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

Nicolas Morales†

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Abstract

This paper examines the relationship between high-skill immigration and multinational activity. I assemble a novel firm-level dataset on high-skill visa applications and show that there is a large home-bias effect. Foreign multinational enterprises (MNEs) in the US tend to hire more migrant workers from their home countries compared to US firms. To quantify the general equilibrium implications for production and welfare, I build and estimate a quantitative model that includes trade, MNE production, and the migration decisions of high-skill workers. I use an instrumental variables approach to show that the relationship between immigration and MNEs proposed by the model holds in the data. The model is then used to run two counterfactual exercises. The first, evaluates the implications of a more restrictive immigration policy in the US. I find that MNEs play a significant role in how immigration affects the location of production and welfare. In the second counterfactual exercise, I increase the barriers to MNE production to calculate the welfare gains generated by MNEs. I show that a model *not* incorporating migration would overestimate the MNE welfare gains for high-skill workers by 35% and underestimate welfare gains for low-skill workers by 8%.

JEL: F16, F22, F23, J61

Keywords: High-skill immigration, H-1B visas, Multinational companies, IT sector

1 Introduction

In recent years, particularly in the United States, policies have been proposed that would curtail high-skill immigration into the country. For example, by rescinding work visas for the spouses of high-skill immigrants or increasing the required lower bound for wages of new high-skill immigrant workers, both of which aim to reduce total high-skill immigration to the US.[1] These policies rely on the argument that immigration reduces employment opportunities for natives whose skills are on par with the immigrants. On the other hand, those who support high-skill immigration argue that such policies are likely to decrease the level of economic activity in the US and lead both US companies and foreign multinational enterprises (MNEs) in high-skill industries, such as IT, to move their operations elsewhere. While both of these arguments are frequently made, there is little quantitative evidence of the extent to which restrictions on high-skill immigration would indeed cause high-skill industries to relocate outside of the US.

In this paper, I quantify the impact that US restrictions to high-skill immigration would have on welfare, MNE activity, and total production in high-skill industries. To establish a link between MNEs and high-skill migration, I present a novel finding that foreign MNEs are more dependent on immigrant labor from their home countries than US companies. I build and estimate a quantitative model with multiple industries and countries that incorporates high-skill migration, trade, and MNE activity, and I validate the model using an instrumental variables approach. I use this model to run two main counterfactual exercises. First, I study the effects of restricting immigration into the US on welfare, production and MNE activity. Second, in order to quantify the welfare gains created by MNEs, I increase the barriers to MNE production and calculate the importance of incorporating migration for estimating the welfare gains from MNEs.

As a first step, I assemble a novel firm-level dataset that relates the nationality of each high-skill migrant hired in the US to the source country of the parent company of the firm. To construct this dataset, I use the universe of H-1B visas granted between 2001 and 2014 and L-1 visas granted between 2012 and 2014, obtained through a Freedom of Information request (FOIA) to the United States Citizenship and Immigration Services.[2] The data include information on wages, worker nationalities, and characteristics of the sponsoring firm such as company name and location. I match this data by name and location to the corporate databases of Orbis and D&B Hoovers to get information on the ownership structure and industry of each firm. The link between the source country of the parent company and the origin of the immigrant workers

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[1]Such policies are the recent comments to rescind the H4 EAD work permits for H-1B spouses in mid-2018 and the "Protect and Grow American Jobs Act" to impose a higher lower bound on H-1B wages introduced in late 2017.

[2]H-1B and L-1 visas are the main visa categories through which college-educated immigrants can get work authorization in the US. The L-1 program focuses on intra-firm transfers while the H-1B is open to everyone. More details on these programs are given in Section 2.

has been missing from previous studies and is key to understanding the relationship between MNEs and high-skill worker migration.

I document a series of facts that relate immigration to MNE activity in the US. First, I show that foreign MNEs in the US have a large "home bias", where on average, they hire 153% more foreign workers from their source country when compared with the number of workers from that source country hired by US companies and other foreign MNEs. There is heterogeneity in the magnitude of the home bias across countries, and this effect is consistently large. Such home bias could be explained by a demand channel where firms need source-country immigrants to produce, or a supply channel where source-country immigrants find it easier to migrate if working for an MNE from their origin country. I show MNEs pay lower wages to their source-country immigrants, suggesting the supply channel is the predominant explanation for the observed home-bias. Finally, I show that higher home bias is positively correlated with higher visa applications, farther distance to the US, and being a non-English speaking country.

Guided by these facts, I build a quantitative model that accounts for several channels through which immigration 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 Alviarez (2018). For instance, if German producers want to sell goods to the US, they will choose the production location that allows them to sell the goods at the lowest price. The model allows them to choose among producing the goods in Germany and shipping them to the US, paying a trade cost; or setting a plant in the US and selling their product domestically, paying an MNE cost; or setting a plant in a third country and selling to the US, paying both trade and MNE costs. Such decisions are at the core of why a company relocates its production when migration restrictions are imposed; their marginal cost is increased, causing them to move. The labor supply side of the model focuses on the decisions of college-educated workers in each country who choose which country to migrate to, industry to work in, and source technology to work with. For example, if a worker is employed by a company whose parent is headquartered in the US, he or she works with US source technology. Workers draw idiosyncratic productivities to work in each country-industry-source triplet, and they sort endogenously across triplets as explained in Roy (1951).[3] If they choose to migrate, workers have to pay a non pecuniary migration cost.

In the model, immigrants affect firm-level production in two ways. 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 countries of origin to have different comparative advantages across industries. The link between MNE and migration appears through three separate channels. From the labor supply side, the migration cost can

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[3]The supply-side of the model is related to the literature that combines Roy (1951) and Eaton and Kortum (2002). Some recent examples using similar labor supply models are Lagakos and Waugh (2013), Hsieh et al. (2019), Lee (2019), Bryan and Morten (2018), Fan (2019), Tombe and Zhu (2019), and Liu (2017)

be lower if workers migrate to work at a company whose source technology is the same as that in the worker's home country. From the labor demand side, foreign MNEs treat workers from their source-country as imperfect substitutes for domestic and other foreign workers; therefore, they treat source-country workers as distinct inputs for production. Additionally, I allow for the possibility of source-country immigrants lowering MNE costs by providing information or networks that facilitate MNE activity.

As a validation for the model, I show well identified, reduced-form evidence that corroborates the positive link between own-country high-skill immigration and MNE employment. Using variation across years, industries, and source countries I construct a shift-share instrumental variable for the number of immigrants from each country working for different industries in the US. I interact the initial share of immigrants from the source-country working in an industry with the total number of immigrants from that country working for US companies in other industries. I show that a 1% increase in source-country immigrants working for a given industry in the US increases total MNE employment by firms from that source country by 0.70%-1.94%. The reduced-form evidence also corroborates that high-skill immigration, as opposed to low-skill immigration, has a predominant effect on MNE activity.

I show that in order to measure the changes in welfare and production between the observed equilibrium and a counterfactual equilibrium, I only need six elasticities and data on observed migration shares, trade shares, MNE shares, and labor expenditure shares. I use the approach proposed by Dekle et al. (2008) and re-write the equilibrium in proportional changes from the observed equilibrium to a counterfactual equilibrium. This move allows me to significantly reduce the number of parameters to be estimated in order to determine the magnitude of endogenous responses of the model to any given exogenous shock, such as an increase in cost of migration. I use my novel dataset to estimate structurally three of the elasticities that are not available in the literature: the labor supply elasticity, the elasticity of substitution between source-country workers and other foreign workers, and the elasticity of MNE costs to immigration. I use an instrumental variables approach based on the trade shocks literature to construct a demand shifter and estimate the elasticity of labor supply. For the elasticity of substitution between foreign high-skill units of labor, I use the immigrant shift-share instrument described above to identify the slope of the relative demand for source-country and other foreign workers. Finally, I estimate the elasticity of MNE costs to immigration through indirect inference, by matching the estimated response of MNE employment to immigration.

I use this estimated model to run two main counterfactual exercises. In the first, I increase the costs of immigration into the US from all other countries to reduce the stock of inbound high-skill immigrants by 10%, consistent with a 0.3% decrease in total US workforce. The decrease of high-skill immigrants would cause US production in high-skill intensive industries such as IT and high-tech manufacturing to decrease by 0.53% and 1.70% respectively. This decrease would be largely driven by foreign MNEs who respond disproportionately to the migration

restrictions. Other countries share in production is expected to increase in response, with the IT sector in India increasing by 0.63% and in Canada by 0.16%. Real wages for US low-skill workers would decrease by 0.35%. High-skill workers are complements in production to low-skill workers such that the decrease in immigration of high-skill workers lowers the demand for low-skill workers and decreases their wages. The increase in labor costs caused by immigration restrictions would also increase prices for US consumers, adding to the negative effect on the real wages of US workers. On the other hand, US high-skill workers would experience a gain of 0.09% in their real wages driven by an increase in the market wages caused by the lower competition from immigrants. Overall, the real wages of US workers decrease by 0.22% when immigration is restricted, which in dollar terms would account for a total long-term loss of $8 billion USD for the US economy.

In the second counterfactual exercise, I increase the barriers to MNE production in order to calculate the welfare gains from MNE activity. Foreign MNEs bring more efficient technologies that lower the costs of production domestically and improve efficiency. Canonical papers in the MNE literature such as Ramondo and Rodriguez-Clare (2013) and Tintelnot (2017) have focused on quantifying the welfare gains of going from MNE "autarky," where MNE costs are prohibitive and MNE flows are zero, to the observed equilibrium in which MNE flows are positive. I use my quantitative model to show that going from MNE autarky to the observed MNE flows would increase welfare for high- and low-skill native workers by 1.16% and 1.42%, respectively. A model that does *not* incorporate migration would overstate the welfare gains for high-skill workers by 35% and understate the gains for low-skill workers by 8.15% since it would not account for the negative impact of immigration on high-skill natives nor the positive impact for low-skill workers. This result shows that the link between MNEs and immigration significantly affects the distributional welfare gains predicted by canonical MNE models that do not incorporate migration.

To my knowledge, this is the first paper that quantifies the impact of high-skill immigration on the welfare of workers and the location of production by taking into account the specific channel of multinational activity. The United States immigration policies concerning high-skill workers, particularly through the H-1B program, have received significant attention in recent years. On one hand, high-skill immigrants are found to increase innovation (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Peri et al., 2015b) and hence increase total factor 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 the employment of native workers (Peri et al., 2015a), others find significant crowd-out effects (Doran et al., 2015). I contribute to the empirical literature by estimating a rich quantitative model to calculate the positive and negative consequences of immigration into the US.

More broadly, several papers have used general equilibrium models to understand how high- and low-skill immigration affects wages and employment of native workers. Among others,

Docquier et al. (2014), Bound, Khanna, and Morales (2018), and Burstein et al. (2018) look at the effects of immigration for native workers with different skills and occupations by focusing on the consequences for the recipient 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 in both receiving and sending countries. Such a global view on migration requires us to incorporate, to some extent, the possibility that production will relocate as a response to changes in immigration policy (Caliendo et al., 2018; Desmet et al., 2018; di Giovanni et al., 2015; Iranzo and Peri, 2009; Khanna and Morales, 2018). This paper contributes to this literature by including the channel of multinational production, which is key to understanding the effects that firms decisions to relocate production due to immigration policies have on welfare and productivity.

A closely related strand of literature has used a mostly reduced-form approach to establish a link between immigration and trade (Gould, 1994; Hiller, 2013), immigration and FDI activity (Burchardi et al., 2019; Cuadros et al., 2019; Glennon, 2018; Javorcik et al., 2011; Wang, 2014; Yeaple, 2018), and the interrelations between migration, trade, and FDI (Aubry et al., 2018). I contribute to this literature by providing new facts on these links as well as building and estimating a quantitative model that allows me to properly quantify the aggregate implications of immigration for MNEs production and for welfare.

