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

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Abstract

This paper aims to understand the relationship between high-skill immigration and multinational activity. I assemble a novel firm-level dataset on high-skill visas and show that there is a large home bias effect: foreign multinationals hire more immigrants from their home countries than from other origins. I then build and estimate a quantitative model that relates multinational production with immigration. First, I impose a restrictive immigration policy in the US and evaluate how it affects production and wages. Second, I increase the barriers to multinational production and show that immigration is an important channel to quantify the welfare gains generated by multinationals.

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1 Introduction

The rise of multinational enterprises (MNEs) has been a notable feature of globalization in the past few decades. From a policy perspective, attracting foreign MNEs into a country can be valuable to fostering innovation (Arkolakis et al., 2018); improving the labor market outcomes of domestic workers (Setzler and Tintelnot, 2021); and enhancing production efficiency through the transfer of goods and technologies across borders. Skilled immigrants might also have an important role in transferring knowledge across countries, as they can embody home-country technology and have skills that facilitate cross-country communication and production (Burchardi et al., 2019; Hanson and Liu, 2023). If foreign MNE affiliates need to communicate and exchange knowledge with their parent company to operate, immigrants can be a particularly valuable input that facilitates global production. However, there is little evidence on how MNE activity and immigration interrelate within a single quantitative framework.

In this paper, I investigate the relationship between high-skill migration and MNE activity. To establish the link empirically, I present a main stylized fact showing that compared to other companies operating in the US, foreign MNEs are more dependent on immigrant labor from their home countries than from other countries. I build and estimate a quantitative model with multiple industries and countries that incorporates high-skill migration, trade, and MNE activity. I then 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, I increase the barriers to MNE production and calculate the relevancy of incorporating migration for estimating the welfare gains generated by 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 their employer, which is the country where its headquarters is located. 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. I match these data to the corporate databases of Orbis and D&B Hoovers to get information on the ownership structure of each firm. The link between the source country of companies and the origin of their immigrant workers has been missing from previous studies and is key to understanding the relationship between MNEs and high-skill worker migration.

I document a main fact that relates immigration to MNE activity. I show that, when compared to other companies in the US, foreign MNEs in the US have a large "home bias," where, on average, they hire 67% more foreign workers from their source country than from other countries. There is heterogeneity in the magnitude of the home bias across countries, and this effect is consistently large. I show that home bias is larger for countries farther away from the US, with languages other than English, and it is particularly strong for small visa applicants that are starting their operations in the US. These suggest home-country immigrants might be important communicators between the parent company and its US affiliate as well as facilitate production of MNEs.

I then look at the observed wages of immigrants reported in the H-1B visas. First, I show that MNEs pay lower wages to their source-country immigrants, suggesting home-country workers with lower ability might find it easier to migrate by working at a source-country MNE. I then move beyond MNEs and focus on understanding broader patterns of high-skill immigration into the US to guide some features of the model. I show that wages largely vary across nationalities. Higher wages are positively correlated with the GDP per capita of the immigrants' origin country and negatively correlated with how many workers have already emigrated from their home country to the US.

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). Producers draw an idiosyncratic productivity to produce in each country and decide whether to serve foreign markets through trade, MNE activity, or a combination of the two, based on which method allows them to sell their goods at the lowest price. 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, which industry to work in, and which source technology to work with. For example, if a worker is employed by a company whose parent company is headquartered in Germany, he or she works with German source technology. Workers draw idiosyncratic productivities to work in each country-industry-source triplet, and they sort endogenously across triplets based on their productivities, observed wages, and migration costs.[1]

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 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 two separate channels. From the labor supply side, the migration cost is deemed to be lower if migrants work for a company whose source country is the same as the worker's home country. From the labor demand side, foreign MNEs treat workers from their source country as imperfect substitutes for domestic and other foreign workers;

[1] 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).

therefore, they treat source-country workers as distinct inputs for production.

I use the 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, high-tech manufacturing, and financial services to decrease by 0.38%, 0.41%, and 0.37%, respectively. This decrease would be largely driven by foreign MNEs that respond disproportionately to the migration restrictions. Other countries' share in production is expected to increase in response, with the IT sector increasing by 0.50% in India and by 0.15% in Canada. Real wages for US low-skill workers would decrease by 0.26%. High-skill workers complement low-skill workers' production so that the decrease in immigration of high-skill workers lowers the demand for low-skill workers and decreases their wages. On the other hand, US high-skill workers would experience a gain of 0.17% in their real wages driven by an increase in the market wages caused by the lower competition from immigrants. In dollar terms, restricting immigration would account for a total long-term loss of $2.9 billion per year for the US economy. A model without foreign MNEs would underestimate the real wage losses from restricting immigration by 8%, as US companies are less sensitive to immigration restrictions than foreign MNEs. I show that the model predictions are robust when allowing for immigrants to decrease information barriers that limit MNE activity and trade.

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 1.46% and 1.73%, respectively. A model that does *not* incorporate migration would overstate the welfare gains for high-skill workers by 38% and understate the gains for low-skill workers by 4.4% since it would not account for the negative impact of immigration on high-skill natives nor the positive impact on low-skill workers. This result shows that the link between MNEs and immigration significantly affects the 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 accounting for the specific channel of multinational activity. 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. (2014a), Bound, Khanna, and Morales (2018), and Burstein et al. (2020) 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 them to incorporate, to some extent, the possibility that production will relocate as a response to changes in immigration policy (Brinatti and Morales, 2022; Caliendo et al., 2021; Desmet et al., 2018; di Giovanni et al., 2015; Iranzo and Peri, 2009; Khanna and Morales, 2021). This paper contributes to this literature by including the channel of multinational production, which is key to understanding the effects that firms' decisions to relocate production due to immigration policies have on welfare and productivity.

A closely related strand of literature has used a mostly reduced-form approach to establish a link between immigration and trade (Gould, 1994; Ottaviano and Peri, 2018), immigration and FDI activity (Burchardi et al., 2019; Cuadros et al., 2019; Glennon, 2022; Javorcik et al., 2011; Wang, 2014; Yeaple, 2018), and the interrelations between migration, trade, and FDI (Aubry and Rapoport, 2019). Similarly, multiple papers have also taken a reduced-form approach to investigate the impact of the H-1B program on productivity, innovation, and the labor market outcomes of native workers (Doran et al., 2022; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Peri et al., 2015). I contribute to this literature by presenting new facts on the relationship between migration and FDI and estimating a quantitative model that allows me to quantify the positive and negative consequences of immigration into the US.

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 on worker outcomes and the transfer of knowledge across countries. Setzler and Tintelnot (2021) highlight that foreign and US MNEs can have a positive impact on domestic workers' wages. Keller and Yeaple (2013) test a model in which MNEs use intermediate inputs to transfer knowledge between the parent company and the affiliate while Oldenski (2012) studies how communication with consumers and task-complexity influence the choice to serve a market through trade or FDI. A related literature also explores how managers transfer knowledge between firms (Mion et al., 2023) and within firms (Gumpert, 2018). This paper proposes international migration as an additional channel for the impact of MNEs on domestic workers and 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 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 there is a lottery to award the visas. Universities and nonprofits are exempt from the cap. The visa program recognizes a dual intent: 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, L-1 visa petitions were 11% of approved H-1B petitions in FY2015. 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 one year in a three-year period prior to admission to the US. L-1 visas are valid for up to five to seven years and are also dual intent. Another employer-tied visa for high-skill immigrants is the TN visa, specific for Canadian and Mexican citizens as a part of the North American Free Trade Agreement (NAFTA), which were 2% of H-1B petitions in FY2015. 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 OPT, Diversity Lottery, family reunification, and other smaller programs. However, the H-1B is by far the main pathway for immigrant college graduates from most nationalities in the world, including Canada.[2]

For this project, I submitted a 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 petition is approved by the Department of Labor. The records only include visa applications that either won the H-1B lottery or were exempt from the lottery in the first place. 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, occupation, country of birth, and wages.

[2]See Appendix A for more details on the H-1B and other visa programs.

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. I combine the FOIA dataset with corporate information from Orbis and DnB Hoovers to get insight into the ownership structure of the employers and determine the country where the Global Ultimate Owner (GUO) 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.

