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

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Abstract

The purpose of this paper is to understand 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, such that foreign multinational enterprises (MNEs) in the US tend to hire more migrant workers from their home countries compared to US firms. I build and estimate a quantitative model that includes trade, MNE production, and the migration decisions of high-skill workers. The model is then used to run two main counterfactual exercises. The first one evaluates the implications of a more restrictive immigration policy in the US. High-skill industries in the US predominantly relocate to India and Canada, while real wages decrease for US workers. In the second counterfactual exercise, I increase the barriers to MNE production and find that modeling migration significantly affects the quantitative welfare gains generated by MNEs.

JEL: F16, F22, F23, J61

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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, the US government imposed a suspension of new H-1B visas aimed at high-skill workers in June 2020, to ensure *"Americans are first in line for scarce jobs"*.[1] These policies rely on the argument that immigration reduces employment opportunities for natives whose skills are on par with the immigrants. On the contrary, 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 have been 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 real wages, MNE activity, and total production in high-skill industries. To establish a link between MNEs and high-skill migration, I present a main stylized fact showing 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. 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 relevancy 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, obtained through a Freedom of Information Act (FOIA) request to the United States Citizenship and Immigration Services. The data include information on wages, worker nationalities, and characteristics of the sponsoring firm, such as company name and location. I match these 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 has been missing from previous studies and is key to understanding the relationship between MNEs and high-skill worker migration.

I document three main 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 117% more foreign workers from their source country than from other countries, when compared with the

[1] Details of this policy can be found in a NY Times article from June 20, 2020. Other recent policies discuss rescinding work visas for the spouses of high-skill immigrants 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.

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 present evidence that both mechanisms are present. On one hand, I show MNEs pay lower wages to their source-country immigrants, suggesting home-country workers with lower ability might find it easier to find work at a source-country MNE in the US. On the other hand, home-bias is larger for countries farther away from the US, with languages other than English, and it is particularly strong for small firms that are starting their operations in the US. These suggest home-country immigrants might be important for communication between the parent company and its US affiliate, and facilitate production of MNEs.

As a second fact, I show well-identified, reduced-form evidence that corroborates the positive impact of source-country high-skill immigration on MNE activity. Using variation across years, industries, and source countries, I construct a shift-share instrumental variable for the number of immigrants from each country working at 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 revenues by firms from that source country by 0.92% and assets by 0.65%. The reduced-form evidence also corroborates that high-skill immigration, as opposed to low-skill immigration, has a predominant effect on MNE activity.

Third, I use individual-level visa data to decompose the wage premium across nationalities and firms and guide some features of the model. I show that there is large variation on wage premiums across nationalities and they are positively correlated with the GDP per capita of the workers' home country and negatively correlated with how many workers have already emigrated from the home country. There is also large variation in the average wages paid across firms from different source countries, even conditional on industry, occupation, and nationality of the workers. This suggests that companies across industries and source countries might have access to different labor pools of immigrants, which, in turn, drive the observed differences on wages.

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 (2019). 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).[2] If they choose to migrate, workers have to pay a non-pecuniary migration cost. I assume low-skill workers to be homogeneous and not mobile across countries.

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 a comparative advantage in specific industries; this advantage will make migration more lucrative for some sectors than others. The link between MNE and migration appears through three separate channels. From the labor supply side, the migration cost is deemed to 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 networks or information that facilitate 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 and to focus on six key elasticities that 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

[2]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 (2020), Bryan and Morten (2019), Fan (2019), Tombe and Zhu (2019), and Liu (2020)

other foreign workers. Finally I estimate the elasticity of MNE costs to immigration through indirect inference by matching the estimated response of MNE revenues 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 0.54% and 1.85% 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 0.64% and in Canada by 0.14%. Real wages for US low-skill workers would decrease by 0.36%. 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 0.08% 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 decreases by 0.23% when immigration is restricted, which in dollar terms would account for a total long-term loss of $8.4 billion 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. I also incorporate additional features that are relevant for the quantitative exercise such as heterogeneity in abilities, which is not considered by di Giovanni et al. (2015) and Khanna and Morales (2018) and heterogeneity across industries, not incorporated by Caliendo et al. (2018) and Desmet et al. (2018).

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 building and estimating a quantitative model that allows me to 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, 2019; Arkolakis et al., 2018; Head and Mayer, 2019; 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) presents a model where

the existence of cross-country teams can affect wage inequality in both countries. Keller and Yeaple (2013) tests a model in which MNEs use intermediate inputs to transfer knowledge between the parent and the affiliate while a related literature explores how managers transfer knowledge between firms (Mion et al., 2018) and within firms (Gumpert, 2018). This 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 one main visa program: the H-1B. 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 postgraduate 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 nonprofit 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.

There are other pathways for high-skill foreign workers to move to the US. For example, the L-1 program 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 visa holders. Another employer-tied visa for high-skill immigrants is the TN visa, specific for Canadian and Mexican citizens as a part of NAFTA. TN visas are specific to some professional occupations and are not dual intent, since recipients cannot apply for a green card while on a TN visa. Other pathways to working in the US include the STEM OPT, Diversity Lottery, family reunification, and other smaller programs. However, the H-1B is by far the main pathway for immigration of college graduates from most nationalities in the world, including Canada.[3]

For this project, I submitted a Freedom of Information Act (FOIA) request for the universe of I-129 forms for H-1B visas submitted between 2001 and 2014. The I-129 form needs to be filed by the employer to the United States Citizen and Immigration Services (USCIS) once the visa was approved by the Department of Labor; that is, after the visa application went through the lottery in the case of the H-1B. The novelty of the dataset is that it contains individual information including the employer name, start and end dates for which the visa is valid,

[3] In Appendix A, I discuss in detail how focusing predominantly on the H-1B might affect the results and why the TN visa for Canadians and Mexicans should not affect the main conclusions of the paper.

occupation, country of birth, and wages. Country of birth is a key variable needed 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 which pools all types of petitions 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. The FOIA data also include records of L-1 visas submitted between 2012 and 2014, but there is no information on wages or occupations for these visas. For such reason, I focus on the H-1B for the main analysis and discuss how results are robust to considering L-1 visas whenever possible. Appendix A explains how I constructed the FOIA dataset and provides details on the matching process with the corporate datasets.

The linked employer-employee data provided by FOIA present a unique opportunity to understand the links between employer characteristics, such as MNE status and source country, and the recruitment patterns of immigrant workers. As shown in Appendix A, Tables 12 and 13, 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 Section 3 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.

3 Facts

I use the novel administrative data on H-1B visas to present a series of facts that shed light on the link between high-skill immigration and MNE activity. In Section 3.1, 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 when compared to MNEs from other countries. I explore potential mechanisms that drive this home-bias result. Foreign MNEs in the US pay their own-country immigrants lower wages relative to MNEs from other countries. At the same time, home-bias is larger for small companies and it gets lower over time, suggesting that home-country workers are particularly useful when the company is setting up its operations in the US. Home-bias is larger for countries whose language is not English and are located farther away from the US.

In Section 3.2, I show that a plausibly exogenous influx of home-country immigrants has a

positive effect on MNE revenues, assets, and labor productivity. Such effect is significant both when considering immigrants working for the home-country MNE as well as immigrants working for any company from the industry. These results suggest that a larger immigrant network in the US has a significant effect for MNE production.

Finally, in Section 3.3, I use the H-1B data to provide evidence on the heterogeneity across worker nationalities and MNE source countries that help motivate some features of the model. Immigrants from richer countries and with lower probabilities of emigration to the US show a larger wage premium. There is also significant heterogeneity in wage premiums across MNE source countries and industries, which highlights that MNEs may have access to very different immigrant labor pools within the US. Appendix B provides details on implementation and robustness for each of these facts.

3.1 Home-bias of foreign MNEs

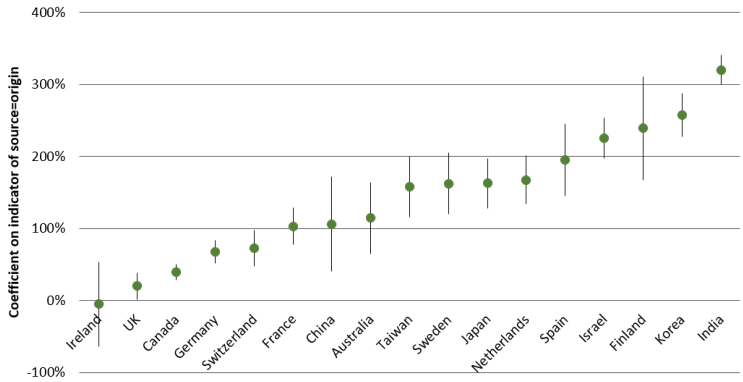
Foreign MNE companies have a "home-bias" toward recruiting workers from their source country when compared to US companies. This is relevant since we should expect foreign companies to respond more to a migration policy change than American companies, which in turn has further implications for changes to the industrial structure and welfare in the US. To find support for this in the H-1B population, I collapse the visa data to the firm (j) - origin (o) - year (t) level and run a regression as in equation 1. I use all visa petitions from firms in industries with at least some MNE activity for the years between 2001 to 2014.[4]

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

The dependent variable in this regression, $Log(N_{j,o,k,s,t})$, stands for the log number of visa petitions by firm j, for workers from nationality o in time t. Subscript s stands for the source country of the company while subscript k stands for industry. For each firm, industry and source country are kept constant over time. The key coefficient of interest is γ_s, which measures how much more likely is a company from source s to hire someone from $o = s$ relative to $o \neq s$ when compared to all other companies from other source countries. $\delta_{j,t}$ is a firm-time fixed effect that captures the trend in visa petitions for all worker origins at the firm level. $\delta_{o,k,t}$ is an origin-industry-time fixed effect that captures the trend in immigration of workers from origin country o in industry k. The results of the home-bias coefficients γ_s can be found in Figure 1. The home-bias is positive and large for most countries in the sample, with significant heterogeneity across source countries. For example, Indian companies are shown to be 320% more likely to recruit workers from India than other countries, relative to non-Indian companies.

[4]For all empirical facts, I exclude industries such as Government, Healthcare, and Education since the MNE activity in such industries is very limited. For the main analysis, petitions for new employment and renewal are included. A firm is the Global Ultimate Owner of the US firms petitioning for the visas.

Figure 1: Estimated coefficient (γ_s) on sourcing regression by country



Appendix B explores further how the regression results change when including observations with 0 value, focusing on new employment visas and running the regression at higher levels of aggregation. The finding of home-bias is very robust to these specifications. As expected, the results are also robust when including L-1 visas into the analysis.

The observed home-bias can be explained by either demand or supply mechanisms. On one hand, we can think of source-country immigrants as having a specific productivity for the firm. For example, they might facilitate communication between the US affiliates and the parent company because of language or cultural proximity. On the other hand, it is possible that workers in the source country find it easier to migrate if they go work for a home-country MNE. Perhaps workers are more likely to find foreign jobs because of networks or employers face a lower screening cost for source-country experience and education credentials. In any case, if migrating is less costly when working for a source country MNE, the foreign MNE in the US will have access to a larger labor pool, lowering its employment costs in the US.

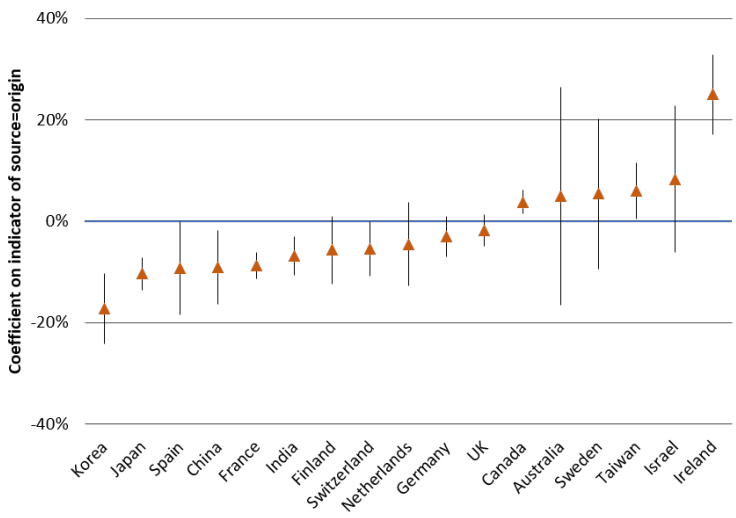
In the remainder of this section, I present empirical evidence suggestive of both supply and demand mechanisms driving the home-bias result. As a first exercise, I use reported data on wages and estimate equation 2.

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

where the dependent variable is the log average wage for each firm-origin pair over time. The right-hand side of the equation is identical to equation 1. 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 was the sole channel, we would expect to see a wage penalty for source-country workers. As shown in Figure 2, a majority of MNE source countries show a wage penalty for source-country workers relative to

other immigrants. For example, Korean firms in the US pay 17.3% less to their Korean workers than to other immigrants when compared to non-Korean firms. As shown in Appendix Table 14, on average, firms pay their source-country workers 3.9% less than immigrants from other origins, when compared to companies from other source countries.

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



To further explore the mechanisms, I look at whether firm size, years since the firm hired immigrants, and other observables explain part of the variation in home-bias across source countries. As a first step, I estimate a variation of equation 1, including an interaction between source country and industry, to get a home-bias coefficient $\gamma_{s,k}$ for each industry-source pair. I then run pairwise correlations between the home-bias coefficient and source country and industry characteristics to find potential drivers of home-bias as shown in Table 1.

Table 1: Pairwise correlation between home-bias and observables

Source country characteristics (s)		**Industry characteristics** (k)	
GDP per worker at s	-0.06	Share of college grads in k	0.12
Common language	**-0.30ˆa**	Average college grads wage in k	0.18
Distance	**0.37ˆa**	Employment share in US	-0.16
Source-Industry characteristics (s, k)			
Industry GDP at s	**-0.23ˆb**	US Employment growth MNEs from s in k	0.19
US Employment MNEs from s in k	-0.07	**Share of US imports from** s **in** k	**-0.31ˆa**

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. 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. MNE employment growth is measured between 2005 and 2014.