As an additional contribution, I provide new evidence on the distributional 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, among other factors, the interrelations between MNE production and trade, intermediate inputs, innovation, and comparative advantage (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 might be 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 contribute to the literature on the role of MNEs for the transfer of knowledge and formation of cross-country teams (Antras et al., 2006; Gumpert, 2018; Keller and Yeaple, 2013; Mion et al., 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 immigration 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 submitted between 2001 and 2014 and L-1 visas submitted between 2012 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 and 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 subsequent analysis to establish the relation between MNE and immigration. 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 fundamental 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 information such as industry indicators for the affiliate and the parent company as well as data on employment and revenues. Appendix A explains how I constructed the FOIA dataset and provides details on the matching process with the corporate datasets.

3   Stylized facts

In this Section, I use the visa data to present some facts that help shed light on the link between high-skill immigration and MNE activity and that motivate the model in Section 4. In a first stage, I show that there is a strong link between MNEs and high-skill immigration captured by

a "home bias" measure that indicates foreign MNEs from a given source country are more likely to hire immigrants from that country than US companies and MNEs from other countries. In a second stage, I show that foreign MNEs in the US pay their own-country immigrants lower wages, suggesting a predominant labor supply mechanism for the observed home bias. Finally, I present evidence that home bias is larger for countries that are farther away from the US and whose native language is not English.

As shown in Appendix A, Tables 13 and 14, the US high-skill immigration system is highly skewed toward IT workers coming from India. US and Indian companies are also the main applicants for H-1B and L-1 visas. However, as noted in the facts presented in this Section as well as the quantitative results throughout this paper, high-skilled migration plays a significant role on the activity of *all* foreign MNEs that operate in the US as well as across high-skill industries other than IT.

Foreign MNE companies have a "home bias" toward workers from their source country

Foreign MNE companies have a "home bias" towards recruiting workers from their source country when compared to US companies. This is relevant since 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 collapse the high-skill visa data to the origin (o) - source (s) - industry level (k) and proceed to run a regression as in equation 1. For example, one observation of the regression is German H-1B and L-1 recipients working for Japanese automotive companies located in the US.

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

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. $\delta_{k,o}$ is an industry-origin fixed effect that captures 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. Equation 1 measures the home bias within industry and compares firms from s with all other firms with $s' \neq s$. The results of the home-bias coefficient γ_s can be found in Figure 1. The home bias is large for most countries in the sample, and there is significant heterogeneity across source countries. For example, Indian companies are shown to be 122% more likely to recruit workers from India than other countries, relative to non-Indian companies.

Figure 1: Estimated coefficient (γ_s) on sourcing regression by country (H-1B+L-1)
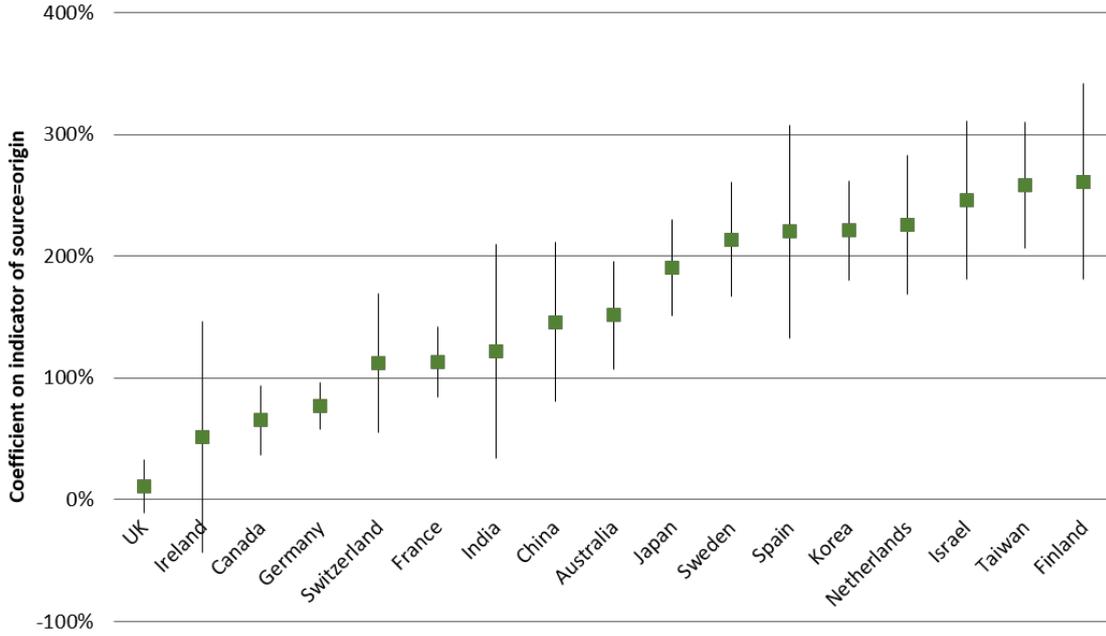
Appendix B explores further how the regression results change when including source-origin pairs with 0 value and running the regression at the source-origin level. The finding of home bias is very robust to these specifications. The results are also robust when only focusing on H-1B visas (excluding L-1 visas), showing that the documented "home bias" is not just a mechanical relationship driven by intra-firm transfers.

The observed home bias can be explained by either demand or supply mechanisms. On the demand side, we can think of source-country immigrants as having a specific productivity for the source-country firm. For example, they might facilitate communication between the US affiliates and the parent company because of language or cultural proximity. On the supply side, it is possible that workers in the source country find it easier to migrate and work for a source-country company abroad. Perhaps workers are more likely to find foreign jobs because of networks in the home country or employers face a lower screening cost for source-country experience and education credentials.

For now, I will not take a stand on whether the home bias is driven by workers being more likely to find a job at a company headquartered in their origin country or by foreign companies having a greater need for workers from their source country. However, I look at wage data and other covariates to see which mechanism might be more relevant to explain the home bias. In the model and subsequent estimation in Sections 4 and 6, I explicitly separate these two channels.

Foreign MNE companies pay lower wages to immigrants from their source country

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As a second exercise, I run equation 1 but using log average wages for each s, k, o as the dependent variable as in equation 2:

$$Ln(\bar{w}_{k,o,s}) = \gamma_0 + \sum_s \beta_s \mathbb{1}(origin = s) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \tag{2}$$

Coefficients β_s can be interpreted as the average wage difference between source-country immigrants and other immigrants for an MNE from country s when compared to companies not from s. If the demand mechanism was the only explanation for the home bias, we would expect source-country workers to have a wage premium over other immigrants. Instead, if the supply mechanism were the sole channel, we would expect to see a wage penalty for source-country workers.

As shown in Figure 2, most MNEs show a wage penalty for source-country workers relative to other immigrants. For example, Korean firms in the US pay 27.4% less to their Korean workers than to other immigrants when compared to non-Korean firms.

Figure 2: Estimated coefficient (γ_s) on wage regression by country (H-1B)
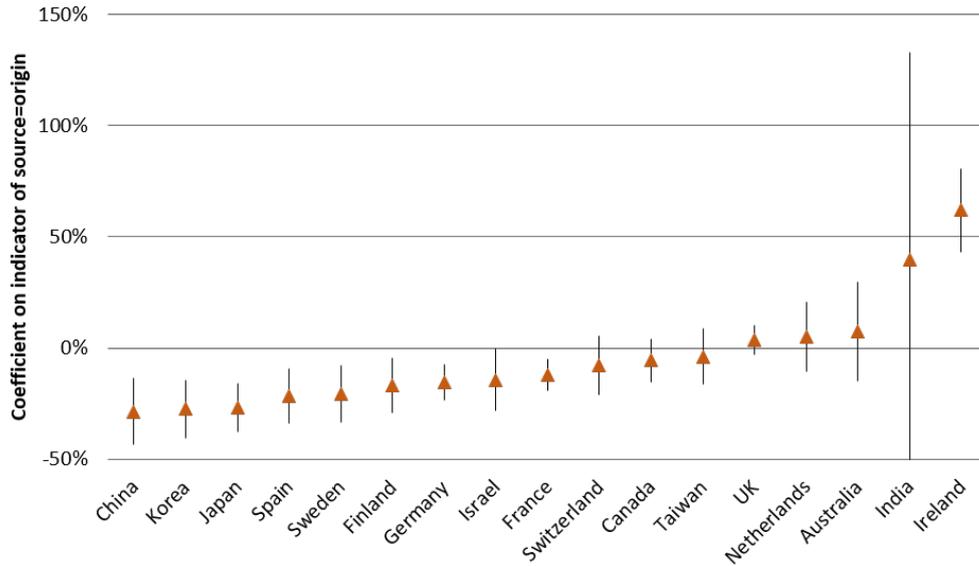
While coefficients β_s contain both supply and demand mechanisms, the negative pattern suggests that the predominant force in explaining the large degree of home-bias might be a supply-side mechanism. If immigrants find it easier to find jobs at source-country companies, the marginal immigrant working for a source-country company will have a lower ability and hence receive a lower wage than the marginal immigrant working for a non-source-country company.

Sources of home bias: Firm size, distance and common language.

To further explore the mechanisms driving the observed home bias, I look at whether firm size and other observables explain part of the variation in home bias across source countries. As a first step, I estimate a version of equation 1 where instead of collapsing the data at the industry-source-nationality level, I collapse it at the firm-nationality level. The insight of this specification is to check the role of large firms on driving the results observed in figure 1, as when aggregating at the source-industry level, firms with more visa applications will tend to drive the results.

As shown in Figure 3, the magnitude of the home-bias is still large and positive for most countries. However, the magnitudes are quite smaller than those shown in Figure 1, indicating that MNEs who apply for a higher number of visas exhibit a larger home bias.

Figure 3: Estimated coefficient (γ_s) on firm-level employment (H-1B+L-1)
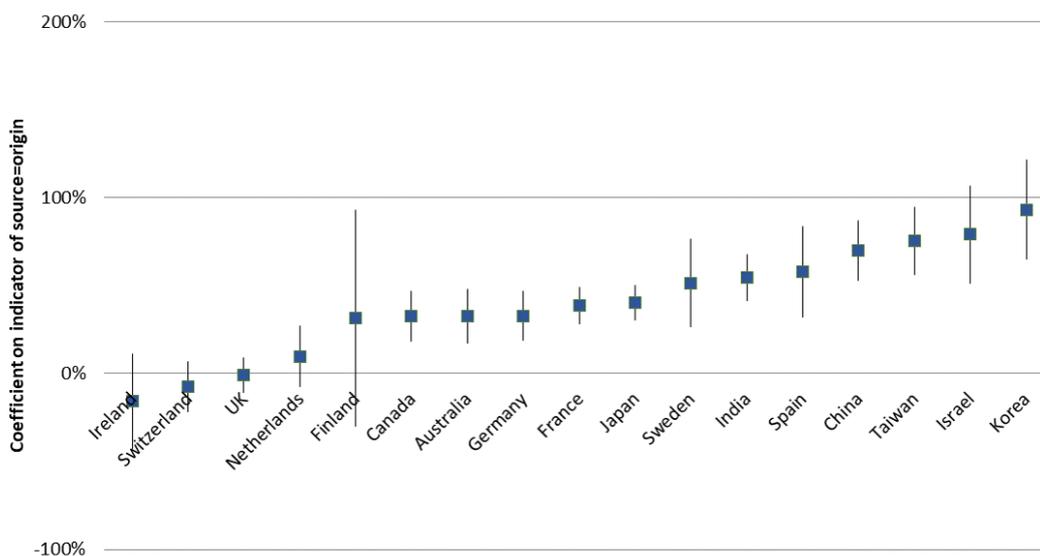
As a second step, I look at simple correlations between country-industry measures of home bias and observables to understand what other factors might drive the observed heterogeneity. I construct the home bias measure at the source-country and industry level by adding industry-country pair interactions to equation 1 and using the estimated coefficients as the home-bias measure. As shown in Table 1, source-country measures seem to drive more of the heterogeneity than industry-specific measures. Countries that are farther away from the US and do not share a common language present higher degrees of home bias, which suggests that home bias is larger for countries where communication between the parent and the affiliate might be more costly.

Industries in which the source country has a larger share of US imports tend to have lower home bias. Countries with larger market shares in the US are likely to have long-lasting trade relationships with the US, and the employment of home-country workers might be less crucial for production.

