US Wages

When investigating the impact of policy reform on average group wage, I am aware that there is a composition change for foreign-born labor group and therefore changes of average

<sup>38</sup>In equation (15), the numerator represents the net inflow of  $\nu$  workers to option  $\mu$ , and the denominator denotes the total number of  $\nu$  type rejectors and equals the sum of the net inflow to everywhere.

group wage reflects the equilibrium occupation wage changes, workers' reallocation behavior across occupations, and the composition change of US immigrants for each group. The effect of interest centers around the average group wage impacts caused by the first two sources, while holding the composition constant.<sup>39</sup>

Table 1 reports the average wage impacts of each education-gender group for US natives, Mexican, Indian and Chinese immigrants. I show the wage impacts of US immigrants from other major sending countries in table 9 of appendix B. Recall my model implies differential between-group substitution based on differences in occupation specialization as illustrated in equation (11), the wage impacts differ across national-origin, education and gender groups of US workers. Wage increases for all non-college educated workers, with a small variation across national-origin and gender groups. This reflects the similarity in occupation specialization among non-college workers. In particular, the wage increase is 1.14% for native male and 1.25% for native female, and is slightly larger for Mexican-born and Chinese-born counterparts, ranging from 1.45% to 1.59%. Indian counterpart experiences a relatively less wage gain.

Table 1: WAGE IMPACT OF US WORKERS BY MAJOR GROUPS

National origin	NCL male	NCL female	CL male	CL female
US natives	1.14%	1.25%	-0.39%	0.54%
Mexico	1.59%	1.59%	0.29%	0.87%
Indian	0.99%	1.24%	-3.78%	-1.90%
China	1.45%	1.45%	-2.91%	-1.38%

Among college educated workers, wage impacts vary dramatically across national-origin and gender groups, reflecting a larger disparity in their occupation specialization. Among US natives, male experience a 0.39% wage loss, while female counterpart gains by a 0.54%. Mexican counterpart experiences a larger wage gain than US natives, raising by 0.29% for male, and by 0.87% for female. However, the adverse impacts are mostly concentrated among Indian and Chinese immigrants, and are stronger for male than for female. Indian and Chinese male immigrants suffer a wage loss by 3.78% and 2.91%, respectively. The wage loss for their female are 1.90% for Indian, and 1.38% for Chinese. Table 17 in appendix F.1 shows the wage impacts when  $A_{\kappa,\sigma}$  is assumed to be a function on the college educated workers.

### (B) US Occupation Structure and Efficiency

I investigate the changes of US employment structure at each of 28 broad occupations, and also provide evidence on the changes of efficiency labor-occupation allocation at each occupation by asking whether jobs are switched from workers who have occupation comparative disadvantages to those who have comparative advantages.

I measure the logarithm of revealed comparative advantage as  $\log \frac{P_{\sigma|\nu,\kappa_{US}}}{P_{\sigma|\nu',\kappa_{US}}} - \log \frac{P_{\sigma'|\nu,\kappa_{US}}}{P_{\sigma'|\nu',\kappa_{US}}}$ ,

<sup>39</sup> I use the following formula to capture the group changes which reflects the equilibrium occupation wage changes, workers' reallocation behavior across occupations, holding composition constant,

$$\widehat{W}_{\nu,\kappa} = \left\{ \sum_{\sigma} \widehat{\Omega}_{\kappa_{US},\sigma}^{\theta} P_{\sigma|\nu,\kappa} \right\}^{\frac{1}{\theta}}.$$

where I choose US natives counterpart as normalization group, and construct the baseline occupation relative to that of native,  $\frac{P_{\sigma'|\nu,\kappa_{us}}}{P_{\sigma'|\nu',\kappa_{us}}}$ , using the geometric average over all occupations as

$$\frac{P_{\sigma'|\nu,\kappa_{us}}}{P_{\sigma'|\nu',\kappa_{us}}} = \exp \left[ \frac{1}{28} \sum_{\omega} \log \frac{P_{\omega|\nu,\kappa_{us}}}{P_{\omega|\nu',\kappa_{us}}} \right].$$

I first focus on the four detailed STEM occupations. Figure 9 shows the changes in occupation employment share of college educated national-origin groups which experience substantial changes (in vertical axis), against their values in log revealed comparative advantage (in horizontal axis).<sup>40</sup> The general message is that 20-30% STEM jobs are switched from college educated US natives to Indian and Chinese counterparts. The line fits has upward sloping among all four occupations, promoting the degree of labor-occupation specialization and suggesting an improvement of efficiency in labor-occupation allocation among STEM occupations.

I then look at another four skill-intensive occupations including executive management, health professional, social scientists, lawyers and judges, and restrict to college educated national-origin groups. As displayed in Figure 10, the slope of line fit becomes less flat comparing to that among STEM occupations. The occupation composition changes are larger at health professional, lawyers and judges occupations, but smaller among the other two. The slope of the line fit suggests the efficiency of labor-occupation allocation does not change much at executive management and social scientists, while improves slightly at health professional. The allocation becomes less efficient at lawyers and judges occupations.

Figure 11 replicates the plot at eight low-skill occupations, but focus on non-college educated national-origin groups.<sup>41</sup> Overall, there is 3-5% low-skill jobs switched from non-college educated workers from Mexico, Central American & Caribbean to non-college US natives. The slope of line fit shows negative among all eight plots, suggesting a lesser degree of occupation specialization by labor group, and hence a lower efficient allocation among low-skill occupation due to policy reform. I also show changes among the other 12 occupations in Figure 12 of appendix E, and the changes among their occupation structures are small.

### (C) On US Unemployment and Labor Force Participation

I analyze the changes on US unemployment rate and labor force participation rate. Table 2 shows the changes in terms of percentage point values of four education-gender US native groups.<sup>42</sup> Non-college US natives are more affected in both terms than college educated natives. The unemployment rate drop about by 0.105 ppts and 0.103 ppts for non-college male and female, respectively. Non-college natives also become more likely to participate in labor force, and the increase for female is 0.454 ppts, about twice as much as that for male. The impacts on unemployment rate and on labor force participation are both small among college educated US natives.

<sup>40</sup>I restrict the plot to college educated labor groups, and aggregate countries into 13 regions by pooling male and female together. Non-college groups are excluded from the plot to keep the plot informative. Since non-college workers are rarely employed in skill-intensive occupations and hence play little role of influencing the efficiency labor-occupation allocation.

<sup>41</sup>For same reasoning, college educated workers are unimportant labor supply at low-skill occupations, and therefore not included in the plot.

<sup>42</sup>The values for ppts changes in unemployment rate are calculated as  $P_{\sigma|\nu,\kappa_{us}} \cdot \hat{P}_{\sigma|\nu,\kappa_{us}} - P_{\sigma|\nu,\kappa_{us}}$ ; the values for ppts changes in LFP rate are calculated as  $P_{\sigma|\nu,\kappa_{us}} - P_{\sigma|\nu,\kappa_{us}} \cdot \hat{P}_{\sigma|\nu,\kappa_{us}}$ .

Table 2: PERCENTAGE POINT CHANGES OF UNEMPLOYMENT RATE AND LABOR FORCE PARTICIPATION RATE AMONG US NATIVES

	NCL male	NCL female	CL male	CL female
Unemployment rate	- 0.105	- 0.103	0.023	- 0.015
LFP rate	0.236	0.454	- 0.051	0.074

As the wage inequality have grown dramatically in US over the past decades, my results suggest that a skill-based immigration reform could be an effective tool to benefit workers at the middle and bottom of income distribution by 1) narrowing the earning gap between non-college and college natives, and 2) promote non-college natives to work and participate in labor force.

#### (D) On the Aggregate Output, and illegal regulation

Calibrate the model yields a aggregate output gain of 2.15%.<sup>43</sup> I then shed light on the extent to which US need to increase government expenditure on border enforcement if maintain the number of illegal migrants the same as observed in 2010. I ask this question by performing an alternative counterfactual in which the green card system is reformed the same way as the baseline counterfactual, but increase border enforcement such that the number of illegal migrants stay unchanged.

The result shows the output gain becomes 2.03% and the take-home wage rate of illegal migration needs to drop to  $\hat{\tau}_{m_i} = 0.977$ . To relating the value of  $\hat{\tau}_{m_i}$  to border enforcement, I borrow the finding in [Gathmann \(2008\)](#) who argue that 1) smuggler price is about 4.1% of the average wage that Mexican illegal immigrants earned in US, and 2) the smuggler price elasticity to border patrol 1000 hours/mile is 0.27. Applying these findings to my situation implies an increase of 2000 border patrol police hours per mile to keep the number of illegal immigration unchanged, roughly 1 full-time policy patrol police.<sup>44</sup> Given the 1969 miles US-Mexican border, this further implies increase the number of border patrol along US-Mexico border by 10.6%.<sup>45</sup>

Results discussed in section 6 are based on the baseline parameter values while assuming  $A_{\kappa,\sigma}$  are exogenous given. Section 8 analyzes the sensitivity of the results under alternative parameter values, and also discusses the the role played by these parameters. Section F.1 shows US wage impacts when  $A_{\kappa,\sigma}$  is assumed as a function of college educated labor forces.

## 7 THE IMPACTS ON GLOBAL ECONOMIES

This section studies the impacts on global economies. I first examine how policy reform would affect the global labor movement. I then discuss the labor market impacts on migration sending countries with an emphasis on India, Mexico, Central America and Caribbean countries, and

<sup>43</sup>There are three sources which potentially generate the output gain such as the skill upgrading of US immigrants, an increase of illegal immigration labor forces, and the changes in efficiency of labor-occupation allocation.

<sup>44</sup>The calculation also implies the smuggler price needs to increase by 54%.

<sup>45</sup>Since 2012, the 1,969 miles of US-Mexican international border was patrolled by 18,516 police agents.

competing destination economies namely OECD Europe, Canada and Oceania countries.

## 7.1 THE GLOBAL LABOR MOVEMENT

I shed light on two questions regarding the counterfactual policy impacts: on the location re-settlement of the net outflow of US family green card rejectors, and on the source of net inflow of employment-mode college educated immigrants.

### (A) *The relocation of US green card Rejectors*

Return to column 4-7 of table 10, it is notable that the relocation pattern of US green card rejectors differ systematically across origin countries and education groups. The results is again guided by the intuition can be illustrated in equation (15). In general, non-college educated green card rejectors are more likely to choose to live at home country than college educate counterparts. For Central America & Caribbean non-college immigrants, 92% relocate to home countries, comparing to 43.3% of their college educated immigrants. Also 82.1% of Mexican non-college immigrants do so, in contrast to 49.5% college educated counterpart. This results are mainly due to that college-educated immigrants have better chance to substitute to the expanded employment-based green card. An exception is those from South America, 85.9% of college educated green card rejectors relocate to home country, in contrast to 80.3% of their non-college counterpart.

Another worth-noting result is that college educates are more likely to substitute to foreign destinations than non-college workers, although the share are small. This result is consistent with the well-documented fact that educated workers are more mobile [Docquier et al. \(2009\)](#).

### (B) *The source of newly attracted US talents*

To analyze the source of newly attracted US talents, I calculate the size of net outflow from each mode or from each country as a share of the total net inflow of US employment-based green card increased. I focus on immigrants who are born at India, East Asia, and OECD Europe, which are the regions that absorb a substantial share of employment-based green card.<sup>46</sup>

Table 11 displays the results. It is evident that among all countries listed, 65-86% of these newly attracted US talents are from immigrants' home country. The share attracted from home country is lower for Germany, Taiwan, Italy, Japan, reflecting the substantial fraction of their college educated natives live abroad as observed in year 2010. Also notice the share are higher for China and India, reflecting the lower degree of their openness to emigration. It is also worth-noting that 11-33% of the newly attracted US talents are those who substitute from family or refugee green card to employment-based green card. Again, to illustrate intuition, I denote each value of table 11 as  $\Lambda_{\mu|\nu}$  and simplify its expression as

$$\Lambda_{\mu|\nu} = \frac{L_{\nu} \cdot P_{\mu|\nu} \cdot (1 - \hat{P}_{\mu|\nu})}{\sum_{\mu'} L_{\nu} \cdot P_{\mu|\nu} \cdot (1 - \hat{P}_{\mu|\nu})} \approx \frac{P_{\mu|\nu}}{\sum_{\mu'} P_{\mu'|\nu}}. \quad (16)$$

Unsurprisingly, the expression and intuition parallels with that of  $\Upsilon_{\mu|\nu}$ . I also provide a simple

<sup>46</sup>Among employment-based visa issued during 1996-2015 (excluding their spouse or children), 20.34% are allocated to workers from Indian, 10.9% to Chinese, 11.3% to other East Asian countries and 9.8% to OECD European countries.

derivation in Appendix G.6.

## 7.2 THE LABOR MARKET IMPACTS ON FOREIGN COUNTRIES

### (A) *On migration sending countries*

Table 12 reports the impacts on four important sending regions including Mexico, Central America, India, and East Asia countries by education and gender groups, in terms of labor force on panel A and in terms of wage on panel B. All values are in percentage changes.

Panel A shows systematic differences on the labor force impacts. The impacts are the largest at Central America & Caribbean countries, where labor force increase among all four groups and college educates become relatively more abundant. There is a 7.44% and 10.96% increase of college educated labor force for male and female, respectively, relative to 2.66% and 2.81% increase for non-college counterpart. Surprisingly, as the country which send the most immigrants to US, the impacts on Mexican labor force are fairly small. College educates become slightly more scarce, with non-college Mexican labor force increase about 2.6-3.1%, in contrast to a 1.45% and 2.70% increase for college male and female, respectively.

India and East Asia experience substantial loss of college educated labor force. The impacts are larger for India which lose 7.22% of college male, and 3.65% of college female labor forces, than for East Asian countries which lose 3.93% of college male and 2.19% college female. The impacts on non-college labor force are small at India and East Asian countries.

The changes in labor force translate to that of wages impacts in an unsurprising way, as reported in Panel B. The impacts are large at Central America & Caribbean countries and India which experience a large impacts of domestic labor forces. However, inequality falls at former but raises at latter. For Central America & Caribbean countries, wage raises among non-college workers of a 0.67% for non-college male and 0.44% for non-college female, while falls among college workers in a slightly smaller magnitude. In contrast, wage increases about 0.5-0.6% among college workers while fall similar magnitude among non-college in India. Also unsurprisingly, the wage impacts are small at Mexico and East Asian countries. Table 13 in appendix B reports the results for other sending regions.

It is useful to emphasize that the small wage impacts are obtained by assuming away the external economies of scale. In appendix F.1, I assume  $A_{\kappa,\sigma}$  as a function of the stock of college educates, and find a large wage impacts in that case.

### (B) *On competing destinations*

I then examine the impacts of labor force and wage structure at other destination countries. Table 14 reports the changes of the four education-gender groups for both natives and immigrants in terms of labor force in panel A, and in terms of wage impacts in panel B.

Focusing on panel A, the impacts on labor force changes tend to be more similar among three destination economies. On one hand, there is a slightly increase in non-college labor force of both native and immigration workers, ranging from 0.12%-0.9%. On the other hand, there stock of college educated workers decrease among all three regions, for both natives and migration workers. Among these three economies, Canada experience the largest decrease of native college educated labor force, by a 7.34% for male and 3.66% for female, whereas Oceania countries experience the largest proportional decrease of foreign-born workers by a 4.13% for



male and 1.69% for female.

The wage impacts at other destination economies are small as reported in Panel B of table 14. Again, consistent with the changes in relative skill abundant reported in panel A, the wage distribution become slightly more unequal.

## 8 ALTERNATIVE PARAMETER VALUES

This section analyzes the results sensitivity to the two elasticity parameters estimated in section 5, namely the labor supply elasticity  $\vartheta$ , and the labor demand elasticity  $\rho_{us}$ .