As shown in Appendix A, Tables A2 and A3, 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 and 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. Throughout the empirical section, I distinguish MNEs by their "source country," denoted by s, which is the country where the GUO of the firm that applied for the H-1B visa is headquartered. A worker's origin country, denoted by o, refers to the H-1B recipient's country of birth, as reported in the visa application. Industries, denoted by k, are determined by the mode industry across all employers that have the same GUO. For each firm, industry and source country are kept constant over time. Time periods, denoted by t, are years grouped into the following categories: 2001-2003; 2004-2006; 2007-2009; 2010-2012; and 2013-2014. Finally, I use subscript i to denote an individual or visa, and subscript j to denote a GUO firm. Individuals cannot be linked over time (for example, by linking petitions for new employment and renewal for a same applicant), so I consider each visa as a unique individual. Appendix B.1 provides details on the data processing for the empirical section and Table B4 summarizes the notation used throughout the paper.

3.1 Home bias of foreign MNEs

I begin the analysis by showing that when compared to companies from other source countries, foreign MNE companies have a "home bias" toward recruiting workers from their source country relative to other nationalities. 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) - time (t) level and estimate equation (1).

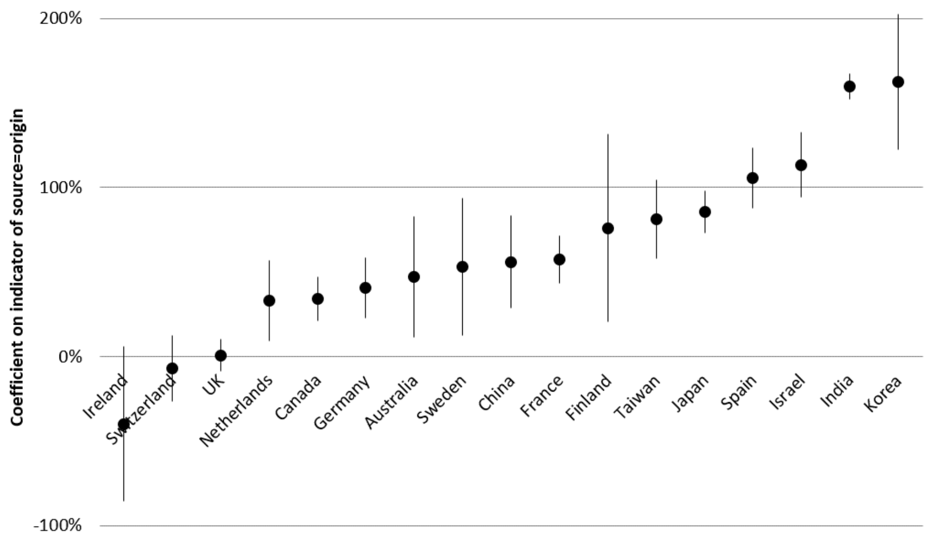
$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_s \gamma_s \mathbb{1}(s = o) + \varrho_{s,k,t} + \omega_{o,k,t} + \xi_{j,o,k,s,t}. \quad (1)$$

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. The key coefficient of interest is γ_s, which measures how much more likely a company from source s would hire someone from $o = s$ relative to $o \neq s$ when compared to all other companies from other source countries (including US companies). Source-industry-time fixed effects, $\varrho_{s,k,t}$, capture the trend in visa petitions for all firms from a given source-industry pair. I also incorporate origin-industry-time fixed effects ($\omega_{o,k,t}$) to control for the trend in immigration of workers from origin country o in industry k. I use all visa petitions from firms in industries with at least some MNE activity for the years between 2001 to 2014.[3] 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 in the US are 159% more likely to recruit workers from India than other countries, relative to non-Indian companies in the US.[4]

[3] 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.

[4] On the other extreme is Ireland, where home bias is negative and not statistically different from zero. Part of the explanation could be that some corporate headquarters are located in Ireland for tax purposes, but the core of their employment is elsewhere making Irish workers not as relevant for Irish MNEs.

Figure 1: Estimated coefficient (γ_s) by source country



I plot the coefficients γ_s and 95% confidence intervals estimated using regression (1). The number of observations is 38,032. Standard errors are clustered at the origin-source-country level.

Adding source-industry-time fixed effects to the regression implies that the identification of the home bias coefficients comes from source-industry pairs that hire both source- and nonsource-country immigrants. US companies are also included in the regression, and while they don't contribute to identifying the home bias, they do help by identifying the origin-industry-time fixed effects, which capture the comparative advantage of workers from a given origin in a specific industry. Immigrants from a given origin country who work at companies with $s \neq o$ in each industry and time period help identify the source-industry-time and origin-industry-time fixed effects. Appendix B.2 explores further how the regression results change when running the regression at the source-origin-industry as opposed to the firm-origin-time level. In these regressions, MNEs that apply for more visas have a larger weight in the estimation than in equation (1), but results are very robust to these specification. Results are also robust to including observations with 0 value through a PPML estimation, and including L-1 visas into the analysis. Finally, I corroborate in Table B6 that all results are robust to controlling for a firm-time fixed effect as opposed to a source-industry-time fixed effect. In this case identification comes from firms that hire both source- and nonsource-country immigrants.[5]

The observed home bias can be explained by multiple factors. On one hand, source-country immigrants may be a specific input in production. For example, they might facilitate communication between the US affiliates and the parent company because of language skills or cultural proximity. On the other hand, it is possible that workers in the source country find it easier to find a job and migrate if they go work for a home-

[5]As shown in Table B5, a majority of the MNEs from every source country hire both source and nonsource immigrants.

country MNE, either because of networks or employers facing a lower screening cost to evaluate source-country experience and education credentials. 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 look into some of the mechanisms that drive the observed home bias. I begin by looking at industry and source-country characteristics that might explain the observed differences in home bias. To distinguish between industry and source country in the regression, I estimate equation (2):

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_k \sum_s \gamma_{s,k} \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \xi_{j,o,k,s,t}, \tag{2}$$

where I interact the sourcing indicator $\mathbb{1}(o = s)$ with a fixed effect for each source country - industry pair. Coefficients $\gamma_{s,k}$ measure, for each industry and source country, how many more immigrants from their source country do MNEs hire relative to other immigrants, when compared to companies in that industry, from other source countries. This estimation procedure yields many coefficients, as there is one estimate per source country and industry pair. In Figure B1, I present the home bias estimates by industry and show that they are large and significant for a wide range of high-skill industries such as machinery, finance, IT, and professional services, among others. I proceed to calculate pairwise correlations between the estimated home bias coefficients $\hat{\gamma}_{s,k}$ and source-country and industry characteristics 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	-0.20^c	Share of college grads in k	-0.11
Country s **in non-English speaking**	0.23^b	Average college grads wage in k	0.03
Distance from s **to US**	0.36^a	Employment share in US	-0.10
Source-industry characteristics (s, k)			
Industry GDP at s	-0.11	US Employment MNEs from s in k	-0.001
Share of US imports from s **in** k	-0.26^b	US Employment growth MNEs from s in k	0.08
Comparative advantage of s in k	-0.09		

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. Subscript s source country, k industry. Coefficients $\gamma_{s,k}$ are estimated using regression (2). I run pairwise correlations between the coefficients and industry-source characteristics. All characteristics are measured at year 2014. MNE employment growth is measured between 2005 and 2014. "Share of college graduates," "Average college graduate wage," and "Employment share in US" are calculated for the US at the industry level using the American Community Survey. GDP per capita comes from the World Bank. Language and distance taken from CEPII. Industry GDP, the share of imports, and comparative advantage come from WIOT. Comparative advantage is measured as the share of global exports from country s in industry k relative to the overall share of global exports from country s. Employment of MNEs in the US comes from the Bureau of Economic Analysis (BEA).

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. NonEnglish-speaking countries have higher home bias, consistent with the idea that workers who speak the source-country language might be particularly useful to facilitate communication between the parent and the affiliate. An alternative interpretation is that MNEs facilitate migration of source-country workers from regions where migration to the US is costly either due to long travel distances or differences in language. Finally, the share of US imports from country s in a given industry is negatively correlated with home bias. A possible interpretation is that when a country has established relations with the US in specific industries, the employment of source-country workers might be less crucial for production in the US.

In Appendix B.4-B.6 I examine other firm-level attributes of the MNEs that apply for H-1B visas. First, in Appendix B.4, I show that the home bias is decreasing on the number of H-1B visa applications. The number of H-1B applications is positively correlated with the size of firms in the US as shown in Appendix B.4.1. Hence, the result of smaller applicants having a larger home bias 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 might be more useful for production.

