

High-Skill Migration, Multinational Companies and the Location of Economic Activity

pseudonym: Aureliano Segundo

1 Introduction

The location of high-skill intensive industries and high-skill migrants are tightly linked. In recent years, particularly in the United States, we often hear about policies trying to curtail high-skill migration into the country with the argument that migration reduces the employment opportunities for natives whose skills are on par with the migrants. Supporters of high-skill migration, on the other hand, argue that such policies are likely to decrease the level of economic activity in the US and lead high-skill intensive industries to relocate abroad. While these arguments have been frequently raised, there is little evidence as to how much would restrictions on high-skill migration indeed cause high-skill industries to relocate outside of the US or the magnitude of the different channels through which we expect the relocation to happen.

I take on the task of quantifying the impact that US restrictions to high-skill migration would have on welfare, industry structure and the location decisions of multinational enterprises (MNEs). The intuition on the relationship between migration, industry structure and MNEs is simple. First, as I will argue throughout the paper, foreign MNEs in high-skill industries who set up an affiliate in the US receive an additional productivity effect from hiring workers from their source country. If migration was restricted, MNEs would be the first to relocate and we should expect a decrease in production and efficiency that affects all US workers. Beyond the channel of MNEs, a restriction in high-skill is expected to change the industry structure away from industries who use high-skill migrants more intensively. Technology intensive industries require skills that might not be readily available in the domestic market pushing them to hire foreign labor with the appropriate skills. Finally, while high-skill migrants compete with natives driving down the overall wage it is also true they bring skills that are complementary to both high- and low- skill native workers. For those natives whose skills are very different to the ones of high-skill migrants (e.g non-college educated workers), the negative impact of restricting migration might be large enough to overcome any benefit these policies aim to achieve.

Additionally, I show that the welfare gains of MNE production (MP) estimated by canonical MNE models like [Ramondo and Rodriguez-Clare \(2013\)](#) will tend to overstate the MNE welfare gains for high-skill workers and understate the gains for low-skill workers. The welfare gain of MP is the change in welfare when we going from a scenario with no MP to the observed equilibrium MNE flows, which is created by new and more efficient technologies that start producing domestically. Given the strong link between MP and high-skill migration, when allowing for MNEs to operate they will push up the inflow of high-skill migrants given their complementarity in production. Such an inflow will drive down the welfare gains for high skill workers who compete with the migrants and will drive up the gains for low-skill workers who benefit from migration. As the canonical models do not include migration they fail to capture this additional effect. A novel firm-level dataset I assembled on high-skill visas linked to the parent company of the firm allows me to establish a link between source country of the MNEs and nationality of the migrants hired which is a piece of data that has

been missing from previous studies. The data covers the universe of H-1B and L-1 visas granted between 2012 to 2014 which were obtained through a Freedom of Information request (FOIA) to the United States Citizenship and Immigration Services and contains information on wages, nationality of the workers and characteristics of the sponsoring firm such as company name, ownership structure and industry.

I begin by documenting three stylized facts that relate migration to MNE activity and industry structure. First, I show that foreign MNEs in the US have a large “home-bias”, where on average, they hire 200% more foreign workers from their source-country than other foreign workers when compared to US companies and other foreign MNEs. While there is heterogeneity on the magnitude of the home-bias across non-US source countries, this effect is consistently large. Second, there is significant heterogeneity across industries in their dependence on high-skill migrants which is positively correlated with the average skill intensity of the industry. Third, I show that workers from different origin countries select into migration to work for industries where their home country has a comparative advantage. Facts 2 and 3 reinforce the importance of accounting for different industries in the quantitative analysis, since a restriction in migration will disproportionately affect high-skill intensive industries.

I build a quantitative model that accounts for these stylized facts and allow for several channels through which migration affects production. The production side of the model allows for trade and MNE activity across multiple industries, similar to the work of [Ramondo and Rodriguez-Clare \(2013\)](#) and [Alvarez \(2018\)](#). If a German producer wants to sell goods to the US, she can either do so by producing the goods in Germany and shipping them to the US by paying a trade cost, setting a plant in the US and selling them domestically by paying an MNE cost, or set a plant in a third country and sell to the US paying both a trade and MNE cost. Such decision is at the core of why production relocates when marginal cost increases due to changes in migration restrictions. The labor supply side focuses on the decisions of college-educated workers in each country, who choose the country to migrate to and the industry and source technology to work with. For example, someone is considered to work with US source technology if that worker is employed by a company whose parent is headquartered in the US. Workers have heterogeneous productivities across country-industry-source triplets which act as a driver of migration and labor supply. Low-skill workers are assumed to be homogeneous and not mobile across countries.

In the model, migrants affect overall production for two reasons. First, as suggested by [Peri and Sparber \(2011\)](#) I allow for imperfect substitution between immigrants and natives in the production function. Second I allow for workers from different origins to have a comparative advantage on specific industries, which will make migration more valuable for some sectors than others. The link between MNE and migration also shows up through two separate channels. From the labor supply side, the migration cost is allowed to be lower if workers migrate to work at a company whose source technology is the same as the worker’s home country. From the labor demand side, foreign MNEs treat workers from their source country as imperfect substitutes to domestic and other foreign workers,

hence receiving a specific productivity effect from own-source workers.

While the model has many parameters, I use the approach proposed by [Dekle et al. \(2008\)](#) and rewrite the equilibrium in proportional changes from the observed equilibrium to a counterfactual equilibrium. This allows me to significantly reduce the number of parameters to be estimated and focus on 4 key elasticities that determine the magnitude of the endogenous responses of the model to a given exogenous shock such as increasing the migration cost. I use my novel dataset to structurally estimate two key elasticities that are not available in the literature: the migration elasticity with respect to migration costs and the elasticity of substitution between high-skill natives, source-country workers and other foreign workers. I use a similar approach to the one proposed by [Lagakos and Waugh \(2013\)](#) and use the observed dispersion on wages across industries, origin countries and source technologies to estimate the elasticity of labor supply. Intuitively, if an individual faces a larger dispersion in her own ability across choices, her labor supply/migration decision will be less responsive to changes in wages or migration costs. For the elasticity of substitution between high-skill units of labor I use a novel instrumental variables approach based on supply shifters that reduce the cost of migration to identify the slope of the relative demand for high-skill natives, source and other foreign workers.

I propose a counterfactual scenario in which I increase migration costs into the US from all other countries to replicate the long term effects of a recently debated policy that imposes a minimum wage to hire foreign high-skill workers in the US. According to my calculations, if a lower bound of \$90,000 annual wage was imposed, it would decrease the long term stock of high skill migrants in the by 70%, consistent with a 2.1% decrease in total US workforce. Through the lens of the model, I quantify that US production in high-skill intensive industries such as IT and skill-intensive manufacturing would decrease between 3.08% and 3.85%. Such decrease will be partly driven by foreign MNEs who disproportionately respond to the migration restrictions. The model predicts that US IT companies would decrease their revenues by 2.94% while Indian companies in the US will decrease by more than 35%. The share in production of other countries is expected to increase as a response, with the IT sector in India increasing by 4.4% and in Canada by 1.19%. Welfare for US low-skill workers would decrease by 2.01% due to the drop in total production while US high-skill workers would experience a gain in welfare of 1.13%. Overall welfare for US workers decreases by 0.98% when migration is restricted. I explore how different mechanisms drive the aggregate result such as MNE production, heterogeneity in industries and origin countries, imperfect substitution across labor units and heterogeneity in productivities and abilities of producers and workers.

Finally, in a second counterfactual, I increase the MNE cost to calculate the welfare gains from MNE activity predicted by my model. Going from MNE “autarky” to the observed MNE flows would increase welfare for high and low skill native workers by 1.17% and 1.42% respectively. A model that does not incorporate migration would overstate the gains for high-skill workers by 34.2% and understate the gains for low-skill workers by 7.9% since it does not account for the negative impact of migration on high-skill natives nor the positive impact for low-skill workers. This result shows that the link between MNEs and migration significantly affects the distributional welfare gains predicted

by canonical MNE models that ignore migration.

High-skill migration policy into the United States, particularly through the H-1B program, has received significant attention in the recent years. On one hand, high skill migrants are found to increase innovation (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Peri et al., 2015b) and hence total productivity in the US. On the other, its empirical estimates on native employment and wages are mixed. While some papers find small to negligible consequences for employment of native workers (Peri et al., 2015a) others find significant crowd-out effects (Doran et al., 2015). A first contribution of my paper is to complement the empirical literature by estimating a sufficiently rich quantitative model to disentangle the positive and negative consequences of migration in the US.

More broadly, several papers have used general equilibrium models to understand how high- and low-skill migration affects wages and employment of native workers. Among others, Docquier et al. (2014) and Burstein et al. (2018) look at the implications of migration for native workers with different skills and occupations by focusing on the consequences for the receiving country and ignoring the implications of migration for the rest of the World. A second set of papers go beyond that and use multi-country models to study the consequences of migration for both receiving and sending countries. Such a global view on migration requires to incorporate, to some extent, the possibility of production relocating as a response to changes in migration policy (Caliendo et al., 2018; Desmet et al., 2018; di Giovanni et al., 2015; Iranzo and Peri, 2009; Khanna and Morales, 2018). My model builds up on some of the features of multi-country models in the literature by adding the channel of multinational production which is deeply linked on how the relocation of production driven by migration affects welfare and productivity.

To my knowledge, this paper is the first to quantify the impact of high skill migration on the location of economic activity by taking into account the specific channel of multinational activity and incorporating the general equilibrium effects that are needed to understand the nature of production responses. Perhaps the closest to this research question is Wang (2014) who uses a calibrated two-country model of the US and Canada that incorporates imperfect substitution between migrants and natives within the MNE. I go beyond that and build a quantitative model that includes multiple countries, industries and an endogenous migration/labor supply decision that allows me to properly quantify the aggregate implications of migration on MNE production and welfare. Additionally, I use high-skill visa data to empirically show there is a link between MNEs and migration and use the data to estimate the quantitative model. Yeaple (2018) also uses high-skill visa data to look into the decision MNE companies make to bring workers to the US either through the L-1 or the H-1B. While he proposes a model of MNE production that captures the trade-off between these two visas at the firm level he does not estimate the parameters needed to run a counterfactual scenario.

A closely related strand of literature has estimated the link between migration and trade (Gould, 1994), migration and FDI activity (Javorcik et al., 2011) and the interrelations between migration, trade and FDI, (Aubry et al., 2018). Due to the lack of firm level data, these papers found a positive

correlation between trade, FDI and migration, but measured migration as the increase in the number of migrants within a country or region, without considering the direct impact these migrants had on their employers. [Hiller \(2013\)](#) used firm level data in Denmark and found that employing migrants led to an increased likelihood that the firm engaged in international trade but did not take into account the general equilibrium implications, nor the FDI response to migration.

As an additional contribution, I provide new evidence on the welfare gains of MNE production. Many of the most notable papers in the multinational production literature have focused on quantifying the welfare gains of MNE production by incorporating the interrelations between MNE production and trade, intermediate inputs, innovation and comparative advantage among others ([Alviarez, 2018](#); [Arkolakis et al., 2018](#); [Head and Mayer, 2018](#); [Ramondo and Rodriguez-Clare, 2013](#); [Tintelnot, 2017](#)). My paper is the first to show how the baseline results found in the literature are expected to change if we were to incorporate the channel of migration, which would significantly affect the distributional welfare gains of MNE production. Finally, I also contribute to the literature on the role of MNEs on the transfer of knowledge. [Keller and Yeaple \(2013\)](#) tests a model in which MNEs use intermediate inputs to transfer knowledge between the parent and the affiliate while a related literature explores how managers transfer knowledge between firms ([Mion et al., 2018](#)) and within firms ([Gumpert, 2018](#)). My paper proposes international migration as an additional channel for knowledge transfer, where MNEs have a specific productivity effect from hiring workers from their source country.

2 Context and Data

High skill migration into the US is possible through two main visa programs: the H-1B and the L-1. The H-1B program started in the early 1990s and was created as a pathway through which firms could hire temporary high-skilled workers in “specialty occupations” for a period of three years with the option to renew it for three more. The main feature of the program is that the number of new visas awarded per year is capped at 65,000 visas with an additional 20,000 for those who have a post-graduate degree awarded by a US institution. If the number of applications exceeds the cap, then a lottery takes place to award the visas. Universities and non-profit organizations are exempt from the cap. The visa program recognizes a dual intent, in which the employees can obtain a green card after their H-1B expires. The L-1 program is lesser known than the H-1B and represents around 10% of total H-1Bs awarded. The total number of L-1 visas is not capped and the program is targeted at MNE companies, since it requires the sponsored employee to have worked at an affiliate of the employer for at least 1 year in a period of 3 years prior to admission to the US. L-1 visas are valid for up to 5 to 7 years and are also dual intent, where employees can get sponsored for a green card after being L-1 holders. Further details on the L-1 and H-1B programs are discussed by [Yeaple \(2018\)](#).

For this project, I submitted a Freedom of Information Act (FOIA) request for the universe of I-129

forms for H-1B and L-1 visas submitted during the years 2012, 2013 and 2014. The I-129 form needs to be filed by the employer to the United States Citizen and Immigration Services (USCIS) once the visa was approved by the Department of Labor, that is, after the visa application went through the lottery in the case of the H-1B. The novelty of the dataset is that it contains individual information including the employer's name, start and end dates for which the visa is valid, occupation, country of birth and wages. Country of birth is a key variable needed for the analysis, as we should expect significant heterogeneity among nationalities in the response to migration restrictions. The dataset also includes information on whether petitions were filed for new employment, a renewal of previously approved employment, or a change in the terms of employment. Such information has an advantage over the H-1B data posted by the Department of Labor where all types of petitions are pooled together and includes petitions that did not win the lottery. I combine the FOIA dataset with corporate information from Orbis, DnB Hoovers and Uniworld, to get insight into the ownership structure of the employers and determine the country where the Global Ultimate Owner of the company is headquartered. This link is key to my analysis as it will reveal the source technology that foreign workers are using when migrating to the US. The corporate datasets also contain useful industry and financial information such as employment and revenues for the consolidated company. Appendix A explains how I constructed the FOIA dataset and provides details on the matching process with the corporate datasets.

3 Stylized facts

To quantify the response of production and industry structure to a policy change that increases the cost of migration into the US it is necessary to understand how immigrants from different nationalities select across industries and how MNE companies from different source countries depend on migration. In this section I show three empirical facts that help shed light on the link between high-skill migration, MNE activity and industry composition and motivate some of the features that will be included in the model in section 4. As a first fact, I show that there is a strong link between MNEs and high-skill migration captured by a “home-bias” measure that suggests foreign MNEs from source country s are more intensive in hiring migrants from s than US companies. In a second step, I present two additional facts that uncover a significant degree of heterogeneity across industries in their dependence on migration. First, skill intensive industries seem to be more intensive on high-skill migrants than non-skill intensive industries. Second, workers from different origin countries seem to select into migration to work in industries where they have a comparative advantage. Such heterogeneity across industries and origin countries will be incorporated to the model and proven to be relevant for the quantitative welfare effects of migration policy.