Table 1: Correlation between home-bias and observables

Source country characteristics (s)	
GDP per worker at s	-0.21
Common language	**-0.52**
Free trade agreement	-0.26
Distance	**0.56**
Industry characteristics (k)	
Share of college grads in k	-0.16
Average college grads wage in k	-0.06
Employment share in US	-0.05
Source-Industry characteristics (k)	
Industry GDP at s	0.12
US Employment MNEs from s in k	0.05
US Employment growth MNEs from s in k	0.09
Share of US imports from s in k	**-0.34**
Share of non-US imports from s in k	-0.01

Correlation coefficient between industry-source measure of home-bias and observables. s source country, k industry. Home-bias measure at the source-industry level calculated by taking the coefficients from a regression as in equation 1 that includes interactions between origin=source dummies and industry dummies. All covariates are measured at year 2014. I highlight in bold correlations over 0.3.

4 Model

To quantify the general equilibrium implications of changes to high-skill immigration policy in the US and guided by the facts in Section 3, I build a quantitative model to disentangle the different mechanisms through which immigration affects production, welfare, and MNE activity. 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 receive wage w_o. On the other hand, high-skill workers have heterogeneous abilities 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 takes an ability draw $\eta_{k,\ell,s}^{i,o}$ to work at each triplet $z = k, \ell, s$ from a Frechet distribution as shown in equation 3:

$$F(\eta_{k,\ell,s}^{i,o}) = exp\left(-\left(\sum_{z=1}^{Z} \tilde{A}_{k,o}^{\frac{1}{1-\rho}} \left(\eta_z^{i,o}\right)^{-\frac{\tilde{\kappa}}{1-\rho}}\right)^{1-\rho}\right) \tag{3}$$

The shape parameter of the distribution $\tilde{\kappa}$ is common across origin countries and governs the dispersion of abilities for each individual. Lower values of $\tilde{\kappa}$ imply that individuals are likely to have very different abilities across triplets k, ℓ, s. ρ represents the correlation across ability draws. In the extreme case of $\rho = 1$, individuals will have the same ability across all triplets of s, k, and ℓ. As in (Bryan and Morten, 2018), it is useful to rewrite $\kappa = \frac{\tilde{\kappa}}{1-\rho}$ such that κ is a combination of ability dispersion and the correlation parameters. As will be shown later, the parameter κ is also the elasticity of labor supply, since it determines how much labor supply choices respond to changes in wages or migration costs.

The scale parameter, $A_{k,o} = \tilde{A}_{k,o}^{\frac{1}{1-\rho}}$, determines the average ability 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 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., 2019; Lagakos and Waugh, 2013; Lee, 2019), as well as both for internal (Bryan and Morten, 2018; Fan, 2019; Tombe and Zhu, 2019) and international migration (Liu, 2017).

Each high-skilled worker, indexed by i, chooses the triplet k, ℓ, s that maximizes their utility as in equation 4. $\eta_{k,\ell,s}^{i,o}$ is the ability draw for individual i in triplet k, ℓ, s, $\frac{w_{k,\ell,s}}{P_\ell}$ is the real wage per effective unit paid in triplet k, ℓ, s and $\varepsilon_{k,\ell,s}^o$ is a mean one log normally distributed random term that captures random shocks that make workers from o more productive at triplet k, ℓ, s.[4] $\phi_{o,\ell,s} \geq 1$ is a non-pecuniary migration cost that is paid when migrating from origin o to location ℓ and source technology s. 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 working for an MNE of a specific source technology. As $\phi_{o,\ell,s}$ is non-pecuniary, the wage that individuals actually receive in the labor market is $W_{k,\ell,s}^o = \eta_{k\ell,s}^{i,o} \times w_{k,\ell,s}$.

$$max \quad_{k,\ell,s} \quad \{U_{k,\ell,s}^{i,o}\} = \eta_{k,\ell,s}^{i,o} \times \varepsilon_{k,\ell,s}^o \times \frac{w_{k,\ell,s}}{P_\ell} \times \frac{1}{\phi_{o,\ell,s}} \tag{4}$$

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[4]The assumption that $A_{k,o}$ only depends on origin and industry is done for convenience in the subsequent estimation. However it would be possible to work with $A_{o,k,\ell,s} = A_{k,o}\varepsilon_{k,\ell,s}^o$ and the estimation results would be identical.

4.2 Production, Trade, and MNE activity

I lay out the consumer problem in two stages. First, individuals take ability draws and choose a triplet k, ℓ, s as explained in 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 K industries as in equation 5

$$U_\ell = \Pi_{k=1}^K Q_{k,\ell}^{\gamma_{k,\ell}} \tag{5}$$

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

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

Each variety $q_{k,\ell,s}^j$ 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.

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

α represents the elasticity of substitution between low- ($l_{k,\ell}$) and high-skill ($h_{k,\ell}$) 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. 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: [5]

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

The parameter λ governs the substitution between effective units of the domestic country and foreign effective units. Parameter ι governs the substitution between source country and other

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[5]If 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.

foreign workers. Having foreign and native workers be imperfect substitutes is consistent with the findings of Peri and Sparber (2011), who find that immigrants 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 where the demand side of the home-bias discussed in Section 3 appears, since foreign MNEs will have a specific value for migrants from their source country.

Share parameters $\psi_{k,\ell,s}^{d}, \psi_{k,\ell,s}^{s}, \psi_{k,\ell,s}^{f}, \psi_{k,\ell,s}^{sf}$ vary across source countries and industries. Differences in this parameters capture why some source-industry pairs might be more intensive on immigrants or source-country immigrants 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 Alviarez (2018) and Arkolakis et al. (2018), among others.

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:

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

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 j, 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:

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

The price increases with the marginal cost of production $c_{s,\ell}^{k}$. Marginal 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 companies 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: $min_{s,\ell}\{p_{s,\ell,n}^{j,k}\}$.

As a final feature, I will allow for the MNE cost $\delta_{s,\ell}^{k}$ to depend on the number of immigrants from s who work in location ℓ, industry k. The rationale behind this modeling assumption is that immigrant diasporas in foreign countries might provide information and business connections that facilitate FDI. The iceberg MNE cost $\delta_{s,\ell}^{k}$ can be written as in equation 11:

$$\delta_{s,\ell}^{k} = \bar{\delta}_{s,\ell}^{k} \left(N_{k,\ell}^{o=s} \right)^{\nu} \tag{11}$$

Where $\bar{\delta}_{s,\ell}^{k}$ is a baseline iceberg cost independent on the number of migrants and $N_{k,\ell}^{o=s}$ is the number of migrants from $o = s$ that work in ℓ, k. The relevance of this mechanism is determined by parameter ν.[6] I assume that firms consider the stock of immigrants $N_{k,\ell}^{o=s}$ as exogenous such that the effect on the MNE costs can be considered as a spillover or externality that is not internalized in the profit maximization process.

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 individual abilities and producer productivities are drawn from Frechet distributions, it is possible to derive tractable, closed-form solutions for migration shares, trade shares, and MNE shares.

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[6]Incorporating immigrants in a gravity framework through the FDI costs has been a common strategy in the literature. See for example Cuadros et al. (2019) and Aubry et al. (2018), among others. All of my qualitative results still hold if we consider $\nu = 0$. I incorporate this feature to help match the magnitude of the MNE employment elasticities to own-country migration estimated in Section 5.

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 12:

$$\pi^{mig}_{o,k,\ell,s} = \frac{A_{o,k} \left(\frac{w_{k,\ell,s}}{P_\ell} \varepsilon^o_{k,\ell,s} \right)^\kappa \phi^{-\kappa}_{o,\ell,s}}{\sum_{\ell',s',k'} A_{o,k'} \left(\frac{w_{i',\ell',s'}}{P_{\ell'}} \varepsilon^o_{k',\ell',s'} \right)^\kappa \phi^{-\kappa}_{o',\ell',s'}} \tag{12}$$

Equation 12 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 $(A_{o,k})$, the real wage per effective unit in triplet k, ℓ, s $\left(\frac{w_{k,\ell,s}}{P_\ell} \right)$, the migration cost from o to ℓ, s $(\phi_{o,\ell,s})$, the random origin-specific term $\varepsilon^o_{k,\ell,s}$, and a combination of these terms for all other triplets, captured by the denominator in equation 12.

Consumers choose the pair ℓ, s from which to buy each variety within each industry. Given the properties of the Frechet distribution, it is possible to write the share of goods bought from pair ℓ, s by consumers in n as in equation 13:

$$\pi^{trade}_{k,\ell,n} = \frac{(\tau^k_{\ell,n})^{-\theta} \tilde{T}^k_\ell}{\sum_{\ell'} (\tau^k_{\ell',n})^{-\theta} \tilde{T}^k_{\ell'}} \tag{13}$$

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: $\tilde{T}^k_\ell = \sum_s T^k_s \left(c^k_{\ell,s} \times \delta^k_{\ell,s} \right)^{-\theta}$. $\tilde{T}^k_\ell$ is a combination of the fundamental technologies T^k_s 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 $c^k_{\ell,s}$ and the MNE iceberg cost $\delta^k_{\ell,s}$.

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 14:

$$\pi^{mne}_{k,s,\ell} = \frac{T^k_s \left(c^k_{\ell,s} \times \delta^k_{\ell,s} \right)^{-\theta}}{\sum_{s'} T^k_{s'} \left(c^k_{\ell,s'} \times \delta^k_{\ell,s'} \right)^{-\theta}} \tag{14}$$

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 rewrite 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. A 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 rewrite all equilibrium equations in proportional changes in Appendix C.1. As an example, it is possible to re-write the migration share (equation 12) as in equation 15:

$$\hat{\pi}_{o,k,\ell,s}^{mig} = \frac{\pi^{mig'}}{\pi^{mig}} = \frac{\hat{A}_{o,k} \left(\frac{\hat{w}_{k,\ell,s}}{\hat{P}_\ell} \hat{\varepsilon}_{k,\ell,s}^o \right)^\kappa \hat{\phi}_{o,\ell,s}^{-\kappa}}{\sum_{k',\ell',s} \hat{A}_{o,k'} \left(\frac{\hat{w}_{k',\ell',s'}}{\hat{P}_{\ell'}} \hat{\varepsilon}_{k',\ell',s'}^o \right)^\kappa \hat{\phi}_{o',\ell',s'}^{-\kappa} \pi_{o,k,\ell,s}^{mig}} \tag{15}$$

As shown by equation 15, this approach allows me to classify each object of the equilibrium into four categories: Endogenous variables such as $\hat{w}_{k,\ell,s}$, $\hat{P}_\ell$, fundamental parameters such as κ, exogenous parameters such as $\hat{\phi}_{o,\ell,s}$, $\hat{\varepsilon}_{k,\ell,s}^o$ and $\hat{A}_{o,k}$, and data on observed allocations $\pi_{o,k,\ell,s}^{mig}$. The model includes many exogenous parameters such as migration costs $\phi_{o,\ell,s}$, 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 they 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 six key elasticities that govern the responses of the endogenous variables: κ the elasticity of migration and labor supply, λ the elasticity of substitution between high-skill domestic and foreign effective units of labor, ι the elasticity of substitution between source-country and other foreign workers, α the elasticity of substitution between college and non-college workers, ν the elasticity of MNE costs on immigration 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.