Second, I investigate how home bias changes over time. As shown in Table B10, home bias in the first period a firm starts applying for H-1B visas is positive and significant, but it decreases in later periods and almost disappears after year 7. Such decreasing trend is particularly strong if we exclude Indian companies and MNEs from countries with high-attrition in the sample. Such results are consistent with firms needing source-country workers more when they are starting their operations in the US.

Finally, in Appendix B.6, I look into the occupations performed by source- and nonsource-country immigrants. As shown in Table B11, source-country workers are more likely to work in communication intensive occupations such as administrative professionals or managers, than non-communication intensive occupations like engineers. While intriguing, the aggregate patterns of home bias are likely not driven by differences in these broad occupation groups, as the results in Figure 1 remain unchanged when only looking at computer scientists and engineers, who represent more than 80% of the H-1B visas.

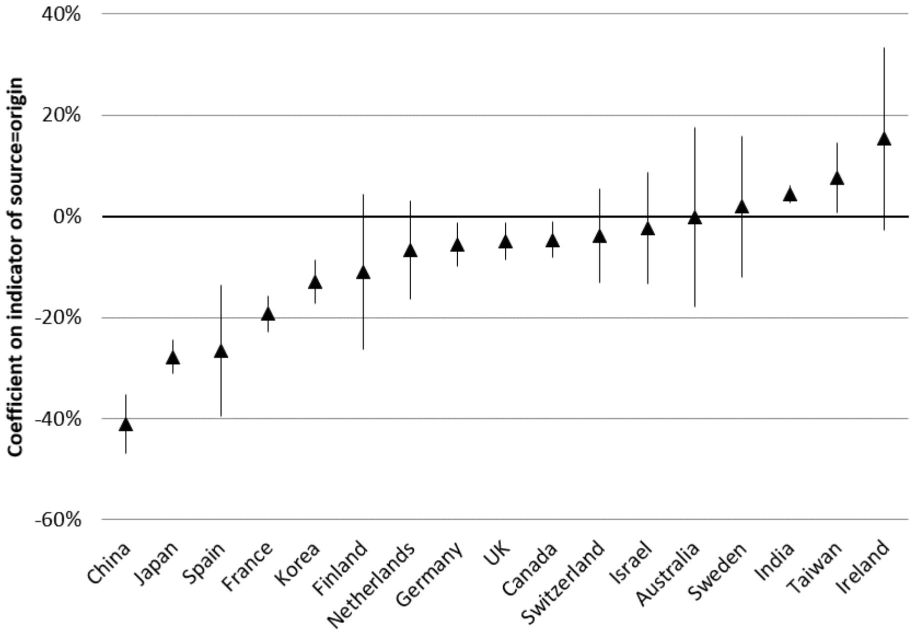
3.2 Analysis on wages

I proceed to use H-1B data on wages for two purposes. First, to further unpack the home bias patterns presented in Section 3.1, and second, to motivate features in the model regarding the high-skill immigration system in the US. An advantage of working with wage data is that it is no longer necessary to aggregate at the firm level, but instead I can run the analysis at the individual visa level, which allows to control for individual characteristics such as occupation. As a first exercise, I use reported data on wages to estimate equation (3):

$$Ln(\bar{w}_{i,o,k,s,t}) = \beta_0 + \sum_s \beta_s \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \zeta X_{i,t} + \xi_{i,o,k,s,t}, \tag{3}$$

where the dependent variable is the log average wage for each individual visa. The right-hand side of the equation is similar to equation (1), where I control for source-industry-time fixed effects ($\varrho_{s,k,t}$), nationality-industry-time fixed effects ($\omega_{o,k,t}$) and other individual level controls ($X_{i,t}$) such as occupation-time fixed effects. Coefficients β_s can be interpreted as the average wage difference between source-country immigrants and other immigrants working for an MNE from country s when compared to immigrants not working at a company from s. The identification of the fixed effects follows a similar intuition to the employment regressions in equation (1). A priori, it is unclear which direction wages are expected to go. On one hand, if source-country workers have a specific productivity impact on the firm, perhaps because of facilitating communication or technology transfer, we would expect them to have a wage premium over other immigrants. Instead, if MNEs make it easier for lower ability workers from the home country to migrate, because of lower screening and recruitment costs of migrant workers, 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, Chinese firms in the US pay 41% less to their Chinese workers than to other immigrants when compared to non-Chinese firms. As shown in Table B6, on average, firms pay their source-country workers 6.4% less than immigrants from other origins when compared to companies from other source countries. In Table B6, I show that the results are quantitatively very similar when running the regression at the firm-origin-time level (as done in Section 3.1) and when controlling for firm-time fixed effects as opposed to source-industry-time fixed effects.

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



I plot the coefficients β_s and 95% confidence intervals estimated using regression (3). The number of observations is 1,727,197. Standard errors are clustered at the origin-source-country level.

In Appendix B.7, I present some of the analysis done in Section 3.1 but using wages as the dependent variable. Most industries pay lower wages to source-country immigrants than to other immigrants, particularly manufacturing industries such as Automotive, Machinery and Chemicals as well as service industries such as Information and Finance. I then look at the characteristics that correlate with the wage difference between source and nonsource workers, as shown in Table B12. Source-country workers receive a larger wage penalty relative to nonsource-country workers when their native language is not English. A possible explanation for this pattern is that home-country MNEs provide a greater reduction in the migration cost when migration is more costly (due to language or distance). If so, low ability workers from such countries who migrate to the US would disproportionately work for home-country MNEs.

As a final set of facts, I use the estimates of equation (3) to document significant heterogeneity across worker origin countries that will inform some features included in the model. The insights of this fact don't necessarily speak exclusively to MNE companies but more generally to the patterns of immigration of high-skill workers to the US. For exposition simplicity, I calculate the average origin wage difference, $\bar{\omega}_o$, by computing the weighted average of the estimates of $\hat{\omega}_{o,k,t}$, using as weights the number of observations in each industry-time pair for each origin country in the regression.

I set the India fixed effect, $\bar{\omega}_{o=in}$, to zero and interpret the estimates for each origin country as the average observed wage difference relative to Indian workers. In Figure 3, I plot the origin wage differentials against origin-country characteristics.[6] As shown in Figure 3a, there is a strong positive correlation between origin wage difference and GDP per capita as a measure of country wealth. Workers from richer countries receive higher wages relative to those from poorer countries, even conditional on firm and occupation, consistent with the idea that workers from richer countries who migrate to the US have a higher average ability, potentially driven by higher college quality in the origin country (Martellini et al., 2022).

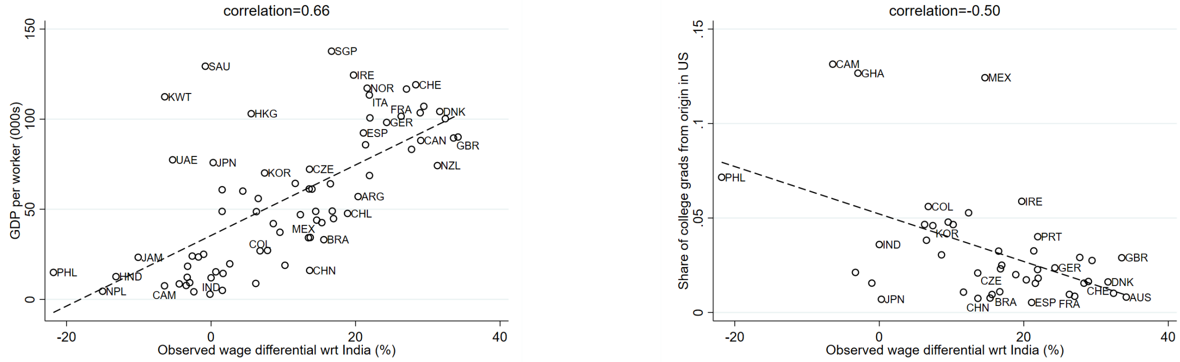
Figure 3b shows a strong negative correlation between the origin wage differential and the number of immigrant college graduates from o in the US as a share of the total college graduates in o.[7] Such patterns suggest that as more immigrants from a given country come into the US, the average ability of that pool of immigrants goes down. This is consistent with the findings of McKenzie and Rapoport (2010) on immigrant networks, where they show that when the diaspora in the US is larger, the average education level of new immigrants decreases. In Section 4.1, I present a model of migration and heterogeneous abilities consistent with these aggregate patterns. If workers in each origin country have heterogeneous 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 new migrants is expected to drop.