Distance from the US and common language stand out as the main variables that are correlated with home-bias. The farther away the country is, the higher the home-bias, consistent with the idea that communication between the parent and the affiliate becomes more costly when distance increases. Common language is negatively correlated with home-bias, consistent with the idea that workers with source-country skills might be particularly useful to facilitate com-

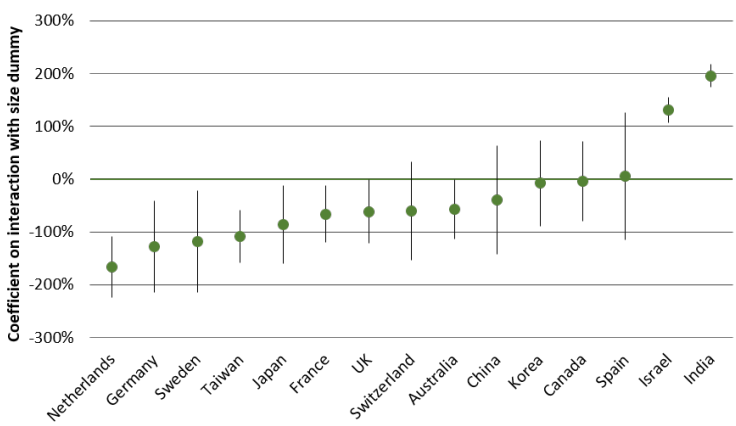
munication between parent and affiliate. Finally, both the industry GDP at s and the share of US imports from country s in a given industry are negatively correlated with home-bias. A possible interpretation is that when a country has large operations in specific industries, the employment of source-country workers might be less crucial for production in the US.

As a second step, I look at the role of firm size. While I don't have good firm-level size measures for MNE operations in the US, I proxy firm size with the average number of visa applications from 2001 to 2014. I estimate equation 3, where in addition to the $source = origin$ indicators, I include an interaction term that takes the value of 1 if the firm is above the median in terms of average visa applications.

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_s \gamma_s \mathbb{1}(o = s) + \sum_s \gamma_s^{p50} \mathbb{1}(o = s) \times \mathbb{1}(\text{avg visas}_j > 50th) + \delta_{j,t} + \delta_{o,k,t} + \epsilon_{j,o,k,s,t} \tag{3}$$

In Figure 3, I plot the estimated coefficients γ_s^{p50} that capture for each source country the differential home-bias for firms whose number of visa applications are above the median among all firms. For a majority of the countries, γ_s^{p50} is negative and significant, such that small firms have a higher degree of home-bias. This is consistent with the hypothesis that when firms have small operations in the US, communication with the parent company might be more important and source-country workers more relevant. A stark exception is India, where large companies have a home bias of 200 percentage points larger than smaller companies. This is driven predominantly by the large Indian outsourcers, whose business model is hiring computer scientists from India through the H-1B program.

Figure 3: Estimated coefficient (γ_s) on firm-level employment (H-1B+L-1)



As a third exercise, I look into how home-bias changes over time, once the firm has been hiring immigrants over a larger number of periods. Since the data only cover visa applications, they won't necessarily capture firm entry, since it is possible firms have been operating in the US for

a while before they start hiring H-1B workers. However, we can still analyze how the home-bias evolves over time through equation 4.

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_{x}^{T} \gamma_x \mathbb{1}(o = s) + \delta_{j,t} + \delta_{o,k,t} + \epsilon_{j,o,k,s,t} \tag{4}$$

In this equation, I interact the sourcing indicator with a series of dummies for how many years from 2001 to 2014 the firm is seen applying for H-1B visas. For exposition simplicity, the coefficient of interest γ_x is no longer different across countries, such that it should be interpreted as the average home-bias across all source countries. In Appendix Figure 6d, I present the results separately by source country. As shown in Table 2, there is a decreasing trend over time in the intensity of the home-bias. Such decreasing trend is particularly stronger if we exclude Indian companies, where the home bias goes from 97% in the first three years observed to 69% for years 13-14. Such results are consistent with firms needing source-country workers more when they are starting their operations in the US. Once again, Indian outsourcers likely drive the opposite result for India, since as the companies get bigger over time they focus on recruiting more and more Indians.

Table 2: Home-bias by years in the sample

	$Log(N_{j,o,t})$	$Log(N_{j,o,t})$
$\mathbb{1}(origin = source) * \mathbb{1}$(years 1 -3)	1.20^a	0.97^a
	(0.26)	(0.21)
$\mathbb{1}(origin = source) * \mathbb{1}$(years 4 -6)	1.21^a	0.96^a
	(0.28)	(0.26)
$\mathbb{1}(origin = source) * \mathbb{1}$(years 7 -9)	1.17^a	0.96^a
	(0.26)	(0.20)
$\mathbb{1}(origin = source) * \mathbb{1}$(years 10 -12)	1.10^a	0.86^a
	(0.24)	(0.14)
$\mathbb{1}(origin = source) * \mathbb{1}$(years 13 -14)	1.16^a	0.69^a
	(0.38)	(0.15)
N obs	26,466	26,236
Sample	All	Excl. Indian companies

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for firm-time and nationality-industry-time fixed effects. Regression is at the firm-nationality-time level. Dependent variable is the log number of visa petitions. Time period is 2001 to 2014. The dummy interactions with the sourcing variable stand for the years since the firm is seen applying for visa petitions. Time dummies pool together 3-year groups (years 1-3 the firm is observed, years 4-6 the firm is observed, etc.). Column 2 excludes Indian companies from the analysis. Standard errors clustered at the nationality-source level.

Finally, I look at the role of occupations to check whether source-country immigrants are hired in specific roles. The data on occupations are somewhat limited, since they are coded from company-reported job titles for which the same occupation might be given different names at different companies. I focus on three main occupations: "Administrative Associate Professionals," "Managers," and "Engineers." I estimate equation 5, using as dependent variable the fraction of workers from origin o in firm j who work in a given occupation.

$$\text{Share in occ}_{j,o,k,s,t} = \gamma_0 + \gamma \mathbb{1}(o = s) + \delta_{j,t} + \delta_{o,k,t} + \epsilon_{j,o,k,s,t} \tag{5}$$

As shown in Table 3, source-country workers are 1.7 percent points more likely to be administrative professionals than non-source-country immigrants relative to companies from other source countries. For managers the pooled results are noisier, but as shown in Appendix figure 6b, countries like the Netherlands, Korea, or India, among others are more likely to hire source-country workers for management positions. On the contrary, when looking at a less communication intensive occupation such as engineering, we see source-country workers being 3.7 percentage points less likely to work in those occupations.

Table 3: Dependent variable: Share of home country immigrants in specific occupations.

	Share of Admins	Share of Managers	Share of Engineers
$\mathbb{1}(source = origin)$	0.017ˆa	0.001	-0.037ˆa
	(0.005)	(0.009)	(0.008)
N obs	26,466	26,466	26,466

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for firm-time and nationality-industry-time fixed effects. Regression is at the firm-nationality-time level. Dependent variable is the share by nationality in a given occupation (Administrators, Managers and Engineers). Standard errors clustered at the nationality-source level.

3.2 Fact 2: Immigration and MNE operations in the US

As a second fact, I will show that an increase in immigration from the source country has a positive and significant effect on MNE operations in the US. As shown in Section 3.1, MNEs are more intensive in source-country immigrants when compared to other companies, suggesting that source-country workers might give firms a certain advantage to produce in the US. The goal of this section is to evaluate whether a plausibly exogenous influx of source-country immigrants indeed has a positive impact on MNE activity.

Given the lack of publicly available data on outcomes at the firm level for foreign MNEs operating in the US, I complement the H-1B visa data with publicly available data on revenues, assets, and employment from the BEA surveys of "Comprehensive Data on the Activities of US affiliates." Such data are collected by the BEA every year and reported for 14 industries and 27 source countries over time.[5]

To estimate the impact of additional source-country immigrants on the operations of MNEs in the US, I want to estimate equation 6:

$$Log(\text{MNE outcome}_{s,k,t+1}) = \phi_{k,t} + \phi_{s,k} + \beta Log(\text{N Immigrants}^{o=s}_{s,k,t}) + \epsilon_{s,k,t+1} \tag{6}$$

[5]BEA is the most comprehensive survey on MNEs operating in the US. A more detailed description of the dataset can be found in Appendix B. An alternative would be to use Orbis for data on US affiliates, but data are somewhat incomplete for non-publicly listed firms and US-based revenues are not always separately reported from global MNE revenues.

where the dependent variable is the log of a specific outcome of MNEs from country s, in industry k and time $t+1$. The main outcomes I will focus on will be US-affiliate revenues, assets, and revenues per employee. The key explanatory variable is $Log(\text{N visas}^{o=s}_{s,k,t})$, the log number of H-1B visas sponsored to college-educated immigrants from origin $o = s$, by firms from source country s, in industry k, and time t. The timing difference between the outcome and the explanatory variable aims to capture a potential delay of firms adjusting their production in response to immigration. I control for industry-time fixed effects $\phi_{k,t}$ to capture US industry-specific demand growth overtime and source-industry fixed effects $\phi_{s,k}$ to capture the time-invariant component of comparative advantage where MNEs from some countries historically specialize in specific industries.

Estimating equation 6 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 productivity of country s in industry k that can simultaneously increase MNE operations 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 the production function of MNEs. As shown in Table 2, MNEs demand fewer source-country immigrants when they have been hiring for a longer time period, as their US workforce learns how to communicate with the parent company over time. This would lead to a negative correlation between MNE operations and immigration, biasing β downward.

I proceed to construct a supply-push instrument in the spirit of Card and Lemieux (2001). As shown in equation 7, the instrument is an interaction between a baseline share and a time-shifter. I use the share of immigrants from $o = s$ who work in industry k in the US in initial year 2003 and interact it with the number of immigrants from s who work for US companies in industries other than k at time t. The time shifter aims to capture changes in labor supply, such as changes in migration policy in the US or preference shocks of migrants, that are plausibly uncorrelated with demand-level shocks to MNEs from source country s in industry k. Such shock is reweighted using the industry allocation in the initial period of workers from s. The initial shares also need to be uncorrelated with unobservables that affect the *changes* in MNE outcomes over time for the instrument to be valid. Once I explain the results, I discuss in detail how I test for the validity of both the initial shares and the time-shifter.

$$\text{Shift Share}_{s,k,t} = \underbrace{\frac{\text{N Immigrants}^{o=s}_{k,2003}}{\text{N Immigrants}^{o=s}_{2003}}}_{\text{Initial Share}} \times \underbrace{(\text{N Immigrants from } o = s,\ s = US,\ k' \neq k,\ t)}_{\text{time shifter}} \tag{7}$$

Table 4 shows the estimates for β under OLS (panel A) and 2SLS (panel B). Looking at the 2SLS results, an increase of 1% of immigrants from $o = s$ working for s, k, t causes an increase of 0.7% in total assets, 0.99% in revenues, and 0.66% in revenues per employee for MNEs from s operating in industry k, time $t+1$. The 2SLS results are larger than the OLS

estimates, consistent with a downward bias of OLS driven by companies demanding fewer source-country workers as they grow their US operations. In Appendix B.3, I discuss several robustness to this result. First, in Appendix Table 16, I evaluate how results change when defining the MNE outcomes using different time periods. It is reassuring that when testing for pre-trends using outcomes at $t-1$, the results are close to zero and not statistically significant. In the current period t, the effect of additional source-country immigrants is positive and statistically significant, but small, meaning that production takes at least one year to adjust to the immigration shock. When using a two-year lead, the magnitudes are similar to the one-year lead results. In Appendix Table 17, I corroborate that the results are still robust to excluding India from the analysis and not accounting for observations with zero visas.

I proceed to discuss the validity of the shift-share instrument by discussing potential concerns with the time-shifter and the initial share 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 growth in the US. Some examples could be trade agreements 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. 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. (2020), it is important to establish that the initial share is not correlated with other observables that also help predict the *growth* of the second stage outcome, the MNE revenues and assets by source country s in industry k in the US. To test for such correlation, I run a regression of the initial share and on several observables that affect MNE revenue and asset growth over time. 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. These covariates are not significantly correlated with the initial immigrant share used in the instrument, which reinforces the validity of the shift-share.

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 all immigrants from $o = s$ who work in industry k as a potential driver of MNE activity, as shown in equation 8. I use the instrument in equation 7 as well, since the exogeneity and relevance arguments of the supply-push instrument also hold in this case.

$$Log(\text{MNE outcome}_{s,k,t+1}) = \phi_{k,t} + \phi_{s,k} + \beta Log(\text{N Immigrants}_{k,t}^{o=s}) + \epsilon_{s,k,t+1} \tag{8}$$

In Table 4, panel C shows that, on average, a 1% increase in the number of immigrants from s working for industry k increases MNE revenues from source country s, industry k by 0.93% and assets by 0.65%.

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).[6] As shown in Appendix Table 19, a 1% increase in the *stock* of college-educated immigrants from country s working in industry k increases MNE revenues by 2.16 % and assets by 2%. A key advantage of doing the analysis with the ACS is to run the same regression using only non-college graduates. The estimates in Appendix Table 19 panel B, 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.[7]

3.3 Fact 3: Wage premium across source and origin countries

As a final set of facts, I use the H-1B wage data to document significant heterogeneity across worker origin countries and firm source countries that will inform some features included in the model. To do so, I run a regression at the individual visa level, as shown in equation 9:

$$\underbrace{Log(\text{wage}_{i,j,o,t})}_{\text{Individual wage}} = \underbrace{\gamma_j}_{\text{Firm FE}} + \underbrace{\delta_o}_{\text{Origin FE}} + \underbrace{\delta_{occ}}_{\text{Occupation FE}} + \underbrace{\delta_t}_{\text{Time FE}} + \underbrace{\epsilon_{i,j,o,t}}_{\text{Error term}} \tag{9}$$

The dependent variable in equation 9, $Log(\text{wage}_{i,j,o,t})$, is the log wage for individual i, at firm j, from origin o, in time t. There is only one observation per individual, since I only keep visas for new employment (excluding renewals). I regress log wages on a series of fixed effects to decompose the sources of wage heterogeneity across H-1B workers. γ_j is a firm fixed effect, δ_o is an origin fixed effect, δ_{occ} is an occupation fixed effect, and δ_t a year fixed effect. Each of the fixed effects can be interpreted as the wage premium relative to the omitted category.