Fact 1: Foreign MNE companies have a “home-bias” towards workers from their source coun-

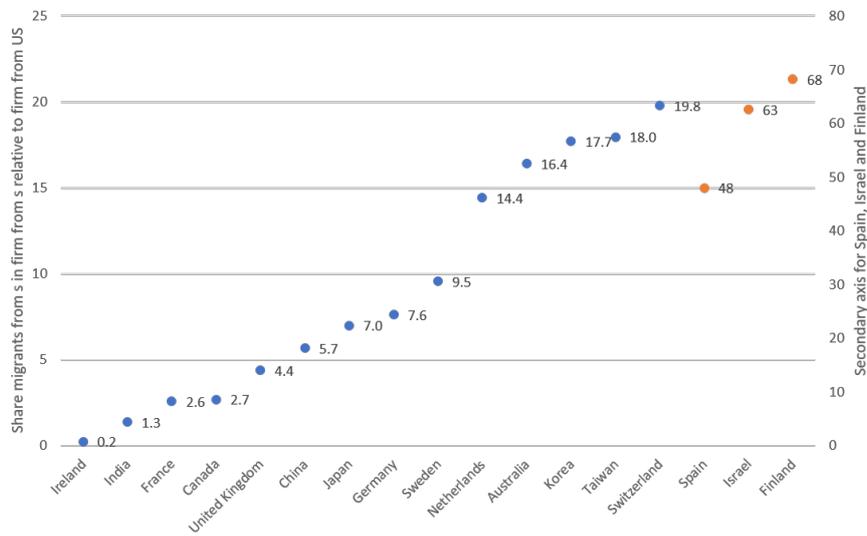
try

Distinguishing foreign MNEs from domestic companies is relevant since MNE companies are more dependent on high-skill migrants. More specifically, foreign MNE companies have a “home-bias” towards recruiting workers from their source country when compared to US companies. This is relevant since, if true, we should expect foreign companies to respond more to a migration policy change than American companies, which in turn has further implications for changes to the industrial structure and welfare in the US. To find support for this in the H-1B and L-1 data, I plot the share of high-skill visas granted to firms from s that go to workers from s relative to the share of high-skill visas granted to US firms that go to workers from s .

$$\text{That is } \frac{\text{N visas to firm from } s, \text{ worker from } s}{\text{N visas to firm from } s} \div \frac{\text{N visas to firm from US, worker from } s}{\text{N visas to firm from US}}$$

As shown in Figure 1 there seems to be a large “home-bias” for most countries in the sample since with the exception of Ireland, all other countries seem to hire more source country workers relative to US companies. For example, the share of visas to Chinese companies that go to Chinese workers is 4.4 times larger than the share of visas to US companies that goes to Chinese workers. For countries like Israel or Finland, the ratio is higher than 60.

Figure 1: Share of high-skill migrants from s hired by firms from s relative to firms from the US



The figure plots the share of migrants from country s among all migrants hired by firms from s in the US relative to the share of migrants from country s among all migrants hired by US firms in the US. The dataset only includes high-skill migrants to the US that arrived between 2012 and 2014 under an H-1B or L-1 visa.

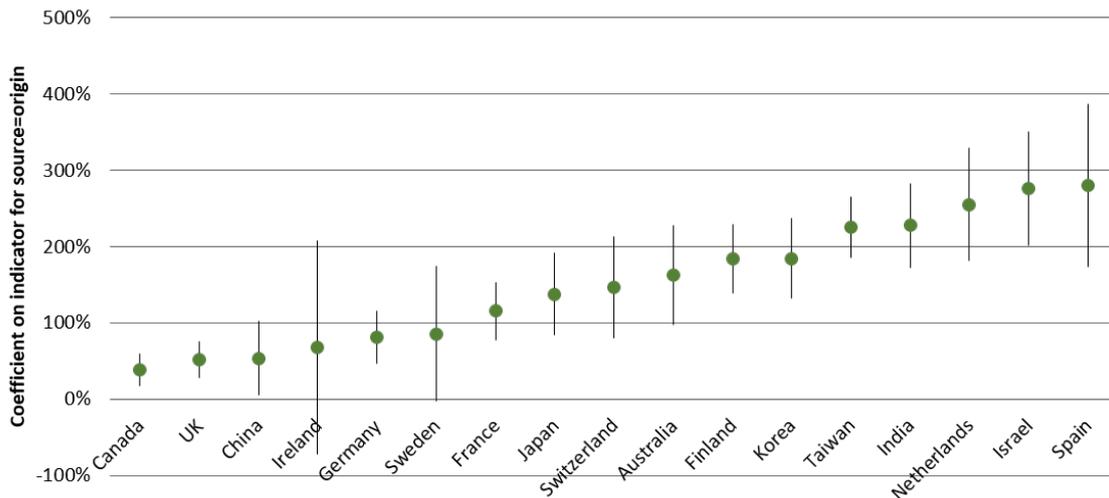
For now, I will not take a stand on whether the home bias is driven by workers being more likely to match with a company headquartered in their origin country, or foreign companies having a greater need for workers from their source country. In the model and subsequent estimation in sections 4

and 5 I explicitly separate and quantify these two channels. The results in Figure 1 pool all industries together so they might be partly driven by a correlation in worker and source country comparative advantage in specific industries. To test whether home bias holds when controlling for this, I try a regression approach by collapsing the high-skill visa data to the origin (o) - source (s) - industry level (k). For example, one observation of the regression is German college graduates working for Japanese automotive companies located in the US. I proceed to run a regression as in equation 1:

$$\ln(N_{k,o,s}) = \gamma_0 + \sum_s \gamma_s \mathbb{1}(\text{origin} = s) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \quad (1)$$

The key coefficient of interest is γ_s which measures how much more likely it is that a company from source s will hire someone from $o = s$ relative to $o \neq s$ when compared to all other companies from other source countries. The results of the home-bias coefficient γ_s can be found in Figure 2. $\delta_{k,o}$ is an industry-origin fixed effect that aims to capture whether migrants from origin o have a specific comparative advantage on industry k . $\delta_{k,s}$ is a source-industry fixed effect that captures any comparative advantage of a company from source country s that is operating in industry k . As shown in Figure 2, the home bias seems to be large for most countries in the sample and there is significant heterogeneity across source countries. Indian companies are shown to be 230% more likely to recruit workers from India than other countries, relative to non-Indian companies. While the regression results reaffirm the patterns observed in Figure 1, some of the magnitudes and relative rankings have changed. Such a difference is driven by equation 1 measuring the home-bias within industry and comparing firms from s with all other firms with $s' \neq s$ instead of just comparing with US firms.

Figure 2: Estimated coefficient (γ_s) on sourcing regression by country (H-1B+L-1)



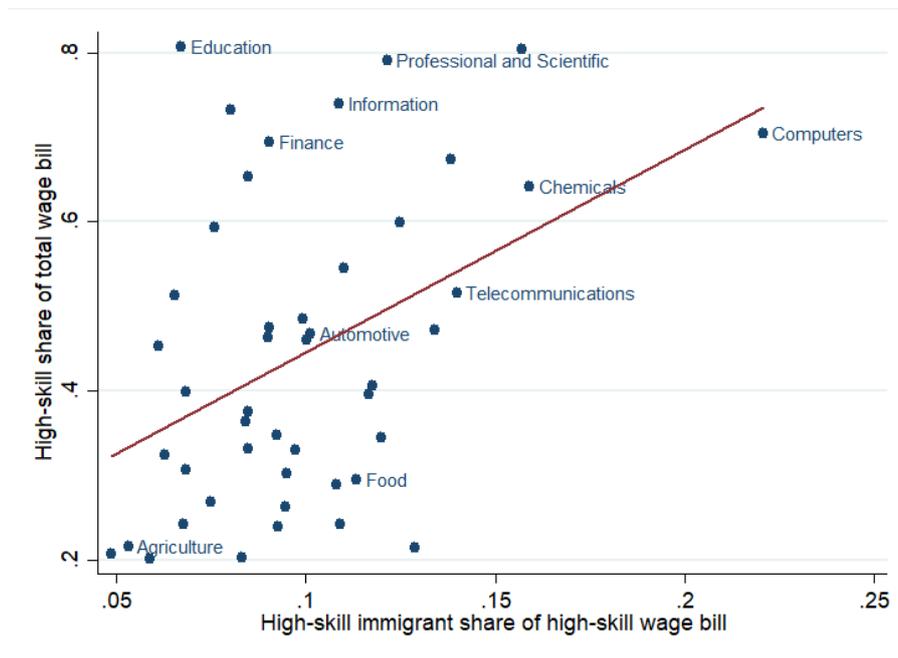
Appendix B explores further how do the regression results change when only using at H-1B visas, including source-origin pairs with 0 value and running the regression at the source-origin level. The

finding of home-bias is very robust to these specifications.

Fact 2: Heterogeneity across industries in recruiting high-skill migrants.

Facts 2 and 3 aim to highlight the relevance of accounting for industry and origin-country heterogeneity to quantify the effect of migration restrictions on production. Beyond the channel of multinational companies, we should expect different responses across industries when restricting migration. More specifically, high-skill industries are expected to be more affected than low skill industries. As shown in Figure 3 we can see that there is a large industry heterogeneity regarding which industries spend a larger share of their college graduate wage bill in migrants, where high-skill intensive industries such as computer manufacturing spend more than 20% of their high-skill wage bill on migrants and chemicals and telecommunications employing around 15%. Figure 3 suggests that high-skill intensive industries, measured through the share of the total wage bill that is spent in college graduates, have a greater need for skills that are harder to find in the local labor market, thus spending a greater share on migrants than low-skill intensive industries.¹ It also highlights the importance of considering industry heterogeneity to understand the implications of migration policy, as different industries depend differently on high-skill migration. As will be shown in section E accounting for multiple industries will be relevant in the quantitative exercise.

Figure 3: Share of college graduate migrants among graduate workers across industries



Vertical Axis: Skill Intensity, share of wage bill spent on college graduates by industry. Horizontal Axis: Share of college graduate wage bill spent on migrants. All industries at the 2-3 digit NAICS level included. Wage bill data taken from the American Community Survey 2012. Correlation 42.14%

¹The correlation between the skill-intensity of an industry and the share of the high-skill wage bill spent on migrants is 42.14%. In Appendix B I show that the correlation is even stronger when only looking at tradable industries (excluding health, education, government etc.) (56.9%) and manufacturing industries (79.1%).

Fact 3: Immigrants are more likely to select into migration to work in industries where the home country has a comparative advantage.

The last fact I present is that it is also relevant to consider the origin of the migrants to understand into which industries they select into. While there are some industries that employ a larger share of migrants, it is also true that migrants from different origins are more likely to select into migration to work in industries in which their home country has a comparative advantage relative to the US. To show this pattern I run a regression at the origin-industry level of the log migrants into the US from origin o that work on industry k on the comparative advantage of industry k in country o relative to the US. The regression is shown in equation 2.

$$\text{Ln}(\text{N employees from } o \text{ in } k) = \beta_0 + \beta_1 \text{Ln} \left(\frac{T_{o,k}}{T_{us,k}} \right) + \delta_k + \delta_o + \epsilon_{k,o} \quad (2)$$

As in the Ricardian literature, comparative advantage can be interpreted as the average productivity of a given industry in country o relative to the average productivity of industry k in the US and is denoted by $\frac{T_{o,k}}{T_{us,k}}$ ². The results in Table 1, Column 1 look at the stock of high-skill migrants, and it is shown that if the comparative advantage of country o in industry k relative to the US increases by 1%, the number of migrants of that origin that work in industry k in the US increases by 0.083%. The results hold for the H-1B and L-1 data form 2014 which can be considered as a flow of migrants instead of the stock measured by the ACS, as shown in Column 2. Finally we can see that this correlation is not driven by foreign MNE companies, as the correlation is almost identical when only migrants that work for American companies are considered (Column 3).

²I calculate this term using the gravity equation and the observed trade flows as in Eaton and Kortum (2002). Details on this estimation can be found in Appendix B

Table 1: Nationality, industry sorting and home-country comparative advantage

	Ln(College Workers from o in ind i)	Ln(H-1B + L-1 from o in ind i)	Ln(H-1B + L-1 from o in ind i)
$Ln\left(\frac{T_{o,i}}{T_{us,i}}\right)$	0.083*** (0.017)	0.092*** (0.027)	0.091** (0.029)
N observations	762	449	362
Sample	All College Migrants 2014	H-1B + L-1 2014	H-1B + L-1 2014
Companies		All Companies	US based companies

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include origin country and industry fixed effects. Column 1: source ACS pooling 2009-2014, and includes 35 origins and 24 industries. Columns 2-3: source FOIA data on H-1B and L-1 for 2014, 35 origins and 24 industries included but not all country-industry pairs had observations, which explains the change in sample sizes. Column 3: excluding foreign MNE companies.

The goal of Table 1 is two-fold. First, it highlights that migrants from different origins are likely to select into migration to work in different industries, which is another channel through which different industries will have heterogeneous responses to a change in migration policy. A second goal is to show that migrants from different origins seem to have a specific productivity for working in each industry which is correlated with their home country productivity level in that same industry. Foreign MNE companies may appear to recruit more immigrants from their home country, but that might simply be because foreign MNEs are more productive in industries where the migrants are also more productive. This highlights the importance of accounting for multiple origins and industries in the quantitative model to properly understand the response of MNE companies to changes in migration policy.

Facts 1-3 aim to characterize the sorting patterns of migrants across origins, industries, and source countries. To understand the implications of high-skill migration policy we should expect different responses depending on the industry and source country of the company as well as the origin of the migrants the company is more likely to hire. In this section, I presented evidence that high skill intensive industries depend more on migration and workers from a given origin are more likely to select into migration to work in specific industries where their home country has a comparative advantage. Finally, within a given industry and origin country, foreign companies seem to depend more on migration than American companies, since they are more likely to recruit workers from their source country than workers from other origins. When thinking about a general equilibrium model that measures the relationship between migration and production, it is relevant to consider multiple industries and origins, as well as to explicitly model inward MNE activity from different countries as an additional

mechanism through which the production structure in the US might change when migration becomes costlier.

4 Model

To understand the general equilibrium implications of changes to high-skill migration policy in the US, we need a quantitative model to disentangle the different mechanisms through which migration affects production and the location of economic activity and measure the response in production, welfare and industrial structure. The model consists of two main parts: a labor market for high-skill workers described in section 4.1 and a product market that includes trade and MNE activity described in section 4.2. The model is static, and consists of O countries. Production can be carried out by local companies or by foreign companies that set up an affiliate outside of their home country.

4.1 Labor Market and Migration Choices

Each country o is endowed with a number of low-skill (\bar{L}_o) and high-skill (\bar{N}_o) workers. Low skill workers are a homogeneous group who cannot migrate and are indifferent about the industry or company that they work for and charge wage w_o . On the other hand, high-skill workers have heterogeneous productivities and are able to choose the location ℓ , industry k and source technology s they want to work with. Source technology refers to the country where the company they work for is headquartered. At the beginning of the period each worker i at origin o draw a productivity $\eta_{k,\ell,s}^{i,o}$ to work at each triplet $z = k, \ell, s$ from a Frechet distribution as shown in equation 3:

$$F(\eta_{k,\ell,s}^{i,o}) = \exp\left(-\sum_{z=1}^Z A_{k,o} (\eta_z^{i,o})^{-\kappa}\right) \quad (3)$$

For expositional purposes the productivity draws are assumed to be i.i.d. but in section 6.1.1 I explore the implications of using correlated draws for my quantitative results³. The shape parameter of the distribution κ is common across origin countries and governs the dispersion of productivities for each individual. Lower values of κ imply that individuals are likely to have very different productivities across triplets k, ℓ, s . As will be shown later, the parameter κ is also related to the elasticity of labor supply, since it determines how much migration flows respond to changes in wages or migration costs. The scale parameter, $A_{k,o}$, determines the average productivity level of each origin in each industry. This allows for workers in a given country to have a comparative advantage at specific industries. This setup is related to the EK-Roy models of comparative advantage, which is a combination of the

³The assumption of iid can be relaxed by adding correlation among the draws for each individual ($\rho > 0$). The Frechet distribution in that case would be $F(\eta_{k,\ell,s}^{i,o}) = \exp\left(-\left(\sum_{z=1}^Z \left(A_{k,o} (\eta_z^{i,o})^{-\kappa}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}\right)$.

Ricardian model of productivities in [Eaton and Kortum \(2002\)](#) and the selection model proposed by [Roy \(1951\)](#). Such a setup has been used to model individual choices of occupations and industries ([Hsieh et al., 2018](#); [Lagakos and Waugh, 2013](#); [Lee, 2017](#)), as well as both for internal ([Bryan and Morten, 2018](#)) and international migration ([Liu, 2017](#)). The parameter $A_{k,o}$ is directly related to Facts 1 and 2 presented in section 3. First, migrants will tend to select into migration to work in industries where they have a comparative advantage as shown in Fact 2. Second, such selection into migration implies we will tend to see more foreign workers in some industries than in others as presented by Fact 1.