**Alternative  $\vartheta$ :** I apply two alternative approaches to estimate  $\vartheta$ , both of which explore the parametric *Fréchet* assumption on wage distribution of US immigrants. First, using the method of matching coefficient of variation as proposed in Hsieh et al. (2013) who rely on the functional form of the first and the second moment of *Fréchet* distribution. Particularly, Hsieh et al. (2013) matches the following moment restriction

$$\frac{\text{Var}[W]}{E[W]^2} = \frac{T_{\nu,\kappa,\sigma}^2 \cdot [\Gamma(1 - 2/\vartheta) - \Gamma(1 - 1/\vartheta)^2]}{T_{\nu,\kappa,\sigma}^2 \cdot \Gamma[1 - 1/\vartheta]^2} = \frac{\Gamma(1 - 2/\vartheta)}{\Gamma(1 - 1/\vartheta)^2} - 1.$$

Also I estimate the LHS moments using ACS 2009-2013 on the hourly earnings of all observations while excluding individuals who earn below federal minimum wages. This gives  $\vartheta = 3.14$ . I also perform maximum likelihood estimation on the distribution of wage residual to eliminate cross-group wage dispersion and obtain an estimate of  $\vartheta = 2.68$ . Again I focus on sample among individuals wage is at least the federal minimum wage with positive hours worked. I also try alternative  $\vartheta$  value equals 1.7 as used in Burstein et al. (2015), and a large value of 5, and holding  $\rho_{us} = 2.18$ ,  $\rho_o = 0.9$  as in the baseline. Table 15 reports the wage of US natives by demographic groups, as well as the impacts on US output.

A predominate feature is that the output increase with respect to  $\vartheta$ . This is because that  $\vartheta$  governs the dispersion of group productivity dispersion, with a larger  $\vartheta$  corresponds to a less dispersion of within-group productivity. Hence as US abstract more talents from countries like India and China, the average productivity of immigrants decline slowly in response to the increase size of college-educated immigrants.

**Alternative  $\rho_{us}$ :** I assign values ranging from 0.9-5 while holding  $\vartheta = 3.66$  and  $\rho_o = 0.9$  for other countries, same as the baseline. As captured by equation (12), relative occupation wage is more responsive to relative labor supply and thus translate to a larger impacts on average wage, when  $\rho_{us}$  takes a smaller value. Results are found to be consistent with this intuition as reported in table 15.

## 9 CONCLUSION

This paper aims to shed light on the economic consequences if US adopts a skill-based immigration reform. My contribute to the literature is to introduce a new conceptual framework of

immigration with mode of entry, in a multi-country general equilibrium environment. I show the model can map any exogenous changes of the number or the distribution of green card changes by category into endogenous labor force changes at each country. The model remains analytically tractable of a large dimension of heterogeneity across many labor groups. I also show that my main model features receive great empirical supports.

I use the model to undertake a counterfactual exercise of policy reform. I find, hypothetically had US shifted green card distribution to the same as that in Canada since 1990, while holding the overall number of green card issued unchanged, would 1) improve the overall US output by 2.15%; 2) it changes the composition of US immigrants, while the impacts are largely mitigated by equilibrium adjustment that workers substitute from family green card to employment category or illegal entry; 3) narrow US college premium and gender wage gap; 4) the impacts on Indian and Central American countries are larger than on other foreign countries. When assuming total factor productivity as a function on the stock of college educated workers, global impacts become larger.

My paper analyzes the economic impacts of one possible policy reform. One limitation is that my results are silent to the optimal immigration policy from US welfare perspective. I pursue this goal in future research.

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## A DATA DESCRIPTION

As discussed in section 3, the empirical exercise has  $\dim(\kappa) = 13$  economies,  $\dim(\nu) = 460$  labor groups,  $\dim(\sigma_{us})=28$  occupation categories for the US economy plus 1 option which is unemployment.  $\dim(\sigma_o) = 20$  for India and Mexico and 9 for the others.

### A.1 THE ALGORITHM OF GENERATING ILLEGAL MIGRANTS IDENTIFIERS

This paper generate identifiers for illegal migrants primarily based on the Algorithm in Borjas (2017), who defines a immigrant as legal if one of the following 9 conditions hold, and then attribute the residual sample as illegal immigrants.

1. That person arrived before 1980;
2. That person is a citizen;
3. That person receives Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance;
4. That person is a veteran, or is currently in the Armed Forces;
5. That person works in the government sector;
6. That person resides in public housing or receives rental subsidies, or that person is a spouse of someone who resides in public housing or receives rental subsidies;
7. That person was born in Cuba (as practically all Cuban immigrants were granted refugee status before 2017);
8. That person's occupation requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers);
9. That person's spouse is a legal immigrant or citizen.

This algorithm may cause high-skill immigrants over-represented in illegal population, since high-skill workers are less likely to be those who arrive before 1980, or receive government welfare program. Using this algorithm, 20.3% of illegal immigrants have college degree and above, and 14% of illegal immigrants work in skill-intensive occupations, such as executive management, engineers, computer and research scientists, etc. I further filter legal immigrants by assuming a immigrants is legal if one the following holds

1. That person has a masters', professional or Doctoral degree
2. That person work in skill-intensive occupations including executive management, mathematical and computer scientists, electrical engineer, social scientists and urban planners, and computer software developers.

## A.2 THE DIMENSION OF LABOR GROUP

I consider immigrants born from  $\text{dim}(\nu) = 115$  countries, the information of which are both available at ACS, IAB and DIOC. These 115 countries together account for more than 95% of migrants to the US. The model has 4 education-sex groups including non-college female, non-college male, college female and college male.

## A.3 OCCUPATION AGGREGATION

**ACS OCCUPATION AGGREGATION:** I aggregate the ACS occupation code into 28 occupations for the US economy. The aggregation aims to pool together jobs whose task intensity are similar, keep the consistency of the broad IPUMS occupation definition. Table 4 shows the 5 widely used Dictionary of Occupational Titles (DOT) tasks measurement. They are General education development (GED), Direction, control and Planning (DCP), Set limits, tolerance and vocational preparation (STS), Eye-hand-foot coordination (EHF) and Finger dexterity (FINGER). I transform the raw DOT task measurement into percentile ranking, and after that each value in table 4 is computed as the average percentile ranking for each of the 28 aggregated occupations. The last column of table 4 shows the fraction supplied by foreign-born workers at each of the 28 occupation.

To match occupations consistent with the aggregation used in NIS sample, I further group the above 28 occupations to 3 broad occupations as below.

- Cognitive occupation: math and science; engineers; health professional; social scientists, lecturers; computer system analyst; computer software developers; management related; lawyers and judges; executive, managerial.
- Routine occupation: teachers, except postsecondary; therapists; health assistants; technicians; sales representatives, finance and business; editors reports, clergy, arts; administrative and financial clerks; information, record and distribution clerks; sales representatives, commodities.
- Manual occupation: mechanics, repairers; precision workers; construction; equipment operators; farm and agriculture; machine operators; personal and cleaning service; food preparation and service; protective service; transportation.

I use the 1-digit International Standard Classification of Occupations (ISCO88) code to have 9 broad occupation categories for the other 12 economies. The purpose is to have a consistent occupation category for these economies and obtain labor market information as many as possible. The 9 occupations are Legislators, senior officials and managers, Professionals, Technicians and associate professional, Clerks, Service workers and market sales, Skilled workers, Craft and related trade workers, Machine operators and assemblers, and Elementary occupations.

**OCCUPATION AGGREGATION OF NEW IMMIGRANT SURVEY:** The New Immigrant Survey (NIS) has 30 detailed occupations excluding military occupation. Each of my broad occupation category are aggregated as follows.



Cognitive occupation: executive, administrative and managerial; management related; mathematical and computer scientists; engineers, architects and surveyors; engineering and related technicians; life and physical scientists; social scientists and related workers; life, physical and social science technicians; Lawyers, judges and legal support workers; health diagnosis and treating practitioners.

Routine occupation: counselors, social and religious workers; teachers; education, training and library workers; entertainers and performers, sports and related workers; media and communication workers; health care technical and support; sales and related workers; office and administrative support workers.

Manual occupation: protective service, food preparations and serving related; cleaning and building service; entertainment attendants and related workers; personal care and service workers; farming, fishing and forestry; construction trades and extraction workers; installation, maintenance, and repair workers; production and operating workers; food preparation; setter, operators and tenders; transportation and material moving workers.

#### A.4 US LABOR MARKET VARIABLES

Information on employment and wages are taken from ACS 2009-2013. To take into account labor hours reported in ACS, I weight each observation using the following weights adjusted by hours worked as

$$\text{ADJUSTED WEIGHTS} = \frac{\text{CENSUS WEIGHT} \times \text{WEEKS WORKED} \times \text{USUAL HOURS PER WEEK}}{2000}$$

Then I modify wages by adjusting the IPUMS variable INCWAGE (representing annual wage and salary income) according to

$$\text{ANNUAL WAGE} = \frac{\text{ANNUAL WAGE AND SALARY INCOME}}{\text{WEEKS WORKED} \times \text{HOURS PER WEEK}} \times 2000$$

Variables of weeks worked of IPUMS Census is reported in interval. We thus take the middle point of each interval to approximate the number of weeks worked last year. Thus the average wage  $W_{\sigma|\nu,\kappa_{us}}$  is measured using the above defined wage weighted by the adjusted weights;  $P_{\sigma|\nu,\kappa}$  is also measured using the adjusted weights.

#### A.5 LABOR MARKET VARIABLES FOR FOREIGN ECONOMIES

Information on employment and wages at the other 12 economies are drawn from IPUMS International, or Luxembourg income study (LIS) whenever the is available near year 2010. For these aggregated economies, variables are computed as the population weighted average on the occupation share and the group wages earned among countries whose data are available, within each economy. When wage information are not available, I combine data from Occupational Wages around the World (OWW) Database and occupation share to impute the average

group wage at each destination.<sup>47</sup> Countries whose data are unavailable are not considered when constructing the measurement for aggregated economies.

Table 3: DATA SOURCE AND COUNTRIES INCLUDED FOR EACH AGGREGATED REGION

Country	Wage	$P_{\omega \nu,\kappa}$	$L_{\nu,\kappa}, P_{\kappa \nu}$	Countries included and year
<b>Mexico</b>	IPUM-Intl	IPUMS-Intl	IPUMS-Intl, IAB	Mexico(2010)
<b>India</b>	LIS	LIS	LIS, IAB	India(2011)
<b>Canada</b>	OWW-DIOC	DIOC	DIOC, IAB	Canada(2010)
<b>Central America</b>	IPUM-Intl	IPUMS-Intl	IAB, Barro & Lee	Costa Rica(2011), Dominican Republic(2010), El Salvador(2007), Nicaragua(2005), Panama(2010)
<b>South America</b>	IPUM-Intl	IPUMS-Intl	IAB, IAB, Barro & Lee	Argentina(2010), Brazil(2010), Bolivia(2001), Colombia(2005), Ecuador(2010), Peru(2007)
<b>OECD Europe</b>	OWW, DIOC	DIOC	DIOC, IAB, Barro & Lee	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Norway, Portugal, Spain, Sweden, Switzerland (all 2010)
<b>Oceania</b>	OWW, DIOC	DIOC	DIOC, IAB, Barro & Lee	Australia(2010)
<b>Africa</b>	IPUM-Intl	IPUM-Intl	IAB, Barro & Lee	Cameroon(2005), Ghana(2010), Liberia(2008), Malawi(2008), Mali(2009), Mozambique(2007), Nigeria(2010), South Africa(2011), South Sudan(2008), Sudan(2008), Zambia(2010)
<b>East Europe</b>	IPUM-Intl+LIS	IPUM-Intl+LIS	IAB, Barro & Lee	Czech Republic(2010), Estonia(2010), Hungary(2009), Poland(2010), Russia(2010), Serbia(2010), Slovak Republic(2010), Slovenia(2010)
<b>East Asia</b>	IPUM-Intl+LIS	IPUM-Intl+LIS	IAB, Barro & Lee	Japan(2008), Korea(2006), Taiwan(2010)
<b>Southeast Asia</b>	IPUM-Intl	IPUM-Intl	IAB, Barro & Lee	Cambodia(2008), Indonesia(2010), Vietnam(2009)
<b>Mid-east &amp; southwest Asia</b>	IPUM-Intl+LIS	IPUM-Intl+LIS	IAB, Barro & Lee	Armenia(2011), Bangladesh(2011), Jordan(2004), Iran(2006), Pakistan(1998), Palestine(2007), Turkey(2000)

- IAB shorthands for IAB brain-drain data available at Institute for Employment Research.

<sup>47</sup>Since Occupational Wages around the World (OWW) database provide the occupation wages at each country, I use group specific occupational share as the weights to impute the average group wages at each country.

## B TABLES

Table 4: DOT OCCUPATION TASK INTENSITY OF 28 US OCCUPATION

Occupation	GED	DCP	STS	FINGER	EHF	% of migration workers
Math & Science	0.941	0.820	0.776	0.447	0.350	28.9
Engineers	0.931	0.854	0.713	0.735	0.530	22.2
Health Professional	0.918	0.780	0.267	0.994	0.689	25.4
Social Scientists, Lecturers	0.881	0.839	0.235	0.214	0.244	25.8
Computer System Analyst	0.874	0.827	0.478	0.184	0.340	24.9
Computer Software Developers	0.872	0.668	0.872	0.189	0.171	37.9
Management Related	0.839	0.827	0.508	0.300	0.226	13.8
Lawyers and Judges	0.819	0.534	0.179	0.103	0.05	5.6
Teachers, Except Postsecondary	0.804	0.924	0.141	0.340	0.350	6.8
Therapists	0.769	0.786	0.410	0.903	0.586	15.1
Executive, Managerial	0.753	0.878	0.260	0.285	0.361	14.4
Health Assistants	0.749	0.555	0.691	0.839	0.547	25.6
Technicians	0.746	0.511	0.745	0.642	0.540	15.4
Sales Representatives, Finance & Business	0.710	0.734	0.264	0.282	0.315	13.2
Editors reports, Clergy, Arts	0.689	0.636	0.320	0.468	0.355	12.4
Mechanics, Repairers	0.636	0.459	0.811	0.810	0.652	20.2
Precision workers	0.602	0.743	0.571	0.582	0.548	18.7
Construction	0.553	0.564	0.681	0.643	0.750	17.8
Administrative & Financial Clerks	0.547	0.530	0.699	0.799	0.173	16.7
Information, Record & Distribution Clerks	0.500	0.521	0.430	0.348	0.260	14.4
Sales Representatives, Commodities	0.465	0.453	0.317	0.425	0.372	10.7
Equipment Operators	0.457	0.378	0.471	0.884	0.140	15.7
Farm & Agriculture	0.399	0.713	0.327	0.279	0.797	8.9
Machine operators	0.347	0.312	0.643	0.618	0.598	21.3
Personal & Cleaning Service	0.330	0.611	0.286	0.350	0.634	19.8
Food Preparation & Service	0.306	0.489	0.387	0.352	0.450	24.9
Protective Service	0.257	0.615	0.139	0.075	0.812	6.9
Transportation	0.229	0.264	0.343	0.271	0.834	24.5

- Each value of DOT task measurement are the average of percentile values.

Table 5: OLS AND 2SLS ESTIMATION RESULTS ON  $\rho_{us}$

	OLS	IV	FIRST STAGE
$-\frac{1}{\rho}$	-0.403*** (0.026)	-0.457*** (0.034)	0.523*** (0.039)
Implied $\rho$	2.481*** (0.160)	2.188*** (0.162)	
Num. of Obs.	116	116	116

Notes: the regression units are 29 occupations in 4 year period of 2000, 2005, 2010 and 2015. Year fixed effects are included in the model. Standard errors are reported in parentheses.