[6] A similar analysis is run by Setzler and Tintelnot (2021) where they plot GDP per capita against MNE source-country wage premium in the US, and Martellini et al. (2022) who plot GDP per capita against college quality in the origin country. In this case, I plot GDP per capita against the H-1B worker nationality fixed effects.

[7] For example, according to Figure 3b, 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 3: Wage differences 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 differential with respect to India as estimated from the weighted average of coefficients $\omega_{o,k,t}$. India is shown in the graphs with a zero premium. The vertical axis in Figure 3a is GDP per person employed (constant 2017 PPP \$) from the World Bank. The vertical axis in Figure 3b 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 or older 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 3b remains very similar when excluding the outliers of Ghana, Cameroon, Mexico, and the Philippines. The total number of observations used to estimate regression (3) is 1,727,197 individuals.

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 that incorporates the different mechanisms in which immigration affects production, welfare, and MNE activity.

4.1 Labor market and migration choices

The model is static and consists of O countries. 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 $w_{L,o}$. 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 worker's company is headquartered. At the beginning of the period, each worker takes an ability draw from a Fréchet distribution as shown in equation (4):

$$F(\eta_{i,o,z}) = exp\left(-\left(\sum_{z=1}^{Z} \tilde{A}_{k,o}^{\frac{1}{1-\rho}} \left(\eta_{i,o,z}\right)^{-\frac{\tilde{\kappa}}{1-\rho}}\right)^{1-\rho}\right), \tag{4}$$

where $\eta_{i,o,z}$ is the ability draw of individual i at origin o to work at each triplet $z = \{k, \ell, s\}$. 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 z. 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. The correlation across ability draws is captured by ρ. In the extreme case of $\rho = 1$, individuals will have the same ability across all triplets z. As in Bryan and Morten (2019), it is useful to rewrite $\kappa = \frac{\tilde{\kappa}}{1-\rho}$ 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).

Conditional on their choice of triplet z, individuals receive a wage as in equation (5):

$$W_{i,o,z} = \eta_{i,o,z} \times w_z \times \varepsilon_{o,z}. \tag{5}$$

The wage depends on the idiosyncratic productivity in triplet z, $\eta_{i,o,z}$; the effective wage per ability unit paid in triplet z, w_z; and a mean one log normally distributed random term that captures random shocks that make workers from o more productive at z, $\varepsilon_{o,z}$.[8] Each worker chooses the triplet z that maximizes their utility as in equation (6):

$$max_z\{U_{i,o,z}\} = \frac{W_{i,o,z}}{P_\ell} \times \frac{1}{\phi_{o,\ell,s}}, \tag{6}$$

where $\frac{W_{i,o,z}}{P_\ell}$ is the real wage per effective unit paid in triplet z. The parameter $\phi_{o,\ell,s} \geq 1$, 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 face a lower migration cost when working for an MNE of a specific source technology.[9] As $\phi_{o,\ell,s}$ is nonpecuniary, it

[8]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 $A_{o,k,\ell,s} = A_{k,o}\varepsilon_{o,k,\ell,s}$, and the estimation results would be identical.

[9]I will not include any hiring cost directly paid by the firm for hiring immigrants (See Brinatti and Morales (2022) for a model with immigrant-hiring costs). 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

is not part of the wage individuals receive in the labor market.

Modeling migration through the EK-Roy setup is consistent with the facts shown in Figure 3. Workers from countries with higher wages 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 that send fewer immigrants. Similarly, if the migration cost to work at a source-country MNE is much lower than to work for a nonsource-MNE we should see larger migration flows to source-country MNEs, higher degrees of home bias, and lower wages for source-country workers abroad.

A key feature of this model is that workers receive the same wage per ability unit as long as they choose the same industry (k), location (ℓ), and source technology (s). Hence, within triplet $z = \{k, \ell, s\}$ there is no heterogeneity across firms in terms of wages paid and can be interpreted as a representative firm within each triplet. In Appendix C.2, I discuss the differences between this model and models of worker-sorting across firms.

4.2 Production

I lay out the consumer problem in two stages. First, individuals take ability draws and choose a triplet $z = \{k, \ell, s\}$ as explained in Section 4.1. Second, conditional on their choice and the wage they receive, they maximize their consumption utility as an individual in ℓ, as in equation (7):

$$U_i = \prod_{k=1}^{K} Q_{i,k}^{\chi_k} \longrightarrow Q_{i,k} = \left(\int q_{i,j,k}{}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}. \tag{7}$$

The utility function is a Cobb-Douglas over K industries, where $Q_{i,k}$ is the consumption of individual i of goods from industry k. Each $Q_{i,k}$ can be written as a continuum of varieties indexed by j, and aggregated CES as in equation (7). The quantity $q_{i,j,k}$ is the consumption of individual i of variety j. Each variety has a production function as in equation (8):

$$q_{j,z} = \underbrace{\epsilon_{j,z}}_{\substack{\text{firm}\\\text{productivity}}} \times \underbrace{\prod_{k'=1}^{K} Q_{j,z,k'}^{\chi_{k'}}}_{\substack{\text{intermediate}\\\text{inputs}}} \times \underbrace{\left(\psi_z^l \left(l_{j,z}\right)^{\frac{\alpha-1}{\alpha}} + \psi_z^h \left(h_{j,z}\right)^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}(1-\bar{\chi})}}_{\substack{\text{labor}\\\text{composite}}}. \tag{8}$$

migrants for whom the migration costs are higher.

A producer of variety j, from an industry-location-source triplet $z = \{k, \ell, s\}$, produces output $q_{j,z}$. They have an idiosyncratic productivity $\epsilon_{j,z}$. Intermediate inputs are combined with a labor composite through a Cobb-Douglas function, and $\chi_{k'}$ is the expenditure share on intermediates from industry k'. Parameter $\bar{\chi}$ stands for $\sum_{k'} \chi_{k'}$. Each producer uses high- and low-skill labor for production, and the elasticity α captures the degree of substitution between the two. Producers from different triplets z are allowed to have different skill intensities (ψ_z^l and ψ_z^h). Low-skill labor ($l_{j,z}$) is assumed to be a homogeneous input while high-skill labor ($h_{j,z}$) is a composite of different types of high-skill labor employed by firm j, as shown in equation (9):

$$h_{j,z} = \left(\underbrace{\psi_z^d \left(h_{j,z}^d\right)^{\frac{\lambda-1}{\lambda}}}_{\text{local workers}} + \underbrace{\psi_z^{sf} \left(\underbrace{\psi_z^s \left(h_{j,z}^s\right)^{\frac{\iota-1}{\iota}}}_{\text{source country}} + \underbrace{\psi_z^f \left(h_{j,z}^f\right)^{\frac{\iota-1}{\iota}}}_{\text{other foreign}} \right)^{\frac{\iota}{\iota-1}\frac{\lambda-1}{\lambda}}}_{\text{all foreign}} \right)^{\frac{\lambda}{\lambda-1}}. \tag{9}$$

Each firm employs college-educated domestic workers ($h_{j,z}^d$), source-country immigrants ($h_{j,z}^s$), and immigrants from other countries ($h_{j,z}^f$). Only foreign MNEs can hire source-country immigrants.[10]

The parameter λ governs the substitution between effective units of the domestic country and foreign effective units. Parameter ι governs the substitution between source-country and other 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 $\psi_z^d, \psi_z^s, \psi_z^f$, and ψ_z^{sf} can also vary across locations, source countries, and industries. Differences in this parameters capture why some source-industry pairs might be more intensive on immigrants than others.

4.3 International trade and MNE activity

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

[10] If a company operates in $\ell = s$, then the source-country workers and other foreign workers are the same, and the only relevant substitution is between natives and foreigners.

Rodriguez-Clare (2013), which is an extension of the Ricardian trade model in Eaton and Kortum (2002). Multisector Ricardian MNE models have been developed by Alviarez (2019) and Arkolakis et al. (2018), among others.