Each high-skilled worker, indexed by i chooses the triplet k, ℓ, s that maximizes their utility as in equation 4:

$$\max_{k,\ell,s} \{U_{k,\ell,s}^{i,o}\} = \eta_{k,\ell,s}^{i,o} \times \frac{w_{k,\ell,s}}{\phi_{o,\ell,s}} \quad (4)$$

Where $\eta_{k,\ell,s}^{i,o}$ is the ability draw for individual i in triplet k, ℓ, s , $w_{k,\ell,s}$ is the wage per effective unit paid in triplet k, ℓ, s and $\phi_{o,\ell,s} \geq 1$ is a non-pecuniary migration cost that is paid when migrating from origin o to location ℓ and source technology s . If $o = \ell$ I assume there is no migration cost, such that $\phi_{\ell,\ell,s} = 1$. Having the migration cost depend on s is the first component of the home-bias discussed in Section 3, since workers from a given origin can have a lower cost when matched with a job in an MNE of a specific source technology.

Note that as $\phi_{o,\ell,s}$ is non-pecuniary, the wage that individuals actually receive in the labor market is $W_{k,\ell,s}^o = \eta_{k,\ell,s}^{i,o} \times w_{k,\ell,s}$.

4.2 Production, Trade and MNE activity

We can think about the consumer problem in two stages. First, individuals draw a productivity and choose a triplet k, ℓ, s as explained in sub section 4.1. Second, conditional on their choice and the wage they receive, they maximize their consumption utility as an individual living in ℓ who has Cobb-Douglas preferences over industries K as in equation 5

$$U_\ell = \sum_{k=1}^K \gamma_{k,\ell} L_n(Q_{k,\ell}) \quad (5)$$

Each $Q_{k,\ell}$ can be written as a continuum of varieties indexed by j , and aggregated CES as in equation 6:

$$Q_{k,\ell} = \left(\int q_{k,\ell}^j \frac{\sigma-1}{\sigma} dj \right)^{\frac{\sigma}{\sigma-1}} \quad (6)$$

Each variety $q_{k,\ell}^j$ is produced using a Cobb-Douglas aggregate of intermediate inputs from each industry K and a composite of low and high skilled labor as in equation 7. α represents the elasticity of substitution between low and high skill units of labor and $\gamma_{\ell,k,k'}$ is the expenditure share for industry k in country ℓ on intermediates from industry k' . Each producer has an idiosyncratic productivity $\epsilon_{k,\ell}^j$. While I omit index j in equations 7 and 8, both equations are at the producer level.

$$q_{k,\ell} = \epsilon_{k,\ell} \prod_{k'=1}^K Q_{k'}^{\gamma_{\ell,k,k'}} \left(\psi_{k,\ell}^l l_{k,\ell}^{\frac{\alpha-1}{\alpha}} + \psi_{k,\ell}^h h_{k,\ell}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1} (1 - \sum_{k'} \gamma_{\ell,k,k'})} \quad (7)$$

I assume high-skill labor $h_{k,\ell}$ is a composite of effective units from the domestic country $h_{k,\ell}^d$, source country $h_{k,\ell}^s$ and other foreign countries $h_{k,\ell}^f$. That is, if the producer uses a source technology in a location $\ell \neq s$ then the aggregate $h_{k,\ell}$ can be written as in equation 8: ⁴

$$h_{k,\ell,s} = \left(\underbrace{\psi_{k,\ell,s}^d (h_{k,\ell,s}^d)^{\frac{\lambda-1}{\lambda}}}_{\text{local workers}} + \underbrace{\psi_{k,\ell,s}^s (h_{k,\ell,s}^s)^{\frac{\lambda-1}{\lambda}}}_{\text{source country}} + \underbrace{\psi_{k,\ell,s}^f (h_{k,\ell,s}^f)^{\frac{\lambda-1}{\lambda}}}_{\text{other foreign}} \right)^{\frac{\lambda}{\lambda-1}} \quad (8)$$

The parameter λ governs the substitution between effective units of the domestic country, source country and other foreign workers. Having foreign and native workers be imperfect substitutes is consistent with the findings of [Peri and Sparber \(2011\)](#) who find that migrants tend to specialize in different tasks than natives. At the same time, having source country workers be an imperfect substitute for other foreign workers and natives, is consistent with the knowledge transfer literature such as [Keller and Yeaple \(2013\)](#) who find that affiliates of US MNEs can use intermediate inputs from the parent country to transfer knowledge from parent to affiliate. This is the second part in which the home-bias discussed in section 3 shows up, since foreign MNEs will have a specific value for migrants from their source country. I allow the share parameters $\psi_{k,\ell,s}^d, \psi_{k,\ell,s}^s, \psi_{k,\ell,s}^f$ to depend on source country and particularly, on industry. This is an additional channel through which the heterogeneity in hiring migrants across industries discussed in Fact 1 in Section 3 shows up, as some industries will be more migrant intensive than others.

4.2.1 International trade and MNE

Up to this point I have been taking the existence of MNE companies as a given. To close the model, I clarify how location decisions of MNEs are made. This setup is a multi-industry extension of the MNE production model proposed by [Ramondo and Rodriguez-Clare \(2013\)](#), which is an extension of the Ricardian trade model in [Eaton and Kortum \(2002\)](#). Multi-sector Ricardian MNE models have been developed by [Alvarez \(2018\)](#) and [Arkolakis et al. \(2018\)](#) among others.

⁴If a company operates in $\ell = s$ then the source and domestic inputs are the same and the only relevant substitution is between natives and foreign.

Producers of each variety j in source country s take a productivity draw $\epsilon_{k,\ell,s}^j$ to produce variety j in each possible location ℓ . Such productivity is drawn from a Frechet distribution as in equation 9:

$$F(\epsilon_{k,\ell,s}) = \exp\left(-\sum_{\ell=1}^{\mathcal{L}} T_{k,s}(\epsilon_{\ell})^{-\theta}\right) \quad (9)$$

Once again, the shape parameter θ governs the productivity dispersion across production locations for a given producer. If θ is low, then there are large gains to MNE production, as a producer might have low productivity in their source country but high productivity at some alternative location. A producer of variety v , in industry k , with source technology s who chooses to locate production at location ℓ and sell their products to destination country n would charge a price as in equation 10:

$$p_{s,\ell,n}^{j,k} = \frac{c_{s,\ell}^k \tau_{\ell,n}^k \delta_{s,\ell}^k}{\epsilon_{k,s,\ell}^j} \quad (10)$$

The price equation is intuitive. The price increases with the marginal cost of production $c_{s,\ell}^k$. Note that the cost depends on both the location of production ℓ and the source technology s since as presented in section 4.1, foreign workers have different costs of migration for domestic and foreign MNEs, which implies that an MNE from source s located in ℓ has access to a specific labor pool and pays a different wage per effective unit of labor than MNEs from other source countries. The location-source specific productivity $\epsilon_{k,s,\ell}^j$ decreases the price, as more efficient producers generate more output for a given combination of inputs. If a producer located in ℓ wants to sell to destination $n \neq \ell$, then they incur in an iceberg trade cost $\tau_{\ell,n}^k$ where part of the good gets lost in transit from ℓ to n . Alternatively, if a company decides to serve market n by setting up an affiliate in $n = \ell$, then if $s \neq \ell$ the company incurs in an iceberg MNE cost ($\delta_{s,\ell=n}^k$), which represents the share of the goods that gets lost when adapting technology s to location ℓ . A third option is for a company from s to locate in $\ell \neq s$ and sell goods to $n \neq s, \ell$ in which case it would pay both trade ($\tau_{\ell,n}^k$) and MNE costs ($\delta_{s,\ell}^k$).

Consumers end up buying each variety from the cheapest producer such that: $\min_{s,\ell} \{p_{s,\ell,n}\}$.

4.3 Equilibrium

The equilibrium in this model can be defined as a set of prices, wages and labor allocations such that: high-skill workers optimally choose the triplet k, ℓ, s to work for, consumers in each location ℓ buy goods from the cheapest producer, labor markets clear and trade is balanced. Since both labor and production productivity are drawn from Frechet distributions, it is possible to derive tractable, closed form solutions for migration shares, trade shares and MNE shares.

The fraction of workers from origin o who choose to migrate to location ℓ and work for industry k

with source technology s can be written as in equation 11:

$$\pi_{o,k,\ell,s}^{mig} = \frac{A_{o,k} w_{k,\ell,s}^{\kappa} \phi_{o,\ell,s}^{-\kappa}}{\sum_{\ell',s',k'} A_{o,k'} w_{\ell',s',k'}^{\kappa} \phi_{o,\ell',s'}^{-\kappa}} \quad (11)$$

Equation 11 implies that the probability of migration from origin o to triplet k, ℓ, s depends on the comparative advantage of origin o in industry k , the wage per effective unit in triplet k, ℓ, s , the migration cost from o to ℓ, s $\phi_{o,\ell,s}$ and a combination of these terms for all other triplets, captured by the denominator in equation 11.

Consumers choose the pair ℓ, s from which to buy each variety within each industry. As the productivities are iid and also Frechet, it is possible to write the share of goods bought from pair ℓ, s by consumers in n as in equation 12:

$$\pi_{k,\ell,n}^{trade} = \frac{(\tau_{\ell,n}^k)^{-\theta} \tilde{T}_{\ell}^k}{\sum_{\ell'} (\tau_{\ell',n}^k)^{-\theta} \tilde{T}_{\ell'}^k} \quad (12)$$

The trade share depends on the bilateral trade cost between production location ℓ and destination country n , as well as on the effective technology parameter in location ℓ : $\tilde{T}_{\ell}^k = \sum_s T_s^k (c_{\ell,s}^k \times \delta_{\ell,s}^k)^{-\theta}$. \tilde{T}_{ℓ}^k is a combination of the fundamental technologies T_s^k of source countries operating in ℓ and the marginal cost for a producer with source s to operate in ℓ . The overall marginal cost is a combination of the marginal cost of production $c_{\ell,s}^k$ and the MNE iceberg cost $\delta_{\ell,s}^k$.

Finally, it is possible to write the share of production in ℓ in industry k that is done by MNEs from country s as in equation 13:

$$\pi_{k,s,\ell}^{mne} = \frac{(c_{\ell,s}^k \times \delta_{\ell,s}^k)^{-\theta}}{\sum_{s'} (c_{\ell,s'}^k \times \delta_{\ell,s'}^k)^{-\theta}} \quad (13)$$

Appendix C shows the complete equilibrium equations including trade balance, labor, and product market clearing conditions and the cost functions.

To solve for the equilibrium in the model, I use the approach suggested by Dekle et al. (2008) and solve the model in proportional changes. This method, also called the exact hat-algebra method, allows me to re-write the equilibrium equations as changes between the real and the counterfactual scenarios. That is, I can re-write each variable x as $\hat{x} = \frac{x'}{x}$ where x is the variable under the real scenario and x' is the value of the variable under the counterfactual. An key advantage of this method is that it allows me to understand more transparently how an exogenous change in for example, migration costs to the US $\hat{\phi}_{o,US,s} > 1$, affect other endogenous variables of the model. I re-write all equilibrium equations in proportional changes in Appendix C. As an example, it is possible to re-write the migration share equation (equation 11) as in equation 14:

$$\hat{\pi}_{o,k,\ell,s}^{mig} = \frac{\pi^{mig'}}{\pi^{mig}} = \frac{\hat{A}_{o,k} \hat{w}_{k,\ell,s}^{\kappa} \hat{\phi}_{o,\ell,s}^{-\kappa}}{\sum_{k',\ell',s} \hat{A}_{o,k'} \hat{w}_{k',\ell',s'}^{\kappa} \hat{\phi}_{o',\ell',s'}^{-\kappa} \pi_{o,k,\ell,s}^{mig}} \quad (14)$$

As shown by the color code in equation 14, this approach allows me to classify each object of the equilibrium into four categories: Endogenous variables such as $\hat{w}_{k,\ell,s}$ (in black), fundamental parameters such as κ (in red), exogenous parameters such as $\hat{\phi}_{o,\ell,s}$ and $\hat{A}_{o,k}$ (in purple), and data on observed allocations $\pi_{o,k,\ell,s}^{mig}$ (in blue). The model includes many exogenous parameters such as migration costs $\hat{\phi}_{o,\ell,s}$, trade costs $\tau_{k,\ell,n}$, MNE costs $\delta_{k,s,\ell}$, fundamental technologies $T_{s,k}$, worker comparative advantages $A_{k,o}$ and labor shares $\psi_{k,\ell,s}$ but there are assumed to stay constant between the real and the counterfactual such that $\hat{x} = 1$. The counterfactual scenario involves changing just some of the exogenous parameters and evaluating how the endogenous variables respond. This strategy helps me avoid having to calibrate all parameters and just focus on four key elasticities that govern the responses of the endogenous variables: κ the elasticity of migration, λ the elasticity of substitution between high-skill effective units of labor, α the elasticity of substitution between college and non-college workers and θ the trade and MNE elasticity. Those elasticities together with data on observed allocations are enough to compute the changes in the endogenous variables of the model. While I also need data on the observed migration, trade shares, MNE shares and labor allocations, I do not need to take a stand on any other parameters of the model which greatly reduces the number of parameters to be estimated.

4.4 Intuition

Before discussing the estimation of the elasticities and the construction of the dataset, I will discuss how exactly a change in migration cost and the four elasticities κ , λ , α and θ will allow me to quantify the endogenous responses of the model. For simplicity and just for this section, I will assume there are only 2 countries the US and India, a single industry and no MNE activity. I want to quantify the production response in the US to an increase in the migration cost from India to the US $\hat{\phi}_{in,us} > 1$.

Using the simplified version of equation 11 and taking logs of the ratio between the migration share of Indians going to the US relative to Indians staying in India, we get an expression like in equation 15:

$$Ln(\pi^{\hat{mig}_{in,us}}) - Ln(\pi^{\hat{mig}_{in,in}}) = \kappa (Ln(\hat{w}_{us}) - Ln(\hat{w}_{in})) - \kappa Ln(\hat{\phi}_{in,us}) \quad (15)$$

An increase in the migration cost from India to the US, will decrease the number of Indians in the US relative to the Indians that stay in India, and the magnitude of the decrease is quantified by κ . The main role of κ is regulate the dispersion of abilities across options for each individual. High

values of κ imply that the abilities across triplets will be very concentrated and that small changes in the migration cost or the wages will generate large responses in the number of workers who migrate, since the ability they have to work in the US will be close to the ability to work elsewhere.