Table 6: ESTIMATION RESULTS ON  $\vartheta$ 

<b>Panel A: OLS log regression</b>			
1) country-occupation as observational unit			
$\vartheta$	3.103*** (0.161)	3.230*** (0.173)	3.288*** (0.177)
PISA Score	average	75 pctl	90 pctl
Num. of Obs.	3213	2998	2998
2) region-occupation as observational unit			
$\vartheta$	2.850*** (0.161)	2.888*** (0.207)	2.937*** (0.214)
PISA Score	average	75 pctl	90 pctl
Num. of Obs.	1433	1377	1377
<b>Panel B: Pseudo-maximum-likelihood (PML)</b>			
1) country-occupation as observational unit			
$\vartheta$	3.655*** (0.071)	3.807*** (0.077)	3.896*** (0.079)
PISA Score	average	75 pctl	90 pctl
Num. of Obs.	3213	3429	3429
2) region-occupation as observational unit			
$\vartheta$	3.827*** (0.114)	3.860*** (0.120)	3.941*** (0.124)
PISA Score	average	75 pctl	90 pctl
Num. of Obs.	1508	1450	1450

Notes: standard errors are reported in parentheses. The full sample is formed by pairwise combination of 64 origin countries and 29 occupations. The sample which used to run log regression include origin-occupation pairs (1) for which the workers-occupation matching is present at US labor market, (2) for which countries' math, science score and linguistic proximity are available, and (3) for which we observe their workers work in baseline management occupation. The sample of pseudo-maximum-likelihood estimation includes origin-occupation pairs for countries whose math, science score and linguistic proximity are available, and for countries that we observe their workers work in baseline management occupations. Panel A2) and B2) groups small countries into region, and replicate OLS and PML estimation using region-occupation as observational units.

Table 7: SHARE OF FOREIGN-BORN US WORKERS BY COUNTRIES

REGION/COUNTRY	OBSERVED ECONOMY			COUNTERFACTUAL ECONOMY		
	ALL	NON-COLLEGE	COLLEGE	ALL	NON-COLLEGE	COLLEGE
<b>CENTRAL AMERICA &amp; CARIBBEAN</b>	<b>17.7%</b>	<b>15.1%</b>	<b>2.6%</b>	<b>13.7%</b>	<b>11.7%</b>	<b>2.0%</b>
El Salvador	3.6%	3.4%	0.2%	3.1%	2.9%	0.2%
Guatemala	2.4%	2.3%	0.1%	2.0%	1.9%	0.1%
Dominican republic	2.4%	2.1%	0.4%	1.5%	1.3%	0.2%
Cuba	2.5%	1.9%	0.6%	2.0%	1.5%	0.5%
Jamaica	1.7%	1.3%	0.4%	1.2%	0.9%	0.3%
Honduras	1.5%	1.4%	0.1%	1.2%	1.1%	0.1%
Haiti	1.5%	1.3%	0.2%	1.1%	0.9%	0.2%
<b>SOUTH AMERICA</b>	<b>7.2%</b>	<b>5.0%</b>	<b>2.2%</b>	<b>6.2%</b>	<b>3.7%</b>	<b>2.5%</b>
Colombia	1.8%	1.2%	0.6%	1.3%	0.8%	0.5%
Ecuador	1.2%	1.0%	0.2%	0.9%	0.8%	0.1%
Peru	1.1%	0.8%	0.3%	0.9%	0.6%	0.3%
Brazil	1.0%	0.6%	0.4%	1.0%	0.5%	0.5%
<b>SOUTHEAST ASIA</b>	<b>10.1%</b>	<b>6.3%</b>	<b>3.8%</b>	<b>8.3%</b>	<b>4.2%</b>	<b>4.1%</b>
Philippines	4.6%	2.3%	2.3%	4.1%	1.5%	2.6%
Vietnam	3.5%	2.6%	1.0%	2.2%	1.7%	0.6%
Thailand	0.6%	0.4%	0.2%	0.5%	0.3%	0.2%
<b>EAST ASIA</b>	<b>9.3%</b>	<b>4.2%</b>	<b>5.1%</b>	<b>13.9%</b>	<b>3.1%</b>	<b>10.8%</b>
China	4.1%	2.1%	2.0%	6.6%	1.5%	5.1%
Korea	2.7%	1.2%	1.5%	3.9%	0.1%	3.0%
Taiwan	1.0%	0.3%	0.7%	1.6%	0.2%	1.4%
Japan	0.7%	0.3%	0.4%	1.1%	0.3%	0.8%
HongKong	0.6%	0.2%	0.4%	0.7%	0.2%	0.5%
<b>MID-EAST &amp; SOUTHWEST ASIA</b>	<b>4.8%</b>	<b>2.5%</b>	<b>2.3%</b>	<b>4.7%</b>	<b>1.8%</b>	<b>2.9%</b>
Iran	0.9%	0.4%	0.5%	0.9%	0.3%	0.6%
Pakistan	0.9%	0.4%	0.5%	0.9%	0.3%	0.6%
Bangladesh	0.5%	0.3%	0.2%	0.4%	0.2%	0.2%
<b>OECD EUROPE</b>	<b>4.4%</b>	<b>2.5%</b>	<b>1.9%</b>	<b>5.4%</b>	<b>1.8%</b>	<b>3.6%</b>
Germany	1.0%	0.6%	0.4%	1.2%	0.4%	0.8%
United Kingdom	0.7%	0.4%	0.3%	0.9%	0.3%	0.6%
Italy	0.6%	0.4%	0.2%	0.6%	0.3%	0.3%
France	0.4%	0.1%	0.2%	0.6%	0.1%	0.5%
<b>EASTERN EUROPE</b>	<b>4.3%</b>	<b>2.3%</b>	<b>2.0%</b>	<b>4.1%</b>	<b>1.8%</b>	<b>2.3%</b>
Poland	1.1%	0.8%	0.3%	1.1%	0.6%	0.5%
Russia	0.8%	0.3%	0.5%	0.7%	0.2%	0.5%
Ukraine	0.7%	0.4%	0.3%	0.7%	0.3%	0.4%
Romania	0.4%	0.2%	0.2%	0.5%	0.2%	0.3%
<b>AFRICA</b>	<b>2.3%</b>	<b>1.3%</b>	<b>1.0%</b>	<b>2.2%</b>	<b>1.0%</b>	<b>1.2%</b>
Ghana	0.4%	0.3%	0.1%	0.3%	0.2%	0.1%
Egypt	0.4%	0.1%	0.3%	0.3%	0.1%	0.2%
Kenya	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%
South Africa	0.2%	0.1%	0.1%	0.4%	0.1%	0.3%
<b>CANADA</b>	<b>1.7%</b>	<b>0.8%</b>	<b>0.9%</b>	<b>2.5%</b>	<b>0.6%</b>	<b>1.9%</b>
<b>OCEANIA</b>	<b>0.4%</b>	<b>0.2%</b>	<b>0.2%</b>	<b>0.4%</b>	<b>0.1%</b>	<b>0.3%</b>
<b>Mexico</b>	<b>32.1%</b>	<b>30.3%</b>	<b>1.8%</b>	<b>25.9%</b>	<b>24.4%</b>	<b>1.5%</b>
<b>India</b>	<b>5.5%</b>	<b>1.2%</b>	<b>4.3%</b>	<b>12.6%</b>	<b>0.8%</b>	<b>11.8%</b>
<b>TOTAL</b>	<b>100%</b>	<b>71.9%</b>	<b>28.1%</b>	<b>100%</b>	<b>55.2%</b>	<b>44.8%</b>

Notes: each value sums over the share of male and female within each education category who are 18 - 64 year old in 2010.

Table 8: THE NET INFLOW OF US ILLEGAL MIGRANTS (IN 1000S)

REGION/COUNTRY	OBSERVED ECONOMY			COUNTERFACTUAL ECONOMY		
	ALL	NON-COLLEGE	COLLEGE	ALL	NON-COLLEGE	COLLEGE
<b>Mexico</b>	<b>6208</b>	<b>5867</b>	<b>341</b>	<b>6778</b>	<b>6417</b>	<b>360.8</b>
<b>CA. &amp; CARIBBEAN</b>	<b>2452</b>	<b>2291</b>	<b>161</b>	<b>2638</b>	<b>2454</b>	<b>184</b>
El Salvador	725.3	711.4	13.9	786.4	770.8	15.6
Dominican republic	624.4	621.9	2.4	671.8	669.0	2.8
Guatemala	506.9	388.1	118.7	546.5	409.9	136.6
Honduras	309.6	302.6	7.0	327.4	319.5	7.9
Jamaica	70.0	67.6	2.3	77.4	74.6	2.8
<b>South America</b>	<b>660</b>	<b>512</b>	<b>148</b>	<b>696</b>	<b>544</b>	<b>151</b>
Ecuador	173.7	166.6	7.2	185.0	177.6	7.4
Colombia	130.8	73.3	57.5	136.5	77.6	58.9
Peru	100.8	82.7	18.0	106.4	87.7	18.8
<b>Southeast Asia</b>	<b>455.7</b>	<b>342.4</b>	<b>113.3</b>	<b>481</b>	<b>364</b>	<b>117</b>
Philippines	135.2	95.4	39.9	142.2	101.1	41.1
Vietnam	120.9	109.5	11.4	129.1	116.6	12.5
Laos	84.1	82.7	1.4	89.7	88.1	1.58
<b>All origins</b>	<b>11400</b>	<b>10196</b>	<b>1203</b>	<b>12262</b>	<b>11025</b>	<b>1238</b>

Table 9: WAGE IMPACT OF US WORKERS BY OTHER MAJOR GROUP

National origin	Non-college male	Non-college female	College male	College female
El Salvador	1.53%	1.60%	0.45%	0.98%
Korea	0.96%	1.28%	-0.68%	0.29%
Vietnam	1.29%	1.52%	-1.89%	-0.15%
Philippines	1.19%	1.39%	-0.10%	0.89%
Canada	0.71%	1.16%	-1.26%	0.19%
Germany	0.77%	1.16%	-1.26%	0%
Poland	1.27%	1.41%	-0.89%	0.45%

Table 10: THE DISTRIBUTION ON THE NET OUTFLOW OF US GREEN CARD REJECTERS

ORIGIN COUNTRIES	IN US		RECEIVED BY FOREIGN ECONOMIES			
	EMPLOYMENT	ILLEGAL	EU	OCEANIA	CANADA	HOME COUNTRY
<b>PANEL A: NON-COLLEGE WORKERS</b>						
<b>Mexico</b>	<b>0.56%</b>	<b>17.27%</b>	<b>0.06%</b>	<b>0%</b>	<b>0.03%</b>	<b>82.08%</b>
<b>CA. &amp; CARIBBEAN</b>	<b>0.43%</b>	<b>6.52%</b>	<b>0.80%</b>	<b>0.01%</b>	<b>0.15%</b>	<b>92.10%</b>
El Salvador	1.30%	20.98%	0.10%	0.03%	0.21%	77.39%
Guatemala	0.73%	13.21%	-0.04%	0%	-0.08%	86.18%
Dominican republic	0.14%	3.18%	0.80%	0%	0.02%	95.86%
Jamaica	0.93%	4.73%	5.48%	0.01%	1.84%	87.01%
Honduras	0.82%	15.62%	-0.21%	0%	-0.04%	83.81%
<b>South America</b>	<b>4.02%</b>	<b>12.72%</b>	<b>0.95%</b>	<b>0.04%</b>	<b>1.94%</b>	<b>80.32%</b>
<b>PANEL B: COLLEGE EDUCATED WORKERS</b>						
<b>Mexico</b>	<b>46.64%</b>	<b>3.50%</b>	<b>0.16%</b>	<b>0.01%</b>	<b>0.17%</b>	<b>49.53%</b>
<b>CA. &amp; CARIBBEAN</b>	<b>45.57%</b>	<b>4.49%</b>	<b>1.85%</b>	<b>0.13%</b>	<b>4.65%</b>	<b>43.30%</b>
El Salvador	53.50%	4.78%	0.50%	0.81%	3.24%	37.16%
Guatemala	47.66%	6.23%	0.90%	0.07%	2.94%	42.21%
Dominican republic	5.39%	1.39%	2.89%	0.01%	0.33%	89.99%
Jamaica	35.67%	1.06%	8.68%	0.14%	18.00%	36.43%
Honduras	43.55%	4.32%	2.14%	0.02%	0.82%	49.13%
<b>South America</b>	<b>14.03%</b>	<b>0.06%</b>	<b>-0.03%</b>	<b>0%</b>	<b>0.01%</b>	<b>85.94%</b>

Notes: each value is calculated as the size of net inflow to each mode or each destination as a share of the total number of US family and other legal green card reduced.



Table 11: THE SOURCE OF NET INFLOW OF EMPLOYMENT-MODE COLLEGE EDUCATES

ORIGIN COUNTRIES	FROM US		FROM FOREIGN ECONOMIES			
	FAMILY-MODE	ILLEGAL	EU	OCEANIA	CANADA	HOME COUNTRY
<b>India</b>	<b>10.94%</b>	<b>0.75%</b>	<b>0.85%</b>	<b>0.26%</b>	<b>0.84%</b>	<b>86.37%</b>
<b>EAST ASIA</b>	<b>18.75%</b>	<b>1.63%</b>	<b>0.34%</b>	<b>0.30%</b>	<b>0.84%</b>	<b>78.14%</b>
China	12.89%	1.82%	0.26%	0.23%	0.49%	84.31%
Taiwan	25.50%	1.85%	0.18%	0.24%	0.63%	71.60%
Japan	22.94%	1.61%	0.17%	0.07%	0.06%	75.15%
Korea	18.41%	1.51%	0.26%	0.22%	0.52%	79.07%
<b>OCED EUROPE</b>	<b>23.25%</b>	<b>0.12%</b>		<b>1.88%</b>	<b>2.05%</b>	<b>70.82%</b>
United Kingdom	20.75%	0.77%	-	4.78%	3.67%	70.04%
Germany	26.18%	3.64%	-	0.36%	0.89%	68.93%
France	15.19%	1.25%	-	0.14%	0.65%	82.78%
Italy	28.97%	2.07%	-	0.69%	1.94%	66.34%

Notes: each value is calculated the size of net outflow from each mode or each destination as a share of the total net inflow of US employment green card increased.

Table 12: IMPACTS ON LABOR FORCE AND WAGES AT SENDING ECONOMY

COUNTRY	NON-COLLEGE	NON-COLLEGE	COLLEGE	COLLEGE
	MALE	FEMALE	MALE	FEMALE
<b>Panel A: Labor Force Impacts</b>				
Mexico	3.08%	2.67%	1.45%	2.70%
Central America & Caribbean	2.66%	2.81%	7.44%	10.96%
India	0.01%	0.01%	-7.22%	-3.65%
East Asia	0.17%	0.03%	-3.93%	-2.19%
<b>Panel B: Wage Impacts</b>				
Mexico	-0.08%	-0.05%	0.06%	0.05%
Central America & Caribbean	0.67%	0.44%	-0.35%	-0.47%
India	-0.55%	-0.61%	0.51%	0.61%
East Asia	-0.01%	-0.01%	0.20%	0.07%

Notes: The results are obtained by setting  $\rho_{us} = 2.18$ ,  $\rho_g = 0.9$  and  $\vartheta = 3.66$ . Each percentage value is computed by subtracting one from the proportional change. For economy that is aggregated, I take weighted average over all countries within each region/economy.

Table 13: IMPACTS ON LABOR FORCE AND WAGES AT OTHER SENDING ECONOMY

COUNTRY	NON-COLLEGE	NON-COLLEGE	COLLEGE	COLLEGE
	MALE	FEMALE	MALE	FEMALE
<b>Panel A: Labor Force Impacts</b>				
South America	0.13%	0.15%	-0.88%	-0.09%
Southeast Asia	0.14%	0.19%	-0.77%	0.25%
East Europe	0.09%	-0.64%	0.13%	-0.19%
Africa	0.03%	0.03%	-0.18%	0.24%
Middle east	0.04%	0.05%	-1.07%	-0.15%
<b>Panel B: Wage Impacts</b>				
South America	-0.03%	0.03%	0.04%	0.05%
Southeast Asia	-0.05%	0.05%	0.11%	0.11%
East Europe	-0.04%	0.24%	0.16%	0.15%
Africa	0%	0%	0.01%	0.01%
Middle east	-0.03%	0.04%	0.14%	0.17%

Notes: The results are obtained by setting  $\rho_{us} = 2.18$ ,  $\rho_g = 0.9$  and  $\vartheta = 3.66$ . Each percentage value is computed by subtracting one from the proportional change in labor force. For economy that is aggregated, I take weighted average over all countries within each region/economy.