As a first step, I focus on the origin fixed effect δ_o. I set the India fixed effect to zero and interpret the estimated fixed effect for each origin country as the wage premium relative to

[6] The construction of the instrument with ACS data is slightly different than in equation 7. I calculate the initial share using the 1990 sample and include in the regressions observations between 2000-14.

[7] 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.

Table 4: The impact of source-country immigration on MNE outcomes

A) OLS			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas for source workers$_{s,k,t}$	0.103^c	0.109^c	0.0245^c
	(0.0565)	(0.0625)	(0.0137)
N	1361	1361	1361
B) 2SLS			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas for source workers$_{s,k,t}$	0.701^a	0.994^a	0.659^a
	(0.159)	(0.187)	(0.154)
N	1361	1361	1361
1st stage F-stat	19.77	19.77	19.77
C) 2SLS - N visas at the industry level			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas for source workers$_{k,t}$	0.654^a	0.927^a	0.615^a
	(0.143)	(0.166)	(0.131)
N	1361	1361	1361
1st stage F-stat	68.63	68.63	68.63

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for industry-time and industry-source fixed effects. Regressions are at the industry-source-time level. The time-period is from 2004 to 2014. Data for Revenues, Assets and Revenues per worker for majority-owned US affiliates of non-US MNEs come from the BEA survey: "Comprehensive Data on the Activities of US affiliates." Dependent variables are at time $t+1$. The independent variable in panels A and B is the log number of visa petitions for workers from source country s, by firms in industry k, time t from source-country s. The independent variable in panel C is the log number of visa petitions for workers from source country s by industry and time only (including petitions by other MNEs and US companies). The instrument used for 2SLS specifications is the one described in equation 7. Zeros in the number of visas are included, using the inverse hyperbolic sine transformation.

Indian workers. In Figure 4, I plot the origin wage premiums against origin country characteristics. As shown in Figure 4a, there is a strong positive correlation between origin wage premium and GDP per capita as a measure of country wealth. Workers from richer countries receive a positive wage premium relative to those from poorer countries even conditional on firm and occupation, consistent with the idea that workers from richer countries need higher compensating differentials in order to want to migrate to the US.

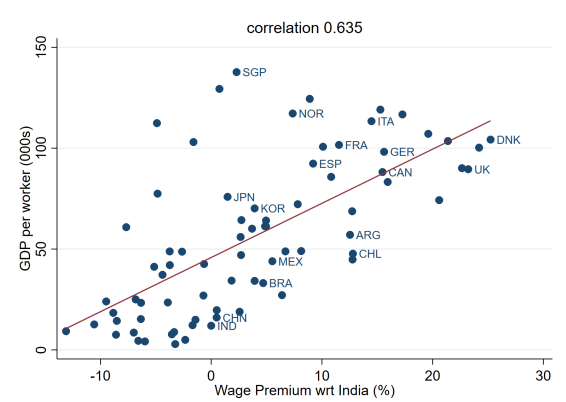
Figure 4b shows a strong negative correlation between the origin wage premium and the number of immigrant college graduates from o in the US as a share of the total college graduates in o.[8] In Section 4.1, I present a model of migration and heterogeneous abilities consistent with these patterns. If workers in each origin country have a distribution of abilities for working in the US, we should expect countries that send fewer migrants to the US to send their very best. As countries send more workers to the US, the average ability of migrants should drop.

As a second step, I focus on firm-specific wage premiums γ_j and plot the distribution of firm wage premiums by source country and industry. I normalize the median US firm to have a premium of 0 such that the fixed effects should be interpreted as the wage premium relative to the median US firm. As shown in Figure 5, there is a large heterogeneity across source countries

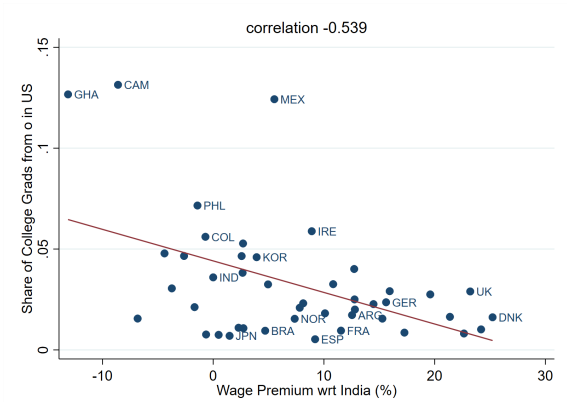
[8]For example, according to Figure 4b, the college-educated migrants from Ghana, Cameroon, and Mexico in the US are between 10-15% of the total college graduates in their respective countries. Even if excluding these three countries, the correlation is almost unchanged.

Figure 4: Wage Premium in US across Origin Countries

(a) GDP per Worker



(b) Share of college graduates from o in US



The horizontal axis in both figures plots the wage premium with respect to India as estimated from coefficient δ_o. India is shown in the graphs with a zero premium. The vertical axis in Figure 4a is GDP per person employed (constant 2017 PPP \$) from the World Bank. The vertical axis in Figure 4b plots the number of college graduates from origin o in the US relative to the number of college graduates in origin o. The numerator comes from IAB brain-drain database, using the number of high-skill migrants in the US by origin country. The denominator comes from the World Bank by multiplying the variables of total population between 15-64 and the share of population +25 who at least completed short-cycle tertiary education. The year used to compute all variables in the vertical axis is 2010. The correlation in Figure 4b remains unchanged when excluding outliers of Ghana, Cameroon, and Mexico.

and industries in terms of wages. The wage paid by US companies relative to foreign MNEs is very different if we look at IT and Consulting or Manufacturing. A large part of the lower wages paid by US companies is driven by the IT sector, while in Manufacturing the distribution is more compressed, with US companies paying among the highest wages.

Somewhat surprising is that Indian and US companies in IT pay very similar wages, which contradicts the popular discourse of Indian companies paying below market wages through the H-1B program. Part of this can be explained by US firms being, on average, smaller than foreign MNEs in IT. At the same time, as shown by Hjort et al. (2020), foreign MNEs tend to anchor wages to their headquarters levels, so it is no surprise that MNEs from countries like India and China pay lower wages than MNEs from richer countries in both industries. In Appendix Figure 8, I present the pooled results of firm fixed effects for all industries.

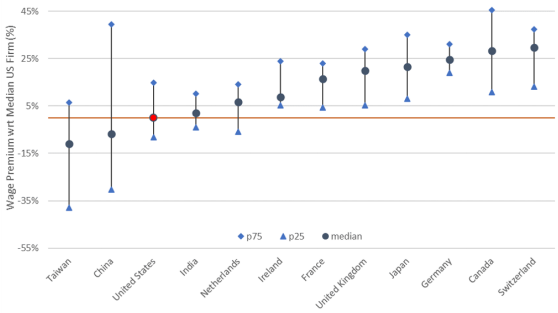
The key message from Figure 5 is that different source countries within industries seem to pay different wages, even conditional on worker origin and occupation. As such, the model in Section 4.1 will incorporate the feature that MNEs across different source countries and industries in the US will have access to different labor pools due to differences in migration costs and worker productivities. In Appendix B.4, I present the distribution of firm wage premiums across more detailed industries as well as the average occupation wage premium, captured by δ_{occ}.

4 Model

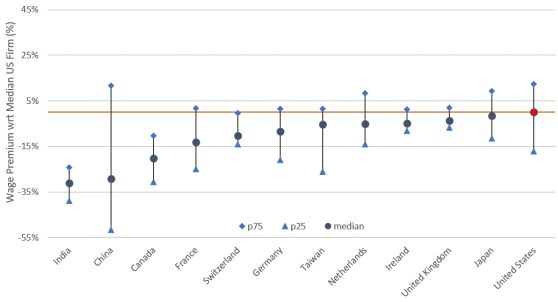
To understand the general equilibrium implications of changes to high-skill immigration policy in the US and guided by the stylized facts in Section 3, I build a quantitative model to dis-

Figure 5: Estimated Wage Premium with respect to Median US Firm by industry

(a) IT and Consulting



(b) Manufacturing



For each source country, the figure plots the 25th, 50th and 75th percentiles of the estimated firm wage premium relative to the median US firm (γ_j). The wage premium for the median US firm is normalized to zero. Figure 5a, looks at firms in the industries of Information and Professional, Scientific, and Technical Services which predominantly include IT and Consulting. Figure 5b, looks at firms in Manufacturing industries.

entangle 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 $\eta^{i,o}_{k,\ell,s}$ to work at each triplet $z = k, \ell, s$ from a Frechet distribution as shown in equation 10:

$$F(\eta^{i,o}_{k,\ell,s}) = exp\left(-\left(\sum_{z=1}^{Z} \tilde{A}^{\frac{1}{1-\rho}}_{k,o} \left(\eta^{i,o}_{z}\right)^{-\frac{\tilde{\kappa}}{1-\rho}}\right)^{1-\rho}\right) \tag{10}$$

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. As will be shown later, the parameter $\tilde{\kappa}$ is also related to the elasticity of labor supply, since it determines how much labor supply choices respond to changes in wages or migration costs. 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, 2019), it is useful to re-write $\kappa = \frac{\tilde{\kappa}}{1-\rho}$ such that κ is a convolution of ability dispersion and the correlation parameters.

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, 2020), as well as both for internal (Bryan and Morten, 2019; Fan, 2019; Tombe and Zhu, 2019) and international migration (Liu, 2020).

Each high-skilled worker, indexed by i, chooses the triplet k, ℓ, s that maximizes their utility as in equation 11. $\eta_{k,\ell,s}^{i,o}$ 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.[9] $\phi_{o,\ell,s} \geq 1$ is a non-pecuniary migration cost that is paid when migrating from origin o to location ℓ and source technology s. If $o = \ell$ I assume there is no migration cost, such that $\phi_{\ell,\ell,s} = 1$. Having the migration cost depend on s is the first component of the home-bias discussed in Section 3, since workers from a given origin can have a lower cost when working for an MNE of a specific source technology.[10] As $\phi_{o,\ell,s}$ is non-pecuniary, the wage that individuals actually receive in the labor market is $W_{k,\ell,s}^{o} = \eta_{k\ell,s}^{i,o} \times w_{k,\ell,s}$.

$$max \quad {}_{k,\ell,s} \quad \{U_{k,\ell,s}^{i,o}\} = \eta_{k,\ell,s}^{i,o} \times \varepsilon_{k,\ell,s}^{o} \times \frac{w_{k,\ell,s}}{P_\ell} \times \frac{1}{\phi_{o,\ell,s}} \tag{11}$$

Modeling migration through the EK-Roy setup is consistent with the facts shown in Figure 4. Workers from countries with higher wages $\frac{w_{k,o,s}}{P_o}$ will require sufficiently high US ability draws in order to decide to migrate. Hence, those who migrate from high-wage countries will get paid higher average wages than those from low-wage countries. Additionally, if a country sends many immigrants to the US (perhaps due to a lower migration cost $\phi_{o,\ell,s}$), the average ability of workers who migrate from such country will be lower than the average ability of workers from countries who send fewer immigrants.

[9] 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.

[10] I will not include any hiring cost directly paid by the firm for hiring immigrants. However, the migration cost $\phi_{o,\ell,s}$ also indirectly captures the costs borne by firms, as firms need to pay higher wages if they want to hire migrants for whom the migration costs are higher.

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 12

$$U_\ell = \Pi_{k=1}^{K} Q_{k,\ell}^{\gamma_{k,\ell}} \tag{12}$$

Each $Q_{k,\ell}$ can be written as a continuum of varieties indexed by j, and aggregated CES as in equation 13:

$$Q_{k,\ell} = \left(\int {q_{k,\ell}^{j}}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} \tag{13}$$

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 14.

$$q_{k,\ell} = \epsilon_{k,\ell} \prod_{k'=1}^{K} Q_{\ell,k,k'}^{\gamma_{\ell,k,k'}} \left(\psi_{k,\ell}^{l} l_{k,\ell}^{\frac{\alpha-1}{\alpha}} + \psi_{k,\ell}^{h} h_{k,\ell}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}(1-\sum_{k'} \gamma_{\ell,k,k'})} \tag{14}$$

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 14 and 15, 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 15: [11]

$$h_{k,\ell,s} = \left(\underbrace{\psi_{k,\ell,s}^{d} \left(h_{k,\ell,s}^{d} \right)^{\frac{\lambda-1}{\lambda}}}_{\text{local workers}} + \underbrace{\psi_{k,\ell,s}^{sf} \left(\underbrace{\psi_{k,\ell,s}^{s} \left(h_{k,\ell,s}^{s} \right)^{\frac{\iota-1}{\iota}}}_{\text{source country}} + \underbrace{\psi_{k,\ell,s}^{f} \left(h_{k,\ell,s}^{f} \right)^{\frac{\iota-1}{\iota}}}_{\text{other foreign}} \right)^{\frac{\iota}{\iota-1}\frac{\lambda-1}{\lambda}}}_{\text{all foreign}} \right)^{\frac{\lambda}{\lambda-1}} \tag{15}$$

The parameter λ governs the substitution between effective units of the domestic country and

[11] 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 effective units. Parameter ι governs the substitution between source country and other foreign workers. Having foreign and native workers be imperfect substitutes is consistent with the findings of Peri and Sparber (2011), who find that 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 the second part in which the home-bias discussed in Section 3 appears, since foreign MNEs will have a specific value for migrants from their source country.

Share parameters $\psi^d_{k,\ell,s}, \psi^s_{k,\ell,s}, \psi^f_{k,\ell,s}, \psi^{sf}_{k,\ell,s}$ 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

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 (2019) and Arkolakis et al. (2018), among others.