A decrease in the number of foreign workers in the US will rise the wage paid for foreign effective units of labor $\hat{w}_{us}^f > 1$. The effect of such increase on marginal cost will depend on the elasticities λ and α . To see this, we know from equation 8 that the unit cost of high skill labor can be written as in equation 16:

$$\hat{c}ost_{h,us} = \left(\hat{\psi}_d^\lambda \hat{w}_{d,us}^{1-\lambda} + \hat{\psi}_f^\lambda \hat{w}_{f,us}^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \quad (16)$$

The higher the λ , the higher the substitution between effective units of foreign and domestic high skill labor, such that the marginal cost of high-skill labor will respond less to an increase in $\hat{w}_{f,us}$. λ will quantify the response of high-skill marginal cost to a change in the migration cost $\hat{\phi}_{in,us}$. Following a similar intuition, if the elasticity of substitution between low and high skill workers α is high, low and high skill effective units are highly substitutable. If the cost for high-skill units increases as a response to the migration cost increase, the firm could simply substitute high for low skill units keeping the overall marginal cost lower, as shown in equation 17.

$$\hat{c}ost_{us} = \left(\hat{\psi}_L^\alpha \hat{w}_{L,us}^{1-\alpha} + \hat{\psi}_H^\alpha \hat{c}ost_{h,us}^{1-\alpha} \right)^{\frac{1}{1-\alpha}} \quad (17)$$

Finally, the parameter θ quantifies how much does an increase in the marginal cost for US firms changes the demand for goods produced in the US. θ regulates the dispersion of productivities across production locations. High values of θ mean that productivity is more concentrated across locations. If an increase in migration cost increases marginal cost for companies in the US, we should expect a larger change in the share of goods other countries buy from the US, as productivities abroad are similar to those in the US and a small change in marginal cost can have significant implications for the location of production. This can be shown by re-working the gravity equation by taking the ratio of the share of goods the US buys from India relative to the share of goods the US buys from itself as shown in equation 18:

$$Ln(\hat{\pi}_{us,in}^{cons}) - Ln(\hat{\pi}_{us,us}^{cons}) = Ln\left(\frac{\hat{T}_{in}}{\hat{T}_{us}}\right) - \theta (Ln(\hat{c}ost_{in}) - Ln(\hat{c}ost_{us})) - \theta Ln(\hat{\tau}_{us,in}) \quad (18)$$

The intuition follows through when considering multiple industries and source technologies. Since specific industries and source technologies have a different intensity on migrant workers, a change in the migration cost will have a heterogeneous effects on the marginal costs across industry-source pairs, generating a change on industry composition and MNE production.

5 Estimation

In this section I proceed to estimate the migration flow elasticity κ and the elasticity of substitution of high-skill effective units λ . While the trade elasticity θ is an important parameter it has been estimated in several papers in the literature and is not the key contribution of this paper. Thus, I just use the value of $\theta = 4$ as estimated by [Simonovska and Waugh \(2014\)](#). Finally, for the elasticity of substitution between college and non-college workers, I set $\alpha = 1.7$ based on an average of different papers that estimate that parameter such as [Katz and Murphy \(1992\)](#), [Card and Lemieux \(2001\)](#) and [Goldin and Katz \(2007\)](#).

5.1 Labor supply elasticity κ

In the model presented in section 4 the shape parameter of the productivity distribution, κ , has two main interpretations. First, it governs the dispersion of productivities, with lower values of κ implying higher dispersion between draws. Second, it can be interpreted as the labor supply elasticity as it captures how much relative migration flows change when the relative wages or migration costs change. I will use the dispersion property to estimate κ using the observed distribution of wages for high-skill migrants. Similar approaches have been used in the EK-Roy literature to estimate the supply elasticity such as in [Lagakos and Waugh \(2013\)](#), [Hsieh et al. \(2018\)](#) and [Lee \(2017\)](#). Before proceeding to the estimation I will present two results based on the Frechet properties.

Proposition 1 *If productivity draws η are distributed Frechet with shape parameter κ , the observed market wages paid to employees $W_{i,\ell,s} = \eta_{o,i,\ell,s} w_{i,\ell,s}^x$ are also distributed Frechet with parameter κ .*

Proposition 2 *If a random variable W is distributed Frechet with shape parameter κ then the coefficient of variation can be written as:*

$$\left(\frac{\sigma}{\mu}\right)^2 = \frac{\Gamma\left(1 - \frac{2}{\kappa}\right)}{\left(\Gamma\left(1 - \frac{1}{\kappa}\right)\right)^2} - 1$$

Where Γ is the Gamma function. Proposition 1 indicates that market wages are also distributed Frechet with shape parameter κ which means that the parameter κ is related to the dispersion of observed wages, conditional on individuals choosing the triplet i, ℓ, s . This proposition indicates that the observed dispersion of wages could be used to make inference on the value of κ . Proposition 2 gives a useful expression to implement the estimation, as it says that the ratio of the observed variance of wages to the square of the mean of observed wages has a parametric relationship with κ .

Based on the results of the propositions above, I can use the H-1B data on wages to calculate the variance and mean wages for each group of workers with origin o who migrate to the US to work in industry k with source technology s . I construct the empirical moments as in equation 19 and estimate

the parameter κ by GMM, choosing a value of κ that minimizes the distance between the empirical moments and the moments from proposition 2.

$$\left(\frac{Var(W_{k,\ell,s}^o)}{(\bar{W}_{k,\ell,s}^o)^2} \right) = \frac{\Gamma(1 - \frac{2}{\kappa})}{\left(\Gamma(1 - \frac{1}{\kappa})\right)^2} - 1$$

I present the baseline results using the H-1B data in table 2. Results are shown for different combinations of origin countries and industry sub-groups. As expected, the variance decreases when the groups become more homogeneous (more industries and more origins) but the estimated value of κ is within the range of 5.95 and 6.99.

Table 2: Estimates for κ

	(1)	(2)	(3)	(4)
Elasticity of Supply (κ)	5.95***	6.41***	6.58***	6.99***
	(0.535)	(0.45)	(0.56)	(0.49)
	697	1202	1078	1624
Industry	NAICS 2-dig	NAICS 2-dig	NAICS 3-dig	NAICS 3-dig
N origin countries	18	63	18	63

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates by GMM using H-1B data on wages by country of origin, industry and source technology.

Moving forward, I choose as my baseline value $\kappa = 5.95$. The H-1B data used to perform this estimation procedure is useful as it gives information on the source-technology linked to nationality and industry of migrants, giving a unique setting that is closely related to the choices in the model. On the other hand, it is reasonable to think that the H-1B workers might show less dispersion than the stock of high-skill migrants in the US, since H-1B workers are newer to the US labor market, while the stock includes workers who migrated a long time ago and might have accumulated more experience, increasing the overall level of wages and dispersion. Since I expect to make predictions regarding how the stock of migrants changes when I change the migration cost in the counterfactual, I proceed to do a robustness exercise using the American Community Survey to understand the differences in dispersion between the H-1B population and the stock of high-skill migrant population. The ACS does not contain information on source technology, so I focus only on industries and origin countries. Indeed, as shown in table 3, the estimated values of κ are lower when using the ACS than the H-1B data, with the values of κ ranging between 4.19-4.42 when looking at the stock instead of the H-1B. I use the value of 4.19 as a lower bound for κ to bound the results as shown in appendix E.

Table 3: κ estimates ACS vs H-1B

	ACS data - Stock	H-1B data - 6 years
2-digit naics, 18 origins	4.19*** (0.09)	5.18*** (0.62)
3-digit naics, 18 origins	4.30*** (0.09)	6.09*** (0.68)
2-digit naics, 63 origins	4.26*** (0.08)	5.91*** (0.49)
3-digit naics, 63 origins	4.42*** (0.08)	6.70*** (0.54)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Both H-1B and ACS groups are industry-origin only, not taking into account source country. N obs - H-1B: 228, 523, 595, 1032. N obs - ACS: 240, 595, 707, 1349

5.2 Elasticity of substitution of high-skill effective units λ

The elasticity of substitution between domestic, source country and other foreign effective units can be interpreted as the demand elasticity for migrants. It is possible to re-work the first order conditions of the components in equation 8 to get to equation 19:

$$Ln \left(\frac{\text{wage bill}_{k,\ell,s}^s}{\text{wage bill}_{k,\ell,s}^f} \right) = (1 - \lambda) Ln \left(\frac{w_{k,\ell,s}^s}{w_{k,\ell,s}^f} \right) + \lambda Ln \left(\frac{\psi_s^s}{\psi_s^f} \right) \quad (19)$$

Equation 8 implies that for an MNE from source s , the ratio of the wage bill spent on source country workers relative to the wage bill spent on other foreign workers is a function of the ratio of effective wage paid to source country workers relative to the effective wage paid to other foreign workers.⁵ If one were to run this regression by OLS, two main issues would arise. First, the effective wage ratio $Ln \left(\frac{w_{k,\ell,s}^s}{w_{k,\ell,s}^f} \right)$ is not observed in the data, as these are wages paid per effective unit. Second, even if the ratio of effective wages was observed, unobserved productivity shocks would likely bias the coefficient upwards, as we would be confounding supply and demand. I proceed to estimate this parameter in two steps. In the first step, I use the estimated value of κ and the supply side of the model to back out the ratio of effective wages. Once I have the explanatory variable, I use an instrumental variables approach to identify λ .

Using the supply side of the model and the properties of the Frechet distribution, we can write the observed average wages for each group as in equation 20:

⁵For estimation purposes, parameters ψ_s^s and ψ_s^f are simplified from those in equation 19 since they no longer include a country sub-index ℓ since I will only use US data for estimation nor an industry sub-index k . Results will be robust to adding industry fixed effects to capture industry heterogeneity.

$$\overline{wage}_{k,\ell,s}^o = w_{k,\ell,s}^x \pi_{k,\ell,s}^{-\frac{1}{\kappa}} A_{i,o}^{\frac{1}{\kappa}} \bar{\Gamma} \quad (20)$$

Where $\overline{wage}_{k,\ell,s}^o$ is the average wage for those from origin o that migrate to triplet k, ℓ, s , conditional on choosing k, ℓ, s . $w_{k,\ell,s}^x$ is the wage per effective unit paid to those who choose triplet k, ℓ, s and the superscript x indicates whether the workers are hired by an MNE with $s = o$ or if they are hired just as regular foreign workers. $\pi_{k,\ell,s}$ is the fraction of workers from o , who migrate to k, ℓ, s and $A_{k,o}$ is the comparative advantage of workers from o in industry k . Finally, $\bar{\Gamma}$ is the Gamma function. By taking the ratio between $\overline{wage}_{k,\ell,s}^{o=s}$ and $\overline{wage}_{k,\ell,s}^{o \neq s}$, taking logs and re-arranging terms, it is possible to get to equation 21:

$$\underbrace{\text{Ln} \left(\frac{\overline{wage}_{k,\ell,s}^s}{\overline{wage}_{k,\ell,s}^o} \right) + \frac{1}{\kappa} \text{Ln} \left(\frac{N_{k,\ell,s}^s}{N_{k,\ell,s}^o} \right)}_{\text{Data}} = \underbrace{\text{Ln} \left(\frac{w_{k,\ell,s}^s}{w_{k,\ell,s}^f} \right) + \frac{1}{\kappa} \text{Ln}(N_s T_{k,s})}_{\text{Source-IndustryFE}} - \underbrace{\frac{1}{\kappa} \text{Ln}(N_o T_{k,o})}_{\text{Origin-IndustryFE}} \quad (21)$$

Equation 21 shows that it is possible to run a regression at the source-origin-industry level using the H-1B data, and calculate the average wages and number of employees by group and regress a combination of those variables on a set of source-industry and origin-industry fixed effects. Once those fixed effects are estimated, it is possible to back out the log ratio of effective wages $\text{Ln} \left(\frac{w_{k,\ell,s}^s}{w_{k,\ell,s}^f} \right)$ which is our object of interest.

I proceed to estimate equation 19, by using the foreign MNEs in my H-1B data and run a firm level regression, using the log ratio of the wage bills of source and foreign workers as the dependent variable, and the log ratio of the effective wages estimated in equation 21 as an explanatory variable. The term $\text{Ln} \left(\frac{\psi_s^s}{\psi_s^f} \right)$ can be captured by a source fixed effect. Since adding a fixed effect for each source would limit the power of the regression, I only add a fixed effect that takes the value of 1 when the company is from India, as Indian companies seem to have a different recruitment process of migrants than other foreign companies. To consistently estimate equation 19, I need an instrument that shifts supply but is uncorrelated with unobserved demand shocks in order to identify the demand parameter $1 - \lambda$. I choose as an instrument the average wage paid in country s . The reason this is a valid instrument is that the wage in the origin country is one of the main predictors of migration flows as shown by [Grogger and Hanson \(2011\)](#) and [Docquier et al. \(2014\)](#), thus a change in the wage level in the origin country is a good predictor of the migration cost. The migration cost is directly related to the supply curve but is not correlated with demand shocks in the US that affect the ratio of effective wages between source and other foreign workers which makes it a good instrument for the relative effective wages in the US.

The OLS and 2SLS results of equation 19 can be found in table 4 and results are coherent with what we would expect. OLS results are upward biased, since they predict a λ lower than one and not

significant. When instrumenting for the effective wages, the estimated λ is 12.89, which is consistent with the estimates of [Ottaviano and Peri \(2012\)](#) who found an elasticity of substitution between native and immigrant college graduates of 12.89, and [Burstein et al. \(2018\)](#) who found an aggregate elasticity of 10.

Table 4: Estimating equation for λ

	OLS	2SLS		First Stage
	Log wage bill ratio	Log wage bill ratio		Log wage effective units ratio
Log wage effective units ratio	0.27 (0.31)	-11.89*** (3.62)	Instrument	0.139*** (0.03)
Source country = India	5.27*** (0.24)	9.71*** (1.41)		0.66*** (0.08)
N	369	369		369
Implied λ	0.73	12.89		-
1st stage F-stat				14.36

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust to controlling for industry FE

5.3 Implementation

To implement the model in a tractable way I need to make some simplifications. First, I assume the world is composed of six regions: United States, Canada, Western Europe, India, China-Taiwan and the Rest of the World (RoW). I also assume there are only three industries: Professional and Technical Services, which mainly includes the IT sector and consulting; high-skill intensive manufacturing which includes Chemicals, Machinery, Computer, Electronic, Electrical Equipment and Transportation manufacturing; and a third sector that includes everything else in the economy. I separate industries this way to focus on the implications for industries that have a high dependence on high-skill migration and where MNEs are predominantly concentrated.

I also impose additional restrictions on MNE production and migration. All sectors engage in international trade and hire domestic and foreign workers but I only allow for MNE activity in IT and high-skill manufacturing sectors. I restrict migration decisions such that workers cannot migrate to India, China-Taiwan or RoW unless they were born there. This captures a salient feature of the data where the main receiving countries for high-skill migrants and the US, Canada and countries in Western Europe.

I set $\theta = 4$, $\alpha = 1.7$, $\kappa = 5.95$ and $\lambda = 12.89$ consistent with the baseline parameters estimated in section 5. Finally, the estimation of the model requires me to use data on observed trade shares by industry, MNE shares by industry, migration shares from each origin o to each triplet i, ℓ, s and skill

shares for domestic, source country and other foreign workers for each triplet i, ℓ, s . In Appendix D I explain how do I construct the dataset to estimate the counterfactual. While the data on migration and skill shares for the US can be constructed using a combination of the ACS and my H-1B dataset, the data availability for migration in Canada and Europe is limited. In Appendix D I also explain how I impute some of the data for those regions using the US data together with additional datasets on global migration and industry structure.

Finally to calculate the equilibrium and following Walras Law I impose the normalization that World output stays constant as in equation 22. This normalization implies that the results should be interpreted as how do the endogenous variables change as a share of total World output.

$$X_{us} + X_{in} + X_{ca} + X_{eu} + X_{ch} + X_{oth} = \bar{X} \quad (22)$$

6 Counterfactual exercises

In this section I use the model to run two main counterfactual exercises that help quantify the link between high-skill migration, MNE activity and the location of production. As my model is expressed in changes between the observed equilibrium and the counterfactual equilibrium, I can feed a given change to the model and calculate how the endogenous variables such as output and welfare respond to such change. As a first exercise, I evaluate the long term implications of a more restrictive high-skill migration policy implemented by the US. In a second counterfactual I use the model to understand how does modeling migration affects the quantification of the welfare gains of MNE production.

6.1 Counterfactual 1: The implications of a more restrictive migration policy

As a first counterfactual exercise, I study how the location of high-skill industries and welfare would change in the long term if the US implements a more restrictive migration policy. To put my results into context, I explore the long term implications of a recent policy discussed in the US regarding high-skill migration and the H-1B program. The “Protect and Grow American Jobs Act” bill introduced by Rep. Darrell Issa in January 2017, proposes among other things to set a minimum wage for H-1B recipients that “is equal to the lesser of \$135,000 or the mean wage for applicants occupation in their area (but subject to a floor of no less than \$90,000)”⁶. The logic of this proposal is to limit migration by imposing a minimum wage such that high-ability individuals still come to the US, while middle skill workers, who presumably have a marginal product below the imposed lower

⁶More details on the proposed bill can be found [here](#).

bounds would not be hired by companies in the US, who would in turn hire American workers for those jobs.⁷.