5   Reduced Form Evidence

Before discussing the estimation procedure, I will show the relationship between high-skill immigration and MNE activity proposed by the model is supported by the data. The predictions of the model can be summarized by using equation 14. First, I take the ratio of the share of US production in industry k by MNEs from source-country s relative to the share of US production in k by US firms. After taking logs and reorganizing terms, we get to equation 16. I add time subscripts t since I will use time variation in the subsequent estimation and remove ℓ subscripts since I am only looking at production in the US.

$$Ln\left(\frac{\pi_{k,s,t}^{mne}}{\pi_{k,US,t}^{mne}}\right) = Ln\left(\frac{T_{s,t}^{k}\left(c_{s,t}^{k}\delta_{s,t}^{k}\right)^{-\theta}}{T_{US,t}^{k}\left(c_{US,t}^{k}\right)^{-\theta}}\right) \rightarrow Ln(X_{k,s,t}) = Ln(T_{s,t}^{k}) - \theta Ln(c_{s,t}^{k}\delta_{s,t}^{k}) + \Phi_{k,t} \quad (16)$$

Where $X_{k,s,t}$ is the production of an MNE from s operating in the US in industry k, time t. $\Phi_{k,t} = T_{US,t}^{k}\left(c_{US,t}^{k}\right)^{-\theta}$ is an industry-time fixed effect that summarizes the US specific variables that are common to all $s \neq US$ in k, t. By inspecting equation 5, there are two channels through which an influx of immigrants from s would affect MNE production by s in the US. First, more immigrants from s will decrease the cost of hiring source-country workers by lowering wages $w_{k,s,t}^{s}$ and expanding the market share of MNEs from s. Second, immigrants from s can lower the MNE cost $\delta_{s,t}^{k}$, further expanding s operations in the US. To check whether the data corroborate this positive relationship, I want to estimate equation 17. [7]

$$Ln(\text{Employment}_{s,k,t}) = \Phi_{k,t} + \Phi_{s,k} + \beta Ln(\text{N Immigrants}_{s,k,t}^{o=s}) + \epsilon_{s,k,t} \quad (17)$$

Following structural equation 16, I control for industry-time fixed effects ($\Phi_{k,t}$). I also include source-industry fixed effects ($\Phi_{s,k}$) to capture the time-invariant component of comparative advantage where MNEs from certain s historically specialize in specific industries. Estimating equation 16 by OLS would yield biased estimates of β, and the direction of the bias is unknown. On one hand, the error term contains time-varying shocks to comparative advantage that can simultaneously increase total employment and number of immigrants. This would cause β to be upward biased. On the other hand, the error term also contains time-varying shocks to cost parameters such as $\psi_{k,s,t}^{s}$ or $\bar{\delta}_{s,t}^{k}$. MNEs might demand fewer source-country immigrants as they increase their US operations since their US workforce learns how to communicate with the parent company over time. This would lead to a negative correlation between employment and immigrants, biasing β downwards.

I proceed to construct a supply-push instrument in the spirit of Card and Lemieux (2001). As shown in equation 18, I use the share of immigrants from $o = s$ who work in industry k in the US in year 2001 (the earliest in the H-1B data) and interact it with the number of immigrants from s that come to the US to work for US companies in industries other than k. The identification assumption is that time-varying shocks to comparative advantage or production function of MNEs are independent from the instrument. Equation 18 aims to capture changes in labor supply, such as changes in migration policy in the US or preference shocks of migrants, that are uncorrelated with demand-level shocks that affect MNE employment in the US.

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[7]I use total employment instead of revenues because the data coverage at BEA has fewer censored values when looking at employment. I combine yearly total US employment data by source-country and industry from the BEA with number of yearly visas by source-country and industry from my H-1B data. Details on the dataset construction can be found on Appendix D.

$$\text{Shift Share}_{s,k,t} = \frac{\text{N Immigrants}_{k,2001}^{o=s}}{\text{N Immigrants}_{2001}^{o=s}} \times (\text{N Immigrants from } o = s, \ s = US, \ k' \neq k, \ t) \quad (18)$$

Table 2 shows the estimates for β under OLS and 2SLS. Looking at column 2, an increase of 1% of immigrants from $o = s$ working for s, k, t causes an increase of 1.71% in total employment for MNEs from s operating in industry k, time t. Column 3 excludes Indian companies from the analysis and shows that the effects are still positive albeit smaller than with the full sample. Indian companies have been the poster child for MNE activity driven by immigration, with US companies bringing migrants from India during the 1990s and Indian tech companies starting operations in the US in the late 2000s predominantly using migrant labor from India. It is reassuring that the results still hold even when excluding the Indian case.

Table 2: Dependent Variable: Log US Employment of MNEs from s in k, t.

	(1)	(2)	(3)
Ln (Imm from $o = s$ in s,k,t)	0.07	1.71***	0.70*
	(0.055)	(0.503)	(0.347)
N obs	616	616	575
Estimation	OLS	2SLS	2SLS
1st stage F-stat		14.4	13.2
Sample	All	All	Excluding India

$*p < 0.1, **p < 0.05, ***p < 0.01$. Industry-Source-Time level regression. Years 2002-2014 included. Standard errors clustered at the source-country level. Industry-time and Source-Industry fixed effects included. Last column excludes observations for Indian MNEs.

I proceed to discuss the validity of the shift-share instrument by discussing potential concerns with the time-varying component and the initial share component of the instrument. First, the instrument could be invalid if the time-varying component is correlated with other shocks happening at the source-country level that affect MNE employment growth in the US. An example could be trade agreements between s and the US that increase both migration from s in all industries and MNE activity from s. To control for this possibility, in Appendix Table 17, I show the results are robust to controlling for a source-time fixed effect instead of an industry-source fixed effect. If I add both industry-source and time-source, the estimates are still robust, although the second stage loses power given the reduced variation allowed by saturating the regression with fixed effects. As additional checks, I show that the estimates are robust to adding time-varying controls that are likely to be correlated with unobserved source-time shocks that affect MNE activity from s such as import share from s, total exports

of s, and total GDP from s.

Second, I discuss the validity of the initial share component of the instrument. Following Goldsmith-Pinkham et al. (2019), it is important to establish that the initial share is not correlated with other observables that also predict the *growth* of the second stage outcome, the MNE employment by country s in industry k in the US. To test for such correlation, I run a regression of the initial share and the observed MNE employment growth on several observables as shown in Appendix Table 18. The industry share of exports from country s and the distance between s and the US are the main covariates that predict MNE growth from s in the US. These covariates are not significantly correlated with the initial immigrant share used in the instrument, which reinforces the validity of the shift-share approach.

Finally, a third concern is that there might be a mechanical correlation between employment and immigration numbers, since immigrants also count as employees in total employment. For non-Indian companies, the number of source-country immigrants is sufficiently small to not make a difference on the estimates if we exclude the number of immigrants from total employment figures. On the other hand, Indian companies do predominantly employ Indian immigrants as their employees, so this mechanical relationship becomes relevant for India. Hence, it is important to keep in mind that part of the Indian disproportionate response when compared to other countries is likely driven by a direct increase in total employment.

As a second set of results, I consider a broader definition of immigrants that can impact MNE activity. If the reason that an influx of immigrants from the source country expand MNE activity is because of networks that facilitate production in the US, we could think that not only immigrants employed by MNEs from s could contribute to this effect. Instead I consider as an explanatory variable all immigrants from $o = s$ who work in industry k as a potential driver of MNE activity as shown in equation 19. I use the instrument in equation 18 as well, since the exogeneity and relevance arguments of the supply-push instrument also hold in this case.

$$Ln(\text{Employment}_{s,k,t}) = \Phi_{k,t} + \Phi_{s,k} + \beta Ln(\text{N Immigrants}_{k,t}^{o=s}) + \epsilon_{s,k,t} \qquad (19)$$

Table 3 shows that on average, a 1% increase in the number of immigrants from s working for industry k, increases MNE employment from source-country s, industry k by 1.34%. Once again, excluding India gives smaller but consistent results. The new explanatory variable does not require information on the source-country of the MNE, just origin and industry of the workers. This allows me to estimate the same regression using the American Community Survey (ACS), which represents the stock of immigrant workers in the US instead of the flow (given by the H-1B data).[8] The advantages of validating the estimates with the ACS are

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[8]The construction of the instrument with ACS data is slightly different than in equation 18. I calculate the initial share using the 1990 sample and include in the regressions observations between 2000-14.

twofold. First, columns 3 and 4 of Table 3 show the estimates for the stock are very similar to those using the flow. Second, it allows me to run the same regression using only non-college graduates. The estimates in column 5 show that an influx of non-college graduates from the source country does not significantly affect MNE activity. Such findings reinforce the decision of focusing exclusively on the immigration of college graduates when studying the link between immigration and MNE activity. [9]

Table 3: Dependent Variable: Log US Employment of MNEs from s in k, t. Broader definition of Immigrants.

	(1)	(2)	(3)	(4)	(5)
Ln (Imm from $o = s$ in k,t)	1.34***	0.84**	1.94***	1.28	0.13
	(0.21)	(0.35)	(0.68)	(1.06)	(0.65)
N obs	1097	1047	2730	2635	2510
1st stage F-stat	152.0	8.8	19.0	17.0	7.0
Sample	H-1B - All	H-1B - no India	ACS - college	ACS - college, no India	ACS - Non-college

$*p < 0.1, **p < 0.05, ***p < 0.01$. 2SLS estimates. Industry-Source-Time level regression. Years 2002-2014 for H-1B, 2000-2014 for ACS. Standard errors clustered at the source-country level. Industry-time and Source-Industry fixed effects included. Columns 2 and 4 exclude India. Column 5 uses only non-college graduate immigrants. The explanatory variable Ln (Imm from $o = s$ in k,t) considers all immigrants from s working in the US for industry k (not just those working for s).

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[9]This is also consistent with the findings of Cho (2018), who shows Korean MNEs disproportionately hire Korean migrants only for managerial occupations, which are high-skill intensive.

6   Estimation

In this Section, I proceed to describe the estimation strategies for the six key elasticities in the model. Labor supply parameter: κ. Production function elasticities: α, λ, and ι. MNE cost spillover: ν and the trade elasticity θ. 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). I will use the H-1B data to estimate κ and ι, set λ and α according to values estimated in the literature. Finally, I will calibrate ν to match the reduced-form results from Section 5 as explained below.

6.1   Labor supply elasticity κ

I use an instrumental variable approach that exploits "trade shocks" across source countries and industries to estimate labor supply elasticity κ. As defined in Section 4.1, κ, has two main interpretations. First, it governs the dispersion of productivities, with higher values of κ implying either lower dispersion between draws (high $\tilde{\kappa}$) or high correlation among the draws (high ρ). Second, it can be interpreted as the labor supply elasticity, as it captures the response of relative migration flows and relative labor supply to changes in relative wages and migration costs. Following Bryan and Morten (2018), and using properties of the Frechet distribution, it is possible to write the conditional expectation of abilities as in equation 20. $\bar{\Gamma}$ is the Gamma function evaluated in $1 - \frac{1}{\kappa(1-\rho)}$. Equation 20 implies that as the share of workers from o that chooses triplet $z = \{k, \ell, s\}$ increases, the average ability of those choosing z decreases.

$$E\left(\eta_z^{i,o}|i \text{ chooses } z\right) = A_{o,k}^{\frac{1}{\kappa}} \left(\pi_{o,z}^{mig}\right)^{-\frac{1}{\kappa}} \bar{\Gamma} \tag{20}$$

A similar logic can be used for calculating the average wages that workers choosing z receive. Suppose individual i chooses z and gets a wage: $wage_z^{i,o} = w_z^x \varepsilon_z^o \eta_z^{i,o}$, where w_z^x is the equilibrium wage per effective unit paid to those who choose triplet z and the superscript x indicates whether the workers are hired by an MNE with $s = o$ or if they are hired just as other foreign workers. ε_z^o is a mean one log normally distributed random term that captures random shocks that make workers from o more productive at triplet z. Using the results in equation 20, it is possible to calculate average wages as in equation 21.

$$E\left(wage_z^{i,o}|i \text{ chooses } z\right) = w_z^x \varepsilon_z^o \left(\pi_{o,z}^{mig}\right)^{-\frac{1}{\kappa}} \bar{\Gamma} \tag{21}$$

By taking logs and reorganizing terms, we get estimating equation 22. Using the US H-1B data, it would be possible to estimate equation 22 by using data on average wages and employment

at the industry-source-orign-time level and controlling for k-s-t-x fixed effects and o-k-t fixed effects.[10]

$$Ln\left(\overline{wage}^o_{z,t}\right) = \underbrace{Ln\left(w^x_z\right)}_{k\text{-}s\text{-}t\text{-}x \text{ FE}} - \frac{1}{\kappa}Ln\left(N_{o,z,t}\right) + \underbrace{\frac{1}{\kappa}\left(Ln\left(A_{o,k,t}\right)Ln\left(N_{o,t}\right)\right)}_{o\text{-}k\text{-}t \text{ FE}} + \underbrace{Ln\left(\varepsilon^o_{z,t}\right)}_{\text{error term}} \quad (22)$$