Producers of each variety j in source country s take a productivity draw $\epsilon^j_{k,\ell,s}$ to produce variety j in each possible location ℓ. Such productivity is drawn from a Frechet distribution as in equation 16:

$$F(\epsilon^j_{k,\ell,s}) = exp\left(-\sum_{\ell=1}^{\mathcal{L}} T_{k,s}\left(\epsilon^j_\ell\right)^{-\theta}\right) \tag{16}$$

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 17:

$$p^{j,k}_{s,\ell,n} = \frac{c^k_{s,\ell}\tau^k_{\ell,n}\delta^k_{s,\ell}}{\epsilon^j_{k,s,\ell}} \tag{17}$$

The price increases with the marginal cost of production $c^k_{s,\ell}$. 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 $\epsilon^{j}_{k,s,\ell}$ 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 $\tau^{k}_{\ell,n}$ 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 ($\delta^{k}_{s,\ell=n}$), 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 ($\tau^{k}_{\ell,n}$) and MNE costs ($\delta^{k}_{s,\ell}$). Consumers end up buying each variety from the cheapest producer such that: $min_{s,\ell}\{p^{j,k}_{s,\ell,n}\}$.

As a final feature, I will allow for the MNE cost $\delta^{k}_{s,\ell}$ 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 $\delta^{k}_{s,\ell}$ can be written as in equation 18:

$$\delta^{k}_{s,\ell} = \bar{\delta}^{k}_{s,\ell} \left(N^{o=s}_{k,\ell}\right)^{\nu} \tag{18}$$

Where $\bar{\delta}^{k}_{s,\ell}$ is a baseline iceberg cost independent on the number of migrants and $N^{o=s}_{k,\ell}$ is the number of migrants from $o = s$ that work in ℓ, k. The relevance of this mechanism is determined by parameter ν.[12] I assume that firms are sufficiently small to consider the stock of immigrants at the industry level ($N^{o=s}_{k,\ell}$) as exogenous such that the effect on the MNE costs can be considered as a spillover that is not internalized in the profit maximization process. Given that US firms are the main employers for immigrants, it is reasonable that MNEs see the stock of immigrants at the industry level as exogenous to their own hiring decisions.

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.

[12] 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 the 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 3.2.

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 19:

$$\pi^{mig}_{o,k,\ell,s} = \frac{A_{o,k}\left(\frac{w_{k,\ell,s}}{P_\ell}\varepsilon^o_{k,\ell,s}\right)^\kappa \phi^{-\kappa}_{o,\ell,s}}{\sum_{\ell',s',k'} A_{o,k'}\left(\frac{w_{i',\ell',s'}}{P_{\ell'}}\varepsilon^o_{k',\ell',s'}\right)^\kappa \phi^{-\kappa}_{o',\ell',s'}} \tag{19}$$

Equation 19 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 19.

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 20:

$$\pi^{trade}_{k,\ell,n} = \frac{(\tau^k_{\ell,n})^{-\theta}\tilde{T}^k_\ell}{\sum_{\ell'}(\tau^k_{\ell',n})^{-\theta}\tilde{T}^k_{\ell'}} \tag{20}$$

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 $\delta^k_{\ell,s}$.

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 21:

$$\pi^{mne}_{k,s,\ell} = \frac{T^k_s \left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta}}{\sum_{s'} T^k_{s'} \left(c^k_{\ell,s'} \times \delta^k_{\ell,s'}\right)^{-\theta}} \tag{21}$$

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

Finally, given the possibility of agglomeration economies created by spillover parameter ν, I discuss the existence of a unique equilibrium. Issues of multiple equilibria are unlikely to arise in this case, since an increase in immigrants will drive up demand by MNEs for both natives and immigrants alike. Since a majority of employment comes from native workers, the additional demand will drive up total labor costs, limiting the expansion of MNE production.

It is reassuring that when I solve for the equilibrium with multiple different initial values, the algorithm converges to the same unique solution.

To solve for the equilibrium in the model, I use the approach suggested by Dekle et al. (2008) and solve the model in proportional changes. This method, also called the exact hat-algebra method, allows me to re-write the equilibrium equations as changes between the real and the counterfactual scenarios. That is, I can re-write each variable x as $\hat{x} = \frac{x'}{x}$ where x is the variable under the real scenario and x' is the value of the variable under the counterfactual. 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 re-write all equilibrium equations in proportional changes in Appendix C.1. As an example, it is possible to re-write the migration share (equation 19) as in equation 22:

$$\hat{\pi}^{mig}_{o,k,\ell,s} = \frac{\pi^{mig'}}{\pi^{mig}} = \frac{\hat{A}_{o,k}\left(\frac{\hat{w}_{k,\ell,s}}{\hat{P}_\ell}\hat{\varepsilon}^{o}_{k,\ell,s}\right)^{\kappa}\hat{\phi}_{o,\ell,s}{}^{-\kappa}}{\sum_{k',\ell',s}\hat{A}_{o,k'}\left(\frac{\hat{w}_{k',\ell',s'}}{\hat{P}_{\ell'}}\hat{\varepsilon}^{o}_{k',\ell',s'}\right)^{\kappa}\hat{\phi}_{o',\ell',s'}{}^{-\kappa}\pi^{mig}_{o,k,\ell,s}} \tag{22}$$

As shown by equation 22, 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 $\hat{\phi}_{o,\ell,s}$, $\hat{\varepsilon}^{o}_{k,\ell,s}$ and $\hat{A}_{o,k}$, and data on observed allocations $\pi^{mig}_{o,k,\ell,s}$. The model includes many exogenous parameters such as migration costs $\hat{\phi}_{o,\ell,s}$, trade costs $\tau_{k,\ell,n}$, MNE costs $\delta_{k,s,\ell}$, fundamental technologies $T_{s,k}$, worker comparative advantages $A_{k,o}$ and labor shares $\psi_{k,\ell,s}$ but 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 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 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, and set λ and α according to values estimated in the literature. Finally, I will calibrate ν to match the reduced-form results from Section 3.2.

5.1 Labor supply elasticity κ

I use an instrumental variable approach that exploits "trade shocks" across source countries and industries to estimate κ. As defined in Section 4.1, κ, has two 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.

In Appendix D.1 I describe the estimation of κ in detail. First, I use Frechet properties to derive an estimating equation that relates the observed average wages for each origin-source-industry triplet with the share of workers from origin o that migrate to the US and work for source s, industry k. Estimating such equation by OLS would yield biased estimates of κ as productivity shocks to individuals from o would positively affect average wages as well as the number of immigrants from o choosing s, k, biasing the estimate of κ upwards. To identify this parameter, I exploit demand shocks that capture changes in the comparative advantage ($T^k_{s,t}$) of source country s in industry k that are independent of time-specific productivity shocks experienced by origin o immigrants. I draw from the literature on trade shocks started by Autor et al. (2018) and construct a shift-share instrument that interacts the share of workers from o that choose triplet $o - s - k$ in 2001 with the share of imports from non-US countries in industry k that come from country s.[13]

As shown in Appendix Table 20, the 2SLS estimate 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 D.1.1 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 (2019) 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

[13] 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 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.

in wages to estimate κ, I get an estimate of $\kappa = 8.28$, which I will use to bound the quantitative results.[14]

5.2 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. As explained in Appendix D.2, it is possible to re-work the first-order conditions of the components in equation 15 to derive a firm-level estimating equation that shows 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. 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.

I propose two instruments that use very different sources of variation to estimate ι. First, I use the shift-share instrument proposed in Section 3.2, equation 7. 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.

The OLS and 2SLS results can be found in Appendix Table 22 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 $\iota = 6.84$.

5.3 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

[14] 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 (2020).

companies from s in ℓ, k decreases by $-\nu\%$. According to the estimates in Table 19, a 1% increase in the number of immigrants from s in k increases MNE employment by 0.927%. I calibrate ν, such that when I increase the number of source-country immigrants in the model by 1%, the average revenues for foreign MNEs in the US increases by 0.927%. Such indirect inference approach yields an estimate of $\nu = 0.315$.

5.4 Implementation

To implement the model in a tractable way, I need to make some simplifications. First, I assume the world is composed of six regions: United States, Canada, Western Europe, India, China-Taiwan, and the Rest of the World (RoW). I also assume there are only three industries: Professional and Technical Services, which mainly includes the IT sector and consulting; high-skill intensive manufacturing, which includes Chemicals, Machinery, Computer, Electronic, Electrical Equipment and Transportation manufacturing; and a third sector that includes everything else in the economy. I separate industries this way to focus on the implications for industries that have a high dependence on high-skill migration and where MNEs 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 $\theta = 4$, $\alpha = 1.7$, $\kappa = 6.17$, $\lambda = 13.1$, $\iota = 2.84$, and $\nu = 0.315$ consistent with the baseline parameters estimated in Section 5. Finally, the estimation of the model requires me to use data on observed trade shares by industry, MNE shares by industry, migration shares from each origin o to each triplet k, ℓ, s, and skill shares for domestic, source-country, and other foreign workers for each triplet k, ℓ, s. In Appendix E, 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 E, 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. (2020) and impose that World output stays constant as in equation 23. This normalization implies that the output results should be interpreted as how do the endogenous variables change as a share of total World output.

$$X_{us} + X_{in} + X_{ca} + X_{eu} + X_{ch} + X_{oth} = \bar{X} \tag{23}$$

6 Counterfactual exercises

In this section, I use the model to run two main counterfactual exercises that help quantify the link between high-skill migration, MNE activity, and the location of production. As the model is expressed in changes between the observed equilibrium and the counterfactual equilibrium, it is possible to 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 modeling migration affects the quantification of the welfare gains of MNE production.

6.1 Counterfactual 1: A more restrictive US migration policy

As a first counterfactual exercise, I study how the location of high-skill industries and welfare would change in the long run 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.

The Frechet assumption might seem at odds with the rationing feature of 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 44. If we think solely on the H-1B program, the feature of positive selection might feel at odds with reality, as 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 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 in the US have a higher likelihood of getting accepted in the lottery. Overall, such features suggest the if the number of immigrants were to be reduced, those still migrating would be positively selected.

As a first set of results, Table 5 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 0.64% in India and 0.14% in Canada, while the high-skill manufacturing sector would also grow the most in India (0.43%) and Canada (1.13%). 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.

Somewhat surprisingly, the high-skill manufacturing sector in the US decreases more than IT and professional services. While IT demands a larger number of visas, the share of workers in the high-skill manufacturing sector that are immigrants (15.4%) is larger than the one in IT and professional services (11.8%), which explains the larger response of manufacturing.

Table 5: Change in the location of economic activity

	baseline			no spillover		
	IT and Prof. Services	High-Skill Manufacturing	Other	IT and Prof. Services	High-Skill Manufacturing	Other
US	-0.54%	-1.85%	-0.41%	-0.39%	-0.43%	-0.34%
India	0.64%	0.44%	0.20%	0.60%	0.29%	0.20%
Western Europe	0.11%	0.25%	0.09%	0.08%	0.06%	0.07%
Canada	0.14%	1.13%	0.00%	0.16%	0.09%	0.10%
China-Taiwan	0.15%	0.25%	0.12%	0.10%	0.11%	0.09%
Rest of the World	0.10%	0.30%	0.07%	0.07%	0.06%	0.06%

Percent changes in country-industry revenues 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 6, both in high-skill manufacturing and IT, foreign MNEs operating in the US experience an output drop larger than US-based companies. Without the spillover, the contrast is particularly big for Indian and Chinese IT firms in the US, whose output would drop by 3.06% and 1.2%, 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 6: Production of MNEs in the US by source country and industry

	baseline		no spillover	
	IT and Prof. Services	High-Skill Manufacturing	IT and Prof. Services	High-Skill Manufacturing
US	-0.03%	1.12%	-0.36%	-0.40%
India	-10.33%	-6.88%	-3.06%	-0.93%
Western Europe	-10.55%	-9.14%	-0.70%	-0.51%
Canada	-9.87%	-8.43%	-0.70%	-0.51%
China-Taiwan	-10.57%	-8.91%	-1.20%	-0.79%

Percent changes in industry-source country revenues for companies in the US, 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 F shows the decomposition of the domestic and foreign MNE contributions to output decline 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 7, high-skill workers would experience an increase of 0.08% 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 0.36% given their complementarity with high-skill workers. Aggregating across skill types, total real wages for US workers would decrease by 0.23% when migration is restricted. Real wages 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 7.

Table 7: Change in Real Wages and Compensating Variation

	Real Wages (percent change)	Wages (percent change)	Compensating Variation (per native worker)
High-skill natives	0.08%	0.09%	-53
Low-skill natives	-0.36%	-0.35%	110
Total US natives	-0.23%	-0.21%	61

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 $110 each year while the gains for each high-skill worker amounts to $53. Overall, restricting high-skill immigration by 10% would cause each US worker to lose on average $61 per year once the economy reaches the steady state. The total loss for US natives would amount to almost $8.4 billion per year.

6.1.1 Mechanisms and Robustness

The baseline results presented in Section 6.1 are a product of multiple mechanisms incorporated to the quantitative model that link migration to production and welfare. In this Section, I proceed to disentangle each mechanism to show how are they driving 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 8, 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 -0.23% to -0.13%. If we assume a larger 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 8: Changes in real wages for different values of the spillover parameter

	$\nu = 0$ (no spillover)	$\nu = 0.315$ (baseline)	$\nu = 0.9$ (same spillover)
High-skill natives	0.17%	0.08%	-0.04%
Low-skill natives	-0.26%	-0.36%	-0.48%
Total US natives	-0.13%	-0.23%	-0.35%

Percent changes in real wages 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 9, 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 assumes all companies producing in the US are domestic companies, so their intensity in hiring migrants is the one observed for US companies. The model without MNE production understates the real wage losses by 48%

(-0.23% 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 6.2, 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 16.2% higher than in the baseline model.

Table 9: Understanding mechanisms - Trade and MNE

	Baseline	no spillover	No MNE	No Trade
High-skill natives	0.08%	0.17%	0.17%	0.05%
Low-skill natives	-0.36%	-0.26%	-0.24%	-0.40%
Total US natives	-0.23%	-0.13%	-0.12%	-0.26%

Percent changes in real wages 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 F 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.