In the model presented in section 4, there is not a direct counterpart to imposing a minimum wage, since abilities are distributed Frechet so despite of the migration cost there will always be some low-ability workers that choose to move to the US. On the other hand, it is true that if I increase the migration cost, fewer workers will migrate to the US and on average, those that do migrate will have higher abilities than those that choose not to migrate after the migration cost increases. Therefore, I can replicate a similar policy by increasing the migration cost from all origins to the US $\hat{\phi}_{o,us,s}$ such that it reduces the number of workers in a similar proportion than the policy would in the long term.

From the American Community Survey, in 2012, 70% of high skill migrants in the US earn below the threshold of \$90,000 a year. In the counterfactual scenario I increase the migration cost such that the total stock of high-skill migrants in the US decreases by 70%. To put these numbers into context, a decrease of 70% in the number of high-skill migrants in the US is consistent with a 7% decrease in the total US high-skill population or a 2.1% decrease in total US workers. The main specification is an extreme version of the long term decrease of migrants so I also present the results for lower decreases in appendix E.

As a first set of results, Table 5 summarizes how the change in migration costs to the US affects the total revenues generated by each sector-country pair relative to World output. High-skill industries in the US decrease their output more than the residual sector. Production in all other regions increase as a result of US migration restrictions. The IT and professional services sector would grow by 4.43% in India and 1.15% in Canada while the high-skill manufacturing sector would grow the most in India (2.18%) and China (0.79%). These results reaffirm the notion that a restriction to high-skill migration will predominantly affect high-skill industries and total economic activity in the US is expected to decrease as a result of such policies.

⁷The closed economy implications of selecting migrants through ability instead of the current quota system were studied by Sparber (2018) who finds that a policy that keeps the same number of migrants but selects them based on ability instead of randomly through a lottery would improve US welfare by 26.5 billion over a 6-year period.

Table 5: Percent Change in production relative to World output

	IT and Professional Services	High-Skill Manufacturing	Other
US	-2.98%	-3.34%	-2.61%
India	4.43%	2.18%	1.48%
Western Europe	0.60%	0.51%	0.52%
Canada	1.15%	0.69%	0.64%
China-Taiwan	0.77%	0.79%	0.68%
Rest of the World	0.57%	0.50%	0.49%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Change relative to World output.

Foreign MNEs in the US disproportionately contribute to such output decline relative to their size because of their greater intensity in migrant labor. As shown in table 6, both in high-skill manufacturing and IT, foreign MNEs operating in the US experience an output drop larger than US based companies. The contrast is particularly big for Indian and Chinese IT firms in the US, whose output would drop by 30.14% and 9.76% respectively. While foreign MNEs are more intensive in foreign workers than American companies, they also have a particular dependence for foreign workers from their own source country. It makes sense then that companies from countries where labor is cheaper are the one who get the biggest hit.

Table 6: Revenues in US by MNE source technology (relative to World output)

	IT and Professional Services	High-Skill Manufacturing
US	-2.77%	-3.06%
India	-30.14%	-7.85%
Western Europe	-5.57%	-3.97%
Canada	-5.59%	-3.97%
China-Taiwan	-9.76%	-6.49%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Change relative to World output.

Foreign MNEs account for 4.8% of production in the US IT sector, but account for 11.4% of the total drop in US IT output caused by the migration restriction. Similarly, in the High-Tech manufacturing sector, foreign MNEs account for 29.2% of production but are responsible for 35.2% of the drop in revenues. Appendix E shows the decomposition of the domestic and foreign MNE contributions in each US industry.

While the drop in production is a relevant channel through which migration restrictions affect welfare for US natives, there are some workers who gain from such restrictions. As shown in table 7 high-skill workers would experience an increase of 1.39% in their welfare due to the migration restriction. When there are fewer migrants firms substitute the missing foreign workers with natives pushing up the US native wage. Low skill workers on the other hand would see their welfare decreased by 2.01% given their complementarity with high-skill workers. Aggregating across skill types, total welfare for US workers would decrease by 0.98% when migration is restricted.

Table 7: Welfare for US natives

	Percent Change
Welfare high-skill US natives	1.39%
Welfare low-skill US natives	-2.01%
Total welfare	-0.98%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Welfare is calculated as average wage divided by the price index.

6.1.1 Mechanisms and Robustness

The baseline results presented in section 6.1 are a product of multiple mechanisms incorporated to the quantitative model that link migration to production and welfare. In this section, I proceed to disentangle each mechanism to show how are they driving my main result.

The stylized facts in section 3 motivated three main additions to the model. Fact 1 highlighted the link between foreign MNE production and migrant intensity, motivating the specific treatment of foreign MNEs in the model. Fact 2 showed that there was significant heterogeneity across industries in their intensity to hire migrants which motivated incorporating multiple industries into the model. Finally, Fact 3 suggested that migrants from different origins are likely to have a different comparative advantage across different industries, motivating to consider multiple origin countries into the analysis. In table 8 I compare the welfare effects of the baseline model with alternative models that remove each channel to understand how they drive the baseline result. Columns 2-3 compare the baseline with a model that does not include MNE production. Such model is equivalent to an multi-country, multi-industry Eaton and Kortum (2002) model that allows for migration. The data used assumes all companies producing in the US are domestic companies, so their intensity in hiring migrants is

the one observed for US companies. The model without MNE production understates the welfare losses by 5.4% since it no longer accounts for the specific productivity derived by foreign MNEs from source-country migrants. The MNE channel is not as big when looking at the aggregate effects since MNEs account for a fairly small share of total production in high-skill industries and the estimated elasticity of substitution between natives, source-country workers and other foreign workers is high. However, as shown in section 6.2 the migration channel does have a large impact in the welfare effects that stem from allowing MNE production.

As a second channel, I explore how do the results depend on incorporating multiple industries by comparing the baseline model to a single-sector model. As shown in columns 4-5, the single sector model overstates the gains for high-skill workers by 24.7% and overstates the losses for low-skill workers by 11.5%. In the baseline model, high-skill workers have a different ability in each sector that acts as a friction to mobility once migration is restricted. The single sector model does not incorporate that friction, so high-skill workers can move more freely to substitute the migrants. For low-skill workers the absence of such frictions is worse, since firms are less likely to substitute high for low skill labor, increasing the welfare losses from restricting migration.

Finally, I look into how the channel of multiple origin countries affects the results by comparing the baseline results with a two-country model. The results in columns 6-7 show that the two-country model overstates the welfare gains of high-skill workers by 7.2% and understates the welfare losses for low-skill workers by 2.6%. In the multi-country model workers from different origins had different comparative advantages across industries, so each origin provides high-effective units of labor to the US. In the two-country origin, we would expect fewer workers taking high ability draws for the US when compared to the multi-country model, hence providing a lower average effective units of migrants. For high-skill workers it becomes easier to replace migrants which in turn, overestimates welfare gains. As the migrants are on average less productive in the two-country model, the negative impact for low skill workers is lower.

Table 8: Understanding mechanisms - modeling assumptions

	Baseline	No MNE		One sector		Two country	
	Percent change	Percent change	Relative to baseline	Percent change	Relative to baseline	Percent change	Relative to baseline
High-skill natives	1.39%	1.41%	1.2%	1.74%	24.7%	1.49%	7.2%
Low-skill natives	-2.01%	-1.94%	-3.4%	-2.24%	11.5%	-1.96%	-2.6%
Total natives	-0.98%	-0.92%	-5.4%	-1.03%	5.8%	-0.91%	-6.8%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Column 1: Baseline results. Column 2-3: Model with no multinational activity. Column 4-5: Model using only one sector in each country. Column 6-7: Two countries US and Rest of the World, migration only allowed from RoW to US. Column "Relative to baseline" shows the percent change between the welfare change in the alternative model relative to the baseline model.

As a second set of mechanisms, I look into the assumptions of imperfect substitution between low and high-skill (regulated by α) and between native, source and other foreign high-skill workers (regulated by λ). In table 9 columns 2-3, I compute the model using $\lambda = 30$, which is closer to a model where there is perfect substitution among high-skill units of labor. The model with high λ underestimates the losses from restricting migration by 10%, since there is a lower productivity effect from migrants coming into the country. In a second test, I compute the model with $\alpha = 5$ to understand how results would change under a model where low and high skill workers are closer to perfect substitutes. Interestingly, as shown in columns 4-5, the welfare effects generated by migration would be highly muted when working with a higher elasticity of substitution. The model with $\alpha = 5$ would underestimate the welfare losses from restricting migration by 56.6%, and make both the gain for high-skill and losses for low-skilled closer to zero.

Table 9: Understanding mechanisms - elasticities

	Baseline	$\lambda = 30$		$\alpha = 5$		$\theta = 8.28$	
	Percent change	Percent change	Relative to baseline	Percent change	Relative to baseline	Percent change	Relative to baseline
High-skill natives	1.39%	1.65%	18.8%	0.18%	-86.9%	1.37%	-1.6%
Low-skill natives	-2.01%	-1.97%	-1.9%	-0.69%	-65.8%	-2.01%	0.2%
Total natives	-0.98%	-0.87%	-10.9%	-0.42%	-56.6%	-0.99%	1.0%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Column 1: Baseline results $\lambda = 12.89$, $\alpha = 1.7$ and $\theta = 4$. Column 2-3: same as baseline but $\lambda = 30$. Column 4-5: same as baseline but $\alpha = 5$. Column 6-7: same as baseline but $\theta = 8.28$. Column “Relative to baseline” shows the percent change between the welfare change in the alternative model relative to the baseline model.

Finally, I compute the model by changing the trade elasticity to use the value suggested by [Eaton and Kortum \(2002\)](#) of $\theta = 8.28$. The trade elasticity controls the dispersion of the producer productivities across countries. Higher values of θ would make productivities of producing in each country to be more concentrated, such that small changes in the marginal cost would create larger swings on where production is located. As shown in table 9, columns 6-7, results are quite similar when changing the dispersion of productivities, with the model with the high θ overstates welfare losses by only 1%. In appendix E I discuss further robustness regarding the elasticity of labor supply κ and incorporating correlation among ability draws. Overall results are not very sensitive to such modifications.

6.2 Counterfactual 2: Migration and the welfare gains of MNE production

Restrictions to migration have big implications for the activity of MNEs in the receiving country. To understand the aggregate implications of such result, I explore how do the welfare gains from MNE activity are affected by the channel of migration. A vast literature in international economics has used

quantitative models to measure the welfare gains from trade by looking at the change in welfare when going from autarky, where trade costs are assumed to be very large such that trade is prohibitive, to the observed trade flows in equilibrium. Similarly, for MNE production, the welfare gains of MNE production is the welfare change when going from an equilibrium where MNE costs are very large (MNE autarky) to an equilibrium where MNE flows are as in the data. Given my estimated model, a first contribution of this paper is to show that incorporating high-skill migration as an additional mechanism into a quantitative MNE model has significant implications for the distributional welfare gains across workers with different skills.

A sufficiently large change in the MNE costs $\hat{\delta}_{s,\ell}^k$ is fed into the model such that MNE flows go from the observed values in equilibrium to 0. By calculating how welfare changes between an “MNE autarky” situation and the observed equilibrium we can calculate the gains from MNE production. As shown in the first column of table 10, both low and high skill workers benefit from MNE production in high-skill industries. Such finding is intuitive since MNEs that move to the US bring new and more efficient technologies to produce some varieties domestically, lowering prices and increasing overall production and welfare. A second finding shown in column 1 is that high-skill migration to the US would increase by 8.2% when allowing for MNE production reinforcing the idea that MNEs have a larger intensity for migrants. Column 2, shows how the gains from MNE change when we consider a model with no migration closer to those used in the literature of MNE production. The model with no migration assumes the high-skill labor supply of each country is not mobile across countries but still allows for reallocation across sectors. The data used in this alternative model just considers the total high-skill workers in each country in the observed equilibrium treating all of them as native workers. As shown in column 2, the total welfare effects of MNE production remain almost unchanged in the model with no migration when compared to the baseline. The model with no migration overestimates the welfare gains of MNE production by only 3.25%.

Interestingly, the channel of migration does matter to quantify the distributional gains of MNE activity between low and high-skill workers. A model with no migration would overestimate the gains from MNE production by 34.21% while underestimating the gains for low-skill workers by 7.91%. When we allow for MNE production, high-skill MNEs bring better technologies that improve welfare but at the same time increase the number of high-skill migrants. Since high-skill migrants compete directly with native high-skill workers, they lower the equilibrium wages which offsets the gains from MNEs. Low skill workers on the contrary are complements to the high-skill migrants that join the country when MNEs are allowed. Therefore, migration contributes an additional gain towards welfare created by MNE production.

Table 10: Welfare gains from MNE production

	Baseline	No migration	Relative to baseline
Welfare high-skill natives US	1.17%	1.57%	34.21%
Welfare low-skill natives US	1.42%	1.31%	-7.91%
Total welfare US	1.35%	1.39%	3.25%
<hr/>			
Migrants in US	8.60%		

Percent changes in welfare of going from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\delta_{s,\ell}^k$ are very high such that MNE is prohibitive. Column 3 shows the welfare change in the no migration setting relative to the welfare change in the baseline model with migration.

The results in table 10 hold when looking at the MNE gains for migrant-receiving regions such as Europe and Canada as shown in Appendix F. For migrant sending countries such as China and India the direction of the results with and without migration are the opposite. In the model with migration, allowing for MNEs increases the demand for migrants in developed countries, taking away high-skill workers predominantly from India, China and Rest of the World. This increases the positive impact for high-skill workers who stay as they face lower competition from the migrants that leave. The model with no migration would therefore understate the MNE gains for high-skill workers in developing countries and overstate the gains for low skill workers in developing countries.

7 Discussion

This paper presents evidence of a strong link between high-skill migration, industry structure and inward MNE activity in the United States. Using a novel dataset on high-skill visas linked to firms global ownership I document the stylized fact that foreign MNEs have a “home-bias” towards hiring migrants from their home country relative to other migrants. The large magnitude of these effects suggest that own-source migrant workers have a productivity effect that helps MNEs operate abroad. I document two additional facts that suggest we should expect heterogeneous responses to migration restrictions across industries. First, high-skill intensive industries are more dependent on migrant labor potentially because they need skills not readily available in the domestic labor market. Second, immigrants from different countries have a comparative advantage in different industries, which further enhances the heterogeneity across industries.

Motivated by these facts, I present a flexible model that includes migration decisions of heterogeneous workers, trade and MNE activity and incorporate the main channels through which migration affects

production. Foreign workers are imperfect substitutes to high-skill natives and MNE companies receive an additional productivity when hiring workers from their own source country. At the same time, I allow for foreign workers to have a comparative advantage when migrating to work for MNEs from their home country which is a second channel through which the home-bias of foreign MNEs is incorporated into the model. I use my novel dataset to structurally estimate two of the key elasticities of the model: the elasticity of migration/labor supply and the elasticity of substitution between source-country workers, natives, and other migrants.

I use the estimated model to run two counterfactual exercises. First, I simulate the long term implications of restricting high-skill migration into the US in line with recent policies discussed to curtail high-skill migration. I increase the migration cost into the US such that it decreases the stock of migrants by 70%, consistent with a 2.1% decrease in total US workforce. The quantitative estimates indicate that production in IT and High-tech manufacturing in the US would decrease by 2.98%-3.34%, disproportionately driven by a drop in foreign MNE activity in the US. Welfare for US native workers would decrease by 0.98% but there are distributional consequences. High-skill workers gain from the reduced labor market competition by 1.39% while low-skill workers lose by 2.01%. In a second counterfactual exercise, I use my model to calculate the welfare gains of MNE production, by calculating welfare gains of going from MNE “autarky” to the observed MNE flows. Given the strong connection between MNEs and high-skill migration I show that a model without migration would overestimate the MNE welfare gains for high-skill workers by 34% and underestimate the MNE gains for low-skill workers by 7.9%. This finding suggests that migration is a relevant channel to quantify the distributional welfare gains of MNEs.