Estimating equation 22 by OLS would yield biased estimates of $-\frac{1}{\kappa}$. The random term $\varepsilon^o_{z,t}$ positively affects average wages as well as the number of immigrants from o choosing z, $N_{o,z,t}$, biasing the estimate of $-\frac{1}{\kappa}$ upwards. To identify this parameter, it is possible to construct demand shocks that capture changes in the production comparative advantage $(T^k_{s,t})$ of source country s in industry k that are independent of time-specific productivity shocks $\varepsilon^o_{z,t}$ experienced by origin o immigrants. I draw from the literature on trade shocks started by Autor et al. (2013) and construct a shift-share instrument that interacts the share of workers from o that choose triplet z in 2001 with the share of imports from non-US countries in industry k that come from country s.[11]

$$\text{Shift Share}_{z,o,t} = \pi^{mig}_{o,z,2001} \times \left(\frac{\text{Exports of } k \text{ from } s \text{ to } \ell \neq US \text{ in } t}{\text{Exports of } k \text{ to } \ell \neq US \text{ in } t}\right) \quad (23)$$

As shown in Table 4, the 2SLS estimates are consistent with the direction of the bias of OLS. The estimated value of κ is 6.17. As defined before, κ is the convolution of the true dispersion parameter $\tilde{\kappa}$ and the correlation among draws ρ. In Appendix E.1 I explain how it is possible to use the observed dispersion in wages to separately identify $\tilde{\kappa}$ and ρ. I estimate $\tilde{\kappa} = 2.08$ and $\rho = 0.66$. While in a very different context, such estimates are consistent with Hsieh et al. (2019) who use $\tilde{\kappa} = 2$ and Bryan and Morten (2018) who find a $\tilde{\kappa} = 2.7$ and a somewhat larger correlation of 0.9. I also show that if I solely use the dispersion in wages to estimate κ, I get an estimate of $\kappa = 8.28$, which I will use to bound the results in the robustness Section.[12]

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[10]Since I will use time variation for estimation, I add a time subscript t. I drop $\bar{\Gamma}$ for exposition purposes. x stands for a dummy variable that takes the value of 1 if $s = o$ and 0 if $s \neq o$. Since the data are only for the US, I do not consider the ℓ subscript, which is common for all observations. I use the property that $\pi^{mig}_{o,z} = \frac{N_{o,z,t}}{N_{o,t}}$

[11]Ideally, I would use MNE flows from s-k to other countries to construct the comparative advantage shocks. However, information is somewhat limited for non-US MNE flows for sufficiently disaggregated industry groups and countries. In the model $T^k_{s,t}$ represents comparative advantage in k for both trade and MNE, such that trade flows from s to other countries should also capture comparative advantage shocks.

[12]Using the observed wage dispersion has been used in the EK-Roy literature to estimate the supply elasticity such as in Lagakos and Waugh (2013), Hsieh et al. (2019), and Lee (2019).

Table 4: Estimates of equation 22

	OLS	2SLS
$Ln\left(N_{k,s,t}^{o}\right)$	-0.031***	-0.162***
	(0.0068)	(0.053)
N obs	2534	2534
Implied κ	32.26	6.17
1st stage F-stat		20.0

$*p < 0.1, **p < 0.05, ***p < 0.01$. o-k-t FE and k-s-t-x FE included. Years 2002 to 2014 used for estimation. To minimize measurement error in average wages I pooled years in pairs (02+03, 04+05,...) and cells with fewer than 5 visa petitions were dropped. Standard errors clustered at the year, industry, and source country.

6.2 Production function parameters α, λ, and ι

I set the elasticity of substitution between college and non-college workers, $\alpha = 1.7$, 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). The aggregate elasticity using $\alpha = 1.7$ is indistinguishable from 1.7. For the elasticity between effective units of high-skill domestic and foreign labor λ, I set $\lambda = 13.1$ to match the aggregate elasticity of 12.6 as estimated by Ottaviano and Peri (2012) for college graduates. Burstein et al. (2018) also find a high elasticity of substitution of 10 for between domestic and foreign workers.

I proceed to estimate ι, the elasticity of substitution between source country and other foreign effective units. It is possible to rework the first-order conditions of the components in equation 8 to get to equation 24:

$$Ln\left(\frac{\text{wage bill}_{z,t}^{s}}{\text{wage bill}_{z,t}^{f}}\right) = (1-\iota)Ln\left(\frac{w_{z,t}^{s}}{w_{z,t}^{f}}\right) + \iota Ln\left(\frac{\psi_{z,t}^{s}}{\psi_{z,t}^{f}}\right) \tag{24}$$

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.[13] If one were to run this regression by OLS, two main issues would arise. First, the effective wage ratio $Ln\left(\frac{w_{z,t}^{s}}{w_{z,t}^{f}}\right)$ 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 upward, as we would be confounding supply

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[13]Once again I add time-subscript t since I will use multiple years of data for estimation. Also, z stands for a given triplet k, ℓ, s.

and demand. I proceed to estimate this parameter in two steps. In the first step, I use the estimated value of κ and data on average wages and employment to back out the implied ratio of effective wages in equilibrium. In a second step, once I have the explanatory variable, I use an instrumental variables approach to identify ι.

In Appendix E.2, I explain how it is possible to use equation 21 and the estimated value of $\kappa = 6.17$ to back out the implied effective wage ratio $\frac{w_{z,t}^s}{w_{z,t}^f}$.

I estimate equation 24 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 47 as an explanatory variable. The term $Ln\left(\frac{\psi_{z,t}^s}{\psi_{z,t}^f}\right)$ is considered part of the error term. I also add time-industry fixed effects to control for time-specific industry shocks. Since the error term includes the preference for source workers relative to other foreign workers $\frac{\psi_{z,t}^s}{\psi_{z,t}^f}$, I need an instrument to consistently estimate equation 24. The instrument should shift supply but be uncorrelated with unobserved demand shocks in order to identify the demand parameter $1 - \iota$.

I propose two instruments that use very different sources of variation to estimate ι. First, I use the shift-share instrument proposed in Section 5, equation 18. The shift-share instrument captures the supply push of immigrants from country s into the US that is independent of time-specific demand shocks experienced by companies from s in the US and is negatively correlated with the ratio of effective wages. Second, I use the log GDP per worker in country s as a proxy for average wages in country s. This is a valid instrument because 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 24 can be found in Table 5 and results are consistent with what we would expect. OLS results are upward biased, since they predict a ι lower than one and not significant. When instrumenting for the effective wages, the estimated ι is 2.84 using the shift-share instrument and $\iota = 6.84$ using the log of the GDP per worker. I will use $\iota = 2.84$ as my baseline value and show robustness with $\iota = 6.84$.

Table 5: Estimating equation for ι

	OLS	2SLS	2SLS
Log wage effective units ratio	-0.0014	-1.84***	-5.84**
	(0.201)	(0.656)	(2.58)
N obs	1,750	1,750	1,750
Implied ι	1.00	2.84	6.84
1st stage F-stat		48.67	25.71

$*p < 0.1, **p < 0.05, ***p < 0.01$. Controlling for time-industry fixed effects. Standard errors bootstrapped with 250 repetitions and clustered at the time-source level. Indian companies are removed from the sample as the small number of non-Indian workers they hire distort the relative wage ratios needed for estimation.

6.3 Spillover parameter ν

Finally, I use indirect inference to estimate the MNE cost spillover parameter ν. When the number of workers from s in industry k, country ℓ increases by 1%, the MNE iceberg cost for companies from s in ℓ, k decreases by $-\nu\%$. According to the estimates in Table 3, a 1% increase in the number of immigrants from s in k increases MNE employment by 1.34%. Such number decreases to 0.84% when excluding Indian companies. I calibrate two separate ν, one for India and another for all other source countries such that it matches the average MNE employment response of 1.34% and 0.84%, respectively. This yields $\nu_{in} = 1.25$ and $\nu_s = 0.27$.

6.4 Implementation

To implement the model I need to make some simplifications, since data on the stock of native and immigrant workers across countries and industries is less detailed for non-US countries. 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 in the US 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 are the US, Canada, and countries in Western Europe.

I set $\theta = 4$, $\alpha = 1.7$, $\kappa = 6.17$, $\lambda = 13.1$, $\iota = 2.84$, $\nu_{in} = 1.25$ and $\nu_s = 0.27$ consistent with the baseline parameters estimated in Section 6. 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 k, ℓ, s, and skill shares for domestic, source country, and other foreign workers for each triplet k, ℓ, s. In Appendix F I explain how I construct the dataset to run the counterfactual exercises. 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 F, 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 employment.

Finally, to calculate the equilibrium I need to impose a normalization. I follow Allen et al. (2018) and impose that World output stays constant as in equation 25. This normalization implies that the output results should be interpreted as how the endogenous variables change as a share of total World output.

$$X_{us} + X_{in} + X_{ca} + X_{eu} + X_{ch} + X_{oth} = \bar{X} \tag{25}$$

7   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 introduce the shock of increasing the migration cost to the US to evaluate the long-term implications of a more restrictive high-skill immigration policy. In a second counterfactual, I introduce the shock of increasing MNE barriers and use the model to understand how does modeling migration affects the quantification of the welfare gains of MNE production.

7.1   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

facilitate the interpretation of the quantitative results, I will change the immigration cost from every country to the US such that it reduces the total stock of high-skill immigrants by 10%. A 10% decrease is consistent with a 0.95% decrease in the college-graduate workforce in the US and a 0.3% decrease in total US workforce.

Despite the apparent rationing feature of the US immigration system, the Frechet assumption captures well the positive selection of immigrants which it is crucial to characterize the US immigration system. Given abilities being distributed Frechet, as the migration cost increases the total number of immigrants decreases and those who still migrate to the US will be positively selected following the intuition of equation 20. For the H-1B program, the number of visas is rationed through a lottery and those who win the lottery might not necessarily be of higher ability than those who lose the lottery. However, I will argue that in the medium run, the US immigration system is well characterized with a positive selection feature as in this model. First, employers pay a fee for applying for H-1Bs, indicating that those sponsored for an H-1B are positively selected among all origin-country college graduates. Second, if a worker with sufficiently higher ability loses the lottery, there are alternative strategies to come to the US, such as getting an L-1, getting sponsored for a green card, or finding a job at a non-lottery-subject company. Third, even if the worker loses the lottery, employers can apply for a new visa again in subsequent years. Finally, workers who receive graduate degrees from US institutions have a higher likelihood of getting accepted in the lottery. Overall, such features suggest the US high-skill immigration is selective and if the number of immigrants were to be reduced, those still migrating would be positively selected.

As a first set of results, Table 6 summarizes how the increase in migration costs to the US affects the total revenues generated by each sector-country pair relative to World output. I present the results for the baseline case and the case where there is no MNE cost spillover ($\nu = 0$) for comparison. High-skill industries in the US decrease their output more than the residual sector. Production in all other regions increases as a result of US migration restrictions. The IT and professional services sector would grow by 0.63% in India and 0.16% in Canada, while the high-skill manufacturing sector would also grow the most in India (0.43%) and Canada (0.96%). 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. The spillover amplifies the production response and results are qualitatively similar except in Canada, where MNEs in manufacturing account for 73% of production, so their increase in production is much larger when there is a spillover.

Table 6: Change in production by country and industry

	baseline			no spillover		
	IT and Prof. Services	High-Skill Manufacturing	Other	IT and Prof. Services	High-Skill Manufacturing	Other
US	-0.53%	-1.70%	-0.40%	-0.39%	-0.43%	-0.34%
India	0.63%	0.43%	0.20%	0.60%	0.29%	0.20%
Western Europe	0.11%	0.24%	0.09%	0.08%	0.06%	0.07%
Canada	0.16%	0.96%	0.01%	0.16%	0.09%	0.10%
China-Taiwan	0.14%	0.24%	0.12%	0.10%	0.11%	0.09%
Rest of the World	0.10%	0.27%	0.07%	0.07%	0.06%	0.06%

Percent changes in production output from increasing migration cost such that the total stock of migrants decreases by 10%. 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. While this is true for both with and without the spillover, results are much larger for the case with the spillover by construction. As shown in Table 7, 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 29.55% and 9.22%, respectively. While foreign MNEs are more intensive in foreign workers than American companies, they also have a particular dependence on foreign workers from their own source country. It makes sense then that companies from countries where labor is cheaper are the one who have the biggest hit.