6.2 Counterfactual 2: 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 do 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.[15] The goal of this counterfactual is to

[15] Other papers in the literature that quantify the gains of MNE production are Ramondo and Rodriguez-Clare (2013), Tintelnot (2017), Arkolakis et al. (2018), Head and Mayer (2019), Alviarez (2019)

quantify how much do real wages change when MNEs start operating in a country. In the model, MNEs have specific comparative advantage in producing certain varieties, hence, the presence of MNEs helps produce more efficiently and increases welfare. 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 $\hat{\delta}^k_{s,\ell}$ is fed into the model such that MNE flows go from the observed values in equilibrium to 0.[16] By calculating how welfare changes between an "MNE autarky" situation and the observed equilibrium, we can calculate the gains from MNE production. As shown in the first column of Table 10, both low- and high-skill workers benefit from MNE production in high-skill industries. Such finding is intuitive since MNEs that move to the US bring new and more efficient technologies to produce some varieties domestically, lowering prices and increasing overall production and welfare. A second finding shown in column 1 is that high-skill migration to the US would increase by 8.69% 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.

The results in Table 10 hold when looking at the MNE gains for migrant-receiving regions such as Europe and Canada as shown in Appendix G. 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,

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

Table 10: 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 $\delta^k_{s,\ell}$ are very high such that MNE is prohibitive. Welfare is measured as the change in real wages. Column 3 shows the welfare change in the no-migration setting relative to the welfare change in the baseline model with migration.

taking away high-skill workers predominantly from India, China and Rest of the World. This increases the positive impact for high-skill workers who stay as they face lower competition from the migrants who 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 G also shows these results are robust for different values of the elasticities.

7 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 $8.4 billion for the US economy, driven by a $10.6 billion loss for low-skill workers and a $2.2 billion gain for high-skill workers. The interrelation between MNEs' activities and immigration is a feature 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 was 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 3.2, 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. 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 said 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 they 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 2001 to 2014, the data provided by USCIS had a total of 3,949,065 H-1B visa petition records and 126,964 associated to L-1 from 2012 to 2014. Wage and occupation data were not available for L-1 visas. Given the shorter time span and the lack of wages, I focus on using the H-1B data and include L-1 as a robustness exercise, whenever possible.

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 visa petitions in a given year between 2001 and 2014. As shown in Table 11, those with fewer than 10 petitions account for 37.8% of the total H-1B petitions, with a larger number of small applicants the earlier years of the sample. As a second step, within those employers with more than 10 petitions, I exclude from the matching employers in the education, healthcare, or government sectors since MNEs are generally not present in these industries. Such employers account for 8.2% of the total H-1B petitions. Finally, a small group of employers are not found in Orbis who account for 8% of H-1B petitions. This leaves us with a match rate of 46.1% for the full H-1Bs and 65.3% for the last three years of the H-1B sample. The FOIA-Orbis dataset is used for two main

purposes. First, to show the stylized facts presented in Section 3 and estimate the parameters in Section 5. In these cases, the regressions include a firm-time or industry-time fixed effect that would account for the differences in the match rate across the years. Second, the 2012-2014 H-1B sample is used to impute the data for MNE companies labor share between source and foreign workers needed to estimate the model. Since no aggregates are calculated using these data, the lower match rate is not a substantive matter in the quantitative exercise. Table 12 presents the distribution of visa petitions matched to Orbis by worker nationality and source country (GUO of company applying for the visa). Table 13 presents the distribution of visa petitions matched to Orbis by industry.

As a final note, I discuss the specific cases of Canada, Mexico and India. As described in Section 2, Canadian and Mexican professionals can also come to the US through TN visas, which are not capped but are also not dual intent, meaning workers cannot apply for a green card while on the TN visa. A potential worry is that the H-1B data might underestimate the number of Canadians and Mexicans in the US. Since there is no public data on TN visa composition, I proceed to compare the H-1B data with the American Community Survey (ACS). From the ACS I obtain, for each year, the total number of college graduates by origin country who migrated in the past 3 years and are employed in the US. I then compare the ACS stocks with the total number of new employment H-1B visas over the past 3 years. For Mexico, the H-1B data only explains 17% of all college educated new immigrants from the ACS. This is likely because in addition to the TN visas, Mexicans also come in large numbers through family reunification. For Canada, however, the H-1B data accounts for 81% of the stock indicated by the ACS, suggesting that the H-1B is also the main path of entry for Canadians. Since Mexican MNEs do not have particularly big operations in the US, the low rate of Mexicans with H-1Bs does not affect the results.

As for India, as shown in Table 12, 18% of the visa petitions are by Indian MNEs and 74.3% of the visas go to Indian immigrants. Such numbers suggest that Indian workers and Indian companies need to be looked at separately to ensure the results are not driven by a single country. For all facts, I explicitly check that excluding India does not drive the results, and while the number of Indians is large, immigration has a significant effect for MNEs from all source countries. For the quantitative results, I also present the results for Indian companies separately. Additionally, the fact that Indian workers dominate the H-1B program is a sign that Indian workers also dominate the US high-skill immigration stock.

Table 11: Sample matched to Orbis

	H-1B		H-1B		H-1B		L-1	
	Count	Share	Count	Share	Count	Share	Count	Share
Total petitions	3,949,065	100.0%	3,015,219	100.0%	933,846	100.0%	126,964	100.0%
Matched to Orbis	1,818,549	46.1%	1,209,042	40.1%	609,507	65.3%	69,519	54.8%
Not matched to Orbis								
Healthcare, Education and Govt	325,627	8.2%	268,610	8.9%	57,017	6.1%	0	0.0%
Fewer than 10 petitions	1,490,804	37.8%	1,254,853	41.6%	235,951	25.3%	56,648	44.6%
Other, not matched	314,085	8.0%	282,714	9.4%	31,371	3.4%	797	0.6%
Years	2001-2014		2001-2011		2012-2014		2012-2014	

Counts include all approved petitions for H-1B visas obtained through FOIA. "Total petitions" include petitions for new employment, renewal, change of employer and amendments. "Fewer than 10 petitions" are petitions by firms who never submitted more than 10 petitions in a given year. "Healthcare, Education and Govt" include petitions by Universities, School Districts, Hospitals, Goverment Agencies, Research Institutes and other institutions that would not be involved in MNE activity.

Table 12: Distribution of visa petitions by country of origin and by source country of MNEs

	MNE Source Country				Worker nationality			
	H-1B	H-1B	H-1B	L-1	H-1B	H-1B	H-1B	L-1
Australia	0.1%	0.0%	0.1%	0.1%	0.3%	0.3%	0.2%	1.0%
Canada	0.6%	0.7%	0.5%	4.1%	2.9%	3.4%	1.7%	17.0%
China	0.1%	0.1%	0.2%	0.8%	5.9%	6.1%	5.6%	5.7%
Finland	0.4%	0.5%	0.2%	0.3%	0.0%	0.0%	0.0%	0.2%
France	1.7%	1.5%	2.2%	3.1%	0.6%	0.7%	0.4%	2.2%
Germany	1.1%	1.2%	0.8%	2.3%	0.5%	0.6%	0.3%	2.4%
India	18.0%	16.3%	21.4%	26.5%	74.3%	70.7%	81.9%	32.6%
Ireland	1.5%	1.0%	2.5%	0.9%	0.2%	0.2%	0.1%	0.9%
Israel	0.0%	0.0%	0.0%	0.1%	0.3%	0.3%	0.2%	1.0%
Japan	1.3%	1.4%	1.2%	2.1%	0.6%	0.7%	0.3%	2.4%
Korea	0.2%	0.2%	0.3%	0.4%	1.0%	1.1%	0.7%	1.9%
Netherlands	0.5%	0.5%	0.5%	0.5%	0.1%	0.1%	0.1%	1.0%
Spain	0.0%	0.0%	0.0%	0.2%	0.2%	0.2%	0.1%	1.2%
Sweden	0.2%	0.2%	0.2%	0.3%	0.1%	0.2%	0.1%	0.6%
Switzerland	1.0%	1.2%	0.6%	1.2%	0.1%	0.1%	0.0%	0.4%
Taiwan	0.3%	0.3%	0.3%	0.0%	0.6%	0.7%	0.4%	0.3%
United Kingdom	1.3%	1.3%	1.1%	2.2%	1.2%	1.4%	0.6%	7.3%
Other	1.8%	1.9%	1.5%	4.4%	11.2%	13.0%	7.2%	21.8%
United States	69.8%	71.4%	66.7%	50.4%				
Total								
Years	2001-2014	2001-2011	2012-2014	2012-2014	2001-2014	2001-2011	2012-2014	2012-2014

The first 4 columns tabulate the share of visa petitions across source countries. Columns 5-8 tabulate the share of visa petitions across worker nationalities. The sample is limited to those companies that were matched to Orbis as described in Table 11. Visa petitions include new employment, renewal and change of employer. The years 2012-2014 are explicitly separated to make the H-1B sample comparable to the L-1. Also, the years 2012-2014 are the years of visa data used to calibrate the model.

Table 13: Distribution of visa petitions by industry

	H-1B	H-1B	H-1B	L-1
Manufacturing				
Chemicals	1.1%	1.3%	0.8%	1.6%
Computer and Electronics	8.5%	9.4%	6.4%	2.8%
Electrical Equipment	0.2%	0.2%	0.2%	1.4%
Food	0.2%	0.2%	0.1%	0.2%
Machinery	0.9%	0.9%	0.9%	1.1%
Metals	0.1%	0.1%	0.1%	0.6%
Transportation Equipment	0.6%	0.6%	0.5%	1.6%
Services				
Finance and Insurance	6.2%	6.8%	4.9%	6.2%
Information	6.2%	6.7%	5.2%	1.9%
Professional, Scientific and Technical	68.1%	65.1%	74.4%	64.7%
Real Estate	0.1%	0.1%	0.1%	0.1%
Other				
Retail	1.9%	1.9%	2.0%	0.7%
Wholesale	0.8%	0.8%	0.7%	1.0%
Other	5.1%	5.8%	3.6%	16.2%
Years	2001-2014	2001-2011	2012-2014	2012-2014

The sample is limited to those companies that were matched to Orbis as described in Table 11. Visa petitions include new employment, renewal and change of employer. The years 2012-2014 are explicitly separated to make the H-1B sample comparable to the L-1. Also, the years 2012-2014 are the years of visa data used to calibrate the model.

B Empirical facts details

B.1 Data description for empirical facts in Sections 3.1-3.3.

For the H-1B data, I predominantly focus on the years between 2001 and 2014. I exclude firms in industries that are not subject to significant MNE activity such as Education, Healthcare, and Government. I pool all type of visa applications, including applications for new employment, renewals, and change of employment except when explicitly noted that I focus on new employment. I only keep firms where either Orbis or D&B Hoovers identifies a Global Ultimate Owner as explained in Section A.

The H-1B occupation data are a firm-reported occupation category for each visa. Many of these categories are somewhat overlapping, for example "Occupations in System Analysis and Programming" and "Computer Related Occupations." I classify them by hand into ISCO-88 3-digit occupations with the exceptions of managers, which I pool into a single category, and Architects, which I separate from Engineers. Industry data at the GUO level come from Orbis.

The MNE outcomes used in Section 3.2 come from the BEA survey of "Comprehensive Data on the Activities of U.S. Affiliates." I collect revenues, assets, and total employment for majority-owned affiliates between 2001 and 2015. The publicly available version of the survey contains disaggregated information for 14 industries and 27 source countries. In cases where few companies are reporting, the BEA censors the datapoint and I treat them as missing.

Export, import, and GDP data used in Tables 1, 17, and 18, come from the World Input-Output Tables. Data on distance, common language and trade agreements come from CEPII. Finally, data used for country characteristics in Figure 4 come from multiple sources. The vertical axis in Figure 4a is GDP per person employed (constant 2017 PPP \$) from the World Bank. The vertical axis in Figure 4b plots the number of college graduates from origin o in the US relative to the number of college graduates in origin o. The numerator comes from IAB brain-drain database, using the number of high-skill migrants in the US by origin country. The denominator comes from the World Bank, by multiplying the variables of total population between 15-64 and the share of population +25 who at least completed short-cycle tertiary education. The year used to compute all variables in the vertical axis is 2010.

The L-1 data are not widely used for the descriptive facts. The reason is that L-1 data only cover 3 years and lack information on wages and occupation. The lack of a longer time period severely limits the analysis of Fact 2, and the lack of wage data limits Fact 3. Section B.2.1 shows alternative versions of Fact 1 using the L-1 data and corroborating the findings of home-bias are robust, but the robustness and mechanisms analysis can only be done for the H-1B.

B.2 Fact 1: Home-bias robustness

The first fact in Section 3 shows that there is a strong home-bias effect, where foreign MNEs hire more migrant workers from their source country s than other companies in the US. In this section, I present additional results that confirm the result holds under different specifications. For expositional simplicity, I present the robustness results with a pooled regression as in equation 24, that calculates the average home-bias effect across source countries.