The evidence provided in this project is useful to inform about the long term implications of migration policy and quantify the relevance of different channels through which migration affects production and welfare. The model is a good first step towards understanding the relationship between MNEs and migration but there is still a long way to go. First, the current paper uses a static model, focusing in the long term implications for MNEs but there are potentially large dynamic implications of the transfer of migrants within the firm as a vehicle for knowledge diffusion and technology transfer. Second, the feature of home-bias is incorporated into the model to match observed outcomes in equilibrium but little is known about the reasons behind this empirical pattern. Future work could delve deeper into the decision of MNEs to hire migrant workers and how it relates to the use of other inputs such as intra-firm intermediate inputs and investment in new technologies.

References

- Alviarez, V. (2018). Multinational Production and Comparative Advantage. *Journal of International Economics*. Forthcoming.
- Arkolakis, C., N. Ramondo, A. Rodriguez-Clare, and S. Yeaple (2018). Innovation and Production in the Global Economy. *American Economic Review*. Forthcoming.
- Aubry, A., H. Rapoport, and A. Reshef (2018). Migration, FDI and the Margins of Trade. *Working paper*.
- Brucker, H., S. Capuano, and A. Marfouk (2013). Education, gender and international migration: insights from a panel-dataset 1980-2010. *mimeo*.
- Bryan, G. and M. Morten (2018). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy*. Forthcoming.
- Burstein, A., G. Hanson, L. Tian, and J. Vogel (2018). Tradability and the Labor-Market Impact of Immigration: Theory and Evidence from the U.S. *Working paper*.
- Caliendo, L., L. Opromolla, F. Parro, and A. Sforza (2018). Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement. *Working Paper*.
- Card, D. and T. Lemieux (2001, May). Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis. *The Quarterly Journal of Economics* 116(2), 705–746.
- Dekle, R., J. Eaton, and S. Kortum (2008). Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers* 55, 511540.
- Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018, June). The Geography of Development. *Journal of Political Economy* 126(3), 903–983.
- di Giovanni, J., A. Levchenko, and F. Ortega (2015, February). A Global View of Cross-Border Migration. *Journal of the European Economic Association* 13(1), 168–202.
- Docquier, F., C. Ozden, and G. Peri (2014, September). The Labour Market Effects of Immigration and Emigration in OECD Countries. *The Economic Journal* 124, 1106–1145.
- Docquier, F., G. Peri, and I. Ruysen (2014). The Cross-country Determinants of Potential and Actual Migration. *International Migration Review* 48(09), S37–S99.
- Doran, K., A. Gelber, and A. Isen (2015). The Effect of High-Skilled Immigration Policy on Firms: Evidence from H-1B Visa Lotteries. *Working Paper*. NBER Working Paper 20668.
- Eaton, J. and S. Kortum (2002). Technology, Geography and Trade. *Econometrica* 70, 1741–1779.

- Goldin, C. and L. F. Katz (2007). Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing. *Brookings Papers on Economic Activity* (2), 135–65.
- Gould, D. (1994, May). Immigrant links to the home country: Empirical implications for U.S. bilateral trade flows. *Review of Economics and Statistics* 76(2), 302–316.
- Grogger, J. and G. Hanson (2011). Income maximization and the selection and sorting of international migrants. *Journal of Development Economics* 95, 42–57.
- Gumpert, A. (2018). The organization of knowledge in multinational firms. *Journal of the European Economic Association*. Forthcoming.
- Head, K. and T. Mayer (2018). Brands in motion: How frictions shape multinational production. *American Economic Review*.
- Hiller, S. (2013). Does immigrant employment matter for export sales? Evidence from Denmark. *Review of World Economics / Weltwirtschaftliches Archiv* 149(2), 369–394.
- Hsieh, C.-T., E. Hurst, C. Jones, and P. Klenow (2018). The Allocation of Talent and U.S. Economic Growth. *Working paper*.
- Hunt, J. and M. Gauthier-Loiselle (2010). How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics* 2:2.
- Iranzo, S. and G. Peri (2009). Migration and trade: theory with an application to the Eastern/Western European integration. *Journal of International Economics* 79, 1–19.
- Javorcik, B. S., C. Ozden, M. Spatareaun, and C. Neagu (2011, March). Migrant networks and foreign direct investment. *Journal of Development Economics* 94(2), 231–241.
- Katz, L. F. and K. M. Murphy (1992, February). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics* 107(1), 35–78.
- Keller, W. and S. Yeaple (2013). The Gravity of Knowledge. *American Economic Review* 103(4), 1414–1444.
- Kerr, W. and W. Lincoln (2010). The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention. *Journal of Labor Economics* 28(3), 473–508.
- Khanna, G. and N. Morales (2018). The IT Boom and Other Unintended Consequences of Chasing the American Dream. *Working Paper*.
- Lagakos, D. and M. E. Waugh (2013, April). Selection, Agriculture, and Cross-Country Productivity Differences. *The American Economic Review* 103(2), 948–980.

- Lee, E. (2017). Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers. *Working paper*.
- Levchenko, A. and J. Zhang (2016, April). The Evolution of Comparative Advantage: Measurement and Welfare Implications. *Journal of Monetary Economics* 78, 96–111.
- Liu, C. (2017). Quantifying the Impacts of a Skill-Based US Immigration Reform. *Working paper*.
- Mion, G., L. Opromolla, and A. Sforza (2018). The Diffusion of Knowledge via Managers Mobility. *Working Paper*.
- Ottaviano, G. I. P. and G. Peri (2012, February). Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association* 10(1), 152197.
- Peri, G., K. Shih, and C. Sparber (2015a). Foreign and Native Skilled Workers: What Can We Learn from H-1B Lotteries? *Working paper*. NBER Working Paper No. 21175.
- Peri, G., K. Shih, and C. Sparber (2015b, July). Foreign STEM Workers and Native Wages and Employment in U.S. Cities. *Journal of Labor Economics* 33(S1), S225–S255.
- Peri, G. and C. Sparber (2011). Highly-Educated Immigrants and Native Occupational Choice. *Industrial Relations* 50:3.
- Ramondo, N. and A. Rodriguez-Clare (2013, April). Trade, Multinational Production, and the Gains from Openness. *Journal of Political Economy* 121(2), 273–322.
- Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford economic papers* 3, 135146.
- Santos Silva, J. M. C. and S. Tenreyro (2006, November). The Log of Gravity. *The Review of Economics and Statistics* 88(4), 641658.
- Simonovska, I. and M. Waugh (2014, January). The elasticity of trade: Estimates and evidence. *Journal of International Economics* 92(1), 34–50.
- Sparber, C. (2018, January). Choosing Skilled Foreign-Born Workers: Evaluating Alternative Methods for Allocating H-1B Work Permits. *Industrial Relations: A Journal of Economy and Society* 57(1), 3–34.
- Tintelnot, F. (2017). Global Production with Export Platforms. *Quarterly Journal of Economics* 132(1), 157–209.
- Wang, C.-K. (2014). Bilateral Migration and Multinationals: On the Welfare Effects of Firm and Labor Mobility. *Working paper*.

Yeaple, S. (2018, May). The Innovation Activities of Multinational Enterprises and the Demand for Skilled-Worker, Non-Immigrant Visas. *NBER book "High-Skilled Migration to the United States and its Economic Consequences"*, 41 – 69. Gordon H. Hanson, William R. Kerr, and Sarah Turner, editors.

A H-1B and L-1 visa dataset construction

A key contribution of this paper is to use a novel dataset on high-skill visas in the US that allows to link demand for foreign high-skill labor to MNE activity. In this section, I describe how such dataset was constructed. As a first step, I submitted a Freedom of Information Act (FOIA) request to the United States Citizenship and Immigration Services (USCIS) for the universe of forms I-129 approved between 2012 and 2014 for H-1B and L-1 visas. The I-129 is submitted to USCIS after the lottery takes place in the case of the H-1Bs so one attractive feature of this data is that it includes only those migrants who effectively end up coming to the US. The dataset obtained through FOIA included for each approved visa, the name of the firm, location, place of work, wage, occupation, start and end date of employment and origin country as main covariates. It also includes the basis for classification of the visas indicating whether the I-129 was filed for new employment, change of employer, renewal, amendment or other purposes. As visas are valid for 3 years but can be renewed for an additional 3 for the H-1B, a new I-129 is needed for such renewal. The data provided by USCIS had a total of 933,838 forms associated to H-1Bs and 126,964 associated to L-1 for the relevant period. Wage data was not available for L-1 visas but all other covariates were complete.

In a second stage, I proceed to match the FOIA database with the corporate database Orbis, to find two key pieces of information: the industry and the country of incorporation of the Global Ultimate Owner (GUO) of the firm that hired the migrant worker in the US. The GUO is the “individual or entity at the top of the corporate ownership structure” who owns the affiliate for more than 50% and its not being majority owned by any other company worldwide. The information from Orbis is complemented by additional corporate ownership information from D&B Hoovers and Uniworld, which complement the information from Orbis and serve as a quality check for some cases where Orbis data is incomplete. The FOIA data and Orbis do not have a common identifier that allows to easily match observations but Orbis has the advantage of having its own statistical matching tool that allows taking the Name and City provided by the FOIA data and finding the the firm record in Orbis for a firm that matches those characteristics. While the Orbis matching algorithm does a good job finding the relevant companies, many records are not matched because of the FOIA record including some variant of the firm name not recognized. These observations have to be dealt with mostly by hand which makes this process very time consuming. To narrow the sample of companies that need to be matched I proceed to limit the sample in two main ways. First, I limit the search to all employers listed in the FOIA data who have submitted at least 10 petitions over the period between 2012-2014. As shown in table 11, those with fewer than 10 petitions account for 21% of the total H-1B petitions and 44.6% of L-1 petitions. As a second step, within those employers with more than 10 petitions I exclude from the matching employers in the education, hospitals or government sectors since MNEs are generally not present in these industries. Such employers account for 8.7% of the total H-1B petitions and 0% of L-1 petitions. Finally, a very small group of employers are not found in Orbis who account for 3.2% of H-1B petitions and 0.6% of L-1 petitions. This leaves us with a match rate of 66.9% for H-1Bs and 54.8% for L-1 petitions. The FOIA-Orbis dataset is used to show the stylized facts presented in section 3 and to impute the data for MNE companies labor share between source and foreign workers needed to estimate the model but no aggregates are calculated using this data which makes the lower match rate not a substantive matter in the quantitative exercise.

Table 11: Sample matched to Orbis

	H-1B		L-1	
	Count	Share	Count	Share
Total petitions	933838	100.0%	126964	100.0%
Matched to Orbis	624777	66.9%	69519	54.8%
Not matched to Orbis				
Hospitals, Colleges and Government	81390	8.7%	0	0%
Less than 10 petitions 2012-14	197515	21.2%	56648	44.6%
Other, not matched	30156	3.2%	797	0.6%

Counts include all petitions between 2012 and 2014, including all basis for classification. “Less than 10 petitions” includes petitions filed by firms who submitted less than 10 petitions in the 2012-2014 period.

B Empirical facts details

Fact 1: Foreign MNE companies tend to recruit more workers from their source country

The first fact in section 3 shows that there is a strong home-bias effect, where foreign MNEs hire more migrant workers from their source country s than other companies in the US. In this section I present additional results that confirm the result holds under different specifications. For expositional simplicity, I present the robustness results with a pooled regression as in equation 23, that presents the average home-bias effect across different source countries.

$$\ln(N_{i,o,s}) = \gamma_0 + \gamma \mathbb{1}(\text{origin} = \text{source}) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \quad (23)$$

Where $\ln(N_{i,o,s})$ is the log number of migrants in k, o, s . $\delta_{k,o}$ is an industry-origin fixed effect and $\delta_{k,s}$ is a source-industry fixed effect. The key coefficient of interest is γ which measures how much more likely it is that a company from source s will hire someone from $o = s$ relative to $o \neq s$ when compared to all other companies from other source countries. As shown in Table 12, we find evidence of home bias both when looking at the H-1B alone and the H-1B together with L-1.

As in the disaggregated regression in section 3 the magnitude of the home bias is large. As shown in Table 12, columns 1-3, controlling for worker and source country fixed effects is relevant to isolate the home-bias effect. Interpreting the result shown in the 3rd column, companies from country s in industry i are 125.6% more likely to hire someone from country s than any other country when compared to companies not from s . Column 4 shows that the result holds and it is even larger when only using the H-1B data. The estimation in section 5 uses data on wages which is only available for H-1Bs so it is reassuring that results hold when excluding L-1 visas. Column 5 shows these results are robust to running the regression at the origin-source level, by aggregating the data across all industries. The aggregate home-bias is a bit larger when not considering industries which is in line with having a positive correlation between origin-industry and source-industry comparative advantage.

Finally column 6 shows the results are robust to including source-origin pairs for which the data shows 0 observations. To handle zero values, I estimate the parameters using a Poisson Pseudo Maximum Likelihood (PPML) to include zero observations as suggested by Santos Silva and Tenreyro (2006).

Table 12: Dependent variable: Log Number of Immigrants from origin o , employed in MNEs from source country s in industry i

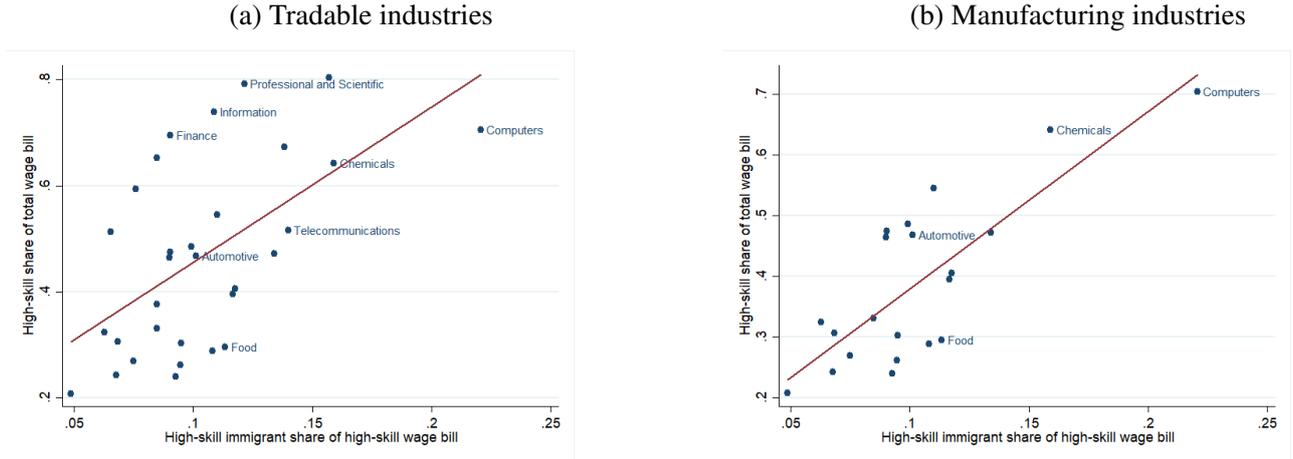
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(source = origin)$	-0.326 (0.288)	0.169 (0.212)	1.256*** (0.173)	1.38*** (0.205)	1.937*** (0.202)	2.289*** (0.101)
N obs	3,369	3,369	3,369	3,369	633	972
Sample	H-1B+L-1	H-1B+L-1	H-1B+L-1	H-1B	H-1B+L-1, no industry	H-1B+L-1, no industry, including zeros
Industry FE	x					
Source-Industry FE		x				
Source-Industry, Origin-Industry FE			x	x		
Source and Industry FE					x	x

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SE clustered at the source-nationality level. Visas for new employment filed in 2012, 2013 and 2014.