Table 7: Production of MNEs in the US by source country

	baseline		no spillover	
	IT and Prof. Services	High-Skill Manufacturing	IT and Prof. Services	High-Skill Manufacturing
US	-0.03%	0.97%	-0.36%	-0.40%
India	-29.55%	-26.32%	-3.06%	-0.93%
Western Europe	-9.14%	-8.00%	-0.70%	-0.51%
Canada	-8.57%	-7.40%	-0.70%	-0.51%
China-Taiwan	-9.22%	-7.83%	-1.20%	-0.79%

Percent changes in revenues from increasing migration cost such that the total stock of migrants decreases by 10%. Change relative to World output.

Even without the spillover effect, MNEs disproportionately drive the drop in production. Foreign MNEs account for 4.8% of production in the US IT sector, but account for 11.1% 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 38.0% of the drop in revenues. MNEs account for almost 100% of the drop in production once we include the spillover effect, as they become even more sensitive to reductions in immigration. Appendix G 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 real wages for US natives, there are some workers who gain from such restrictions. As shown in Table 8, high-skill workers would experience an increase of 0.09% in their real wages 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 real wages decreased by 0.35% given their complementarity with high-skill workers. Aggregating across skill types, total real wages for US workers would decrease by 0.22% when migration is restricted. Real wage is calculated as the average wage for each group divided by the price index. A restriction in migration affects real wages predominantly through changes in wages as shown in column 2 of Table 8.

Table 8: Change in Real Wages and Compensating Variation

	Real Wages (percent change)	Wages (percent change)	Compensating Variation (per native worker)
High-skill natives	0.09%	0.11%	-60
Low-skill natives	-0.35%	-0.33%	108
Total US natives	-0.22%	-0.20%	57

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. Real wages are calculated as average wage divided by the price index. Compensating variation is the dollar value each worker would need to be compensated to leave their utility the same after restricting immigration

Finally, to put these numbers into context I calculate the compensating variation for low and high-skill workers. The compensating variation is the amount of income that workers need to be compensated in the counterfactual to hold their utility levels as in the real. Each low-skill worker in the US would need to be compensated by \$108 each year while the gains for each high-skill worker amounts to \$60. Overall, restricting high-skill immigration by 10% would cause each US worker to lose on average \$57 per year once the economy reaches the steady state. The total loss for US natives would amount to almost \$8 billion per year.

7.1.1 Mechanisms and Robustness

The baseline results presented in Section 7.1 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 baseline results. First, as noted in the production results above, the spillover of immigrants on MNE costs significantly amplifies the magnitude of the results. In Table 9, I compare how the results affect real wages for different values of ν. With no spillover, qualitative results hold, but the effect of restricting immigration drops from -0.22% to -0.13%. If we assume a common, large spillover such as $\nu = 0.9$, restricting immigration would generate losses for both low- and high-skill workers as the exit of high-productivity MNEs would reduce labor demand and increase prices in the US, harming all workers.

Table 9: Changes in the spillover parameter

	$\nu_{in} = \nu_s = 0$ (no spillover)	$\nu_{in} = 1.25, \nu_s = 0.27$ (baseline)	$\nu_{in} = \nu_s = 0.9$ (same spillover)
High-skill natives	0.17%	0.09%	-0.03%
Low-skill natives	-0.26%	-0.35%	-0.48%
Total US natives	-0.13%	-0.22%	-0.34%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. Real wages are calculated as average wage divided by the price index.

A large part of the literature on the effects of immigration has used implicitly or explicitly closed-economy models (Bound et al., 2018; Burstein et al., 2018; Docquier et al., 2014). One of the contributions of this paper is incorporating both trade and MNE activity as channels through which production relocates as a consequence of restricting immigration. In Table 10, I compare the welfare effects of the baseline model with alternative models that remove trade and MNE activity to understand how they drive the baseline result.

Column 3 compares the baseline and the no-spillover model with a model that does not include MNE production. Such model is equivalent to a multi-country, multi-industry Eaton and Kortum (2002) model that allows for migration. The data used assume 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 real wage losses by 45% (-0.22% vs -0.12%) since it no longer accounts for the role of immigration in bringing more productive foreign companies' which lower the price index in the US and increase real wages. When comparing it to the no spillover model, the model with no MNEs understates real wage losses by 6% (-0.13% vs -0.12%). In this case, 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 and foreign workers is high. However, as shown in Section 7.2, the migration channel does have a large impact in the welfare gains that stem from allowing MNE production regardless of the spillover.

Column 4 looks at an alternative model where MNE activity is allowed but trade costs are prohibitive such that there is no trade. Restricting immigration generates a larger real wage loss under the model with no trade and also lowers the gains for high skill workers. When no trade is allowed, production does not relocate and consumers have to buy goods produced in the US, which without immigration become more expensive than when trade is allowed. The overall welfare loss under no trade is 15.7% higher than in the baseline model.

Table 10: Understanding mechanisms - Trade and MNE

	Baseline	no spillover	No MNE	No Trade
High-skill natives	0.09%	0.17%	0.17%	0.06%
Low-skill natives	-0.35%	-0.26%	-0.24%	-0.39%
Total US natives	-0.22%	-0.13%	-0.12%	-0.25%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. Column 1: Baseline results. Column 2: Model with no spillover. Column 3: Model with no multinational activity. Column 4: Model with no international trade.

As a second set of mechanisms, I look into how the results for real wages change for different values of the key elasticities. Appendix G shows that very low values of λ or high values of α could lead high-skill workers to lose from restricting immigration. However, total real wage losses have a similar magnitude among plausible values for the elasticities.

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

Restrictions to migration have big consequences on the activity of MNEs in the receiving country. To understand the aggregate implications of such result, I explore how the welfare gains from MNE activity are affected by incorporating migration into the model. 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 MNEs, the welfare gains from MNE production are 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 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.[14] 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 11, 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,

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[14]Note that the spillover does not play a role anymore, since I am exogenously changing MNE cost $\hat{\delta}_{s,\ell}^k$.

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 8.69% 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 3.17%.

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 34.92% while underestimating the gains for low-skill workers by 8.15%. 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 who join the country when MNEs are allowed. Therefore, migration contributes an additional gain toward welfare created by MNE production.

Table 11: Welfare gains from MNE production

	Baseline	No migration	Relative to baseline
High-skill natives	1.16%	1.56%	34.92%
Low-skill natives	1.42%	1.30%	-8.15%
Total US natives	1.34%	1.38%	3.17%
Migrants in US	8.69%	0.00%	

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 11 hold when looking at the MNE gains for migrant-receiving regions such as Europe and Canada as shown in Appendix H. 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 the 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. Appendix H also shows these results are robust for different values of the elasticities.

8   Discussion

The results presented in this paper have useful implications for immigration policy in the United States. A reduction of 10% in the stock of migrants would cause a total loss of 8 billion USD for the US economy, driven by a $10 billion loss for low skill workers and a $3 billion gain for high-skill workers. The interrelation between MNEs activities and immigration is crucial to consider when designing policies that aim to attract FDI into the country since restrictions in immigration will be likely to mitigate the inflows of MNE activity.

While this paper focuses on high-skill migration, an important policy question is how the results would change if I were to incorporate low-skill migration as well. Restricting low-skill immigration is expected to have effects that mirror the results in this paper, improving welfare for low-skill natives and reducing welfare for high-skill natives. The net welfare resulting from the restriction of both types of migration is hard to predict *a priori* without data on low skill immigration and the appropriate elasticities of supply and substitution, which might be different for low-skill workers. The effects of immigration on MNE activity on the other hand, are expected to be different for low- and high-skill immigration. As shown in Section 5, the entry of MNEs is likely to have a stronger link to high-skill immigration than low-skill immigration.

The findings of this project open the door to future research on the relationship between MNE activity and immigration. A natural first next step would be to study the dynamic implications resulting from the transfer of migrants within a firm as a vehicle for knowledge diffusion and technology transfer. The use of dynamic models to understand how MNEs adjust to a shock in migration policy could help improve our understanding of the frictions MNEs face in transferring technology across countries. Second, the feature of home bias uncovered in this paper raises questions about the underlying reasons behind this empirical pattern. Future work might delve deeper into the decisions of MNEs to hire immigrant workers, and such hiring relates to the use of other production factors such as intra-firm intermediate inputs and investment in new technologies.

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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 me 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 2001 and 2014 for H-1B visas and between 2012 to 2014 for 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 these data is that it include 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. For years 2012 to 2014, 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 were not available for L-1 visas, but all other covariates were complete.

In a second step, 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 to serve as a quality check for some cases where Orbis data are incomplete. The FOIA data and Orbis do not have a common identifier that allows me to easily match observations between datasets. 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 2001-2014. As shown in Table 12, 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 these data, which makes the lower match rate not a substantive matter in the quantitative exercise. Table 13 presents the distribution of visa petitions by worker nationality and source country (GUO of company applying for the visa). Table 14 presents the distribution by industry.

Table 12: 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%
Fewer 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. "Fewer than 10 petitions" includes petitions filed by firms who submitted fewer than 10 petitions in the 2012-2014 period.

Table 13: Distribution across source countries and nationalities

| | MNE Source Country | | Worker nationality | |
Country	H-1B	L-1	H-1B	L-1
Australia	0.1%	0.1%	0.2%	1.0%
Canada	0.5%	4.1%	1.7%	17.0%
China	0.2%	0.8%	5.6%	5.7%
Finland	0.2%	0.3%	0.0%	0.2%
France	2.2%	3.1%	0.4%	2.2%
Germany	0.8%	2.3%	0.3%	2.4%
India	21.4%	26.5%	81.9%	32.6%
Ireland	2.5%	0.9%	0.1%	0.9%
Israel	0.0%	0.1%	0.2%	1.0%
Japan	1.2%	2.1%	0.3%	2.4%
Korea	0.3%	0.4%	0.7%	1.9%
Netherlands	0.5%	0.5%	0.1%	1.0%
Spain	0.0%	0.2%	0.1%	1.2%
Sweden	0.2%	0.3%	0.1%	0.6%
Switzerland	0.6%	1.2%	0.0%	0.4%
Taiwan	0.3%	0.0%	0.4%	0.3%
United Kingdom	1.1%	2.2%	0.6%	7.3%
Other	1.5%	4.4%	7.2%	21.8%
United States	66.7%	50.4%	-	-
Total	100%	100%	100%	100%

Table 14: Distribution by industry

	H-1B	L-1
Manufacturing		
Chemicals	0.80%	1.62%
Computer and Electronics	6.43%	2.82%
Electrical Equipment	0.22%	1.37%
Food	0.13%	0.17%
Machinery	0.86%	1.06%
Metals	0.13%	0.58%
Trasportation Equipment	0.54%	1.64%
Services		
Finance and Insurance	4.87%	6.24%
Information	5.20%	1.86%
Professional, Scientific and Technical	74.40%	64.71%
Real Estate	0.07%	0.06%
Other		
Retail	1.96%	0.69%
Wholesale	0.74%	0.97%
Other	3.64%	16.22%
Total	100.0%	100.0%

B Empirical facts details

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 not from s. 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 26, that presents the average home-bias effect across different source countries.

$$Ln(N_{k,o,s}) = \gamma_0 + \gamma \mathbb{1}(origin = source) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \tag{26}$$

Where $Ln(N_{k,o,s})$ 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 in the disaggregated regression in Section 3, the magnitude of the home bias is large. As shown in Table 15, controlling for worker and source-country fixed effects is relevant to isolate

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the home-bias effect. Interpreting the result shown in the fifth column, companies from country s in industry k are 153% more likely to hire someone from country s than any other country when compared to companies not from s.