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \gamma \mathbb{1}(o = s) + \delta_{j,t} + \delta_{o,k,t} + \epsilon_{j,o,k,s,t} \tag{24}$$

where $Ln(N_{j,o,k,s,t})$ is the log number of visa petitions by firm j, for workers from nationality o in time t. Subscript s stands for the source country of the company, while subscript k stands for industry. $\delta_{j,t}$ is an firm-time fixed effect, and $\delta_{o,k,t}$ is a nationality-industry-time 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 3.1, the magnitude of the home bias is large. As shown in Table 14, MNEs are, on average, 118% more likely to hire immigrants from their source country relative to other nationalities when compared to companies from other source countries. Results do not change if we just look at visas for new employment. Column 3 shows the results are larger when including

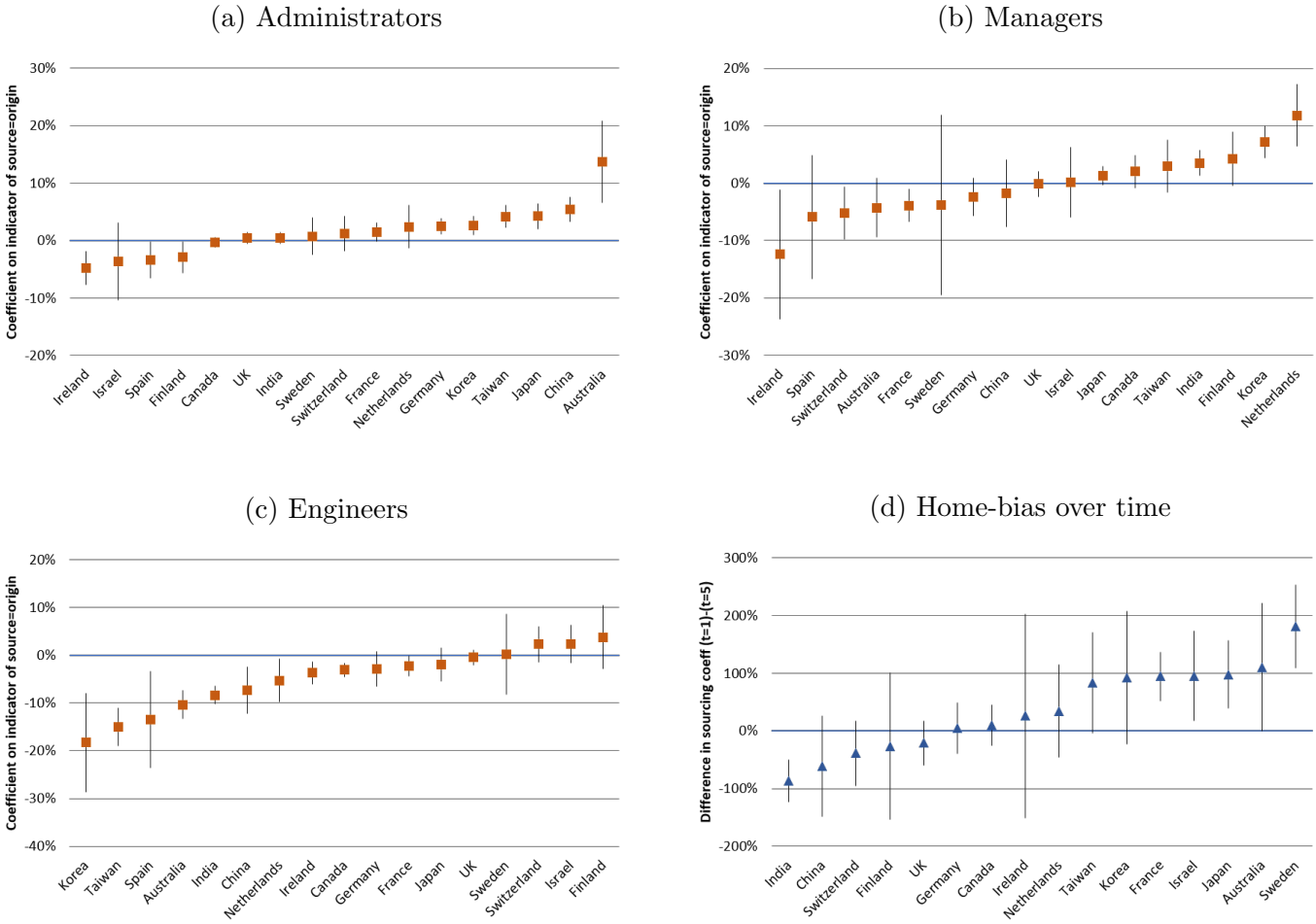
firm-nationality pairs for which the data show 0 visa applications. To handle zero values, I estimate the parameters using a Poison Pseudo Maximum Likelihood (PPML) to include zero observations as suggested by Santos Silva and Tenreyro (2006). Columns 4 and 5 show the pooled regression for average wages. On average, MNEs pay their source-country workers 3.9% lower wages relative to workers from other nationalities when compared to firms from other source countries.

Table 14: Home-bias regressions for employment and wages

	Log N visas	Log N visas	Log N visas	Log avg wage	Log avg wage
$\mathbb{1}(source = origin)$	1.17ˆa	1.18ˆa	2.32ˆa	-0.039ˆa	-0.036ˆa
	(0.262)	(0.280)	(0.185)	(0.014)	(0.017)
N obs	26,466	22,064	333,572	26,466	22,064
Sample	All	New employment	All PPML	All	New employment

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for firm-time and nationality-industry-time fixed effects. Regression is at the firm-nationality-time level. First three columns use as dependent variable the log number of visas while the last two columns have the log average wage. Columns 1, 3 and 4 include all H-1B petitions from 2001 to 2014. Columns 2 and 5 include only visas for new employment (excluding renewals). Column 3 estimates the PPML regression to incorporate observations with zero employment. Standard errors clustered at the nationality-source level.

Figure 6: Home-bias Robustness: Occupations and Intensity Over Time



Figures 6a-6c plot the coefficient (γ_s) by country from a regression like equation 5, but with source country separate dummies. Figure 6d plots, for each source country, the difference between the home-bias coefficient on the first three years observed in the sample minus the coefficient on the last two years observed in the sample.

B.2.1 Aggregate analysis including H-1B and L-1 visas

As a final analysis regarding home-bias, I explore how results change when including L-1 visas. The FOIA data on L-1 visas are much more limited than the H-1B. They only cover years between 2012 and 2014 and do not contain information on wages or occupation. At the same time, the number of L-1 visas is just 10% of the applications for H-1Bs. Due to the smaller sample size and the lack of a long time series, I proceed to aggregate the data to the source-origin-industry level (as opposed to the firm level) and run a regression as shown in equation 25:

$$Log(N_{k,o,s}) = \gamma_0 + \gamma \mathbb{1}(o = s) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \tag{25}$$

The dependent variable, $Log(N_{k,o,s})$, is the log number of visa applications at the source country, origin, industry level. $\delta_{k,o}$ is an origin-industry fixed effect that captures the comparative advantage of workers from origin o in industry k, and $\delta_{k,s}$ is a source-industry fixed effect to capture source-country comparative advantage in industry k. Finally, the key explanatory variable $\mathbb{1}(o = s)$ is a

dummy variable that takes the value of 1 if the origin country of the worker is equal to the source country of the firm. As shown in Table 15, home-bias is positive and significant when looking at both the H-1B and the L-1 in columns 1-3. Surprisingly, the H-1B shows a stronger home-bias than the L-1. Part of the reason for this pattern is that the L-1 is also heavily used by US companies to bring workers from their foreign affiliates domestically. However, given the large size of the H-1B program relative to the L-1, the effects of the H-1B largely dominate the aggregate effect. When looking at PPML estimates, L-1 becomes no longer significant due to the large number of 0s in the regression, which dominate the effect. Figure 7 shows the effects by source country, corroborating that for both the H-1B and the L-1, the home-bias effect is present across most countries.

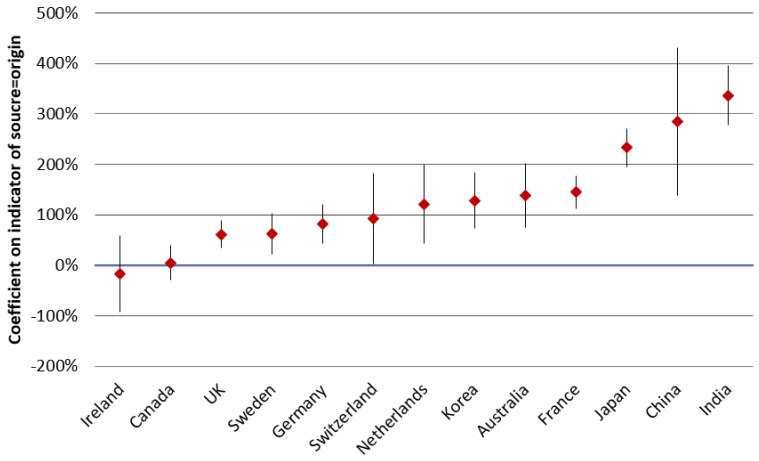
Table 15: Home-bias: Aggregate regressions for H-1B and L-1

	OLS			PPML		
$\mathbb{1}(source = origin)$	0.66ˆa	1.27ˆa	0.30ˆa	1.10ˆa	2.20ˆa	0.07
	(0.17)	(0.28)	(0.09)	(0.23)	(0.14)	(0.09)
N obs	1,162	1,162	1,162	3,588	3,588	3,588
Sample	H-1B+L-1	H-1B	L-1	H-1B+L-1	H-1B	L-1

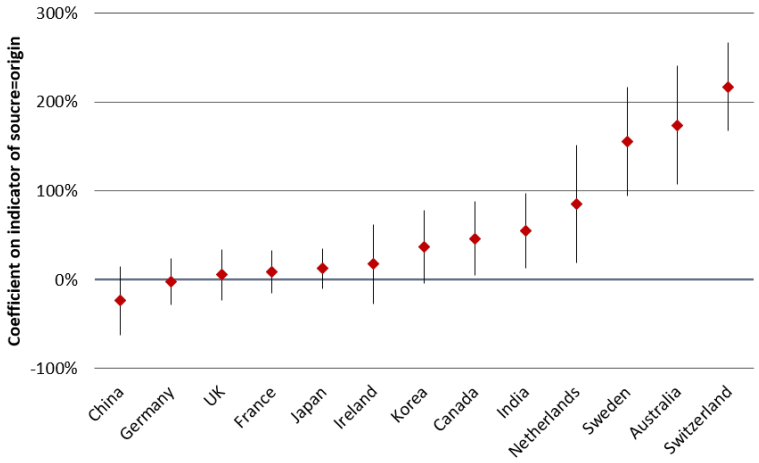
$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for source-industry and nationality-industry and year fixed effects. Regression is at the source-nationality-industry level. Dependent variable is the log number of visa petitions. Time period is 2012 to 2014. Columns Standard errors clustered at the nationality-source level.

Figure 7: Estimated coefficient (γ_s) on sourcing regression by country (H-1B vs. L-1)

(a) H-1B



(b) L-1



B.3 Fact 2: The impact of source-country immigration on MNEs

Table 16: Alternative time period for dependent variables

A) One-year lag dependent variable			
	Log Assets$_{s,k,t-1}$	Log Revenues$_{s,k,t-1}$	Log Rev. per Worker$_{s,k,t-1}$
Log N visas for source workers$_{s,k,t}$	0.002	-0.0251	-0.0145^{c}
	(0.0318)	(0.0287)	(0.00749)
N	1458	1458	1458
1st stage F-stat	191.16	191.16	191.16
B) Current time dependent variable			
	Log Assets$_{s,k,t}$	Log Revenues$_{s,k,t}$	Log Rev. per Worker$_{s,k,t}$
Log N visas for source workers$_{s,k,t}$	0.0830^{b}	0.0709^{a}	0.00845
	(0.0301)	(0.0227)	(0.0202)
N	1470	1470	1470
1st stage F-stat	261.2	261.2	261.2
C) Two-year lead dependent variable			
	Log Assets$_{s,k,t+2}$	Log Revenues$_{s,k,t+2}$	Log Rev. per Worker$_{s,k,t+2}$
Log N visas for source workers$_{s,k,t}$	0.777^{c}	1.296^{b}	0.887^{b}
	(0.405)	(0.530)	(0.421)
N	1240	1240	1240
1st stage F-stat	5.31	5.31	5.31

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for industry-time and industry-source fixed effects. Regressions are at the industry-source-time level. The time-period is from 2004 to 2014. Data for Revenues, Assets, and Revenues per worker for majority-owned US affiliates of non-US MNEs come from the BEA survey: "Comprehensive Data on the Activities of US affiliates." Dependent variables are at time $t-1$ in panel A, t in panel B, and $t+2$ in panel C. The independent variable is the log number of visa petitions for workers from source country s, by firms in industry k, time t, from source country s. The instrument used for 2SLS specifications is the one described in equation 7. Zeros in the number of visas are included, using the inverse hyperbolic sine transformation.

Table 17: Robustness checks on the impact of source-country immigrants on MNEs

A) No India			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas$_{s,k,t}$	1.007^a	1.254^a	0.377^a
	(0.332)	(0.358)	(0.116)
N	1319	1319	1319
1st stage F-stat	69.21	69.21	69.21
B) Not including zeros			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas$_{s,k,t}$	0.593^b	0.883^a	0.565^b
	(0.260)	(0.267)	(0.208)
N	468	468	468
1st stage F-stat	7.43	7.43	7.43
C) Source-time fixed effects			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas$_{s,k,t}$	0.458^a	0.627^a	0.00334
	(0.0445)	(0.0524)	(0.0224)
N	1359	1359	1359
1st stage F-stat	427.33	427.33	427.33
D) Controlling for Source-Industry Covariates			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log N visas$_{s,k,t}$	0.535^a	0.845^a	0.694^a
	(0.136)	(0.142)	(0.179)
N	1325	1325	1325
1st stage F-stat	44.3	44.3	44.3

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. Panels A, B, and D control for industry-time and industry-source fixed effects. Panel C controls for source-time and industry-time fixed effects. Regressions are at the industry-source-time level. The time period is from 2004 to 2014. Data for Revenues, Assets, and Revenues per worker for majority-owned US affiliates of non-US MNEs come from the BEA survey: "Comprehensive Data on the Activities of US affiliates." Dependent variables are at time $t+1$. The independent variable is the log number of visa petitions for workers from source country s, by firms in industry k, time t, from source country s. The instrument used for 2SLS specifications is the one described in equation 7. Panel A excludes Indian MNEs from the analysis, Panel B only includes observations with positive values for visa applications (excluding zeros). Panel D includes other source-industry characteristics such as GDP at s, total exports from s, the share of US imports coming from s, and the share of non-US imports coming from s. Zeros in the number of visas are included, using the inverse hyperbolic sine transformation.