Fact 2: Heterogeneity across industries in recruiting high-skill migrants.

As shown by fact 2 in section 3 there is a positive relationship between the share of the wage bill spent in college graduates and the share of the college graduate wage bill spent in migrants. As an additional exercise, I show that the correlation is even stronger when just looking at a more comparable set of industries. As shown in Figure 4a when narrowing the sample to tradable industries (excluding education, health, government and other non-tradable industries), the correlation increases from 42.1% to 56.9%. When just looking at manufacturing industries, the correlation goes up to 79.1%.

Figure 4: Skill and migrant intensity



Vertical Axis: Skill Intensity, share of wage bill spent on college graduates by industry. Horizontal Axis: Share of college graduate wage bill spent on migrants. Left panel includes all tradable industries at the 2-3 digit NAICS level. Right panel includes only manufacturing industries. Wage bill data taken from the American Community Survey 2012.

Fact 3: Immigrants are more likely to select into migration to work in industries where the home country has a comparative advantage.

The final fact in section 3 shows that workers from different origins have a different comparative advantage across industries. The comparative advantage of the origin country in each industry relative to the US is used as a proxy for the comparative advantage of the workers from each origin across industries. To calculate the relative comparative advantage term I follow the methodology proposed by Eaton and Kortum (2002) (EK) and extended to a multi-industry setting as in Levchenko and Zhang (2016). Using the gravity equation of a multi sector EK model together with data on the bilateral trade flows and wages it is possible to back out the comparative advantage term for each country and industry.⁸ From EK we know that the share of goods bought by country n from country ℓ relative to the share of goods country n buys from itself can be written as in equation 24:

$$\frac{\pi_{n,\ell}^k}{\pi_{n,n}^k} = \frac{T_\ell^k (c_\ell^k \tau_{n,\ell}^k)^{-\theta}}{T_n^k (c_n^k)^{-\theta}} \quad (24)$$

Where T_ℓ^k , T_n^k are the comparative advantage terms for ℓ and n in industry k . c_ℓ^k and c_n^k are the unit costs for ℓ and n in industry k and $\tau_{n,\ell}^k$ is the iceberg trade costs of selling goods from ℓ to n . As a first step I approximate log trade costs using a bilateral measure of distance ($d_{n,\ell}^k$), common language indicator ($b_{n,\ell}^k$), common currency union indicator ($CU_{n,\ell}^k$), regional trade agreement indicator ($RTA_{n,\ell}^k$), an importer fixed effect ($im_{n,\ell}^k$) and an error term ($v_{n,\ell}^k$) as in Eaton and Kortum (2002) presented in equation 25.

⁸This model is nested in the model explained in section 4. The two models are the same when MNE costs and migration costs are prohibitive (such that countries only trade) and the elasticity of substitution between low and high skill workers is infinity (homogeneous labor). While the comparative advantage estimated in the full model would be different than the one estimated through this exercise, the simple model should give a good first-order approximation of the relative comparative advantages in each country-industry.

$$\log(\tau_{n,\ell}^k) = d_{n,\ell}^k + b_{n,\ell}^k + CU_{n,\ell}^k + RTA_{n,\ell}^k + im_{n,\ell} + v_{n,\ell}^k \quad (25)$$

By taking logs on equation 24 and using the trade cost specification in equation 25, I ran an industry level equation to back out the convolution of relative productivities and relative unit costs between country ℓ and the US for each industry as in equation 26:

$$\underbrace{\text{Observed trade flows}}_{Ln\left(\frac{\pi_{n,\ell}^k}{\pi_{n,n}^k}\right)} = \underbrace{Ln(T_\ell^k(c_\ell^k)^{-\theta})}_{\text{Exporter FE}} - \underbrace{Ln(T_n^k(c_n^k)^{-\theta})}_{\text{Importer FE}} - \underbrace{\theta im_{n,\ell} - \theta d_{n,\ell}^k - \theta b_{n,\ell}^k - \theta CU_{n,\ell}^k - \theta RTA_{n,\ell}^k}_{\text{Trade costs approximation}} + \underbrace{v_{n,\ell}^k}_{\text{Error term}} \quad (26)$$

After estimating equation 26, the exporter fixed effect gives us for each country an estimate for $Ln(T_\ell^k(c_\ell^k)^{-\theta})$ relative to the omitted country (US). In the homogeneous single factor model, the unit cost (c_ℓ^k) is the wage, so using relative wages between each country ℓ and the US, and $\theta = 4$ following [Simonovska and Waugh \(2014\)](#) it is possible to back out the relative technologies in industry k between each country ℓ and the US.

C Equilibrium details

The equilibrium of the model can be characterized by the following set of equations:

1. MNE shares - one for each s - k - ℓ triplet

$$\pi_{k,s,\ell}^{mne} = \frac{\left(c_{\ell,s}^k \times \delta_{\ell,s}^k\right)^{-\theta}}{\sum_{s'} \left(c_{\ell,s'}^k \times \delta_{\ell,s'}^k\right)^{-\theta}} \quad (27)$$

2. Effective technology in country ℓ - one for each k - ℓ pair:

$$\tilde{T}_\ell^k = \sum_s T_s^k \left(c_{\ell,s}^k \times \delta_{\ell,s}^k\right)^{-\theta} \quad (28)$$

3. Trade shares - one for each k - ℓ - n triplet.

$$\pi_{k,\ell,n}^{trade} = \frac{(\tau_{\ell,n}^k)^{-\theta} \tilde{T}_\ell^k}{\sum_{\ell'} (\tau_{\ell',n}^k)^{-\theta} \tilde{T}_{\ell'}^k} \quad (29)$$

4. Domestic price index - one for each k - n pair

$$P_{k,n} = \bar{\Gamma} \left(\sum_\ell (\tau_{\ell,n}^k)^{-\theta} \tilde{T}_\ell^k \right)^{-\frac{1}{\theta}} \quad (30)$$

Where $\bar{\Gamma} = \Gamma \left(\frac{1-\sigma+\theta}{\theta} \right)$

5. Unit cost in country ℓ industry k , source technology s

$$c_{\ell,s}^k = \bar{\gamma} \prod_{k'=1}^K P_{k',\ell}^{\gamma_{\ell,k,k'}} \left((\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha} \right)^{\frac{1}{1-\alpha} (1 - \sum_{k'} \gamma_{\ell,k,k'})} \quad (31)$$

Where $\bar{\gamma}$ is a constant that depends on $\gamma_{\ell,k,k'}$. $w_{L,\ell}$ is the low-skill labor wage in country ℓ which is the same across industries and source technologies in ℓ given free mobility of low-skill labor. $c_{k,\ell,s}^h$ is the high-skill labor unit cost which is different for each triplet k, ℓ, s given that high skill workers have different abilities for each triplet, which makes companies in each triplet to face a different labor pool of effective units, hence a different high-skill labor cost. Firms employ domestic d , source-country s and other foreign f effective units of high-skill labor. If a company is located in their source country, source and native effective units are perfect substitutes.

$$c_{k,\ell,s}^h = \left((\psi_{k,\ell,s}^d)^\lambda (w_{k,\ell,s}^d)^{1-\lambda} + (\psi_{k,\ell,s}^s)^\lambda (w_{k,\ell,s}^s)^{1-\lambda} + (\psi_{k,\ell,s}^f)^\lambda (w_{k,\ell,s}^f)^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \quad (32)$$

6. Share of non-college ($\Theta_{k,\ell,s}^L$), college ($\Theta_{k,\ell,s}^H$) - one for each k - ℓ - s triplet.

$$\Theta_{k,\ell,s}^L = \frac{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha}}{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}} \quad \Theta_{k,\ell,s}^H = \frac{(\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}}{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}} \quad (33)$$

7. Share of native ($\Theta_{k,\ell,s}^d$), source ($\Theta_{k,\ell,s}^s$), other foreign ($\Theta_{k,\ell,s}^f$) expenditure - one for each k - ℓ - s triplet.

$$\Theta_{k,\ell,s}^x = \frac{(\psi_{k,\ell,s}^x)^\lambda (w_{k,\ell,s}^x)^{1-\lambda}}{\sum_{x'} (\psi_{k,\ell,s}^{x'})^\lambda (w_{k,\ell,s}^{x'})^{1-\lambda}} \quad \text{for } x, x' = \{d, s, f\} \quad (34)$$

8. Demand for low-skill (L), native (d), source (s), other foreign (f) workers - one for each k - ℓ - s triplet.

$$w_{L,\ell} L_{k,\ell,s} = \left(1 - \sum_{k'} \gamma_{\ell,k,k'} \right) \Theta_{k,\ell,s}^L \pi_{k,s,\ell}^{mne} I_{\ell,k} \quad (35)$$

$$w_{x,\ell} H_{k,\ell,s}^x = \left(1 - \sum_{k'} \gamma_{\ell,k,k'} \right) \Theta_{k,\ell,s}^H \Theta_{k,\ell,s}^x \pi_{k,s,\ell}^{mne} I_{\ell,k} \quad \text{with } x = d, s, f \quad (36)$$

9. Trade balance - Budget constraint - one for each ℓ . $I_{\ell,k}$ is the revenues gained in ℓ industry k , X_n is the total labor income in country n , \bar{L}_ℓ total low skill labor supply.

$$I_{\ell,k} = \sum_n \pi_{k,\ell,n}^{trade} \gamma_{k,n} X_n \quad (37)$$

$$X_n = w_{L,\ell} \bar{L}_\ell + \sum_{k,\ell,s,x} w_{k,\ell,s}^x H_{k,\ell,s}^x \quad \text{with } x = d, s, f \quad (38)$$

10. Low-skill market clearing - one for each ℓ

$$\sum_{k,s} w_{L,\ell} L_{k,\ell,s} = w_{L,\ell} \bar{L}_\ell \quad (39)$$

11. Migration shares - one for each o - k - ℓ - s group

$$\pi_{o,k,\ell,s}^{mig} = \frac{A_{o,k} w_{k,\ell,s}^\kappa \phi_{o,\ell,s}^{-\kappa}}{\sum_{\ell',s',k'} A_{o,k'} w_{\ell',\ell',s'}^\kappa \phi_{o',\ell',s'}^{-\kappa}} \quad (40)$$

12. High-skill market clearing, native (d), source (s), other foreign (f) - one for each k - ℓ - s triplet. N_o is the total number of workers born in o .

$$w_{k,\ell,s}^d H_{k,\ell,s}^d = w_{k,\ell,s}^d (\pi_{o,k,\ell=s,o}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,\ell}^{\frac{1}{\kappa}} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \quad (41)$$

$$w_{k,\ell,s}^s H_{k,\ell,s}^s = w_{k,\ell,s}^s (\pi_{o,k,\ell \neq o,s=o}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,s}^{\frac{1}{\kappa}} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \quad (42)$$

$$w_{k,\ell,s}^f H_{k,\ell,s}^f = \sum_{o \neq \{\ell,s\}} w_{k,\ell,s}^f (\pi_{o,k,\ell \neq o,s \neq o}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,o}^{\frac{1}{\kappa}} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \quad (43)$$

C.1 Writing the equilibrium in proportional changes

Following Dekle et al. (2008), I re-write all equilibrium equations in proportional changes. That is, I can re-write each variable x as $\hat{x} = \frac{x'}{x}$ where x is the variable under the real scenario and x' is the value of the variable under the counterfactual. In the remainder of this section, I show how this approach allows me to distinguish 4 components needed to estimate the model: **parameters needed for estimation**, endogenous variables, **parameters not needed for estimation** and **data**. I use the color scheme together with the equilibrium equations to clearly see how the different components affect the estimation of the model. Equations 35, 36, 41 and 42 are multiplicative so I omit them in the analysis below to focus on the ones that require data to be calculated.

1. MNE shares / Effective technology in country ℓ

$$\hat{\pi}_{k,s,\ell}^{mne} = \frac{(\hat{c}_{\ell,s}^k \times \hat{\delta}_{\ell,s}^k)^{-\theta}}{\sum_{s'} (\hat{c}_{\ell,s'}^k \times \hat{\delta}_{\ell,s'}^k \pi_{k,s,\ell}^{mne})^{-\theta}} ; \quad \hat{T}_\ell^k = \sum_s \hat{T}_s^k (\hat{c}_{\ell,s}^k \times \hat{\delta}_{\ell,s}^k \pi_{k,s,\ell}^{mne})^{-\theta}$$

2. Trade shares/ Domestic price index

$$\hat{\pi}_{k,\ell,n}^{trade} = \frac{(\hat{\tau}_{\ell,n}^k)^{-\theta} \hat{T}_\ell^k}{\sum_{\ell'} (\hat{\tau}_{\ell',n}^k)^{-\theta} \hat{T}_{\ell'}^k \pi_{k,\ell,n}^{trade}} ; \quad \hat{P}_{k,n} = \left(\sum_{\ell} (\hat{\tau}_{\ell,n}^k)^{-\theta} \hat{T}_\ell^k \pi_{k,\ell,n}^{trade} \right)^{-\frac{1}{\theta}}$$

3. Unit cost / high-skill unit cost

$$\hat{c}_{\ell,s}^k = \prod_{k'=1}^K \hat{P}_{k',\ell}^{\gamma_{\ell,k,k'}} \left((\hat{\psi}_{k,\ell}^l)^\alpha \hat{w}_{L,\ell}^{1-\alpha} \Theta_{k,\ell,s}^L + (\hat{\psi}_{k,\ell}^h)^\alpha (\hat{c}_{k,\ell,s}^h)^{1-\alpha} \Theta_{k,\ell,s}^H \right)^{\frac{1}{1-\alpha} (1-\sum_{k'} \gamma_{\ell,k,k'})}$$

$$\hat{c}_{k,\ell,s}^h = \left((\hat{\psi}_{k,\ell,s}^d)^\lambda (\hat{w}_{k,\ell,s}^d)^{1-\lambda} \Theta_{k,\ell,s}^d + (\hat{\psi}_{k,\ell,s}^s)^\lambda (\hat{w}_{k,\ell,s}^s)^{1-\lambda} \Theta_{k,\ell,s}^s + (\hat{\psi}_{k,\ell,s}^f)^\lambda (\hat{w}_{k,\ell,s}^f)^{1-\lambda} \Theta_{k,\ell,s}^f \right)^{\frac{1}{1-\lambda}}$$

4. Trade balance / Budget constraint (with $x = d, s, f$)

$$\hat{I}_{\ell,k} = \sum_n \hat{\pi}_{k,n,\ell}^{trade} \hat{X}_n \underbrace{\frac{\pi_{k,n,\ell}^{trade} \gamma_{k,n} X_n}{\sum_n \pi_{k,n,\ell}^{trade} \gamma_{k,n} X_n}}_{\text{Share sold to } n: \Lambda_{k,n,\ell}} ; \quad \hat{X}_\ell = \hat{w}_{L,\ell} \hat{L}_\ell \underbrace{\frac{w_{L,\ell} \bar{L}_\ell}{X_\ell}}_{\text{Low-skill share } \Lambda_\ell^L} + \sum_{k,\ell,s,x} \hat{w}_{k,\ell,s}^x \hat{H}_{k,\ell,s}^x \underbrace{\frac{w_{k,\ell,s}^x H_{k,\ell,s}^x}{X_\ell}}_{\text{High-skill share } \Lambda_{k,\ell,s}^x}$$

5. Low-skill market clearing / Migration share

$$\sum_{k,s} \hat{w}_{L,\ell} \hat{L}_{k,\ell,s} \underbrace{\frac{w_{L,\ell} L_{k,\ell,s}}{\sum_{k,s} w_{L,\ell} L_{k,\ell,s}}}_{\text{Low-skill share } \Lambda_{k,\ell,s}^L} = \hat{w}_{L,\ell} \hat{L}_\ell ; \quad \hat{\pi}_{o,k,\ell,s}^{mig} = \frac{\hat{A}_{o,k} \hat{w}_{k,\ell,s}^\kappa \hat{\phi}_{o,\ell,s}^{-\kappa}}{\sum_{\ell',s',k'} \hat{A}_{o,k'} \hat{w}_{i',\ell',s'}^\kappa \hat{\phi}_{o',\ell',s'}^{-\kappa} \pi_{o,k,\ell,s}^{mig}}$$