Producers of each variety j, in triplet $z = \{k, \ell, s\}$, take a productivity draw to produce in each possible location ℓ from a Fréchet distribution as in equation (10):

$$F(\epsilon_{j,z}) = exp\left(-\sum_{\ell=1}^{\mathcal{L}} T_{k,s}\left(\epsilon_{j,z}\right)^{-\theta}\right). \tag{10}$$

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, who chooses to locate production at location ℓ and sell their products to destination country n, would charge a price as in equation (11):

$$p_{j,z,n} = \frac{c_z \times \tau_{k,\ell,n} \times \varphi_{k,\ell,s}}{\epsilon_{j,z}}. \tag{11}$$

The price increases with the marginal cost of production c_z. Marginal cost depends on the industry k, the location of production ℓ, and the source technology s. 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 firm specific productivity $\epsilon_{j,z}$ 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 $\ell \neq n$, then they incur 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 $\ell = n$, then if $s \neq \ell$, the company incurs an iceberg MNE cost ($\varphi_{k,\ell=n,s}$), 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 ($\varphi_{k,\ell,s}$). Consumers end up buying each variety from the cheapest producer.

4.4 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 $z = \{k, \ell, s\}$ 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 Fréchet distributions, it is possible to derive tractable, closed-form solutions for migration shares, trade shares, and MNE shares. Appendix C shows the complete equilibrium equations including trade balance, labor, and product market clearing conditions and the cost functions.

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

The model includes many exogenous parameters such as migration costs $\phi_{o,\ell,s}$, trade costs $\tau_{k,\ell,n}$, MNE costs $\varphi_{k,\ell,s}$, fundamental technologies $T_{s,k}$, worker comparative advantages $A_{k,o}$, and labor shares ψ_z; but it's assumed they stay constant between the real and the counterfactual such that $\hat{y} = 1$. 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 five 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 noncollege workers, and θ the trade and MNE elasticity. Those elasticities together with data on observed allocations are enough to compute the changes in the endogenous variables of the model. While I also need data on the observed migration, trade shares, MNE shares, and labor allocations, I do not need to take a stand on any other parameters of the model, which greatly reduces the number of parameters to be estimated.

4.5 Assumptions and limitations of the model

In Appendix C.2, I discuss in detail three main limitations of the model. First, there is a representative firm within a given industry-location-source triplet. This implies that the model will not be able to capture dynamics on firm and worker sorting documented by the literature (Dostie et al., 2023; Setzler and Tintelnot, 2021). However, the model is well suited to study the *aggregate* effects of immigration into the US and its relationship with MNEs which are the focus of this paper.

Second, the model implies that the most skilled workers are the first ones to migrate. This is at odds with some features of the US immigration system, where the quantity of high-skill migrants is rationed and assigned through a lottery. In the medium run, however, the US immigration system is well characterized with a positive selection feature as in this model. H-1B applicants are already highly selected relative to the global pool of college graduates and even if someone with high-ability loses the lottery, they can apply again next year or come through other visa programs.

Finally, the model ignores the possibility of low-skill workers to migrate to the US. While low-skill immigrants are the subject of important policy discussions, the relationship between MNEs and immigration is particularly relevant for high-skill immigrants as documented by Cho (2018) for Korean MNEs.

5 Estimation

In this section, I proceed to describe the estimation strategies for the five key elasticities in the model: Labor supply parameter, κ; production function elasticities, α λ, and ι; and the trade elasticity, θ. I will use the H-1B data to estimate κ and ι, and set θ, λ, and α according to values estimated in the literature.

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). Similarly, I set the elasticity of substitution between college and noncollege 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, I set $\lambda = 13.25$ to match the aggregate elasticity of 12.6 as estimated by Ottaviano and Peri (2012) for college graduates. Burstein et al. (2020) also find a high elasticity of substitution of 10 between domestic and foreign workers.[11]

The labor supply elasticity, κ, is estimated through an instrumental variable approach that exploits "trade shocks" across source countries and industries (Autor et al., 2013). To identify this parameter, I exploit demand shocks that capture changes in the comparative advantage ($T_{k,s,t}$) that affect the employers from source country s in industry k that are independent of time-specific productivity shocks that determine migration decisions of origin o immigrants. In Appendix D.1, I describe the estimation of κ in detail. My preferred estimate of κ is 6.17.

[11]The papers that estimate the elasticities of substitution do so at the "aggregate" labor market level. Hence, the aggregate elasticity might be different than the within firm elasticity of substitution that is the object of interest to calibrate in the paper. I follow Burstein et al. (2020) and use the model to compute what is the corresponding within firm elasticity for a given aggregate elasticity of substitution.

Finally, I proceed to estimate ι, the elasticity of substitution between source country and other foreign effective units. I propose two instruments that use very different sources of variation and can be interpreted as immigrant supply shifters, which help identify the relative demand between source- and nonsource-country immigrants. Appendix D.2 describes the estimation in detail. The preferred estimate of ι is 3.75.

5.1 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 four industries: professional and technical services, which mainly includes the IT sector and consulting services; high-skill intensive manufacturing, which includes chemicals, machinery, computer, electronic, electrical equipment, and transportation manufacturing; financial services; and a fourth sector that includes everything else in the economy. This allows me to focus on 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, high-skill manufacturing, and the financial service sector. 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 destinations for high-skill migrants are the US, Canada, and Western Europe.[12]

I set $\theta = 4$, $\alpha = 1.7$, $\kappa = 6.17$, $\lambda = 13.25$, and $\iota = 3.75$ 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 $z = \{k, \ell, s\}$, and skill shares for domestic, source country, and other foreign workers for each triplet z. In Appendix E, I explain how I construct the dataset to run the counterfactual exercises.

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 (12), shown below. This normalization implies that the output results should be interpreted as how do the endogenous variables change as a share of total World output.

[12] According to the OECD, the US, Western Europe, and Canada receive 85% of all college-educated immigrants (US 37.4%; Western Europe 37.5%, and Canada 10.5%). Other immigrant destinations that follow are Russia (8.4%), Australia (5.4%), Israel (2.3%), and Japan (0.9%). However, given their lower importance as immigrant-receiving countries, I do not consider them separately in the analysis.

$$X_{us} + X_{in} + X_{ca} + X_{eu} + X_{ch} + X_{oth} = \bar{X} \tag{12}$$

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.

6.1 Counterfactual 1: A restrictive US migration policy

As a first counterfactual exercise, I study how the location of high-skill industries and real wages 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 (approximately 450,000 fewer workers).

As a first set of results, the top panel of Table 2 summarizes how the decrease in migrants to the US affects the revenues generated by each sector-country pair. 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 and high-skill industries grow the most in Canada and India. IT and professional services sector would grow by 0.5% in India and 0.15% in Canada, and high-skill manufacturing sector would grow by 0.26% in India and 0.13% in Canada. Similarly, the financial services sector would grow by 0.2% and 0.11% in India and Canada, respectively. 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.

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 who are immigrants (15.4%) is larger than the one in IT (11.8%), which explains the larger response of manufacturing.

Table 2: Change in the location of economic activity

Panel A: Total production by country and industry.				
	IT and Prof. Services	High-Skill Manuf.	Financial Services	Other
US	-0.38%	-0.41%	-0.37%	-0.34%
India	0.50%	0.26%	0.20%	0.18%
Western Europe	0.08%	0.06%	0.07%	0.07%
Canada	0.15%	0.13%	0.11%	0.10%
China-Taiwan	0.10%	0.09%	0.09%	0.08%
Rest of the World	0.08%	0.07%	0.09%	0.07%
Panel B: Production of MNEs in the US by source-country and industry.				
	IT and Prof. Services	High-Skill Manuf.	Financial Services	Other
US	-0.34%	-0.40%	-0.26%	-
India	-2.91%	-1.69%	-2.48%	-
Western Europe	-1.26%	-0.43%	-1.09%	-
Canada	-0.42%	-0.44%	-0.39%	-
China-Taiwan	-0.56%	-2.22%	-3.30%	-

Panel A: Percent changes in country-industry revenues from increasing migration cost such that the total stock of migrants decreases by 10%. Panel B: 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%. Changes relative to World output.