Table 14: IMPACTS ON LABOR FORCE AND WAGES AT OTHER DESTINATION ECONOMIES

COUNTRY	NATIONAL	NON-COLLEGE MALE	NON-COLLEGE FEMALE	COLLEGE MALE	COLLEGE FEMALE
<b>Panel A: Labor Force Impacts</b>					
OECD Europe	Natives	0.12%	0.17%	-2.84%	-1.16%
	Foreign	-0.06%	-0.71%	-3.15%	-0.87%
Canada	Natives	0.31%	0.52%	-7.34%	-3.66%
	Foreign	0.09%	0.27%	-1.92%	0.36%
Oceania	Natives	0.05%	0.08%	-1.17%	-0.12%
	Foreign	0.28%	0.29%	-4.13%	-1.69%
<b>Panel B: Wage Impacts</b>					
OECD Europe	Natives	-0.08%	-0.06%	0.14%	0.14%
	Foreign	-0.11%	-0.09%	0.11%	0.13%
Canada	Natives	-0.17%	-0.10%	0.11%	0.15%
	Foreign	-0.17%	-0.14%	0.11%	0.11%
Oceania	Natives	-0.04%	-0.02%	0.07%	0.07%
	Foreign	-0.03%	-0.02%	0.06%	0.06%

Notes: The results are obtained by setting  $\rho_{us} = 2.18$ ,  $\rho_9 = 0.9$  and  $\vartheta = 3.66$ . Each percentage value is computed by subtracting one from the proportional change. For economy that is aggregated, I take weighted average over all countries within each region/economy.

Table 15: WAGE IMPACT ON US NATIVES BY EDUCATION AND GENDER GROUPS, WITH ALTERNATIVE  $\rho_{us}$  AND  $\vartheta$  AND SETTING  $\rho_o=0.9$  AND  $\gamma = 0$

$\vartheta$	$\rho_{us}$	NCL male	NCL female	CL male	CL female	Output
1.7	2.18	0.64%	0.73%	-0.31%	0.29%	0.27%
2.68	2.18	1.03%	1.14%	-0.40%	0.48%	1.36%
3.14	2.18	1.10%	1.22%	-0.40%	0.52%	1.77%
5	2.18	1.14%	1.24%	-0.34%	0.54%	2.87%
3.66	0.9	1.68%	1.81%	-0.56%	0.74%	1.82%
3.66	1.5	1.37%	1.49%	-0.46%	0.63%	2.01%
3.66	4	0.77%	0.86%	-0.27%	0.39%	2.38%
3.66	5	0.66%	0.74%	-0.23%	0.3%	2.45%

## C HETEROGENEOUS AVERAGE NATIVE WAGES ELASTICITY

Figure 6 displays the simulated changes on the wage earned by US natives averaged over all education and sex groups, against the number of immigrants from a given country-education

group as a share of the overall US immigrants. Each orange circle denotes a counterfactual of increase 0.1 million inflow of non-college educated immigrants from a given country, and each green triangle denotes a counterfactual of increase 0.1 million inflow of college educated immigrants from a given country.

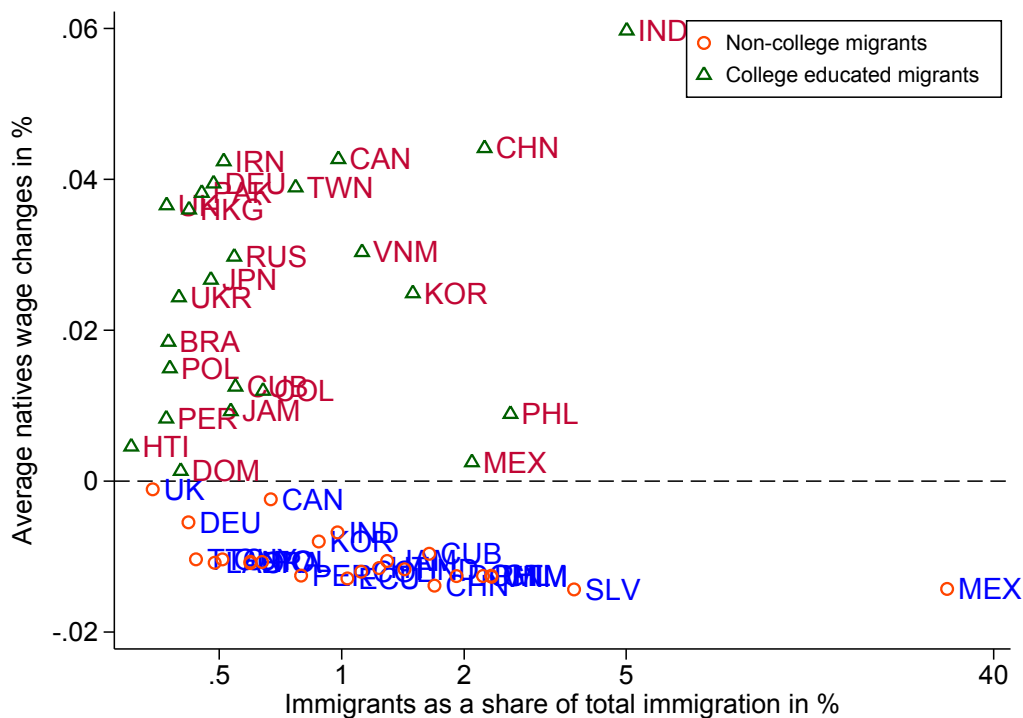


Figure 6: SIMULATED CHANGES ON AVERAGE WAGE EARNED BY US NATIVES IN RESPONSE TO AN INFLUX IMMIGRANTS, AGAINST IMMIGRANTS AS A SHARE OF THE TOTAL US IMMIGRANTS

Two things are worth noting from Figure 6. First, the average earnings of US natives are negatively affected by an increase of non-college educated immigrants, irrespective of their country of origin; whereas an increase of college educated immigrants lead to a gain on the average wage earned by US workers. In addition, green triangle are more dispersed vertically than those orange circle, indicating that college immigration inflow from different countries are more heterogeneous in affecting natives wage than that of non-college immigrants. Second, there is a systematic difference across education groups between the number of immigrants that US have received from a given origin country and the extent to which their immigrants impact native wages. Among non-college educated workers, countries which have sent a larger number of non-college workers to the US, such as Mexico, EL Salvador, their workers tend to have a larger adverse wage impact on US natives. However, the opposite case holds among college educates. Countries which have sent a larger number of college workers to the US, such as India and China, their workers have a stronger positive impact on natives wages.

## D ADDITIONAL VALIDATION EVIDENCE

This section first provides an additional scatter plots of replicating the validation exercises by excluding outliers. I also use H-1B visa program to provide an additional exercise to validate origin-occupation comparative advantage and mode-linkage of migration.

## D.1 AN ADDITIONAL FIGURE ON FAMILY-VISA

Figure 7 compares the model predicted share VS DHS data on the actual non-employment green card across countries, when excluding Mexico in panel (a), excluding India in panel (b), excluding Cuba in panel (c) and excluding Mexico in panel (d). Table 16 also shows the correlation coefficient on these samples. Unsurprisingly, the correlation coefficient drops slightly.

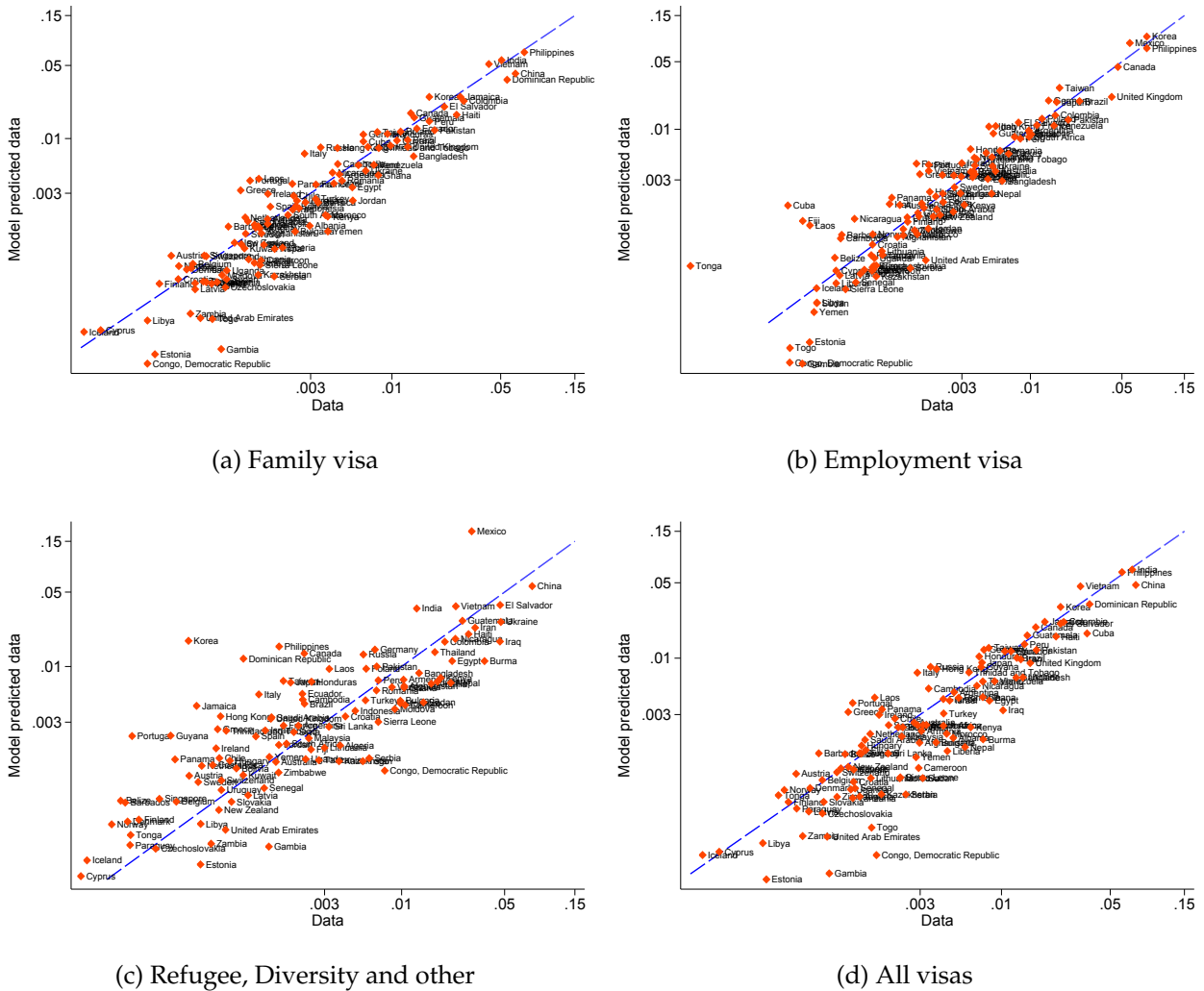


Figure 7: MODEL PREDICTED VS THE ACTUAL GREEN CARD ALLOCATION ACROSS COUNTRIES BY TYPES

Table 16: CORRELATION WHEN EXCLUDING OUTLIERS

Panel	(a)	(b)	(c)	(d)
Correlation	0.959	0.971	0.536	0.947

## D.2 H-1B VALIDATION

This section maps the number of H-1B visa issued in the past to model primitives, and ask if these H-1B visa had not been issued, can model generate heterogeneity migration elasticity re-

sponse across origin countries that is consistent with the aggregate H-1B visa allocation across countries.<sup>48</sup> I draw data from US Citizenship and Immigration Services (USCIS) report of Characteristics of Specialty Occupation Workers (H-1B) from year 2000 to 2014 to obtain the total number of I-129 petition approved for each occupation, and also compute the share of H-1B visa awarded to each of the top 20-25 origin countries during this period while acknowledging that USCIS's number of I-129 petition approved could be slightly different from the actual number of H-1B workers admitted each year.<sup>49</sup>

In this validation exercise, I assume H-1B visa holder managed to stay in US through employment-visa in the long run. Intuitively, this assumption makes sense because origin country's demand for H-1B visa reflects how difficulty through which their college educated workers enter US, relative to other alternatives such as family-base admission, refugee admission, diversity or illegal entry. At each occupation I take to the model each time the total number of occupational specific I-129 petition approved, and solving the model to absorb the same occupational labor increase implied by I-129 petition by letting changes of  $\hat{\tau}_{\sigma,m}$  among college workers, without discriminating immigrants country of origin.

For each counterfactual of increasing occupational labor stock, the model generates the number of college educated workers drawn from each origin country and sex group. I then aggregate across occupations to compute the model predicted origin share and compare it with the data reported by USCIS.

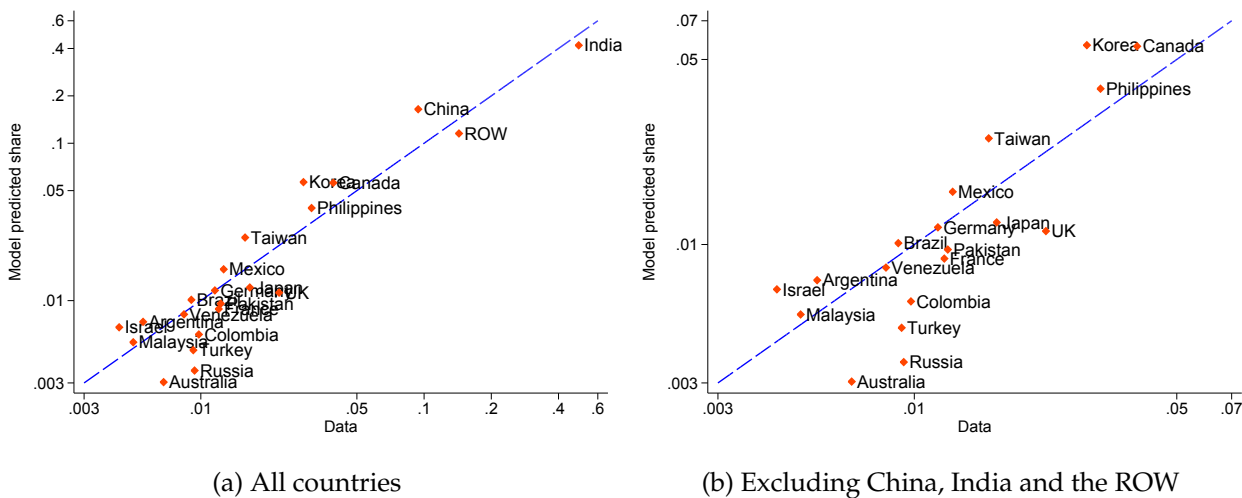


Figure 8: MODEL PREDICTED VS THE ACTUAL GREEN CARD ALLOCATION ACROSS COUNTRIES BY TYPES

Figure 8 plots the predicted H1-B allocation across countries against the actual observation for the top 21 countries reported by USCIS and 1 rest of the world (ROW) on the left panel, while plot based on countries without outliers (China, India, and ROW) on the right panel. The blue dash line plots the 45 degree line, and the log scale are used for both the horizontal

<sup>48</sup>I perform this exercise through a backward calculation by taking year 2010 as the initial equilibrium, and restricting migration frictions of employment-mode.

<sup>49</sup>H-1B visa application involve two main steps. First, the employer sends a Labor Condition Application (LCA) for the employee to the United States Department of Labor. Second, with an approved LCA, the employer files the I-129 Petition form requesting H-1B classification for the worker. Once the Form I-129 is approved, the worker may begin working. I use data during 2000-2014 which are available to me.

and vertical axis. Both plot shows that observations align well along the blue line, and the correlation coefficient between model predicted value and the data is 0.977 for the left panel and 0.903 for the right panel.