Table 18: Correlation between observables, change on MNE outcomes and initial shares

	Δ Revenues	Δ Assets	Share 03
Industry GDP share in s	-2.647	-6.402	1.141^c
	(3.719)	(4.412)	(0.632)
Industry exports share in s	-1.744	-2.904	0.549
	(2.000)	(2.372)	(0.340)
Share of MNE from s in US in non-k	-2.198^c	-2.778^b	0.136
	(1.169)	(1.387)	(0.199)
Share of US imports from s in k	-1.451	-2.023	-0.152
	(1.885)	(2.236)	(0.320)
Share of non-US imports from s in k	2.812	3.593	-0.478
	(3.452)	(4.095)	(0.587)
Common language s and US	-0.008	-0.124	0.031
	(0.178)	(0.211)	(0.0302)
Regional Trade agreement s and US	0.552	0.576	0.022
	(0.492)	(0.584)	(0.0837)
Distance between s and US	0.106^b	0.111^b	0.007
	(0.041)	(0.048)	(0.007)
N	83	83	83
R-sq	0.208	0.229	0.092

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. Columns 1 and 2 have as dependent variable, the change in Revenues and Assets between 2005 and 2014. Column 3 has as a dependent variable the initial shares used to construct the instrument in equation 7. The regressions are at the industry-source level using characteristics defined in 2001 as explanatory variables. Data on exports, imports, and industry GDP come from the World Input Output Tables for 2001. Distance, common language, and regional trade agreements come from CEPII.

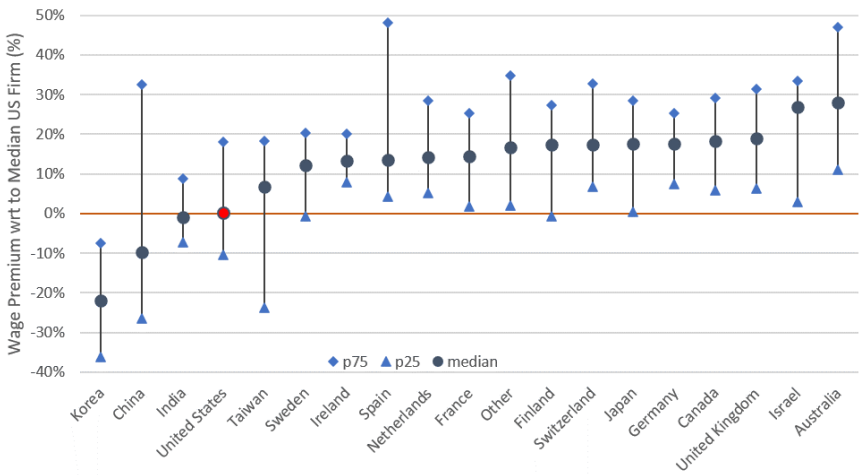
Table 19: Regressions using Stock of Immigrants as Independent Variable

A) College Graduates Stock			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log Immigrants$_{k,t}$ college	2.023^b	2.160^b	0.979^c
	(0.791)	(0.779)	(0.477)
N	1506	1506	1506
1st stage F-stat	9.679	9.679	9.679
B) Non-College Graduates Stock			
	Log Assets$_{s,k,t+1}$	Log Revenues$_{s,k,t+1}$	Log Rev. per Worker$_{s,k,t+1}$
Log Immigrants$_{k,t}$ non-college	-0.556	0.44	1.172^b
	(1.256)	(0.920)	(0.507)
N	1506	1506	1506
1st stage F-stat	9.422	9.422	9.422

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for industry-time and industry-source fixed effects. Regressions are at the industry-source-time level. The time-period is from 2000 to 2014. Data for Revenues, Assets, and Revenues per worker for majority-owned US affiliates of non-US MNEs come from the BEA survey: "Comprehensive Data on the Activities of US affiliates." Dependent variables are at time $t+1$. The independent variable in panel A is the log of the stock of immigrant college graduates from origin s, who work at industry k at time t. In panel B, it is the log of the stock of non-college graduates from country s, working in industry k, in time t. The stock of college and non-college graduates comes from the ACS. The instrument used for 2SLS specifications is the one described in equation 7 but with the initial shares calculated with the 1990 ACS.

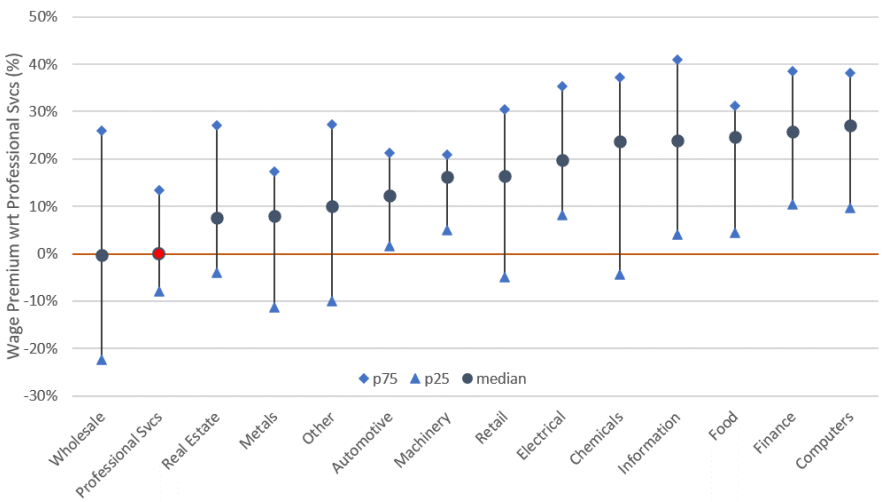
B.4 Fact 3: Nationality and Source Country Heterogeneity

Figure 8: Estimated Wage Premium with respect to Median US Firm



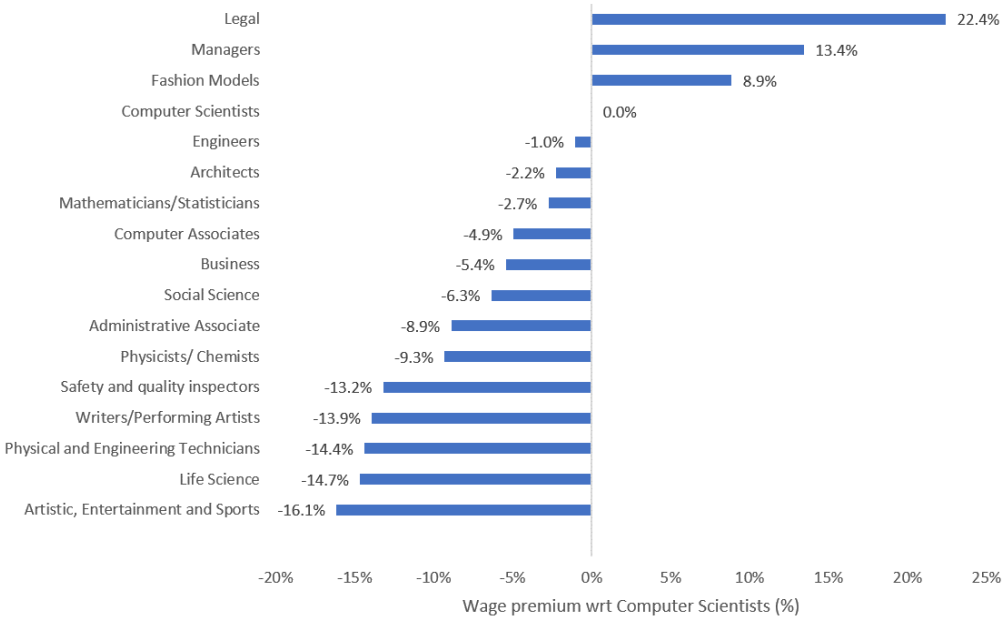
For each source country, the figure plots the 25th, 50th, and 75th percentiles of the estimated firm wage premium relative to the median US firm (γ_j). The median US firm wage premium is normalized to zero.

Figure 9: Estimated wage premium across industries



For each industry, the figure plots the 25th, 50th, and 75th percentiles of the estimated firm wage premium relative to the median firm in the Professional Services sector (γ_j). The wage premium for the median firm in the Professional Services sector is normalized to zero.

Figure 10: Estimated wage premium across occupations



The figure plots the occupation wage premium relative to computer scientists captured by fixed effect δ_{occ}. The wage premium for computer scientists is normalized to zero.

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

$$\pi^{mne}_{k,s,\ell} = \frac{T^k_s \left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta}}{\sum_{s'} T^k_{s'} \left(c^k_{\ell,s'} \times \delta^k_{\ell,s'}\right)^{-\theta}} \tag{26}$$

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

$$\tilde{T}^k_\ell = \sum_s T^k_s \left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta} \tag{27}$$

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

$$\pi^{trade}_{k,\ell,n} = \frac{(\tau^k_{\ell,n})^{-\theta} \tilde{T}^k_\ell}{\sum_{\ell'} (\tau^k_{\ell',n})^{-\theta} \tilde{T}^k_{\ell'}} \tag{28}$$

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

$$P_{k,n} = \bar{\Gamma} \left(\sum_\ell (\tau^k_{\ell,n})^{-\theta} \tilde{T}^k_\ell \right)^{-\frac{1}{\theta}} \tag{29}$$

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

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

$$c^k_{\ell,s} = \bar{\gamma} \prod_{k'=1}^{K} P^{\gamma_{\ell,k,k'}}_{k',\ell} \left((\psi^l_{k,\ell})^\alpha w^{1-\alpha}_{L,\ell} + (\psi^h_{k,\ell})^\alpha (c^h_{k,\ell,s})^{1-\alpha} \right)^{\frac{1}{1-\alpha}(1-\sum_{k'} \gamma_{\ell,k,k'})} \tag{30}$$

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. $c^h_{k,\ell,s}$ is the high-skill labor unit cost, which is different for each triplet k, ℓ, s given that high-skill workers have different abilities for each triplet, which makes companies in each triplet to face a different labor pool of effective units, hence a different high-skill labor cost. Firms employ domestic d, source country s, and other foreign f effective units of high-skill labor. If a company is located in their source country, source and native effective units are perfect substitutes.

$$c^h_{k,\ell,s} = \left((\psi^d_{k,\ell,s})^\lambda (w^d_{k,\ell,s})^{1-\lambda} + (\psi^{fs}_{k,\ell,s})^\lambda (c^{fs}_{k,\ell,s})^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \tag{31}$$

$$c^{fs}_{k,\ell,s} = \left((\psi^s_{k,\ell,s})^\iota (w^s_{k,\ell,s})^{1-\iota} + (\psi^f_{k,\ell,s})^\iota (w^f_{k,\ell,s})^{1-\iota} \right)^{\frac{1}{1-\iota}} \tag{32}$$

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

$$\Theta^L_{k,\ell,s} = \frac{(\psi^l_{k,\ell})^\alpha w^{1-\alpha}_{L,\ell}}{(\psi^l_{k,\ell})^\alpha w^{1-\alpha}_{L,\ell} + (\psi^h_{k,\ell})^\alpha (c^h_{k,\ell,s})^{1-\alpha}} \quad \Theta^H_{k,\ell,s} = \frac{(\psi^h_{k,\ell})^\alpha (c^h_{k,\ell,s})^{1-\alpha}}{(\psi^l_{k,\ell})^\alpha w^{1-\alpha}_{L,\ell} + (\psi^h_{k,\ell})^\alpha (c^h_{k,\ell,s})^{1-\alpha}} \tag{33}$$

7. Share of native ($\Theta^d_{k,\ell,s}$), source ($\Theta^s_{k,\ell,s}$), other foreign ($\Theta^f_{k,\ell,s}$) expenditure - one for each k-ℓ-s triplet.

$$\Theta^d_{k,\ell,s} = \frac{(\psi^d_{k,\ell,s})^\lambda (w^d_{k,\ell,s})^{1-\lambda}}{\sum_{x'} (\psi^{x'}_{k,\ell,s})^\lambda (w^{x'}_{k,\ell,s})^{1-\lambda}} \quad \text{for x'={d,sf}} \quad \Theta^x_{k,\ell,s} = \frac{(\psi^x_{k,\ell,s})^\iota (w^x_{k,\ell,s})^{1-\iota}}{\sum_{x'} (\psi^{x'}_{k,\ell,s})^\iota (w^{x'}_{k,\ell,s})^{1-\iota}} \quad \text{for x,x'={s,f}} \tag{34}$$

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.

$$w_{L,\ell} L_{k,\ell,s} = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta^L_{k,\ell,s} \pi^{mne}_{k,s,\ell} I_{\ell,k} \tag{35}$$

$$w_{x,\ell} H^x_{k,\ell,s} = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta^H_{k,\ell,s} \Theta^x_{k,\ell,s} \pi^{mne}_{k,s,\ell} I_{\ell,k} \quad \text{with } x = d, s, f \tag{36}$$

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

$$I_{\ell,k} = \sum_n \pi^{trade}_{k,\ell,n} \gamma_{k,n} X_n \tag{37}$$

$$X_n = w_{L,\ell} \bar{L}_\ell + \sum_{k,\ell,s,x} w^x_{k,\ell,s} H^x_{k,\ell,s} \quad \text{with } x = d, s, f \tag{38}$$

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

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

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

$$\pi^{mig}_{o,k,\ell,s} = \frac{A_{o,k} \left(\frac{w_{k,\ell,s}}{P_\ell} \varepsilon^o_{k,\ell,s} \right)^\kappa \phi^{-\kappa}_{o,\ell,s}}{\sum_{\ell',s',k'} A_{o,k'} \left(\frac{w_{i',\ell',s'}}{P_{\ell'}} \varepsilon^o_{k',\ell',s'} \right)^\kappa \phi^{-\kappa}_{o',\ell',s'}} \tag{40}$$