Table 15: Alternative fixed effects for sourcing regression

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(source = origin)$	-0.162	0.107	0.894***	1.275***	1.53***
	(0.313)	(0.160)	(0.120)	(0.171)	(0.224)
N obs	1,928	1,928	1,928	1,928	1,928
Sample	H-1B	H-1B	H-1B	H-1B	H-1B
Origin FE		x	x	x	
Source FE			x	x	
Industry FE				x	
Source-Industry, Origin-Industry FE					x

$*p < 0.1, **p < 0.05, ***p < 0.01$. All regressions control for year fixed effects. All visa petitions filed in 2012, 2013, and 2014. Standard errors clustered at the source-origin level.

Table 16 shows that the result holds under several alternative specifications. Column 1 shows the results are very similar when only considering visa petitions for new employment (excluding renewals and job changes). Column 2 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 advantages. Column 3 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 Poison Pseudo Maximum Likelihood (PPML) to include zero observations as suggested by Santos Silva and Tenreyro (2006).

Finally, columns 4 and 5 look at the differences in home bias by L-1 and H-1B visas. Surprisingly, the estimated home-bias is much smaller when looking at L-1 visas. However, since the H-1B program is much larger, the aggregate effects are dominated by the H-1B. The estimation in Section 6 uses data on wages, which are only available for H-1Bs so it is reassuring that L-1 visas are not driving the observed results. In Figure 4, I plot the disaggregated regression across source countries where we can see that there is a positive home-bias for both H-1B and L-1, but the effects are larger when looking at the H-1B.

Table 16: Alternative specifications for sourcing regression

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(source = origin)$	1.397***	2.227***	2.619***	0.311**	1.078***
	(0.211)	(0.240)	(0.172)	(0.104)	(0.166)
N obs	1,928	664	972	1,162	1,928
Sample	Only new employment visas	No industries	No industries - Including zeros	L-1	H-1B+L1

$*p < 0.1, **p < 0.05, ***p < 0.01$. All regressions control for year FE, source-industry FE, and origin-industry FE. All visa petitions filed in 2012, 2013, and 2014. Standard errors clustered at the source-origin level.

In Figure 4, I plot the disaggregated regression across source countries where we can see that there is a positive home-bias for both H-1B and L-1, but the effects are larger when looking at the H-1B.
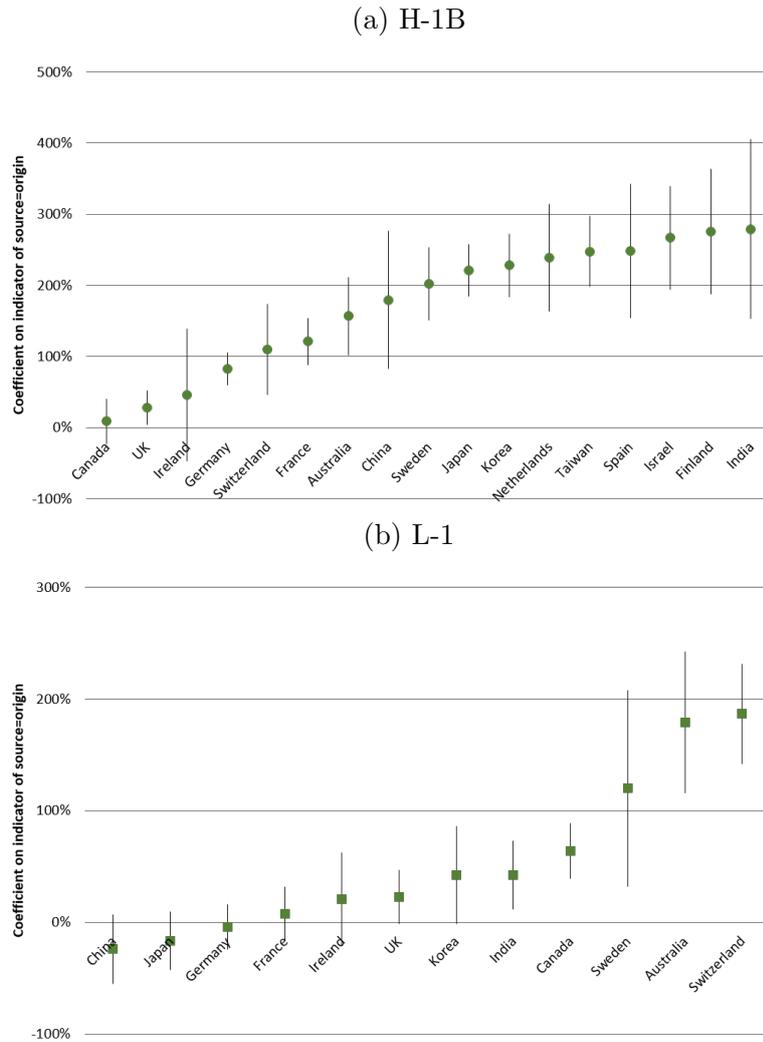
Figure 4: Estimated coefficient (γ_s) on sourcing regression by country (H-1B vs. L-1)

(a) H-1B

(b) L-1

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

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

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

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

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

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

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

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

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

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

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

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 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.

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

$$c_{k,\ell,s}^{fs} = \left((\psi_{k,\ell,s}^s)^\iota (w_{k,\ell,s}^s)^{1-\iota} + (\psi_{k,\ell,s}^f)^\iota (w_{k,\ell,s}^f)^{1-\iota} \right)^{\frac{1}{1-\iota}} \tag{33}$$

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

$$\Theta_{k,\ell,s}^L = \frac{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha}}{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}} \quad \Theta_{k,\ell,s}^H = \frac{(\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}}{(\psi_{k,\ell}^l)^\alpha w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^h)^\alpha (c_{k,\ell,s}^h)^{1-\alpha}} \tag{34}$$

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.

$$\Theta_{k,\ell,s}^d = \frac{(\psi_{k,\ell,s}^d)^\lambda (w_{k,\ell,s}^d)^{1-\lambda}}{\sum_{x'} (\psi_{k,\ell,s}^{x'})^\lambda (w_{k,\ell,s}^{x'})^{1-\lambda}} \quad \text{for x'=\{d,sf\}} \quad \Theta_{k,\ell,s}^x = \frac{(\psi_{k,\ell,s}^x)^\iota (w_{k,\ell,s}^x)^{1-\iota}}{\sum_{x'} (\psi_{k,\ell,s}^{x'})^\iota (w_{k,\ell,s}^{x'})^{1-\iota}} \quad \text{for x,x'=\{s,f\}} \tag{35}$$

8. Demand for low-skill (L), native (d), source (s), other foreign (f) workers - one for each k-ℓ-s triplet. Where $I_{\ell,k}$ are the revenues for industry k in country ℓ.

$$w_{L,\ell} L_{k,\ell,s} = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta_{k,\ell,s}^L \pi_{k,s,\ell}^{mne} I_{\ell,k} \tag{36}$$

$$w_{x,\ell} H_{k,\ell,s}^x = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta_{k,\ell,s}^H \Theta_{k,\ell,s}^x \pi_{k,s,\ell}^{mne} I_{\ell,k} \quad \text{with } x = d, s, f \tag{37}$$

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, $\bar{L}_\ell$ total low skill labor supply.

$$I_{\ell,k} = \sum_n \pi_{k,\ell,n}^{trade} \gamma_{k,n} X_n \tag{38}$$

$$X_n = w_{L,\ell} \bar{L}_\ell + \sum_{k,\ell,s,x} w_{k,\ell,s}^x H_{k,\ell,s}^x \quad \text{with } x = d, s, f \tag{39}$$

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

$$\sum_{k,s} w_{L,\ell} L_{k,\ell,s} = w_{L,\ell} \bar{L}_\ell \tag{40}$$

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

$$\pi_{o,k,\ell,s}^{mig} = \frac{A_{o,k} \left(\frac{w_{k,\ell,s}}{P_\ell} \varepsilon_{k,\ell,s}^o \right)^\kappa \phi_{o,\ell,s}^{-\kappa}}{\sum_{\ell',s',k'} A_{o,k'} \left(\frac{w_{k',\ell',s'}}{P_{\ell'}} \varepsilon_{k',\ell',s'}^o \right)^\kappa \phi_{o',\ell',s'}^{-\kappa}} \tag{41}$$

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.

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

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

$$w_{k,\ell,s}^s H_{k,\ell,s}^s = \sum_{o\neq\{\ell,s\}} w_{k,\ell,s}^f \varepsilon_{k,\ell,s}^o (\pi_{o,k,\ell\neq o,s\neq o}^{mig})^{\frac{\kappa-1}{\kappa}} N_o A_{k,o}^{\frac{1}{\kappa}} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \tag{44}$$

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 rewrite 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 36, 37, 42, and 43 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

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

2. Trade shares/ Domestic price index

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

3. Unit cost / high-skill unit cost

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

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

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

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

$$\hat{I}_{\ell,k} = \sum_{n}\hat{\pi}_{k,n,\ell}^{trade}\hat{X}_{n}\underbrace{\frac{\pi_{k,n,\ell}^{trade}\gamma_{k,n}X_{n}}{\sum_{n}\pi_{k,n,\ell}^{trade}\gamma_{k,n}X_{n}}}_{\text{Share sold to } n: \Lambda_{k,n,\ell}} \quad ;$$

$$\hat{X}_{\ell} = \hat{w}_{L,\ell}\hat{\bar{L}}_{\ell}\underbrace{\frac{w_{L,\ell}\bar{L}_{\ell}}{X_{\ell}}}_{\text{Low-skill share } \Lambda_{\ell}^{L}} + \sum_{k,\ell,s,x}\hat{w}_{k,\ell,s}^{x}\hat{H}_{k,\ell,s}^{x}\underbrace{\frac{w_{k,\ell,s}^{x}H_{k,\ell,s}^{x}}{X_{\ell}}}_{\text{High-skill share } \Lambda_{k,\ell,s}^{x}}$$

5. Low-skill market clearing / Migration share

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

6. Other-foreign market clearing

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

The equations above imply that the change in the endogenous variables can be computed as long as I have estimates of the 6 key elasticities (θ, α, λ, ι, ν, 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 F.

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 ($\tau_{\ell,n}^{k}$), production function labor shares ($\psi_{k,\ell}^{l}$, $\psi_{k,\ell}^{h}$, $\psi_{k,\ell,s}^{d}$, $\psi_{k,\ell,s}^{s}$, $\psi_{k,\ell,s}^{f}$, $\psi_{k,\ell,s}^{fs}$), Total low-skill ($\bar{L}_{\ell}$) and high-skill (N_{ℓ}) labor born in ℓ, individual ability comparative advantage ($A_{o,k}$), origin-specific productivity ($\varepsilon_{k,\ell,s}^{o}$), 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 7.2 and 7.1 will compute how the equilibrium changes after an exogenous change of the MNE cost in all countries $\delta_{\ell,s}^{k}$ or the migration cost to the US $\phi_{o,us,s}$.

D   Details of reduced-form exercise

The dataset to run the regressions in Section 5 is constructed by merging publicly available data on MNE employment from the BEA with the H-1B dataset described in Section 2. I exclude L-1 visas from the analysis since L-1 data are only available for 2012 to 2014. I group both datasets into 26 source countries and 13 industry groups. The BEA data comes from a survey administered by the BEA to foreign MNEs who have operations in the US. The dataset is called "Comprehensive Data on the Activities of U.S. Affiliates" and I use the survey for majority-owned affiliates. I use "Employment of Affiliates, Country of UBO by Industry of Affiliate," which provides US employment at the source-country level for 42 countries and 14 industries.

As shown in Table 17, column 1 shows that the estimates are larger but similar in magnitude when including industry-source pairs with zero visa petitons. Results are robust to controlling for source-time fixed effects as shown in columns 2 and 3. Columns 4-6 show that adding source-time covariates does not affect the estimates of the immigrants coefficient in the second stage.