Foreign MNEs in the US disproportionately contribute to such output decline relative to their size because of their greater intensity in migrant labor. As shown in the bottom panel of Table 2, in high-skill manufacturing, financial services, and IT, foreign MNEs in the US experience an output drop larger than US-based companies. The contrast is particularly big for Indian IT firms, whose output would drop by 2.91%. Similarly, Chinese MNEs in high-skill manufacturing and financial services would decrease their operations by 2.22% and 3.3%, respectively. While foreign MNEs are more intensive in foreign workers than American companies, they also have a particular dependence on foreign workers from their source country. It makes sense then that companies from countries where labor is cheaper are the ones that have the biggest hit. Canadian companies, which have a lower home bias (as shown in Figure 1) and similar immigrant intensity than American companies, decrease revenues in similar magnitudes than US companies.

Foreign MNEs disproportionately drive the drop in production. In the US IT sector, foreign MNEs account for 4.5% of production but account for 15.5% of the total drop in US IT output. In the high-tech manufacturing sector, foreign MNEs account for 24.3% of production but are responsible for 26.2% of the drop in revenues. The financial services sector accounts for the largest difference, where foreign MNEs account for 15.2% of production but drive 40.1% of the decrease in output. Table F16 breaks down the contribution of foreign and domestic MNEs to US output decline.

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 3, high-skill workers would experience an increase of 0.17% in their real wages. 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 0.26% given their complementarity with high-skill workers. Aggregating across skill types, real wages for US workers would decrease by 0.13% when migration is restricted. Real wages are 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 3.

Table 3: Change in real wages and compensating variation

	Baseline model				Alternative models	
	Real Wages (% change)	Wages (% change)	CV ($ billions)	CV ($ per immigrant)	No MNE (% change)	No Trade (% change)
High-skill natives	0.17%	0.25%	-4.76	-10489	0.15%	0.17%
Low-skill natives	-0.26%	-0.18%	7.66	16872	-0.24%	-0.27%
Total US natives	-0.13%	-0.05%	2.90	6382	-0.12%	-0.14%

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 (CV) is the dollar value each skill group would need to be compensated to leave their utility the same after restricting immigration. The last column calculates the compensating variation per immigrant who leaves the US due to the immigration restriction. Column "No MNE": Model with no multinational activity. Column "No Trade": Model with no international trade.

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 scenario. Low-skill workers in the US would need to be compensated by $7.66 billion each year while the gains for high-skill workers amounts to $4.76 billion. Overall, restricting high-skill immigration by 10% would cause US workers an aggregate loss of $2.9 billion per year once the economy reaches the steady state. Each migrant that leaves the US in the counterfactual causes a loss of $6,328 for US workers.

6.1.1 Mechanisms and robustness

A large part of the literature on the effects of immigration has used closed economy models (Bound et al., 2018; Burstein et al., 2020; Docquier et al., 2014a). One of the contributions of this paper is incorporating both trade and MNE activity as channels through which production relocates when immigration is restricted. In the last two columns of Table 3, 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 5 compares the baseline results with a model that does not include MNE production. Such model is equivalent to a multicountry, 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 8.3% (-0.13% 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. While MNEs account for a relevant share of total production and are more intensive on immigrants, their quantitative role is not as big when looking at the aggregate effects of restricting immigration, since US companies in high-skill sectors are also highly intensive in immigrants, and the elasticity of substitution between natives and immigrants 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.

Column 6 looks at an alternative model where MNE activity is allowed but trade costs are prohibitive. Restricting immigration under the model with no trade generates a larger real wage loss for low-skill workers and 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 5.6% higher than in the baseline model.

As a second set of robustness checks, 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 could lead high-skill workers to lose from restricting immigration. Higher values of α also significantly mute the gains for high-skill workers. However, total real wage losses have a similar magnitude among plausible values of these elasticities.

Finally, in Appendix F.1, I explore how results change when allowing for immigrants to lower information barriers, which facilitates MNE activity and trade across countries (Burchardi et al., 2019; Ottaviano and Peri, 2018). I expand the model to allow for the stock of immigrants from a given origin to decrease either the trade cost with that origin ($\tau_{k,\ell,n}$), or the MNE cost for companies from that origin ($\varphi_{k,\ell,s}$). This additional channel increases the losses for US workers from restricting immigration but the effect is quantitatively small. In Appendix F.2, I quantify what is the impact of source-country immigrants in expanding MNE production. In the baseline model, a 10% increase in immigrants from a given country increases employment of MNEs from that source country by 0.18%.

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 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.[13] In the model, MNEs have a specific comparative advantage in producing certain varieties, hence, the presence of MNEs helps produce more efficiently and increases welfare. A contribution of this paper is to show that incorporating high-skill migration into a quantitative MNE model has significant implications for the welfare gains generated by MNEs.

A sufficiently large change in the MNE costs $\hat{\varphi}_{k,\ell,s}$ is fed into the model such that MNE flows go from the observed values in equilibrium to 0. By calculating how welfare changes between an "MNE autarky" situation and the observed equilibrium, we can calculate the gains from MNE production. As shown in the first column of Table 4, 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 3.25%, reinforcing the idea that MNEs have a larger intensity for migrants. Column 2, shows how the gains from MNEs change when we consider a model with no migration. 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 are larger in the model with no migration when compared to the baseline. The model with no migration overestimates the welfare gains of MNE production by 7.03%.

Interestingly, the channel of migration primarily matters 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 for high-skill workers by 38.01% while underestimating the gains for low-skill workers by 4.39%. When we allow for MNE production, high-skill MNEs bring better technologies that improve welfare but at the

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

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, complement high-skill migrants who join the country when MNEs are allowed. Therefore, migration contributes an additional gain toward welfare created by MNE production. Monetarily, MNEs generate a total surplus of $90.48 billion per year for the US economy and the model with no migration would overestimate the welfare gains of MNEs by $15 billion.

Table 4: Welfare gains from MNE production

	Baseline	No migration	Relative to baseline
High-skill natives	1.46%	2.02%	38.01%
Low-skill natives	1.73%	1.65%	-4.39%
Total US natives	1.65%	1.76%	7.03%
Migrants in US	3.25%	0.00%	
High-skill CV ($ billions)	-40.60	-55.73	
Low-skill CV ($ billions)	-49.87	-47.72	

Percent changes in welfare from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\varphi_{k,\ell,s}$ 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. Compensating variation is the dollar value each skill group would need to be compensated to leave their utility the same than in MNE autarky.

The results in Table 4 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 India, China, and the RoW, results are more nuanced. In the model with migration, foreign MNEs increase the demand for non-Indian immigrants relative to Indian immigrants, given that US companies are more intensive on Indians (with the exception of Indian MNEs which are small on the aggregate). Hence, MNEs take away high-skill workers from China and RoW, which increases the positive impact for high-skill workers who stay in those countries 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 such countries and overstate the gains for low-skill workers. For India, the effects are different as US companies are highly intensive on Indians, so allowing for MNEs lowers the aggregate demand for Indians, increasing the number of high-skill workers in India, and reducing the skill premium when compared to the model with no migration. 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 US. A reduction of 10% in the stock of migrants would cause a total loss of \$2.9 billion for the US economy, driven by a \$7.66 billion loss for low-skill workers and a \$4.76 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.

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 how 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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Appendix - for online publication

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 petitions are only processed by USCIS if a firm wins the H-1B lottery or if a firm is lottery-exempt. Therefore, 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. 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. Visas are valid for three years but can be renewed for an additional three for the H-1B; a new I-129 is needed for such renewal. Between 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 majority owned by any other company worldwide. The information from Orbis is complemented by additional corporate ownership information from D&B Hoovers to serve as a quality check for some cases where Orbis data are incomplete. Hoovers data also provide information on the number of foreign subsidiaries of US companies to distinguish US-based MNEs from non-MNEs. 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 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 the FOIA record includes some variant of the firm name not recognized. These observations have to be addressed 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 that have submitted at least ten visa petitions in a given year between 2001 and 2014. As shown in Table A1, those with fewer than ten petitions account for 37.8% of the total H-1B petitions, with a larger number of small applicants in the earlier years of the sample. Second, 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 that 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 and L-1 samples are 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 A2 presents the distribution of visa petitions matched to Orbis by worker nationality and source country (GUO of company applying for the visa). Each GUO can have many different employers in the H-1B data that belong to different industries. I assign the modal industry for each GUO to keep these consistent over time. Table A3 presents the distribution of visa petitions matched to Orbis by industry.

Finally, 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 three 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 three years. For Mexico, the H-1B data only covers 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.