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

$$w^d_{k,\ell,s} H^d_{k,\ell,s} = w^d_{k,\ell,s} \varepsilon^d_{k,\ell,s} (\pi^{mig}_{o,k,\ell=o,s=o})^{\frac{\kappa-1}{\kappa}} N_\ell A^{\frac{1}{\kappa}}_{k,\ell} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \tag{41}$$

$$w^s_{k,\ell,s} H^s_{k,\ell,s} = w^s_{k,\ell,s} \varepsilon^s_{k,\ell,s} (\pi^{mig}_{o,k,\ell\neq o,s=o})^{\frac{\kappa-1}{\kappa}} N_s A^{\frac{1}{\kappa}}_{k,s} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \tag{42}$$

$$w^s_{k,\ell,s} H^s_{k,\ell,s} = \sum_{o\neq\{\ell,s\}} w^f_{k,\ell,s} \varepsilon^f_{k,\ell,s} (\pi^{mig}_{o,k,\ell\neq o,s\neq o})^{\frac{\kappa-1}{\kappa}} N_o A^{\frac{1}{\kappa}}_{k,o} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)} \right) \tag{43}$$

C.1 Writing the equilibrium in proportional changes

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

1. MNE shares / Effective technology in country ℓ

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

2. Trade shares/ Domestic price index

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

3. Unit cost / high-skill unit cost

$$\hat{c}^k_{\ell,s} = \prod_{k'=1}^{K} \hat{P}^{\gamma_{\ell,k,k'}}_{k',\ell}\left((\hat{\psi}^l_{k,\ell})^\alpha \hat{w}^{1-\alpha}_{L,\ell}\Theta^L_{k,\ell,s} + (\hat{\psi}^h_{k,\ell})^\alpha(\hat{c}^h_{k,\ell,s})^{1-\alpha}\Theta^H_{k,\ell,s}\right)^{\frac{1}{1-\alpha}(1-\sum_{k'}\gamma_{\ell,k,k'})}$$

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

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

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

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

5. Low-skill market clearing / Migration share

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

6. Other-foreign market clearing

$$\hat{w}^s_{k,\ell,s}\hat{H}^s_{k,\ell,s} = \sum_{o\neq\ell,s}\hat{w}^f_{k,\ell,s}\hat{\varepsilon}^o_{k,\ell,s}(\hat{\pi}^{mig}_{o,k,\ell\neq o,s\neq o})^{\frac{\kappa-1}{\kappa}}\hat{N}_o\hat{A}_{k,o}{}^{\frac{1}{\kappa}}\underbrace{\frac{w^f_{k,\ell,s}\varepsilon^o_{k,\ell,s}(\pi^{mig}_{o,k,\ell\neq o,s\neq o})^{\frac{\kappa-1}{\kappa}}N_oA^{\frac{1}{\kappa}}_{k,o}}{\sum_{o\neq\{\ell,s\}}w^f_{k,\ell,s}\varepsilon^o_{k,\ell,s}(\pi^{mig}_{o,k,\ell\neq o,s\neq o})^{\frac{\kappa-1}{\kappa}}N_oA^{\frac{1}{\kappa}}_{k,o}}}_{\text{Share } o \text{ in } \ell,s,k\text{: } \Lambda^o_{k,\ell,s}}$$

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 ($\pi^{trade}_{k,\ell,n}$); MNE shares ($\pi^{mne}_{k,s,\ell}$); Migration shares ($\pi^{mig}_{o,k,\ell,s}$); Share of wage bill spent in low-skill ($\Theta^L_{k,\ell,s}$) and high-skill ($\Theta^H_{k,\ell,s}$) for each k, ℓ, s; Share of high-skill wage bill spent on natives ($\Theta^d_{k,\ell,s}$), source workers ($\Theta^s_{k,\ell,s}$), and other foreign ($\Theta^f_{k,\ell,s}$); 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 ($\Lambda^x_{k,\ell,s}$); Share of low-skill employed in k,ℓ,s ($\Lambda^L_{k,\ell,s}$); Share of wage bill of k,ℓ,s on migrants from $o \neq \{\ell,s\}$ ($\Lambda^o_{k,\ell,s}$) and production shares ($\Lambda_{k,n,\ell}$). I explain how the dataset is constructed in Appendix E.

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 ($\delta^k_{\ell,s}$), producer comparative advantage (T^k_s), trade costs ($\tau^k_{\ell,n}$), production function labor shares ($\psi^l_{k,\ell}$, $\psi^h_{k,\ell}$, $\psi^d_{k,\ell,s}$, $\psi^s_{k,\ell,s}$, $\psi^f_{k,\ell,s}$, $\psi^{fs}_{k,\ell,s}$), 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 ($\varepsilon^o_{k,\ell,s}$), and the migration costs ($\phi_{o,\ell,s}$). The hat-algebra approach makes it easier to calculate the counterfactuals. For example, the counterfactuals computed in Sections 6.2 and 6.1 will compute how the equilibrium changes after an exogenous change of the MNE cost in all countries $\delta^k_{\ell,s}$ or the migration cost to the US $\phi_{o,us,s}$.

D Estimation details

D.1 Estimating κ using trade shocks

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 (2019), and using properties of the Frechet distribution, it is possible to write the conditional expectation of abilities as in equation 44. $\bar{\Gamma}$ is the Gamma function evaluated in $1 - \frac{1}{\kappa(1-\rho)}$. Equation 44 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.

$$E\left(\eta^{i,o}_z | i \text{ chooses } z\right) = A^{\frac{1}{\kappa}}_{o,k}\left(\pi^{mig}_{o,z}\right)^{-\frac{1}{\kappa}}\bar{\Gamma} \tag{44}$$

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: $wage^{i,o}_z = w^x_z \varepsilon^o_z \eta^{i,o}_z$, where w^x_z 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^o_z 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 44, it is possible to calculate average wages as in equation 45.

$$E\left(wage^{i,o}_z | i \text{ chooses } z\right) = w^x_z \varepsilon^o_z A^{\frac{1}{\kappa}}_{o,k}\left(\pi^{mig}_{o,z}\right)^{-\frac{1}{\kappa}}\bar{\Gamma} \tag{45}$$

By taking logs and re-organizing terms, we get estimating equation 46. Using the US H-1B data, it would be possible to estimate equation 46 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.[17]

$$Ln\left(\overline{wage}^{o}_{z,t}\right) = \underbrace{Ln\left(w^{x}_{z}\right)}_{k\text{-}s\text{-}t\text{-}x \text{ FE}} - \frac{1}{\kappa} Ln\left(N_{o,z,t}\right) + \underbrace{\frac{1}{\kappa}\left(Ln\left(A_{o,k,t}\right) Ln\left(N_{o,t}\right)\right)}_{o\text{-}k\text{-}t \text{ FE}} + \underbrace{Ln\left(\varepsilon^{o}_{z,t}\right)}_{\text{error term}} \tag{46}$$

Estimating equation 46 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 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. (2018) 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.[18]

$$\text{Shift Share}_{z,o,t} = \pi^{mig}_{o,z,2001} \times \left(\frac{\text{Exports of } k \text{ from } s \text{ to } \ell \neq US \text{ in } t}{\text{Exports of } k \text{ to } \ell \neq US \text{ in } t}\right) \tag{47}$$

As shown in Table 20, 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 D.1.1 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 (2019) 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.[19]

[17] 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 $\pi^{mig}_{o,z} = \frac{N_{o,z,t}}{N_{o,t}}$

[18] 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.

[19] 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 (2020).

Table 20: Estimates of equation 46

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

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. *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 less than 5 visa petitions were dropped. Standard errors clustered at the year, industry and source country.

D.1.1 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 D.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 (2020). 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., 2019). Second, I will use the observed wage dispersion and the estimate of κ from D.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 $W^{i,o}_{k,\ell,s} = \eta^{i,o}_{k,\ell,s} w_{k,\ell,s}$ 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 $\tilde{\kappa}$.

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 48 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.

$$\left(\frac{Var(W^o_{k,\ell,s})}{\left(\overline{W}^o_{k,\ell,s}\right)^2}\right) = \frac{\Gamma\left(1-\frac{2}{\kappa}\right)}{\left(\Gamma\left(1-\frac{1}{\kappa}\right)^2\right)} - 1 \tag{48}$$

I present the baseline results using the H-1B data in Column (1) of Table 21. An alternative strategy is to use the estimate of $\kappa = 6.17$ from D.1 and equation 48 by replacing κ by $\kappa(1-\rho)$. Table 21 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 21: Estimates for κ using dispersion of wages

	Only using dispersion	Using trade shock and dispersion
κ	8.28^a	6.17^a
	(0.138)	(2.012)
$\tilde{\kappa}$	8.28^a	2.08^a
	(0.138)	(0.00016)
Implied ρ	0	0.34
	2,534	2,534

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

D.2 Estimating effective wage ratio

To estimate ι, it is possible to re-work the first order conditions of the components in equation 15 to get to equation 49:

$$Ln\left(\frac{\text{wage bill}^s_{z,t}}{\text{wage bill}^f_{z,t}}\right) = (1-\iota)Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right) + \iota Ln\left(\frac{\psi^s_{z,t}}{\psi^f_{z,t}}\right) \tag{49}$$

Equation 15 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.[20] If one were to run this regression by OLS, two main issues would arise. First, the effective wage ratio $Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right)$ 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

[20] 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.

upwards, as we would be confounding supply and demand. I proceed to estimate this parameter in two steps. In the first step, I use the estimated value of κ and 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.

As a first step, I explain how it is possible to use equation 45 and the estimated value of $\kappa = 6.17$ to back out the implied effective wage ratio $\frac{w^s_{z,t}}{w^f_{z,t}}$. Using the the properties of the Frechet distribution, we can write the observed average wages for each group as in equation 50:

$$\overline{wage}^o_{z,t} = w^x_{z,t}\pi_{o,z,t}^{-\frac{1}{\kappa}}A^{\frac{1}{\kappa}}_{k,o,t}\bar{\Gamma}\varepsilon^o_{z,t} \tag{50}$$

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 re-arranging terms, it is possible to get to equation 51:

$$\underbrace{Ln\left(\frac{\overline{wage}^s_{z,t}}{\overline{wage}^o_{z,t}}\right) + \frac{1}{\kappa}Ln\left(\frac{N^s_{z,t}}{N^o_{z,t}}\right)}_{\text{Data}} = \underbrace{Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right) + \frac{1}{\kappa}Ln(N_{s,t}A_{k,s,t})}_{\text{Source-Industry-Time FE}} - \underbrace{\frac{1}{\kappa}Ln(N_{o,t}A_{k,o,t})}_{\text{Origin-Industry-Time FE}} + \underbrace{Ln\left(\frac{\varepsilon^o_{z,t}}{\varepsilon^o_{z,t}}\right)}_{\text{Error term}} \tag{51}$$

Equation 51 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.

I estimate equation 49, 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 51 as an explanatory variable. The term $Ln\left(\frac{\psi^s_{z,t}}{\psi^f_{z,t}}\right)$ 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 $\frac{\psi^s_{z,t}}{\psi^f_{z,t}}$, I need an instrument to consistently estimate equation 49. 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 3.2, equation 7. 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 49 can be found in Table 22 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 22: Estimating equation for ι

	OLS	2SLS	2SLS
Log wage effective units ratio	-0.0014	-1.84^a	-5.84^b
	(0.20)	(0.66)	(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

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. 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.

E Dataset for counterfactual

This section describes how the dataset needed to compute the model is constructed. The description is based on the simplifications explained in Section 5.4 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 importsy, 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 ($\pi^{mne}_{k,s,\ell}$): to compute the MNE shares, I need the revenues of MNEs by industry and source country in the US, India, Western Europe, China-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 (2019), 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 ($\pi^{mig}_{o,k,\ell,s}$): 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 ($\Theta^L_{k,\ell,s}$, $\Theta^H_{k,\ell,s}$, $\Theta^d_{k,\ell,s}$, $\Theta^s_{k,\ell,s}$, $\Theta^f_{k,\ell,s}$, Λ^L_ℓ, $\Lambda^x_{k,\ell,s}$, $\Lambda^L_{k,\ell,s}$, $\Lambda^o_{k,\ell,s}$): A final piece of data needed is several shares of labor expenditure for different skill groups across countries, industries, and source technologies. The labor allocations data described above computes counts of workers so wage data 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 is not available at the industry-skill level so I use the high-skill to low-skill wage premium in Canada to impute wages in Europe and the skill premium in India to impute wages in China-Taiwan and RoW.

F Counterfactual 1: A restrictive migration policy

In this section, I present additional results from restricting migration into the US. As noted in Table 5, foreign MNEs in the US respond more in terms of revenues than US companies. Table 23 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 11.1%, while they only account for 4.8% of production in IT.

Table 23: Contribution of MNEs to output drop

		Percent change in Revenues		Share of US production
		Spillover	No spillover	
IT and Prof.Services	Total	-0.54%	-0.36%	
	US	-0.03%	-0.35%	95.16%
	Foreign	-0.51%	-0.04%	4.84%
	Share of Foreign MNEs in output drop	94.2%	11.1%	
High-Skill Manufacturing	Total	-1.85%	-0.36%	
	US	0.80%	-0.40%	70.84%
	Foreign	-2.65%	-0.15%	29.16%
	Share of Foreign MNEs in output drop	100%	38.0%	

Percent changes in revenues by industry and source country 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 24, 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 24, 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 D.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 24: Understanding mechanisms - elasticities

	Baseline	$\lambda = 7$	$\lambda = 2$	$\alpha = 3$	$\theta = 8.28$	$\iota = 6.84$	$\kappa = 8.28$
High-skill natives	0.08%	0.03%	-0.26%	-0.01%	0.10%	0.08%	0.09%
Low-skill natives	-0.36%	-0.36%	-0.37%	-0.26%	-0.34%	-0.36%	-0.38%
Total US natives	-0.23%	-0.25%	-0.34%	-0.18%	-0.20%	-0.23%	-0.24%

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 $\theta = 4$. The rest of the columns change only one parameter at a time and leave all others as in the baseline.

G Counterfactual 2: Welfare gains of MNE production

The results for MNE welfare gains with and without migration presented in Section 6.2 only looked at the gains for the US. Table 26 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 25: 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 real wages of going from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\delta^k_{s,\ell}$ are very high such that MNE is prohibitive.

Table 26: Real wage 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 real wages of going from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\delta^k_{s,\ell}$ are very high such that MNE is prohibitive. Column 3 shows the real wage change in the no migration setting relative to the real wage change in the baseline model with migration.