## E STRUCTURE CHANGES AT OTHER OCCUPATIONS

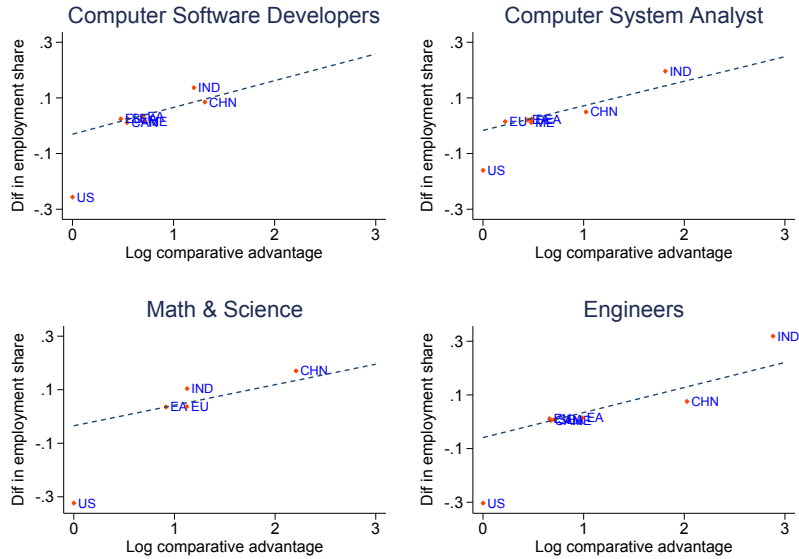


Figure 9: LINEAR DIFFERENCE OF EMPLOYMENT SHARE AGAINST LOG COMPARATIVE ADVANTAGES AT STEM OCCUPATIONS

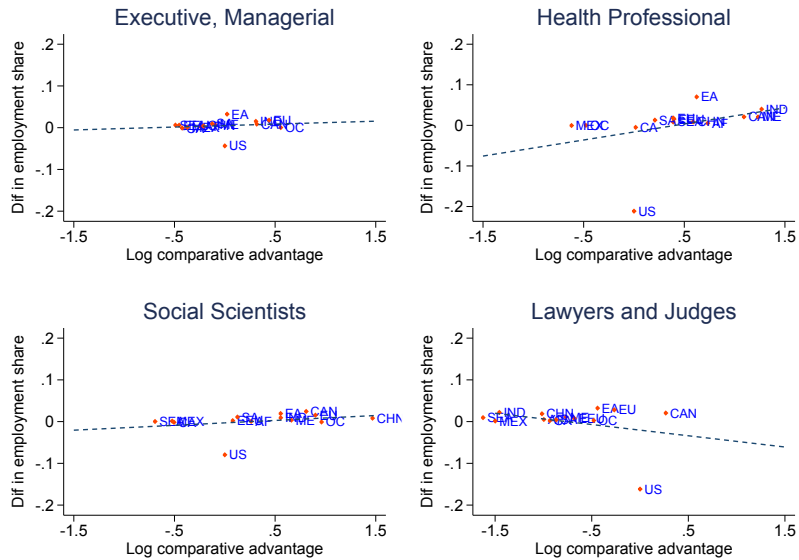


Figure 10: LINEAR DIFFERENCE OF EMPLOYMENT SHARE AGAINST LOG COMPARATIVE ADVANTAGES AT NON-STEM SKILL-INTENSIVE OCCUPATIONS

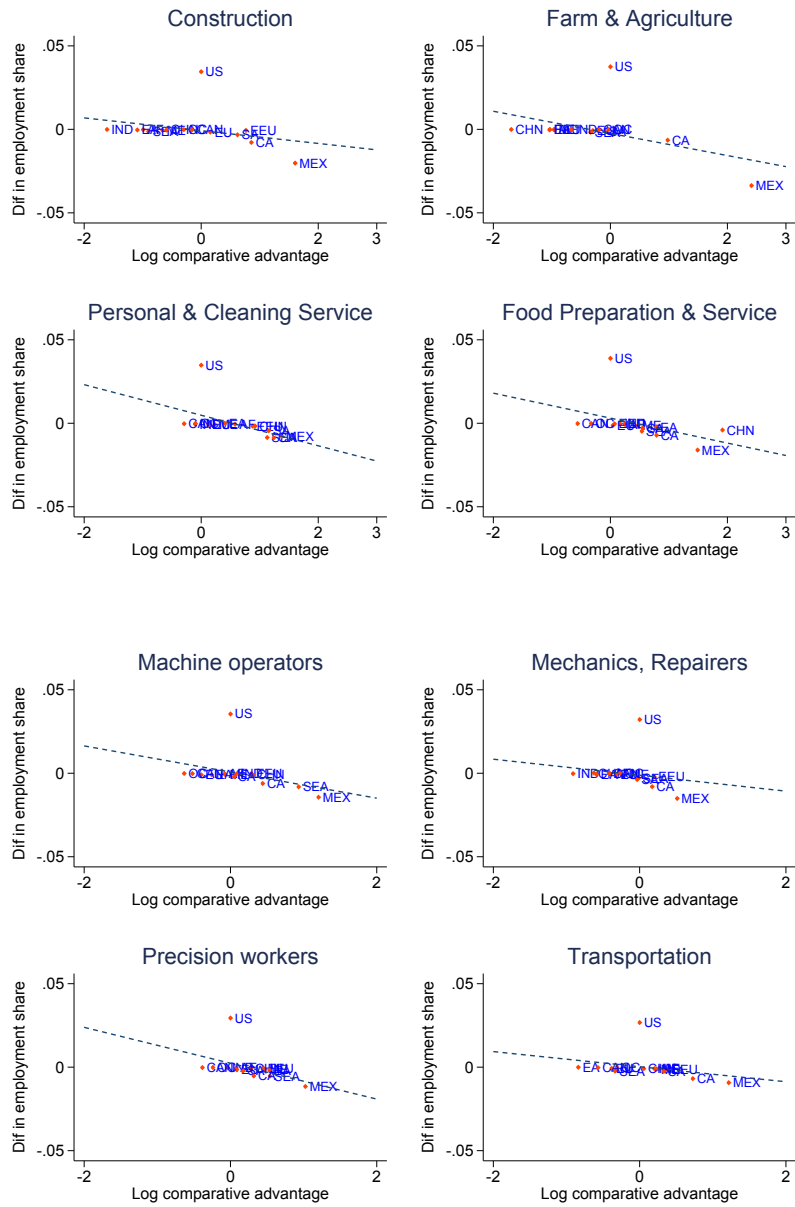


Figure 11: LINEAR DIFFERENCE OF EMPLOYMENT SHARE AGAINST LOG COMPARATIVE ADVANTAGES AT LOW-SKILL OCCUPATIONS



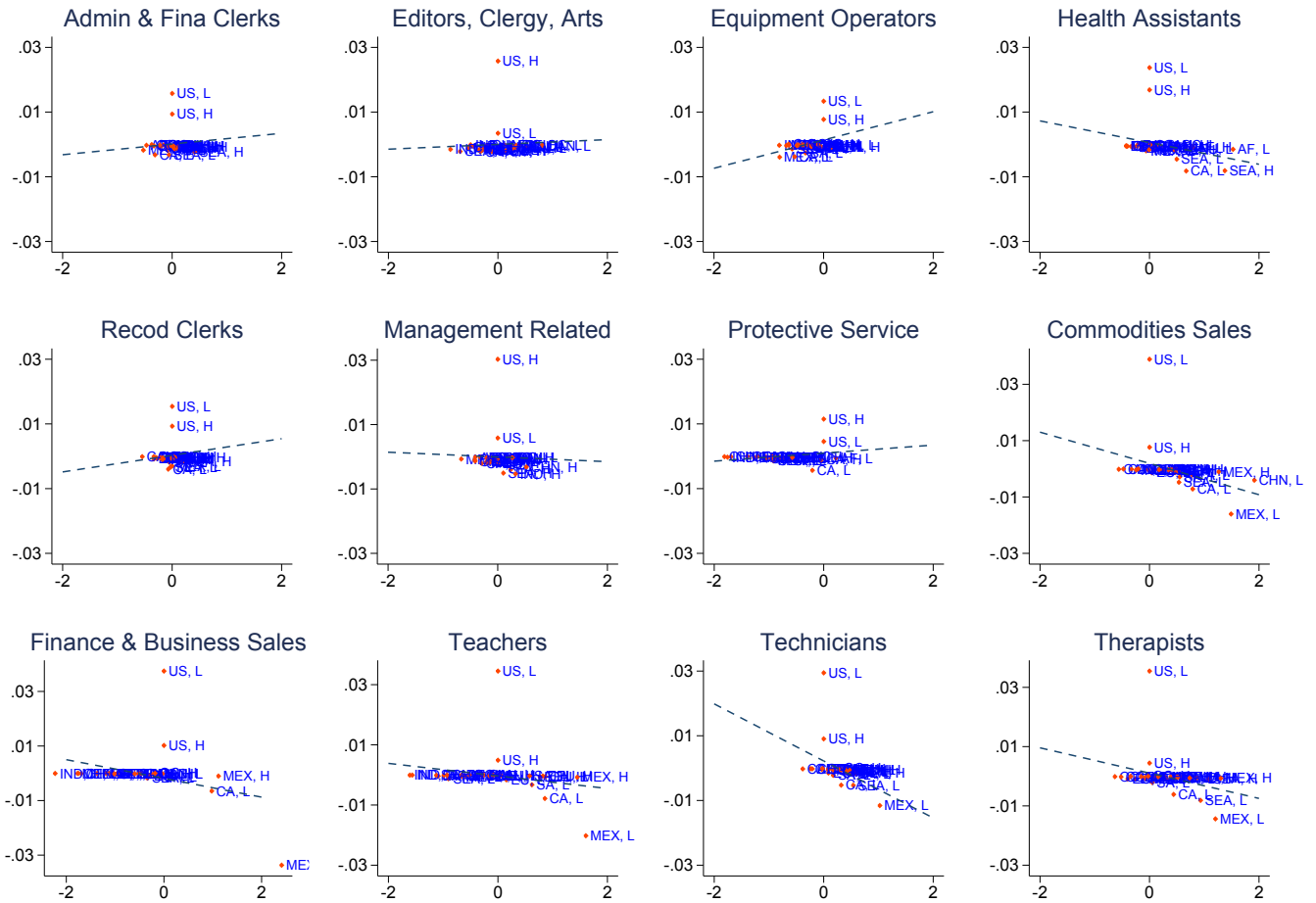


Figure 12: LINEAR DIFFERENCE OF EMPLOYMENT SHARE AGAINST LOG COMPARATIVE ADVANTAGES AT OTHER 12 OCCUPATIONS

Comparing to the aforementioned STEM and low-skill occupations in which immigrants are overrepresented, the changes in labor composition is far less dramatic among the other 12 occupations. I replicate Figure 4 for other 12 occupations, and present in Figure 12. The plot is based on labor groups of both non-college and college education and above for 13 aggregate regions. 8 out of 12 occupations exhibits downward slopes. A positive slope is find at equipment operators occupation, and flat lines at editors, clergy & Arts, and protective service occupations.

## F EXTENSION

### F.1 ENDOGENOUS TECHNOLOGY

This section extends the baseline model by allowing country-occupation total factor productivity as a function of the total stock of college educated workers in each country. Specifically, I assume  $A_{\kappa,\sigma} = \bar{A}_{\kappa,\sigma} H_{\kappa}^{\gamma}$ , where  $H_{\kappa}$  denotes the overall labor hours supplied by college educated workers. The model remains perfect competition, and the positive effects on TFP is external to firm.  $\gamma$  governs the elasticity of TFP changes with respect to the stock of college workers, and is assumed to be constant across all countries and occupations.

In this model, most equilibrium conditions remain the same, with only the total efficiency units of labor demanded at each country and occupation becomes

$$L_{\kappa,\sigma}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}} H_{\kappa}^{\rho_{\kappa}\gamma}$$

Again I solve the model in proportional changes by setting  $\rho_{\kappa} = 2.18$ ,  $\theta = 3.666$  and  $\rho_o = 0.9$ . I set  $\gamma = 0.03$  which lies in the range surveyed by [Combes & Gobillon \(2015\)](#). The wage impacts on US workers is reported in table 17. Unsurprisingly, as the stock of college educated labor force increase in US, the wage gain are larger (or the wage loss are smaller) for all US labor groups, compared to the baseline results reported in table 1.

Table 17: WAGE IMPACT OF US WORKERS BY MAJOR GROUPS, SETTING  $\gamma = 0.03$

National origin	NCL male	NCL female	CL male	CL female
US natives	1.71%	1.80%	0.14%	1.07%
Mexico	2.19%	2.18%	0.84%	1.41%
Indian	1.55%	1.79%	-3.30%	-1.40%
China	2.02%	2.02%	-2.41%	-0.88%

The wage impacts are reported in table 18 for four important migration sending countries. The results are primarily driven by the forces of external economies. Central America & Caribbean experience the largest increase on the stock of college educated labor force, and so does wages. The wage impacts range from 4.87% for college educated female, to 6.73% for non-college educated male. Mexican experience modest wage increase ranges from 0.66% for non-college male to 0.78% college male.

In contrast, Indian experience the largest loss of human capital and wages. The wage loss is smallest for college educated female, equaling to 1.77%, and is largest for non-college educated female, equaling to 2.95%. Finally, east Asian countries experience a modest wage loss ranging from 0.49% for college male to 0.68% for non college workers.

Table 18: WAGE IMPACT AT SENDING COUNTRIES, SETTING  $\gamma = 0.03$

National origin	NCL male	NCL female	CL male	CL female
Central America & Caribbean	6.73%	6.34%	5.06%	4.87%
Mexico	0.66%	0.69%	0.78%	0.77%
India	-2.89%	-2.95%	-1.87%	-1.77%
East Asia	-0.68%	-0.68%	-0.49%	-0.61%

Table 19 reports the wage impacts at three competing destinations. Again, the results are mainly driven by the forces of external economies. The wage falls substantially at Canada, ranging from 1.87% for college educated female to 2.19% for non-college educated male. The wage decline are at modest for OECD European ranging from 0.67% to 0.84%, and are small at Oceania countries.