For India, as shown in Table A2, 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 observed 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 A1: 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%	69,479	54.7%
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%	56,873	44.8%
Other, not matched	314,085	8.0%	282,714	9.4%	31,371	3.4%	612	0.5%
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 that never submitted more than ten petitions in a given year. "Healthcare, Education and Govt" include petitions by universities, school districts, hospitals, government agencies, research institutes and other institutions that would not be involved in MNE activity.

Table A2: Distribution of visa petitions by nationality and 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%	0.1%	0.1%	0.2%	0.3%	0.3%	0.2%	1.0%
Canada	0.6%	0.7%	0.4%	4.4%	2.9%	3.3%	1.5%	16.9%
China	0.1%	0.1%	0.1%	1.0%	5.9%	5.9%	6.0%	5.7%
Finland	0.4%	0.5%	0.2%	0.4%	0.0%	0.0%	0.0%	0.3%
France	1.7%	1.5%	2.5%	3.1%	0.6%	0.7%	0.4%	2.3%
Germany	1.1%	1.1%	0.8%	2.7%	0.5%	0.5%	0.2%	2.3%
India	18.0%	17.3%	20.3%	20.8%	74.3%	72.1%	82.4%	32.7%
Ireland	1.5%	1.3%	2.4%	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%	1.3%	1.2%	2.5%	0.6%	0.7%	0.2%	2.4%
Korea	0.2%	0.2%	0.3%	0.6%	1.0%	1.1%	0.7%	1.9%
Netherlands	0.5%	0.5%	0.6%	0.8%	0.1%	0.1%	0.1%	1.0%
Spain	0.0%	0.0%	0.0%	0.3%	0.2%	0.2%	0.1%	1.2%
Sweden	0.2%	0.2%	0.2%	0.4%	0.1%	0.1%	0.1%	0.6%
Switzerland	1.0%	1.1%	0.5%	1.3%	0.1%	0.1%	0.0%	0.4%
Taiwan	0.3%	0.3%	0.2%	0.1%	0.6%	0.7%	0.4%	0.3%
United Kingdom	1.3%	1.3%	1.1%	2.8%	1.2%	1.3%	0.6%	7.3%
Other	1.8%	1.9%	1.5%	5.0%	11.2%	12.4%	6.8%	21.8%
USA MNE	35.8%	35.6%	36.2%	52.6%				
USA non-MNE	34.1%	34.8%	31.4%	-				
Years	2001-2014	2001-2011	2012-2014	2012-2014	2001-2014	2001-2011	2012-2014	2012-2014

The first four 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 A1. 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. USA MNEs are companies whose ultimate owner is a US company with subsidiaries in at least one other country.

Table A3: Distribution of visa petitions by industry

	H-1B	H-1B	H-1B	L-1
Manufacturing				
Chemicals	1.1%	1.2%	0.8%	2.2%
Computer and Electronics	8.3%	8.9%	6.5%	3.5%
Electrical Equipment	0.2%	0.2%	0.2%	1.3%
Food	0.1%	0.1%	0.1%	0.5%
Machinery	0.8%	0.9%	0.8%	1.9%
Metals	0.1%	0.1%	0.1%	1.0%
Transportation Equipment	0.6%	0.6%	0.5%	2.0%
Services				
Finance and Insurance	6.2%	6.6%	5.1%	6.8%
Information	6.3%	6.6%	5.3%	2.9%
Professional, Scientific and Technical	68.4%	66.9%	74.2%	56.0%
Real Estate	0.1%	0.1%	0.1%	0.2%
Other				
Retail	1.9%	1.9%	2.1%	1.0%
Wholesale	0.8%	0.7%	0.6%	1.4%
Other	4.9%	5.3%	3.7%	19.4%
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 A1. 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, 2012-2014 are the years of visa data used to calibrate the model.

B Empirical facts details

Table B4: Notation used throughout the paper.

s	MNE source country	j	Firm	f	Foreign labor (non-source)
ℓ	Location	i	Individual	fs	Foreign labor (all)
k	Industry	t	Time	l	Low-skill labor
z	Triplet $\{k, \ell, s\}$	n	Export destination	h	High-skill labor
o	Worker origin	d	Domestic labor	x	Indicator $\{o = \ell, o = s, o \neq s, \ell\}$

B.1 Data description

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 I explicitly note that I focus on new employment. I only keep firms where either Orbis or D&B Hoovers identifies a GUO as explained in Appendix A. In Table B5, I present the count of firms by source country of the MNE. The number of firms follows closely the aggregate distribution shown in Table A2. As shown in columns 4-6, a majority of the foreign MNEs in the sample apply for visas for both, home- and nonhome-country immigrants.

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 three-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.

Export, import, and GDP data used in Table 1 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 3 come from multiple sources. The vertical axis in Figure 3a is GDP per person employed (constant 2017 PPP $) from the World Bank. The vertical axis in Figure 3b 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 and older 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 three years and lack information on wages and occupation. The lack of a longer time period limits the analysis of the home bias estimation in Section 3.1, and the lack of wage data limits the analysis on wages in Section 3.2. Appendix B.3 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.

Table B5: Number of firms in the sample by source country

	Total	Large applicants	Hire every period	Hire source and nonsource	Hire only nonsource	Hire only source
Australia	14	2	3	8	6	0
Canada	53	19	24	35	16	2
China	26	6	4	16	6	4
Finland	7	1	4	3	4	0
France	48	21	22	41	7	0
Germany	68	24	28	38	29	1
India	137	84	58	97	0	40
Ireland	14	10	11	7	7	0
Israel	8	3	2	5	2	1
Japan	67	26	39	47	16	4
Korea	20	4	5	10	0	10
Netherlands	33	16	16	13	19	1
Spain	12	2	2	6	6	0
Sweden	13	4	9	10	3	0
Switzerland	35	17	23	20	15	0
Taiwan	11	4	6	10	0	1
United Kingdom	95	37	44	70	25	0
United States MNE	1,123	576	568	0	1,123	0
United States non-MNE	4,307	1,849	926	0	4,307	0
Other	117	34	34	98	15	4
Total	6208	2739	1828	534	5606	68

The number of firms that applied for H-1B visas and were matched to Orbis, by MNE source country. US MNE are companies whose ultimate owner is a US company and with subsidiaries in at least one other country, according to D&B Hoovers. Column 2 counts firms above the median in terms of average visa applications. Column 3 counts firms that apply for at least one visa every three years. Column 4 counts firms that hire both source and nonsource country immigrants through the H-1B, column 5 counts those that only hire nonsource-country immigrants, and column 6 counts those that hire only source-country immigrants.

B.2 Alternative specifications

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 from other countries, when compared to other companies in the US. In this section, I present additional results that confirm the result holds under alternative specifications. For expositional simplicity, I present the robustness results with a pooled regression as in equation (13), that calculates the average home bias effect across source countries:

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \gamma \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \xi_{j,o,k,s,t}, \tag{13}$$

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. I add source-industry-time fixed effects ($\varrho_{s,k,t}$) and origin-industry-time fixed effects ($\omega_{o,k,t}$) as controls. 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. In Table B6, MNEs are, on average, 67% more likely to hire immigrants from their source country relative to other nationalities when compared to companies from other source countries. In column 2 I investigate whether results change if controlling for a firm-time fixed effect as opposed to a source-industry-time fixed effect. When adding a firm-time fixed effect, identification of the home bias comes from firms that hire both source-and nonsource country workers. The estimated coefficient is larger when exploiting within firm variation. Column 3 shows the results are larger when including firm-nationality pairs in which the data show zero 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 4-7 show the pooled regression for average wages. As discussed in Section 3.2, my preferred specification is column 6 where I run the regression at the individual level and add source-industry-time fixed effects. On average, MNEs pay their source-country workers 6.4% lower wages relative to workers from other nationalities when compared to firms from other source countries. I corroborate the wage results are robust to two alternative specifications. First, in columns 4 and 5, I run the wage regression at the firm-origin-time level same as the regression for employment in Section 3.1. Second, I add a firm-time fixed effect in columns 5 and 7. In both cases, results are quantitatively very similar to the specification in column 6.