6. Other-foreign market clearing

$$\hat{w}_{k,\ell,s}^s \hat{H}_{k,\ell,s}^s = \sum_{o \neq \ell,s} \hat{w}_{k,\ell,s}^f (\hat{\pi}_{o,k,\ell \neq o, s \neq o}^{mig})^{\frac{\kappa-1}{\kappa}} \hat{N}_\ell \hat{A}_{k,o}^{\frac{1}{\kappa}} \underbrace{\frac{w_{k,\ell,s}^f (\pi_{o,k,\ell \neq o, s \neq o}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,o}^{\frac{1}{\kappa}}}{\sum_{o \neq \{\ell,s\}} w_{k,\ell,s}^f (\pi_{o,k,\ell \neq o, s \neq o}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,o}^{\frac{1}{\kappa}}}}_{\text{Share } o \text{ in } \ell, s, k: \Lambda_{k,\ell,s}^o}$$

The equations above imply that the change in the endogenous variables can be computed as long as I have estimates of the 4 key elasticities (θ , α , λ and κ), the Cobb-Douglas share on intermediate inputs $\gamma_{\ell,k,k'}$ and data on the following equilibrium allocations: Trade shares ($\pi_{k,\ell,n}^{trade}$); MNE shares ($\pi_{k,s,\ell}^{mne}$); Migration shares ($\pi_{o,k,\ell,s}^{mig}$); Share of wage bill spent in low-skill ($\Theta_{k,\ell,s}^L$) and high-skill ($\Theta_{k,\ell,s}^H$) for each k, ℓ, s ; Share of high-skill wage bill spent on natives ($\Theta_{k,\ell,s}^d$) source workers ($\Theta_{k,\ell,s}^s$) and other foreign ($\Theta_{k,\ell,s}^f$); Share of low-skill in total labor income (Λ_ℓ^L); Share of high-skill type x in s, ℓ, k in total labor income ($\Lambda_{k,\ell,s}^x$); Share of low-skill employed in k, ℓ, s ($\Lambda_{k,\ell,s}^L$); Share of wage bill of k, ℓ, s on migrants from $o \neq \{\ell, s\}$ ($\Lambda_{k,\ell,s}^o$) and production shares ($\Lambda_{k,n,\ell}$). I explain how the dataset is constructed in Appendix D.

One of the advantages of the exact hat algebra procedure is that several parameters do not change between the real and the counterfactual so they do not need to be explicitly solved for. These parameters are MNE costs ($\delta_{\ell,s}^k$), producer comparative advantage (T_s^k), trade costs ($\tau_{k,\ell,n}^k$), production function labor shares ($\psi_{k,\ell}^l, \psi_{k,\ell}^h, \psi_{k,\ell,s}^d, \psi_{k,\ell,s}^s, \psi_{k,\ell,s}^f$), Total low-skill (\bar{L}_ℓ) and high-skill (N_ℓ) labor born in ℓ , individual ability comparative advantage ($A_{o,k}$) and the migration costs ($\phi_{o,\ell,s}$). The hat-algebra approach makes it easier to calculate the counterfactuals. For example, the counterfactuals computed in sections 6.2 and 6.1 will compute how the

equilibrium changes when the MNE cost in all countries $\delta_{\ell,s}^k$ or the migration cost to the US $\phi_{o,us,s}$ exogenously change.

D Dataset for counterfactual

This section describes how the dataset needed to compute the model is constructed. The description is based on the simplifications explained in section 5.3 and the data needed as outlined in appendix C.1. I construct the database for 6 regions of the World. US, Canada, India, China-Taiwan, Western Europe (including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom) and the Rest of the World that includes a set of 41 countries who have available production data in the OECD. Industries are grouped into 3 categories using NAICS 2007 as the basis for classification: “IT and Professional Services” includes NAICS 51 (Information) and NAICS 54 (Professional Scientific and Technical Services); “High-Tech Manufacturing” includes NAICS 325 (Chemicals), 333 (Machinery), 334 (Computer and Electronic), 335 (Electrical Equipment, Appliance and Components) and 336 (Transportation Equipment). All other industries are grouped into “Other”.

Trade Shares ($\pi_{k,\ell,n}^{trade}$), **production shares** ($\Lambda_{k,n,\ell}$) and **intermediate input shares** ($\gamma_{\ell,k,k'}$): Trade and production shares are computed using the Trade in Value Added database of the OECD. I use gross exports, gross imports and output data for 2011. For “IT and Professional Services” I use the OECD industries “C64 - Post and telecommunications”, “C72 - Computer and related activities” and “C73T74 - R&D and other business activities”. For “High-tech manufacturing” I use the OECD industries “C24 - Chemicals”, “C29 - Machinery and Equipment”, “C30-C31 - Computer, Electronic and optical equipment; Electrical machinery and apparatus” and “C34-C35 - Transportation equipment”. All other industries are classified as “Other”. For intermediate input expenditure shares I use the World Input-Output tables (WIOT) for year 2012.

MNE shares ($\pi_{k,s,\ell}^{mne}$): To compute the MNE shares I need the revenues of MNEs by industry and source country in the US, India, Western Europe, Chin-Taiwan and Canada. The main source used is the BEA surveys of “US Direct Investment Abroad” for revenues of US companies abroad and the “Foreign Direct Investment in the United States” for revenues of non-US companies with subsidiaries in the US. I use the revenues reported for majority-owned affiliates in the NAICS sectors described above for the year 2012. While the BEA provides sufficient information for MNE activity involving the US, it does not provide revenues between the non-US regions by industry. To compute the non-US MNE revenues that are missing I use the revenues reported by Orbis in 2012 for each source-destination-industry triplet. As shown by [Alviarez \(2018\)](#) Orbis provides a good approximation of MNE revenues by source and industry when compared to other aggregate datasets such as the OECD.

Migration shares and labor allocations ($\pi_{o,k,\ell,s}^{mig}$): Migrant and native counts by origin country and industry in the US are taken from the 2012 American Community Survey (ACS) and for Canada from IPUMS International for the year 2011. For Europe, not all countries have micro data available so I use the surveys for France, Ireland and Spain in IPUMS international to calculate the distribution of migrants across industries. Total migrant counts for Europe are taken from the IAB brain-drain data ([Brucker et al., 2013](#)). A key piece of information that is not available in any survey is whether workers are employed by a domestic or foreign company. To

impute such data, I use the FOIA dataset on H-1B and L-1 to back out the proportion of native, source-country and other foreign workers in the US by MNE source. As a first step, I compute the total ratio of foreign workers employed by firms from source s relative to US firms using the FOIA data. Second, from the BEA data used to calculate MNE shares, I calculate the relative size of MNEs with source technology s in industry k relative the size of US firms in industry k . These two ratios allow me to back out the likelihood of firms from s to employ foreign workers relative to US firms. I then use the FOIA data to calculate how many source vs other foreign workers are employed by non-US MNEs in each industry. Since the FOIA data is just for the US, I impute the ratio of foreign to native college graduates for Europe and Canada. The ratios of Canadian firms in the US are used for US firms abroad. The results are robust to alternative imputation methods.

Industry employment of high- and low-skill workers in India is taken from IPUMS International for the year 2009. China-Taiwan and Rest of the World total high- and low-skill worker counts are taken from International Labour Organization LABORSTA database. The ratio of low to high skill employment within industry is imputed using the values for India and the total employment by industry is taken from the OECD. The distribution across source technologies in India and China-Taiwan is imputed using the MNE shares in those countries.

Labor expenditure shares ($\Theta_{k,l,s}^L, \Theta_{k,l,s}^H, \Theta_{k,l,s}^d, \Theta_{k,l,s}^s, \Theta_{k,l,s}^f, \Lambda_{k,l,s}^L, \Lambda_{k,l,s}^x, \Lambda_{k,l,s}^L, \Lambda_{k,l,s}^o$): A final piece of data needed is several shares of labor expenditure for different skill groups across countries, industries and source technologies. The labor allocations data described above computes counts of workers so wage data is needed to map counts into expenditure shares. For the US the ACS is used to compute the average wages for workers across skill types, origin countries and industries. Such average wages together with the labor counts are used to compute the expenditures. A similar process is used for Canada and India using wage data from the IPUMS International surveys for each country. Individual wage data for Europe, China-Taiwan and Rest of the World is not available at the industry-skill level so I use the high-skill to low-skill wage premium in Canada to impute wages in Europe and the skill premium in India to impute wages in China-Taiwan and RoW.

E Counterfactual 1: A more restrictive migration policy

In this section I present additional results from restricting migration into the US. Since high-skill migrants are concentrated in high-skill industries such as IT and High-tech manufacturing, once we restrict migration we see an inflow of native high-skill workers into the high-skill industries as shown in table 13. High-tech manufacturing receives the largest hit, so the share of low-skill workers in that industry goes down.

Table 13: Percent changes in employment shares

	Share of high-skill natives employed in:	Share of low-skill natives employed in:
IT and Professional Services	1.35%	0.59%
High-Skill Manufacturing	2.82%	-0.22%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Change in employment shares. Omitted category “Other” industry.

The restriction on migration increases marginal cost for companies located in the US, which makes US goods more expensive. As shown in table 14, the US decreases the share it buys from itself in all industries, but predominantly the industries that are largely affected by the migration restriction. The drop in the domestic share for IT and professional services is compensated by an increase in the share bought from Western Europe while in High-tech manufacturing it is compensated by a larger share bought from China-Taiwan and the Rest of the World.

Table 14: Percent point changes in US trade shares

	Information Technology and Professional	High-Skill Manufacturing	Other Industries
Percent-point change in US domestic trade share	-0.24%	-0.87%	-0.03%
India	0.03%	0.03%	0.001%
Western Europe	0.08%	0.19%	0.005%
Canada	0.04%	0.09%	0.013%
China-Taiwan	0.03%	0.27%	0.002%
Rest of the World	0.06%	0.29%	0.006%

Percent point changes in trade share in the US from increasing migration cost such that the total stock of migrants decreases by 70%. The sum of each column equals to 0.

As noted in table 5, foreign MNEs in the US respond more in terms of revenues than US companies. Table 15 decomposes the contribution to total output drop in the US by source country. Foreign MNEs in the IT sector are more intensive in migrants so their contribution to total output drop is of 11.7% while they only account for 4.8% of production in IT.

Table 15: Contribution of MNEs to output drop

	IT and Professional Services			High-Skill Manufacturing		
	Percent change in Revenues	Share of US production	Share of migration effect	Percent change in Revenues	Share of US production	Share of migration effect
Total	-2.99%			-3.37%		
US	-2.64%	95.16%	88.35%	-2.16%	70.84%	64.13%
India	-0.09%	0.29%	2.88%	-0.03%	0.35%	0.82%
Western Europe	-0.24%	4.37%	8.14%	-1.08%	27.08%	31.87%
Canada	-0.02%	0.19%	0.63%	-0.10%	1.54%	2.95%
China-Taiwan	0.00%	0.00%	0.00%	-0.01%	0.19%	0.22%
Foreign MNE total		4.8%	11.7%		29.2%	35.9%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. Columns 1,4: contribution to output drop. Columns 2,5: Share of production in the US by MNE source. Columns 3,6: Share of total contribution to output drop.

So far the results presented for the last counterfactual involved changing the migration cost such that the total stock of high-skill migrants in the US decreases by 70%. In table 16 I run the same exercise but changing the size of the decrease to lower values. While the results are qualitatively consistent, the magnitude of the effects decreases as expected. A policy that decreases the stock of migrants by 10% decreases welfare by 0.13%, such that less extreme policy changes are expected to have a small impact on aggregate welfare.

Table 16: Welfare implications for alternative counterfactuals

	70% decrease (baseline)	40% decrease	20% decrease	10% decrease
High-skill natives	1.39%	0.73%	0.35%	0.17%
Low-skill natives	-2.01%	-1.07%	-0.52%	-0.26%
Total natives	-0.98%	-0.52%	-0.25%	-0.13%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%, 40%, 20% and 10%.

As a final robustness I explore how do the main results change when changing the degree of dispersion in individual abilities and the correlation of such ability draws. A larger value of κ implies that individual ability draws are more concentrated among triplets k, ℓ, s , so small changes in the wage or migration cost can cause large swings in migration flows. As a first exercise I compute the model for $\kappa = 4.16$, the lower bound estimated in table 3 where the ability dispersion is greater than in the baseline and an arbitrarily high value of $\kappa = 10$ where the ability dispersion is very low. As shown in table 17, results are fairly similar for alternative values of κ , indicating that selection does not play a very large role in terms of the migration restriction effects. When abilities are more concentrated, migration response and sector reallocation become more sensitive to changes in the migration cost. For high-skill workers it becomes easier to relocate and change sectors to replace the migrants so their gains are amplified. On the contrary, low-skill workers get hurt from this extra mobility of high-skill workers, since firms don't substitute high for low skill labor as much. Finally, I look into the implications of a model that incorporates correlation in the ability draws. Results are shown for a correlation among draws of $\rho = 0.1$ and $\rho = 0.5$ and yield similar results to the baseline specification.

Table 17: Robustness for ability dispersion and correlation

	Baseline	$\kappa = 4.16$	$\kappa = 10$	$\rho = 0.1$	$\rho = 0.5$
High-skill natives	1.39%	1.32%	1.44%	1.40%	1.45%
Low-skill natives	-2.01%	-1.91%	-2.09%	-2.03%	-2.11%
Total natives	-0.98%	-0.92%	-1.02%	-0.99%	-1.03%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 70%. $\kappa = 5.95$ in the baseline.

F Counterfactual 2: Welfare gains of MNE production

Results for MNE welfare gains with and without migration presented in section 6.2 only looked at the gains for the US. Table 18 shows the welfare gains of MNE for the baseline model with migration and an alternative model without migration. The bias on the effects of the model without migration goes in opposite directions depending if the country is a migrant-receiving or migrant-sending country. The results for Europe and Canada are equivalent to those in the US, the model with no migration overestimates the welfare gains for high-skill workers and underestimates the effects for low-skill workers. When MNE is allowed, MNE companies in migrant receiving countries push up the demand for migrants lowering the wages for native high-skill workers and increasing the wage for native low skill workers due to complementarity. The mirror image of such results is experienced by sending countries such as India and China-Taiwan. Allowing for MNE activity increases the demand for high-skill migrants in US, Canada and Western Europe, decreasing the number of high-skill workers in India and China-Taiwan. Such decrease raises wages for high-skill and lowers wages for low-skill and such effects are not captured by the model that does not include migration.

Table 18: Welfare gains of MNE production by country

		Baseline	No migration	Relative to baseline
US	High-Skill	1.17%	1.57%	34.21%
	Low-Skill	1.42%	1.31%	-7.91%
	All	1.35%	1.39%	3.25%
Western Europe	High-Skill	1.73%	2.19%	25.96%
	Low-Skill	1.09%	0.91%	-16.20%
	All	1.26%	1.25%	-0.77%
Canada	High-Skill	1.07%	5.42%	406.22%
	Low-Skill	6.96%	5.30%	-23.89%
	All	5.55%	5.33%	-3.96%
India	High-Skill	0.99%	0.56%	-44.13%
	Low-Skill	0.15%	0.27%	81.25%
	All	0.22%	0.30%	35.84%
China-Taiwan	High-Skill	0.49%	0.15%	-68.57%
	Low-Skill	0.25%	0.37%	45.98%
	All	0.27%	0.35%	29.34%

Percent changes in welfare of going from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\delta_{s,\ell}^k$ are very high such that MNE is prohibitive. Column 3 shows the welfare change in the no migration setting relative to the welfare change in the baseline model with migration.