Table 19: WAGE IMPACT AT COMPETING DESTINATIONS, SETTING  $\gamma = 0.03$

National origin	NCL male	NCL female	CL male	CL female
Canada	-2.19%	-2.11%	-1.92%	-1.87%
Oceania	-0.23%	-0.22%	-0.15%	-0.15%
OECD European	-0.83%	-0.84%	-0.67%	-0.67%

## F.2 IMPERFECT SUBSTITUTION OF UNDOCUMENTED IMMIGRANTS

To address the concern that undocumented immigrants could be underpaid by employers, I present an extended version of my model in which natives and legal immigrants are perfect substitutes at each occupation, while undocumented immigrants are imperfect substitutes to them. Again, the final good is produced according to occupation CES technology at each country  $\kappa$ .

$$Y_{\kappa} = \left[ \sum_{\sigma} A_{\kappa,\sigma} L_{\kappa,\sigma}^{\frac{\rho_{\kappa}-1}{\rho_{\kappa}}} \right]^{\frac{\rho_{\kappa}}{\rho_{\kappa}-1}},$$

the overall efficiency units of labor at each country and occupation is aggregated according to

$$L_{\kappa,\sigma} = \left[ \alpha_{\kappa,\sigma,g} L_{\kappa,\sigma,g}^{\frac{\mu_{\kappa}-1}{\mu_{\kappa}}} + \alpha_{\kappa,\sigma,u} L_{\kappa,\sigma,u}^{\frac{\mu_{\kappa}-1}{\mu_{\kappa}}} \right]^{\frac{\mu_{\kappa}}{\mu_{\kappa}-1}},$$

denote natives or legal immigrants with subscript  $n$ , and denote illegal immigrants with subscript  $u$ . Also denote the wage efficiency unit per labor as  $\Omega_{\kappa,\sigma,g}$  for natives and legal immigrants, and as  $\Omega_{\kappa,\sigma,u}$  for illegal immigrants.  $\mu_{\kappa}$  denotes the elasticity of substitution between two types of workers at each occupation. Also Denote the set of legal mode as  $M_g$ , and illegal mode as  $m_u$ , the close-form of expression for legal mode  $m \in M_g$  is

$$P_{\kappa,\sigma,m|\nu} = \frac{T_{\nu,\kappa,\sigma}^{\vartheta} \Omega_{\kappa,\sigma,g}^{\vartheta} \tau_{\nu,\kappa,\sigma,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\sigma'} \left( \sum_{m' \in M_g} T_{\nu,\kappa',\sigma'}^{\vartheta} \Omega_{\kappa',\sigma',g}^{\vartheta} \tau_{\nu,\kappa',\sigma',m'}^{\vartheta} + T_{\nu,\kappa',\sigma'}^{\vartheta} \Omega_{\kappa',\sigma',u}^{\vartheta} \tau_{\nu,\kappa',\sigma',m_u}^{\vartheta} \right)}$$

For undocumented immigrants, the close-form expression as

$$P_{\kappa,\sigma,m_u|\nu} = \frac{T_{\nu,\kappa,\sigma}^\vartheta \Omega_{\kappa,\sigma,u}^\vartheta \tau_{\nu,\kappa,\sigma,m_u}^\vartheta}{\sum_{\kappa'} \sum_{\sigma'} \left( \sum_{m' \in M_g} T_{\nu,\kappa',\sigma'}^\vartheta \Omega_{\kappa',\sigma',g}^\vartheta \tau_{\nu,\kappa',\sigma',m'}^\vartheta + T_{\nu,\kappa',\sigma'}^\vartheta \Omega_{\kappa',\sigma',u}^\vartheta \tau_{\nu,\kappa',\sigma',m_u}^\vartheta \right)}$$

the overall efficiency units of labor supply for undocumented immigrants is

$$L_{\kappa,\sigma,u}^{\text{supply}} = \sum_{\nu} E[\eta_{\nu,\kappa,\sigma,m_u} | \kappa, \sigma, m_u] \cdot L_{\nu} \cdot P_{\kappa,\sigma,m_u|\nu} = \frac{1}{\Omega_{\kappa,\sigma,u}} \sum_{\nu} W_{\sigma,m_u|\nu,\kappa} \cdot L_{\nu} \cdot P_{\kappa,\sigma,m_u|\nu}.$$

Similarly, the overall efficiency units of labor supply for legal immigrants is

$$L_{\kappa,\sigma,g}^{\text{supply}} = \sum_{\nu} \sum_{m \in M_g} E[\eta_{\nu,\kappa,\sigma,m} | \kappa, \sigma, m] \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu} = \frac{1}{\Omega_{\kappa,\sigma,g}} \sum_{\nu} \sum_{m \in M_g} W_{\sigma,m|\nu,\kappa} \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu}$$

without loss of generality,  $L_{\kappa,\sigma,n}^{\text{supply}}$  also sum over natives.<sup>50</sup> The labor demand for undocumented immigrants can be expressed as

$$L_{\kappa,\sigma,u}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma,u}^{\mu_{\kappa}}} \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}} \alpha_{\kappa,\sigma,u}^{\mu_{\kappa}}$$

Similarly, the labor demand for native and legal immigrants can be expressed as

$$L_{\kappa,\sigma,g}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma,g}^{\mu_{\kappa}}} \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}} \alpha_{\kappa,\sigma,g}^{\mu_{\kappa}}$$

where  $\Omega_{\kappa,\sigma} = \left[ \alpha_{\kappa,\sigma,g}^{\frac{1}{\mu_{\kappa}}} \Omega_{\kappa,\sigma,g}^{1-\mu_{\kappa}} + \alpha_{\kappa,\sigma,u}^{\frac{1}{\mu_{\kappa}}} \Omega_{\kappa,\sigma,u}^{1-\mu_{\kappa}} \right]$ .  $\Omega_{\kappa,\sigma,g}$  clears the market such that  $L_{\kappa,\sigma,g}^{\text{demand}} = L_{\kappa,\sigma,g}^{\text{supply}}$ , and  $\Omega_{\kappa,\sigma,u}$  clears the market such that  $L_{\kappa,\sigma,u}^{\text{demand}} = L_{\kappa,\sigma,u}^{\text{supply}}$ .

### E.3 IMPERFECT SUBSTITUTION BETWEEN NATIVE AND IMMIGRANTS

This subsection allows the possibility that immigrants and natives are imperfect substitutes. Again, the final good is produced according to occupation CES technology at each country  $\kappa$ . The overall efficiency units of labor at each country and occupation is aggregated according to

$$L_{\kappa,\sigma} = \left[ \alpha_{\kappa,\sigma,n} \Omega_{\kappa,\sigma,n}^{\frac{\lambda_{\kappa}-1}{\lambda_{\kappa}}} + \alpha_{\kappa,\sigma,f} \Omega_{\kappa,\sigma,f}^{\frac{\lambda_{\kappa}-1}{\lambda_{\kappa}}} \right]^{\frac{\lambda_{\kappa}}{\lambda_{\kappa}-1}},$$

where subscript  $n$  denotes natives, and  $f$  denotes immigrants. Also denote the wage efficiency unit per labor as  $\Omega_{\kappa,\sigma,n}$  for natives, and as  $\Omega_{\kappa,\sigma,f}$  for immigrants.  $\lambda_{\kappa}$  denotes the elasticity of substitution between immigrants and natives at each occupation. For immigrants

$$P_{\kappa,\sigma,m|\nu} = \frac{T_{\nu,\kappa,\sigma}^\vartheta \Omega_{\kappa,\sigma,f}^\vartheta \tau_{\nu,\kappa,\sigma,m}^\vartheta}{\sum_{\kappa'} \sum_{\sigma'} \sum_{m'} T_{\nu,\kappa',\sigma'}^\vartheta \Omega_{\kappa',\sigma',f}^\vartheta \tau_{\nu,\kappa',\sigma',m'}^\vartheta}$$

<sup>50</sup>This can be viewed as a special case in which one abstract mode  $m$  from all expressions.

The expression for natives can be written analogously. The overall efficiency units of labor supply for immigrants is

$$L_{\kappa,\sigma,f}^{\text{supply}} = \sum_{\nu} E[\eta_{\nu,\kappa,\sigma,m} | \kappa, \sigma, m] \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu} = \frac{1}{\Omega_{\kappa,\sigma,f}} \sum_{\nu} W_{\sigma,m|\nu,\kappa} \cdot L_{\nu} \cdot P_{\kappa,\sigma,m|\nu}.$$

the overall efficiency units of labor supply for natives can be expressed analogously, denoted as  $L_{\kappa,\sigma,n}^{\text{supply}}$ . The efficiency units of labor demanded at each market is given from the nested-CES as

$$L_{\kappa,\sigma,f}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma,f}^{\lambda_{\kappa}}} \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}} \alpha_{\kappa,\sigma,f}^{\lambda_{\kappa}}$$

Similarly, the labor demand for native can be expressed as

$$L_{\kappa,\sigma,n}^{\text{demand}} = \frac{1}{\Omega_{\kappa,\sigma,n}^{\lambda_{\kappa}}} \frac{1}{\Omega_{\kappa,\sigma}^{\rho_{\kappa}}} Y_{\kappa} A_{\kappa,\sigma}^{\rho_{\kappa}} \alpha_{\kappa,\sigma,n}^{\lambda_{\kappa}}$$

where  $\Omega_{\kappa,\sigma} = \left[ \alpha_{\kappa,\sigma,f}^{\frac{1}{\mu_{\kappa}}} \Omega_{\kappa,\sigma,f}^{1-\mu_{\kappa}} + \alpha_{\kappa,\sigma,n}^{\frac{1}{\mu_{\kappa}}} \Omega_{\kappa,\sigma,n}^{1-\mu_{\kappa}} \right]$ .  $\Omega_{\kappa,\sigma,f}$  clears the market such that  $L_{\kappa,\sigma,f}^{\text{demand}} = L_{\kappa,\sigma,f}^{\text{supply}}$ , and  $\Omega_{\kappa,\sigma,n}$  clears the market such that  $L_{\kappa,\sigma,n}^{\text{demand}} = L_{\kappa,\sigma,n}^{\text{supply}}$ .

## F.4 TRADE IN OCCUPATION

This section extends the model with trade in occupation in a Armington fashion following the recent work by [Burstein et al. \(2017\)](#).

$$Y_{\kappa} = \left[ \sum_{\sigma} A_{\kappa,\sigma} Y_{\kappa,\sigma}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}$$

$Y_{\kappa,\sigma}$  is the absorption of tasks  $\sigma$  in country  $\kappa$ , and it is a CES aggregator of tasks at each country

$$Y_{\kappa,\sigma} = \left[ \sum_o Y_{o,\kappa,\sigma}^{\frac{\alpha-1}{\alpha}} \right]^{\frac{\alpha}{\alpha-1}}$$

where  $Y_{o,\kappa,\sigma}$  is the task produced by country  $o$  and shifted to  $\kappa$ .  $\alpha > \rho$  is the elasticity of substitution between countries for task  $\sigma$ . The task output  $Q_{\kappa,\sigma}$  is a linear function of the overall efficient unit of labor. Also assume the the factor productivity equals 1 and is absorbed by  $A_{\kappa,\sigma}$ , and it implies  $p_{\kappa,\sigma} = \Omega_{\kappa,\sigma}$ , the per unit price of task equals wage efficiency unit per labor. Optimality condition and CES leads to the following equilibrium characterization

$$Y_{\kappa,\sigma} = \left( \frac{\bar{p}_{\kappa,\sigma}}{p_{\kappa}} \right)^{-\rho} Y_{\kappa}, \quad p_{\kappa} = \left[ \sum_{\sigma} A_{\kappa,\sigma}^{\rho} \bar{p}_{\kappa,\sigma}^{1-\rho} \right]^{\frac{1}{1-\rho}}$$

$$Y_{o,\kappa,\sigma} = \left( \frac{d_{o,\kappa,\sigma} p_{j,\sigma}}{\bar{p}_{\kappa,\sigma}} \right)^{-\alpha} Y_{\kappa,\sigma}, \quad \bar{p}_{\kappa,\sigma} = \left[ \sum_o d_{o,\kappa,\sigma} \Omega_{\kappa,\sigma}^{1-\alpha} \right]^{\frac{1}{1-\alpha}}$$

where  $p_{\kappa}$  is price of final goods at country  $\kappa$ , and  $\bar{p}_{\kappa,\sigma}$  is absorption price at country  $\kappa$  and occupation  $\sigma$ . Next, the demand of total efficiency unit of labor in country  $\kappa$  and occupation  $\sigma$  is

$$L_{\kappa,\sigma}^{\text{demand}} = \Omega_{\kappa,\sigma}^{-\alpha} \sum_o d_{\kappa,o,\sigma}^{1-\alpha} \bar{p}_{o,\sigma}^{\alpha-\rho} p_o^{\rho} Y_o$$

the supply side of labor market remains the same as that in the baseline model. I can then express the equilibrium in changes as follows

$$\widehat{L}_{\kappa,\sigma}^{\text{demand}} = \widehat{\Omega}_{\kappa,\sigma}^{-\alpha} \sum_o \Phi_{\kappa,o,\sigma} \widehat{p}_{o,\sigma}^{\alpha-\rho} \widehat{p}_o^{-1} \widehat{Y}_o$$

$$\widehat{p}_{o,\sigma} = \left( \sum_{\kappa} \Psi_{\kappa,o,\sigma} \widehat{\Omega}_{\kappa,o}^{1-\alpha} \right)^{\frac{1}{1-\alpha}}$$

$$\widehat{p}_o = \left( \sum_{\kappa} S_{o,\sigma} \widehat{p}_{o,\sigma}^{1-\rho} \right)^{\frac{1}{1-\rho}}$$

$S_{o,\sigma}$  is the absorption share of occupation  $\sigma$ ,  $\Psi_{\kappa,o,\sigma}$  is the share of country  $o$ 's absorption produced by country  $\kappa$  within occupation  $\sigma$ , and  $\Phi_{\kappa,o,\sigma}$  is the share of  $\kappa$  output that is absorbed by country  $o$  in occupation  $\sigma$ .

## G DERIVATION & PROOF

### G.1 EQUILIBRIUM DERIVATIONS

#### Derivation on the expression of $P_{\kappa,\omega,m|\nu}$

Since workers maximize their perceived wage over all global labor markets, the probability that a worker in type  $\nu$  choose country  $\kappa$ , occupation  $\omega$  by mode  $m$  can be written as

$$\begin{aligned} P_{\kappa,\omega,m|\nu} &= P(\tau_{\nu,\kappa,\omega,m} \eta_{\nu,\kappa,\omega,m} \Omega_{\kappa,\omega} > \tau_{\nu,\kappa',\omega',m'} \eta_{\nu,\kappa',\omega',m'} \Omega_{\kappa',\omega'}, \forall \kappa' \neq \kappa, \forall \omega' \neq \omega, \forall m' \neq m) \\ &= P(\eta_{\nu,\kappa',\omega',m'} < \frac{\tau_{\nu,\kappa,\omega,m} \eta_{\nu,\kappa,\omega,m} \Omega_{\kappa,\omega}}{\tau_{\nu,\kappa',\omega',m'} \Omega_{\kappa',\omega'}}, \forall \kappa' \neq \kappa, \forall \omega' \neq \omega, \forall m' \neq m) \\ &= \prod_{\kappa' \neq \kappa, \omega' \neq \omega, m' \neq m} P(\eta_{\nu,\kappa',\omega',m'} < \frac{\tau_{\nu,\kappa,\omega,m} \eta_{\nu,\kappa,\omega,m} \Omega_{\kappa,\omega}}{\tau_{\nu,\kappa',\omega',m'} \Omega_{\kappa',\omega'}}) \\ &= \int \vartheta T_{\nu,\kappa,\omega}^\vartheta \eta_{\nu,\kappa,\omega,m}^{-\vartheta-1} \exp\left\{-\sum T_{\nu,\kappa,\omega}^\vartheta \left(\frac{\tau_{\nu,\kappa,\omega,m} \Omega_{\kappa,\omega}}{\tau_{\nu,\kappa',\omega',m'} \Omega_{\kappa',\omega'}}\right)^{-\vartheta} \eta_{\nu,\kappa,\omega,m}^{-\vartheta}\right\} d\eta_{\nu,\kappa,\omega,m} \\ &= \int \vartheta T_{\nu,\kappa,\omega}^\vartheta \eta_{\nu,\kappa,\omega,m}^{-\vartheta-1} \exp\left\{-\sum T_{\nu,\kappa,\omega}^\vartheta \left(\frac{\tau_{\nu,\kappa,\omega,m} \Omega_{\kappa,\omega}}{\tau_{\nu,\kappa',\omega',m'} \Omega_{\kappa',\omega'}}\right)^{-\vartheta} \eta_{\nu,\kappa,\omega,m}^{-\vartheta}\right\} d\eta_{\nu,\kappa,\omega,m} \\ &= \frac{T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \int \vartheta \frac{\tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \eta_{\nu,\kappa,\omega,m}^{-\vartheta-1} \exp\left\{-\frac{\tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \eta_{\nu,\kappa,\omega,m}^{-\vartheta}\right\} d\eta_{\nu,\kappa,\omega,m} \\ &= \frac{T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \int_0^\infty -e^{-z} d(-z) \\ &= \frac{T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \end{aligned}$$

where  $z = \frac{\tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta}{\sum T_{\nu,\kappa,\omega}^\vartheta \tau_{\nu,\kappa,\omega,m}^\vartheta \Omega_{\kappa,\omega}^\vartheta} \eta_{\nu,\kappa,\omega,m}^{-\vartheta}$  in the last second line.