Table 17: Dependent Variable: Log US Employment of MNEs from s in k, t

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (Imm from $o = s$ in s,k,t)	1.94***	0.80***	1.21	1.68***	1.79***	1.62***
	(0.46)	(0.118)	(0.737)	(0.496)	(0.577)	(0.489)
Share of US imports from s in k, t				5.25**		
				(1.95)		
Total GDP at s, t					-0.22*	
					(0.12)	
Total Exports from s, t to US						-7.63
						(9.78)
N obs	1167	616	616	616	616	616
1st stage F-stat	28.6	343.0	6.3	14.6	14.4	15.8
Industry-Source FE	x		x	x	x	x
Source-Time FE		x	x			

$*p < 0.1, **p < 0.05, ***p < 0.01$. 2SLS estimates. Industry-Source-Time level regression. Years 2002-2014 included. Standard errors clustered at the source-country level. Industry-time FE included in all regressions. Column 1 adds 1 to each observation to avoid dropping zeros.

Table 18: Correlation between observables and MNE employment growth

	Growth MNE employment	Initial Shares
Industry GDP share in s	3.81	1.25**
	(3.63)	(0.50)
Industry exports share in s	-3.47**	0.33
	(1.56)	(0.21)
Share of MNEs from s in US in non-k	-1.52	0.22
	(1.18)	(0.16)
Share of US imports from s in k	0.47	0.00
	(1.79)	(0.25)
Share of non-US imports from s in k	1.29	-0.42
	(2.86)	(0.39)
Common language s and US	0.19	0.01
	(0.19)	(0.03)
Regional Trade agreement s and US	0.26	0.02
	(0.44)	(0.06)
Distance s and US	0.11***	0.006
	(0.04)	(0.005)
N	126	126

$*p < 0.1, **p < 0.05, ***p < 0.01$. 2SLS estimates. Shares and covariates at 2001. Log growth in MNE employment from country s in industry k between 2014 and 2004. Distance expressed in thousands of population weighted miles. Results are robust to regressing each covariate separately with the dependent variables.

E Estimation details

E.1 Estimating κ using the wage dispersion

The purpose of this Section is twofold. First, I will use variation in the observed wage dispersion for high-skill immigrants to estimate κ as a way of validating the estimate in Section 6.1, which uses a very different source of variation. 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. (2019) and Lee (2019). While this approach relies on the distributional assumptions for the ability draws, the Frechet distribution has been shown to provide a good approximation of the observed wage distribution (Burstein et al., 2018). Second, I will use the observed wage dispersion and the estimate of κ from Section 6.1 to separate the dispersion parameter κ and the correlation ρ.

I will start by ignoring ρ and assuming $\kappa = \tilde{\kappa}$. 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 $W_{k,\ell,s}^{i,o} = \eta_{k,\ell,s}^{i,o} w_{k,\ell,s}$ 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 observed 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 k, ℓ, s. This proposition indicates that the observed dispersion of wages can be used to make inference on the value of $\tilde{\kappa}$. 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 45 and estimate the parameter $\tilde{\kappa}$ by GMM, choosing a value of $\tilde{\kappa}$ that minimizes the distance between the empirical moments and the moments from proposition 2.

$$\left(\frac{Var(W^o_{k,\ell,s})}{\left(\overline{W}^o_{k,\ell,s}\right)^2}\right) = \frac{\Gamma\left(1 - \frac{2}{\kappa}\right)}{\left(\Gamma\left(1 - \frac{1}{\kappa}\right)^2\right)} - 1 \tag{45}$$

I present the baseline results using the H-1B data in Column (1) of Table 19. An alternative strategy is to use the estimate of $\kappa = 6.17$ from Section 6.1 and equation 45 by replacing κ by $\kappa(1 - \rho)$. Table 19 compares the different approaches and shows that, overall, both yield similar values of κ even if the underlying assumptions for estimation are very different.

Table 19: Estimates for κ using dispersion of wages

	Only using dispersion	Using trade shock and dispersion
κ	8.28***	6.17***
	(0.138)	(2.012)
$\tilde{\kappa}$	8.28***	2.08***
	(0.138)	(0.00016)
Implied ρ	0	0.66
	2,534	2,534

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

E.2 Estimating effective wage ratio

To estimate equation 24 it is necessary to have information on the ratio of effective wages. Using the the properties of the Frechet distribution, we can write the observed average wages for each group as in equation 46:

$$\overline{wage}^o_{z,t} = w^x_{z,t}\pi^{-\frac{1}{\kappa}}_{o,z,t}A^{\frac{1}{\kappa}}_{k,o,t}\bar{\Gamma}\varepsilon^o_{z,t} \tag{46}$$

Where $\overline{wage}^o_{z,t}$ is the average wage for those from origin o that migrate to triplet $z = k, \ell, s$ at time t, conditional on choosing z. $w^x_{z,t}$ is the equilibrium wage per effective unit paid to those who choose triplet z and the superscript x indicates whether the workers are hired by an MNE with $s = o$ or if they are hired just as other foreign workers. $\pi_{o,z,t} = \frac{N^o_{z,t}}{N^o_t}$ is the fraction of workers from o, who migrate to z, and $A_{k,o,t}$ is the comparative advantage of workers from o in industry k. Finally, $\bar{\Gamma}$ is the Gamma function.

By taking the ratio between $\overline{wage}^{o=s}_z$ and $\overline{wage}^{o\neq s}_z$, taking logs and rearranging terms, it is possible to get to equation 47:

$$\underbrace{Ln\left(\frac{\overline{wage}^s_{z,t}}{\overline{wage}^o_{z,t}}\right) + \frac{1}{\kappa}Ln\left(\frac{N^s_{z,t}}{N^o_{z,t}}\right)}_{\text{Data}} = \underbrace{Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right) + \frac{1}{\kappa}Ln(N_{s,t}A_{k,s,t})}_{\text{Source-Industry-Time FE}} - \underbrace{\frac{1}{\kappa}Ln(N_{o,t}A_{k,o,t})}_{\text{Origin-Industry-Time FE}} + \underbrace{Ln\left(\frac{\varepsilon^o_{z,t}}{\varepsilon^o_{z,t}}\right)}_{\text{Error term}}$$

$$(47)$$

Equation 47 shows that it is possible to run a regression at the source-origin-industry level using the H-1B data for average wages ($\overline{wage}^{o=s}_{z,t}$ and $\overline{wage}^{o\neq s}_{z,t}$) and number of employees by group ($N^s_{z,t}$, $N^o_{z,t}$) together with the estimated value of κ, 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 equilibrium effective wages $Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right)$, which is our object of interest.

F   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 6.4 and the data needed as outlined in appedix 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 that 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 ($\pi^{trade}_{k,\ell,n}$), 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 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 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 are 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 2009. China-Taiwan and the 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 ($\Theta_{k,\ell,s}^{L}$, $\Theta_{k,\ell,s}^{H}$, $\Theta_{k,\ell,s}^{d}$, $\Theta_{k,\ell,s}^{s}$, $\Theta_{k,\ell,s}^{f}$, Λ_{ℓ}^{L}, $\Lambda_{k,\ell,s}^{x}$, $\Lambda_{k,\ell,s}^{L}$, $\Lambda_{k,\ell,s}^{o}$): 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 compute counts of workers so wage data are 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 the Rest of the World are 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.

G   Counterfactual 1: A more restrictive migration policy

In this Section, I present additional results from restricting migration into the US. As noted in Table 6, foreign MNEs in the US respond more in terms of revenues than US companies. Table 20 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 20: Contribution of MNEs to output drop

		Percent change in Revenues		Share of US production
		Spillover	No spillover	
IT and Prof.Services	Total	-0.53%	-0.36%	
	US	-0.03%	-0.35%	95.16%
	Foreign	-0.50%	-0.04%	4.84%
	Share of Foreign MNEs in output drop	94.2%	11.1%	
High-Skill Manufacturing	Total	-1.70%	-0.40%	
	US	0.68%	-0.28%	70.84%
	Foreign	-2.39%	-0.15%	29.16%
	Share of Foreign MNEs in output drop	100%	38.0%	

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. Columns 1,2: contribution to output drop. Column 3: Share of production in the US by MNE source.

In Table 21, columns 2 and 3, I compute the model using lower values of $\lambda = 7$ and $\lambda = 2$, which is closer to a model where immigrants and natives are less substitutable. The model with low λ significantly changes the wage effects for high-skill native, who can even lose from restricting immigration when λ is sufficiently low. However, as we are looking at all college graduates, we would expect the elasticity to be on the higher end. In a second test, I compute the model with $\alpha = 3$ to understand how results would change under a model where low and high skill workers are closer to perfect substitutes. Interestingly, as shown in column 4, the welfare effects generated by migration would be somewhat muted when working with a higher elasticity of substitution. The model with $\alpha = 3$ would make high-skill workers lose from restricting immigration, as firms find it easier to substitute low for high-skill labor when high-skill labor becomes more expensive. Negative effects for low-skill natives are reduced.

In column 5, 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 foreign companies and MNEs would have similar productivities. As shown in Table 21, columns 6, real wage losses are lower with the model with the high θ as the exit of MNEs generates a lower productivity loss. Using the upper bound for $\iota = 6.84$ does not change the results but mainly because of the nature of the counterfactual. Since I am increasing the migration costs from all origins by the same magnitude, and all countries face the same elasticity of supply κ, firms reduce their number of source and other foreign units by the same amount. If migration policy would specifically target some origins, ι would have a larger presence in the quantitative results. Finally, I try $\kappa = 8.28$ as estimated using the wage dispersion method in Section E.1. A higher κ implies that abilities are more concentrated and high-skill workers are more sensitive to changes in the wage. When immigration is restricted, wages go up and high-skill workers relocate more when abilities are more concentrated. As such, their real wages increase more than in the baseline. Low-skill workers on the other hand lose more, since firms find it easier to find natives to replace the immigrants.

Table 21: Understanding mechanisms - elasticities

	Baseline	$\lambda = 7$	$\lambda = 2$	$\alpha = 3$	$\theta = 8.28$	$\iota = 6.84$	$\kappa = 8.28$
High-skill natives	0.09%	0.04%	-0.25%	-0.01%	0.11%	0.09%	0.10%
Low-skill natives	-0.35%	-0.36%	-0.36%	-0.25%	-0.33%	-0.35%	-0.37%
Total US natives	-0.22%	-0.24%	-0.33%	-0.17%	-0.20%	-0.22%	-0.23%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. 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.

H   Counterfactual 2: Welfare gains of MNE production

The results for MNE welfare gains with and without migration presented in Section 7.2 only looked at the gains for the US. Table 23 shows the welfare gains of MNE for the baseline model with migration and an alternative model without migration. The bias on the welfare gains 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 a 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 22: Robustness to key elasticities

	$\alpha = 3$		$\lambda = 7$		$\theta = 8.28$		$\kappa = 8.5$	
	Baseline	No migration	Baseline	No migration	Baseline	No migration	Baseline	No migration
High-skill natives	1.21%	1.58%	1.18%	1.56%	0.61%	0.96%	1.04%	1.47%
Low-skill natives	1.32%	1.25%	1.41%	1.30%	0.75%	0.71%	1.40%	1.26%
Total US natives	1.28%	1.35%	1.34%	1.38%	0.71%	0.78%	1.29%	1.32%
Migrants in US	9.06%	0.00%	7.87%	0.00%	5.85%	0.00%	9.32%	0.00%

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.

Table 23: Welfare gains of MNE production by country

		Baseline	No migration	Relative to baseline
US	High-Skill	1.16%	1.56%	35%
	Low-Skill	1.42%	1.30%	-8%
	All	1.34%	1.38%	3%
Western Europe	High-Skill	1.71%	2.17%	27%
	Low-Skill	1.09%	0.91%	-17%
	All	1.26%	1.24%	-1%
Canada	High-Skill	1.00%	5.39%	437%
	Low-Skill	6.97%	5.28%	-24%
	All	5.54%	5.31%	-4%
India	High-Skill	0.98%	0.55%	-44%
	Low-Skill	0.15%	0.27%	84%
	All	0.21%	0.29%	37%
China-Taiwan	High-Skill	0.49%	0.15%	-69%
	Low-Skill	0.25%	0.36%	48%
	All	0.26%	0.35%	31%

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.