#### Close from expression of $P_{\kappa|\nu}$ , $P_{\kappa,\omega|\nu}$ , $P_{\kappa,m|\nu}$

First, based on the expression of  $P_{\kappa,\omega,m|\nu}$ , one can derive three sets of unconditional probability in a coarser cell. Summing over options within a country, one can derive the bilateral migration rate for group  $\nu$  is

$$P_{\kappa|\nu} = \frac{\sum_{\omega} \sum_m T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\omega'} \sum_{m'} T_{\nu,\kappa',\omega'}^{\vartheta} \Omega_{\kappa',\omega'}^{\vartheta} \tau_{\nu,\kappa',\omega',m'}^{\vartheta}}.$$

Summing over modes within a country, one can derive the fraction of people who migrate to  $\kappa$  and work in occupation  $\omega$

$$P_{\kappa,\omega|\nu} = \frac{\sum_m T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\omega'} \sum_{m'} T_{\nu,\kappa',\omega'}^{\vartheta} \Omega_{\kappa',\omega'}^{\vartheta} \tau_{\nu,\kappa',\omega',m'}^{\vartheta}}.$$

Summing over occupations within a country, one can derive the fraction of people who migrate to  $\kappa$  by mode  $m$

$$P_{\kappa,m|\nu} = \frac{\sum_{\omega} T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\kappa'} \sum_{\omega'} \sum_{m'} T_{\nu,\kappa',\omega'}^{\vartheta} \Omega_{\kappa',\omega'}^{\vartheta} \tau_{\nu,\kappa',\omega',m'}^{\vartheta}}.$$

Close from expression of  $P_{\omega|\nu,\kappa}$ ,  $P_{m|\nu,\kappa}$ ,  $P_{m|\nu,\kappa,\omega}$ ,  $P_{\omega,m|\nu,\kappa}$

According to the definition of conditional probability, I then have the following three conditional probability among immigrants in a given country  $\kappa$ . Among immigrants of country  $\kappa$ , the fraction that work in occupation  $\omega$

$$P_{\omega|\nu,\kappa} = \frac{P_{\kappa,\omega|\nu}}{P_{\kappa|\nu}} = \frac{\sum_m T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\omega'} \sum_{m'} T_{\nu,\kappa,\omega'}^{\vartheta} \Omega_{\kappa,\omega'}^{\vartheta} \tau_{\nu,\kappa,\omega',m'}^{\vartheta}}.$$

and among immigrants of country  $\kappa$ , the fraction that enter through mode  $m$

$$P_{m|\nu,\kappa} = \frac{P_{\kappa,m|\nu}}{P_{\kappa|\nu}} = \frac{\sum_{\omega} T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\omega'} \sum_{m'} T_{\nu,\kappa,\omega'}^{\vartheta} \Omega_{\kappa,\omega'}^{\vartheta} \tau_{\nu,\kappa,\omega',m'}^{\vartheta}}.$$

and among immigrants who work in country  $\kappa$  and occupation  $\omega$ , the fraction that enter through mode  $m$

$$P_{m|\nu,\kappa,\omega} = \frac{\tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{m'} \tau_{\nu,\kappa,\omega,m'}^{\vartheta}}.$$

Finally, it is also useful to have the fraction among people living in country  $\kappa$ , the fraction that work in occupation  $\omega$  and mode  $m$

$$P_{\omega,m|\nu,\kappa} = \frac{P_{\kappa,\omega,m|\nu}}{P_{\kappa|\nu}} = \frac{T_{\nu,\kappa,\omega}^{\vartheta} \Omega_{\kappa,\omega}^{\vartheta} \tau_{\nu,\kappa,\omega,m}^{\vartheta}}{\sum_{\omega'} \sum_{m'} T_{\nu,\kappa,\omega'}^{\vartheta} \Omega_{\kappa,\omega'}^{\vartheta} \tau_{\nu,\kappa,\omega',m'}^{\vartheta}}.$$

## G.2 EQUILIBRIUM IN PROPORTIONAL CHANGES

### Derivation of Equilibrium in Proportional Changes

Below I show the derivation of equilibrium labor flow  $P_{\kappa,\omega,m|\nu}$  in proportional changes. Proportional changes in  $\hat{P}_{\omega,m|\nu,\kappa}$ ,  $\hat{P}_{\kappa|\nu}$ ,  $\hat{P}_{m|\nu,\kappa,\omega}$ ,  $\hat{P}_{\omega,m|\nu,\kappa}$  can be obtained analogously.

$$\begin{aligned}
\hat{P}_{\kappa,\omega,m|\nu} &= \frac{\Lambda_{\nu,\kappa,\omega,m,1}}{\Lambda_{\nu,\kappa,\omega,m,0}} = \frac{T_{\nu,\kappa,\omega,1}^\vartheta \Omega_{\kappa,\omega,1}^\vartheta \tau_{\nu,\kappa,\omega,m,1}^\vartheta}{\sum_{\kappa} \sum_{\omega} \sum_m T_{\nu,\kappa,\omega,1}^\vartheta \Omega_{\kappa,\omega,1}^\vartheta \tau_{\nu,\kappa,\omega,m,1}^\vartheta} / \frac{T_{\nu,\kappa,\omega,0}^\vartheta \Omega_{\kappa,\omega,0}^\vartheta \tau_{\nu,\kappa,\omega,m,0}^\vartheta}{\sum_{\kappa} \sum_{\omega} \sum_m T_{\nu,\kappa,\omega,0}^\vartheta \Omega_{\kappa,\omega,0}^\vartheta \tau_{\nu,\kappa,\omega,m,0}^\vartheta} \\
&= \frac{(T_{\nu,\kappa,\omega,1}/T_{\nu,\kappa,\omega,0})^\vartheta (\Omega_{\kappa,\omega,1}/\Omega_{\kappa,\omega,0})^\vartheta (\tau_{\nu,\kappa,\omega,m,1}/\tau_{\nu,\kappa,\omega,m,0})^\vartheta}{\sum_{\kappa} \sum_{\omega} \sum_m \frac{T_{\nu,\kappa,\omega,1}^\vartheta \Omega_{\kappa,\omega,1}^\vartheta \tau_{\nu,\kappa,\omega,m,1}^\vartheta}{T_{\nu,\kappa,\omega,0}^\vartheta \Omega_{\kappa,\omega,0}^\vartheta \tau_{\nu,\kappa,\omega,m,0}^\vartheta}} \\
&= \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\sum_{\kappa} \sum_{\omega} \sum_m \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\frac{T_{\nu,\kappa,\omega,0}^\vartheta \Omega_{\kappa,\omega,0}^\vartheta \tau_{\nu,\kappa,\omega,m,0}^\vartheta}{T_{\nu,\kappa,\omega,0}^\vartheta \Omega_{\nu,\kappa,\omega,0}^\vartheta \tau_{\nu,\kappa,\omega,m,0}^\vartheta}}} \\
&= \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\sum_{\kappa} \sum_{\omega} \sum_m \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta P_{\kappa,\omega,m,0|\nu}} \\
&= \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\sum_{\kappa} \sum_{\omega} \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta P_{\kappa,\omega,0|\nu} B_{\nu,\kappa,\omega}}
\end{aligned}$$

where  $B_{\nu,\kappa,\omega} = \sum_m \left[ \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta P_{m|\nu,\kappa,\omega} \right]$ . Analogously, one can show that

$$\begin{aligned}
\hat{P}_{\omega,m|\nu,\kappa} &= \frac{P_{\omega,m,1|\nu,\kappa}}{P_{\omega,m,0|\nu,\kappa}} = \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\sum_{\omega} \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta P_{\omega,0|\nu,\kappa} B_{\nu,\kappa,\omega}} \\
\hat{P}_{m|\nu,\kappa,\omega} &= \frac{P_{m,1|\nu,\kappa,\omega}}{P_{m,0|\nu,\kappa,\omega}} = \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta \hat{\tau}_{\nu,\kappa,\omega,m}^\vartheta}{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta B_{\nu,\kappa,\omega}}
\end{aligned}$$

According to the definition of conditional probability

$$\hat{P}_{\kappa|\nu} = \frac{\hat{P}_{\kappa,\omega,m|\nu}}{\hat{P}_{\omega,m|\nu,\kappa}} = \frac{\sum_{\omega} \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta P_{\kappa,\omega,0|\nu} B_{\nu,\kappa,\omega}}{\sum_{\kappa} \sum_{\omega} \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta P_{\kappa,\omega,0|\nu} B_{\nu,\kappa,\omega}}$$

also

$$\hat{P}_{\omega|\nu,\kappa} = \frac{\hat{P}_{\omega,m|\nu,\kappa}}{\hat{P}_{m|\nu,\kappa,\omega}} = \frac{\hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta B_{\nu,\kappa,\omega}}{\sum_{\omega} \hat{T}_{\nu,\kappa,\omega}^\vartheta \hat{\Omega}_{\kappa,\omega}^\vartheta P_{\omega,0|\nu,\kappa} B_{\nu,\kappa,\omega}}$$

It is also follow immediately if one plug  $\hat{P}_{\omega,m|\nu,\kappa}$  into  $\hat{W}_{\sigma,m|\nu,\kappa}$  to have

$$\hat{W}_{\sigma,m|\nu,\kappa} = \frac{1}{\hat{\tau}_{\nu,\kappa,\omega,m}} \left\{ \sum_{\omega'} \hat{T}_{\nu,\kappa,\omega'}^\vartheta \hat{\Omega}_{\kappa,\omega'}^\vartheta P_{0,\omega'|\nu,\kappa} B_{\nu,\kappa,\omega} \right\}^{\frac{1}{\vartheta}} \hat{P}_{\kappa|\nu}^{-\frac{1}{\vartheta}}$$

### G.3 DERIVATION OF MIGRATION ELASTICITY

Consider there is a marginal change of migration frictions in a given mode and occupation. Without loss of generality we consider a marginal increase in  $\Delta\tau_{\nu,\kappa,\omega',m'}$ , while keeping  $\hat{\Omega}_{\kappa,\omega} = \hat{T}_{\nu,\kappa,\omega'} = 1$ , at occupations other than  $\omega'$  and mode other than  $m'$ . To ease notation, I will express  $\Delta\tau_{\nu,\kappa,\omega',m'}$  as  $\Delta\tau_{\omega',m'}$ . Since  $\Delta\tau_{\omega',m'}$  is the only change in variable,  $\hat{P}_{\kappa|\nu}$  can then be written as



$$\frac{P_{\kappa|\nu} + \Delta P_{\kappa|\nu}}{P_{\kappa|\nu}} = \frac{\left(\frac{\tau_{\omega',m'} + \Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)^\vartheta P_{\omega',m'|\nu,\kappa} + 1 - P_{\omega',m'|\nu,\kappa}}{\left(\frac{\tau_{\omega',m'} + \Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)^\vartheta P_{\kappa,\omega',m'|\nu} + 1 - P_{\kappa,\omega',m'|\nu}}$$

subtracting 1 one both side of equation to have

$$\frac{\Delta P_{\kappa|\nu}}{P_{\kappa|\nu}} = \frac{\left(\frac{\tau_{\omega',m'} + \Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)^\vartheta \left(P_{\omega',m'|\nu,\kappa} - P_{\kappa,\omega',m'|\nu}\right) - \left(P_{\omega',m'|\nu,\kappa} - P_{\kappa,\omega',m'|\nu}\right)}{\left(\frac{\tau_{\omega',m'} + \Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)^\vartheta P_{\kappa,\omega',m'|\nu} + 1 - P_{\kappa,\omega',m'|\nu}}$$

Next using Taylor expansion to write  $\left(\frac{\tau_{\omega',m'} + \Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)^\vartheta = 1 + \vartheta \frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}} + \mathcal{O}\left(\frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)$  and plug into the above equation to have

$$\frac{\Delta P_{\kappa|\nu}}{P_{\kappa|\nu}} = \frac{\left(\vartheta \frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}} + \mathcal{O}\left(\frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)\right) \left(P_{\omega',m'|\nu,\kappa} - P_{\kappa,\omega',m'|\nu}\right)}{\left(\vartheta \frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}} + \mathcal{O}\left(\frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)\right) P_{\kappa,\omega',m'|\nu} + 1}$$

multiplying  $\frac{\tau_{\omega',m'}}{\Delta\tau_{\omega',m'}}$  on both sides to have

$$\frac{\Delta P_{\kappa|\nu}}{P_{\kappa|\nu}} \cdot \frac{\tau_{\omega',m'}}{\Delta\tau_{\omega',m'}} = \frac{\left(\vartheta + \mathcal{O}(1)\right) \left(P_{\omega',m'|\nu,\kappa} - P_{\kappa,\omega',m'|\nu}\right)}{\left(\vartheta \frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}} + \mathcal{O}\left(\frac{\Delta\tau_{\omega',m'}}{\tau_{\omega',m'}}\right)\right) P_{\kappa,\omega',m'|\nu} + 1}$$

limiting the changes to a infinitely small increase to have

$$\frac{\partial P_{\kappa|\nu}}{\partial \tau_{\omega',m'}} \cdot \frac{\tau_{\omega',m'}}{P_{\kappa|\nu}} = \vartheta \left(P_{\omega',m'|\nu,\kappa} - P_{\kappa,\omega',m'|\nu}\right) = \vartheta \cdot P_{\omega',m'|\nu,\kappa} \cdot \left(1 - P_{\kappa|\nu}\right)$$

Analogously, one can simply show that having a change of  $\Delta\tau_{\kappa,m'}$

$$\frac{\partial P_{\kappa|\nu}}{\partial \tau_{\kappa,m'}} \cdot \frac{\tau_{\kappa,m'}}{P_{\kappa|\nu}} = \vartheta \left(P_{m'|\nu,\kappa} - P_{\kappa,m'|\nu}\right) = \vartheta \cdot P_{m'|\nu,\kappa} \cdot \left(1 - P_{\kappa|\nu}\right)$$

Next, consider a mode-neutral infinitesimal change in the return of migrating to a country  $\kappa$  and occupation  $\sigma$ . Without loss of generality, I assume a change in  $\Delta\Omega_{\nu,\kappa,\omega}$ .<sup>51</sup> The bilateral migration elasticity is equal to

$$\frac{\partial P_{\kappa|\nu}}{\partial \Omega_{\kappa,\omega}} \cdot \frac{\Omega_{\kappa,\omega}}{P_{\kappa|\nu}} = \vartheta \cdot \left(1 - P_{\kappa|\nu}\right) \cdot P_{\omega|\nu,\kappa}$$

The derivation is analogous to the proof provided above. This elasticity is of particular interest in job-polarization literature (Autor, Levy & Murnane 2003). It says there will be a larger increase of bilateral migration flow (1) if productivity distribution is less dispersed, i.e.,  $\vartheta$  is large, and hence the density of infra-marginal worker is large; (2) if a larger fraction of the group  $\nu$  are not live in the US and hence the pool of potential incoming migrants is large, i.e.,  $P_{\kappa|\nu}$  is small; and (3) if the group  $\nu$  migrants work in US are more specialized in occupation  $\omega$ , i.e.,  $P_{\omega|\nu,\kappa}$  is

<sup>51</sup>The elasticity are proven to be the same if one consider an increase in occupation productivity  $T_{\nu,\kappa,\omega}$ , or mode-neutral migration friction  $\tau_{\nu,\kappa,\omega}$ .

large.

## G.4 DERIVATION OF CROSS WAGE ELASTICITY

The expression of each direct elasticity and its property is discussed below.

- (a) The three sets of elasticity provided in equation (11) has the following expression such that  $\frac{\partial L_\sigma}{\partial L_\lambda} \frac{L_\lambda}{L_\sigma} = \frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu} = P_{\omega|\nu,\kappa}$ .

$$\frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega} = \begin{cases} \frac{1}{\rho} R_\sigma - \frac{1}{\rho}, & \text{if } \omega = \sigma, \\ \frac{1}{\rho} R_\sigma, & \text{if } \omega \neq \sigma. \end{cases}$$

where  $R_\sigma$  denotes the occupational labor wage bill as a share of the total, which captures the occupation size of the entire economy.

- (b)  $\nu$  wage elasticity in response to changes in occupation labor, and its sign are the following

$$\frac{\partial W_\nu}{W_\nu} \bigg/ \frac{\partial L_\sigma}{L_\sigma} = \frac{R_\sigma - P_{\sigma|\nu,\kappa}}{\rho} = \begin{cases} < 0, & \text{if } R_\sigma < P_{\sigma|\nu,\kappa}, \\ > 0, & \text{if } R_\sigma > P_{\sigma|\nu,\kappa}, \\ = 0, & \text{if } R_\sigma = P_{\sigma|\nu,\kappa}. \end{cases}$$

- (c) The  $\frac{\partial W_\nu}{W_\nu} \bigg/ \frac{\partial L_\sigma}{L_\sigma}$  is monotonic decrease in  $P_{\sigma|\nu,\kappa}$ .

The expression of  $\frac{\partial W_\nu}{W_\nu} \bigg/ \frac{\partial L_\sigma}{L_\sigma}$  is derived according to  $\sum_\omega \frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu} \times \frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega}$ . It embeds a substitution and a complimentary effect which is inherited from CES production function. The intuition of Lemma b) is that the difference between  $R_\sigma$  and  $P_{\sigma|\nu,\kappa}$  captures the occupation specialization of  $\nu$  workers relative to the US economy. If  $\nu$  workers are disproportionately employed in at  $\sigma$ , such that  $R_\sigma < P_{\sigma|\nu,\kappa}$ , substitution effect dominates. Therefore an increase of  $\sigma$  occupation labor leads to a wage decline of  $\nu$  workers. The argument when complementary effects dominates hold analogously, and also notice a special case that substitution and complimentary effects fully offset when  $R_\sigma = P_{\sigma|\nu,\kappa}$ .

Lemma c) says the more specialized of a group of workers in occupation  $\sigma$  such that  $P_{\sigma|\nu,\kappa}$  is larger, the larger the adverse wage impacts in response to increase of labor supply at  $\sigma$  occupation. Following the above Lemma and equation (11), it is straightforward to have the expression of cross-wage elasticity. Normalize it by the group size  $L_\lambda$  to have expression of normalized group elasticity as follows

Cross-group wage elasticity is derived by showing the analytical expression of  $\frac{\partial L_\sigma}{\partial L_\lambda} \frac{L_\lambda}{L_\sigma}$ ,  $\frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu}$  and  $\frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega}$ . After that one can obtain analytical expression for cross-group wage elasticity by following equation (11). Below provide steps of how to calculate each elasticity in details.

### 1. Derivation of $\frac{\partial L_\sigma}{\partial L_\lambda} \frac{L_\lambda}{L_\sigma}$

It is straightforward to show occupation labor elasticity in response to labor supply of group  $\lambda$ , denoted as  $\frac{\partial L_\sigma}{\partial L_\lambda} \frac{L_\lambda}{L_\sigma}$ , equals the number of  $\lambda$  workers as a share of total employment in

occupation  $\sigma$ , denoted as  $\Lambda_{\lambda,\sigma}$ . To show this, notice that  $\frac{\partial L_\sigma}{\partial L_\lambda} = P_{\sigma|\lambda,\kappa}$ , the conclusion follows immediately since  $P_{\sigma|\lambda,\kappa} \frac{L_\lambda}{L_\sigma} = \Lambda_{\lambda,\sigma}$ .<sup>52</sup>

## 2. Derivation of $\frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu}$

I show that  $\frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu} = P_{\omega|\nu,\kappa}$ . Holding other model primitives constant, such that  $\widehat{\tau}_{\nu,\kappa,\omega,m} = \widehat{T}_{\nu,\kappa,\omega} = 1$ , and have a small change of  $\Delta \Omega_\omega$ , and  $\widehat{\Omega}_{\kappa,\sigma} = 1$  at other occupations when  $\sigma \neq \omega$ , one have

$$\frac{W_\nu + \Delta W_\nu}{W_\nu} = \left[ \left( \frac{\Omega_\omega + \Delta \Omega_\omega}{\Omega_\omega} \right)^\theta P_{\omega|\nu,\kappa} + \sum_{\sigma \neq \omega} P_{\sigma|\nu,\kappa} \right]^{\frac{1}{\theta}} = \left[ \left( \frac{\Omega_\omega + \Delta \Omega_\omega}{\Omega_\omega} \right)^\theta P_{\omega|\nu,\kappa} + 1 - P_{\omega|\nu,\kappa} \right]^{\frac{1}{\theta}}$$

subtracting 1 on both side of the above equation, and apply Taylor expansion in a way  $\left( \frac{\Omega_\omega + \Delta \Omega_\omega}{\Omega_\omega} \right)^\theta = 1 + \theta \frac{\Delta \Omega_\omega}{\Omega_\omega} + \mathcal{O}\left(\frac{\Delta \Omega_\omega}{\Omega_\omega}\right)$ . I rewrite

$$\frac{\Delta W_\nu}{W_\nu} = \left[ \left( 1 + \theta \frac{\Delta \Omega_\omega}{\Omega_\omega} + \mathcal{O}\left(\frac{\Delta \Omega_\omega}{\Omega_\omega}\right) \right) P_{\omega|\nu,\kappa} + 1 - P_{\omega|\nu,\kappa} \right]^{\frac{1}{\theta}} - 1 = \left[ 1 + \theta \frac{\Delta \Omega_\omega}{\Omega_\omega} P_{\omega|\nu,\kappa} + \mathcal{O}\left(\frac{\Delta \Omega_\omega}{\Omega_\omega}\right) P_{\omega|\nu,\kappa} \right]^{\frac{1}{\theta}} - 1$$

applying Taylor expansion again to have

$$\frac{\Delta W_\nu}{W_\nu} = 1 + \frac{\Delta \Omega_\omega}{\Omega_\omega} P_{\omega|\nu,\kappa} + \frac{1}{\theta} \mathcal{O}\left(\frac{\Delta \Omega_\omega}{\Omega_\omega}\right) P_{\omega|\nu,\kappa} - 1 = \frac{\Delta \Omega_\omega}{\Omega_\omega} P_{\omega|\nu,\kappa} + \frac{1}{\theta} \mathcal{O}\left(\frac{\Delta \Omega_\omega}{\Omega_\omega}\right) P_{\omega|\nu,\kappa}$$

multiplying  $\frac{\Omega_\omega}{\Delta \Omega_\omega}$  and limit the change to be infinitely small to have

$$\frac{\partial W_\nu}{\partial \Omega_\omega} \frac{\Omega_\omega}{W_\nu} = P_{\omega|\nu,\kappa} + \frac{1}{\theta} \mathcal{O}(1) P_{\omega|\nu,\kappa} = P_{\omega|\nu,\kappa}.$$

## 3. Derivation on the expression of $\frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega}$

I show that the elasticity of wage unit in response to changes in occupation labor supply has the following expression. Differentiate CES production function with respect to  $L_\sigma$  to have wage unit

$$\Omega_\sigma = \left[ \sum_{\sigma} A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\sigma L_\sigma^{-\frac{1}{\rho}}$$

differentiate the above equation with respect to  $L_\sigma$  to have

$$\frac{\partial \Omega_\sigma}{\partial L_\sigma} = \frac{1}{\rho} \left[ \sum_{\sigma} A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{2-\rho}{\rho-1}} A_\sigma L_\sigma^{-\frac{2}{\rho}} - \frac{1}{\rho} \left[ \sum_{\sigma} A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\sigma L_\sigma^{-\frac{1}{\rho}-1}$$

<sup>52</sup>  $\frac{\partial L_\sigma}{\partial L_\lambda} = \Phi_{\lambda,\sigma}$  holds because an infinitesimal changes in  $L_\sigma$  does not cause general equilibrium effects of changes in wage units and labor re-allocation. In other word, holding wage units unchanged, the increasing amount of labor will sorting into occupation  $\sigma$  exactly the same way as the initial equilibrium.

multiplying  $\frac{L_\sigma}{\Omega_\sigma}$  on both sides to have

$$\begin{aligned}\frac{\partial \Omega_\sigma}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\sigma} &= \frac{\frac{1}{\rho} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{2-\rho}{\rho-1}} A_\sigma L_\sigma^{\frac{\rho-2}{\rho}} - \frac{1}{\rho} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\sigma L_\sigma^{-\frac{1}{\rho}}}{\left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\sigma L_\sigma^{-\frac{1}{\rho}}} \\ &= \frac{1}{\rho} A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{-1} - \frac{1}{\rho} \\ &= \frac{1}{\rho} R_\sigma - \frac{1}{\rho}\end{aligned}$$

where  $R_\sigma$  denotes the wage bill earned by workers in  $\sigma$  occupation. The last equality hold as it is straightforward to show that, under a CES production function

$$R_\sigma = \frac{A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}}}{Y} = A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{-1}.$$

Analogous, I obtain elasticity expression when  $\omega \neq \sigma$  by first differentiating CES production function with respect to  $L_\omega$  to have

$$\Omega_\omega = \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\omega L_\omega^{-\frac{1}{\rho}}$$

next differentiating the above equation with respect to  $L_\sigma$  to have

$$\frac{\partial \Omega_\omega}{\partial L_\sigma} = \frac{1}{\rho} A_\sigma A_\omega L_\sigma^{-\frac{1}{\rho}} L_\omega^{-\frac{1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{2-\rho}{\rho-1}}$$

multiplying  $\frac{L_\sigma}{\Omega_\omega}$  on both sides to have

$$\frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega} = \frac{\frac{1}{\rho} A_\sigma A_\omega L_\sigma^{1-\frac{1}{\rho}} L_\omega^{-\frac{1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{2-\rho}{\rho-1}}}{\left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{\frac{1}{\rho-1}} A_\omega L_\omega^{-\frac{1}{\rho}}} = \frac{1}{\rho} A_\sigma L_\sigma^{1-\frac{1}{\rho}} \left[ \sum_\sigma A_\sigma L_\sigma^{\frac{\rho-1}{\rho}} \right]^{-1} = \frac{1}{\rho} R_\sigma.$$

In sum, we obtain

$$\frac{\partial \Omega_\omega}{\partial L_\sigma} \frac{L_\sigma}{\Omega_\omega} = \begin{cases} \frac{1}{\rho} R_\sigma - \frac{1}{\rho}, & \text{if } \omega = \sigma, \\ \frac{1}{\rho} R_\sigma, & \text{if } \omega \neq \sigma. \end{cases}$$

where  $R_\sigma$  is occupational labor wage bill as a share of the total wage bill. It captures the occupation size relative to the entire economy. The result comes exclusively from CES production function. Notice that the own wage elasticity is always negative since  $R_\sigma < 1$  due to substitution effect, whereas cross wage elasticity is always positive due to complementary effect.

## G.5 PROOF OF PROPOSITION 1

First one can rewrite equation (12) in two occupation case to have

$$\frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{1} = \frac{1}{\rho} \left[ R_{\sigma_1} - P_{\sigma_1|\nu_1, \kappa} \right] \times \left[ \left( \frac{1}{l_{\sigma_1}} + \frac{1}{l_{\sigma_2}} \right) P_{\sigma_1|\nu_2, \kappa} - \frac{1}{l_{\sigma_2}} \right]$$

without loss of generality, suppose  $R_{\sigma_1} - P_{\sigma_1|\nu_1, \kappa} > 0$ , then one can reach conclusion that a larger difference in occupation specialization leads to a larger  $\frac{\partial W_{\nu_1}}{W_{\nu_1}} \bigg/ \frac{\partial L_{\nu_2}}{1}$ .

Next, using the separable assumption that  $\tau_{\nu, \kappa, \omega, m} = \tau_{\nu, \kappa, m} \times \tau_{\kappa, \omega, m}$ , one can rewrite the equation (1) in a two occupation case  $P_{\sigma_1|\nu, \kappa}$  as

$$P_{\sigma_1|\nu, \kappa} = \frac{T_{\nu, \kappa, \sigma_1}^\vartheta \Omega_{\kappa, \sigma_1}^\vartheta \sum_m \tau_{\kappa, \sigma_1, m}^\vartheta}{T_{\nu, \kappa, \sigma_1}^\vartheta \Omega_{\kappa, \sigma_1}^\vartheta \sum_m \tau_{\kappa, \sigma_1, m}^\vartheta + T_{\nu, \kappa, \sigma_2}^\vartheta \Omega_{\kappa, \sigma_2}^\vartheta \sum_m \tau_{\kappa, \sigma_2, m}^\vartheta} = \frac{1}{1 + \left(\frac{T_{\nu, \kappa, \sigma_2}}{T_{\nu, \kappa, \sigma_1}}\right)^\vartheta \left(\frac{\Omega_{\kappa, \sigma_2}}{\Omega_{\kappa, \sigma_1}}\right)^\vartheta \frac{\sum_m \tau_{\kappa, \sigma_2, m}^\vartheta}{\sum_m \tau_{\kappa, \sigma_1, m}^\vartheta}}.$$

notice 1)  $\nu$  only appears in terms of  $\frac{T_{\nu, \kappa, \sigma_2}}{T_{\nu, \kappa, \sigma_1}}$ , and 2)  $P_{\sigma_1|\nu, \kappa}$  is strictly monotonically decreasing in  $\frac{T_{\nu, \kappa, \sigma_2}}{T_{\nu, \kappa, \sigma_1}}$ , and therefore a large differences in occupation comparative advantage, denoted as  $\left| \frac{T_{\nu_1, \kappa, \sigma_2}}{T_{\nu_1, \kappa, \sigma_1}} - \frac{T_{\nu_2, \kappa, \sigma_2}}{T_{\nu_2, \kappa, \sigma_1}} \right|$  corresponds to a more distant occupation specialization. The result of proposition 1 follows.

## G.6 DERIVATION OF LOCATION ADJUSTMENT

To derive approximation for  $\Upsilon_{\mu|\nu}$ , I substitute the expression  $\widehat{P}_{\mu|\nu}$  into  $\Upsilon_{\mu|\nu}$ . After that divide both numerator and denominator by  $\sum_{\omega'} \widehat{\Omega}_{\kappa', \omega'}^\vartheta P_{\mu, \omega'|\nu}$ , and setting  $\widehat{T}_{\nu, \kappa, \omega} = 1$  and  $\widehat{\tau}_{\nu, \kappa, \omega} = 1$  for foreign countries to have

$$\Upsilon_{\mu|\nu} = \frac{P_{\mu|\nu} \sum_{\omega} \widehat{\Omega}_{\mu, \omega}^\vartheta P_{\omega|\nu, \mu}}{\sum_{\mu'} P_{\mu'|\nu} \sum_{\omega} \widehat{\Omega}_{\mu, \omega}^\vartheta P_{\omega|\nu, \mu}} \approx \frac{P_{\mu|\nu}}{\sum_{\mu'} P_{\mu'|\nu}}$$

the approximate sign hold because the estimated occupational wage changes is close to one for most foreign economies, thus  $\sum_{\omega} \widehat{\Omega}_{\mu, \omega}^\vartheta P_{\omega|\nu, \mu} \approx 1$ .

To deriving approximation for  $\Lambda_{\mu|\nu}$ , I first substitute the expression of  $\widehat{P}_{\mu|\nu}$  into  $\Lambda_{\mu|\nu}$ . After that divide both numerator and denominator by  $\sum_{\mu', \omega'} \widehat{\Omega}_{\mu', \omega'}^\vartheta P_{\mu', \omega'|\nu}$ , and setting  $\widehat{T}_{\nu, \kappa, \omega} = 1$  and  $\widehat{\tau}_{\nu, \kappa, \omega} = 1$  for foreign countries to have

$$\Lambda_{\mu|\nu} = \frac{P_{\mu'|\nu} \sum_{\mu'} \sum_{\omega} \widehat{\Omega}_{\mu', \omega}^\vartheta P_{\mu', \omega|\nu}}{\sum_{\mu'} \left[ P_{\mu'|\nu} \sum_{\mu'' \neq \mu'} \sum_{\omega} \widehat{\Omega}_{\mu'', \omega}^\vartheta P_{\mu'', \omega|\nu} \right]} \approx \frac{P_{\mu|\nu}}{\sum_{\mu'} P_{\mu'|\nu}}.$$

recall the estimated occupational wage changes is close to one for all foreign economies, thus  $\sum_{\omega} \widehat{\Omega}_{\mu'', \omega}^\vartheta P_{\mu'', \omega|\nu} \approx 1$ , and hence the approximate sign holds. The derivation abuses notation  $\mu$  with  $\kappa$ , and  $\mu$  refer to country where wage unit appears.