Table B6: Home bias regressions for employment and wages

	Log N visas	Log N visas	Log N visas	Log avg wage	Log avg wage	Log avg wage	Log avg wage
$\mathbb{1}(source = origin)$	0.67^a	1.17^a	2.26^a	-0.064^a	-0.040^a	-0.064^a	-0.046^a
	(0.129)	(0.267)	(0.176)	(0.022)	(0.014)	(0.005)	(0.005)
N obs	38,032	26,715	512,288	38,032	26,715	1,727,197	1,726,002
Sample	All	All	All - PPML	All	All	All	All
Source-industry-time FE	Yes	No	Yes	Yes	No	Yes	No
Firm-time FE	No	Yes	No	No	Yes	No	Yes
Level of regression	j-o-t	j-o-t	j-o-t	j-o-t	j-o-t	i	i

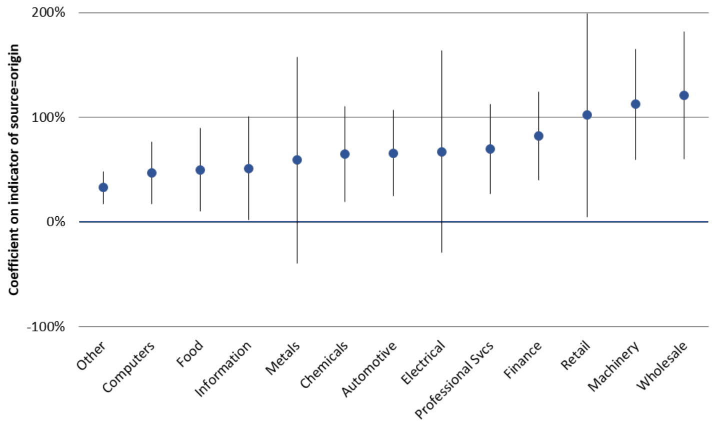
$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for nationality-industry-time fixed effects and either source-industry-time fixed effects or a firm-time fixed effect. Regression is at the firm-nationality-time level except for columns 6 and 7 that are at the individual level. The first three columns use as dependent variable the log number of visas, columns 4 and 5 use the log average wage, while columns 6 and 7 use the individual log wage. All H-1B petitions from 2001 to 2014 are included. Column 3 estimates the PPML regression to incorporate observations with zero employment. Standard errors are clustered at the nationality-source level.

I also look into the role of industry in explaining the home bias of MNEs. To do so, I run a regression as in equation (14), where I measure home bias separately by industry:

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_k \gamma_k \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \xi_{j,o,k,s,t}. \tag{14}$$

Each coefficient, γ_k, now captures how many more workers from their own source country do MNEs from each industry hire relative to nonsource-country workers, when compared to companies from other source countries. As shown in Figure B1, home bias is positive and large for a majority of industries, including notable high-tech industries such as machinery, finance, IT, and professional services.

Figure B1: Estimated coefficient (γ_k) by industry



I plot the coefficients γ_k and 95% confidence intervals estimated using regression (14). The number of observations is 38,032. Standard errors are clustered at the origin-source-country level.

B.3 Aggregate analysis including H-1B and L-1 visas

I proceed to 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-year level) and run a regression as shown in equation (15):

$$Log(N_{o,k,s}) = \gamma_0 + \gamma \mathbb{1}(o = s) + \varrho_{s,k} + \omega_{o,k} + \xi_{o,k,s}. \tag{15}$$

The dependent variable, $Log(N_{o,k,s})$, is the log number of visa applications at the source country, origin, industry level. Parameter $\omega_{o,k}$ is an origin-industry fixed effect that captures the comparative advantage of workers from origin o in industry k, and $\varrho_{s,k}$ 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 B7, 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 hire workers from a more diverse set of countries where their foreign affiliates that are located. 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 B2 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.

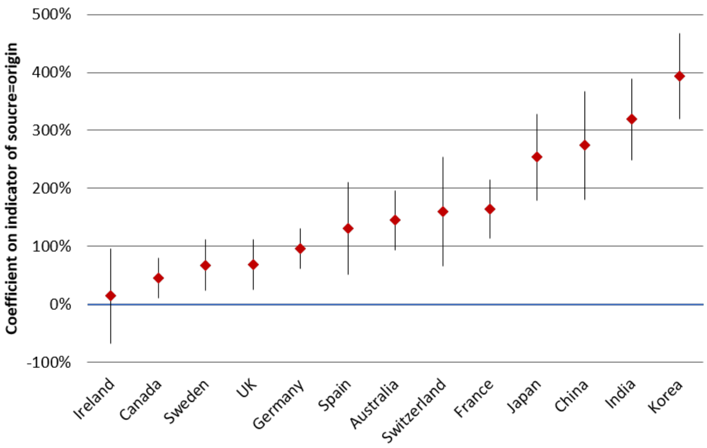
Table B7: Home bias: Aggregate regressions for H-1B and L-1

	OLS			PPML		
$\mathbb{1}(source = origin)$	0.99^a	1.50^a	0.42^a	1.11^a	2.34^a	0.02
	(0.14)	(0.27)	(0.11)	(0.17)	(0.15)	(0.06)
N obs	494	494	494	1278	1278	1278
Sample	H-1B+L-1	H-1B	L-1	H-1B+L-1	H-1B	L-1

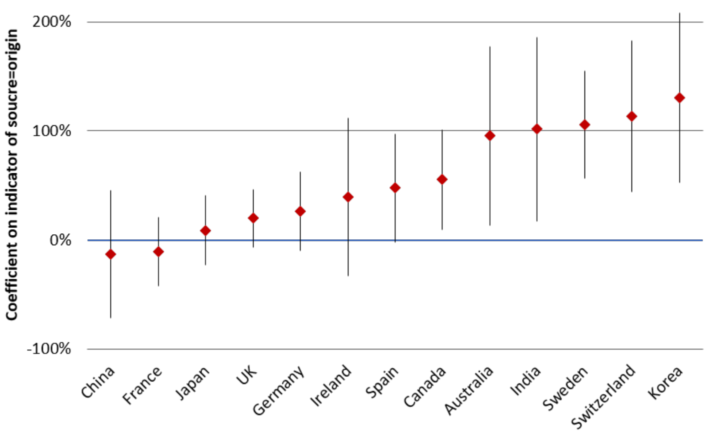
$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for source-industry and nationality-industry fixed effects. Regression is at the source-nationality-industry level. Dependent variable is the log number of visa petitions. Visas are aggregated for years 2012 to 2014. Standard errors are clustered at the nationality-source level. Sample is kept consistent across specifications to those source-industry pairs that hire both L-1s and H-1Bs (except in the PPML specification).

Figure B2: Estimated coefficient (γ_s) on sourcing regression by country (H-1B vs. L-1)

(a) H-1B



(b) L-1



I plot coefficients γ_s and their 95% confidence interval. The number of observations is 494. Standard errors are clustered at the origin-source level. All regressions control for source-industry and nationality-industry FEs. The regression is at the source-origin-industry level. Time period is 2012 to 2014. I limit the sample to observations that have both H-1B and L-1 visas.

B.4 Home bias and number of H-1B applications

To look beyond industry and source-country characteristics, I examine other firm-level attributes of the MNEs that apply for H-1B visas. For exposition simplicity, I begin by not differentiating across source countries, such that the estimates should be interpreted as the average home bias across all foreign MNEs. First, I focus on the total number of visa applications. Large applicants might have specific needs for H-1B workers which makes them more intensive on hiring immigrants, or they might have overall larger operations in the US. To test how large applicants compare to smaller applicants in terms of home bias, I run regression (16):

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_{s} \gamma \mathbb{1}(o = s) + \sum_{\bar{q}=2}^{\bar{q}=4} \gamma_{\bar{q}} \mathbb{1}(o = s) \times \mathbb{1}(\text{avg visas}_j \in \bar{q}) + \zeta X_{j,o,k,s,t} + \xi_{j,o,k,s,t}, \tag{16}$$

where the dependent variable is the same as in equation (1). I divide firms into quartiles $\bar{q}$ based on their average number of visa applications, with quartile 4 having the largest applicants.[14] I then estimate equation (16), where I include interaction terms between the $o = s$ indicator and dummy variables that indicate if the firm is in visa quartiles 2 to 4. The control variables $X_{j,o,k,s,t}$ include the source-industry-time fixed effects, origin-industry time fixed effects, and size bin fixed effects.

In Table B8, I present the estimated coefficients γ_q that capture the differential home bias for firms that fall in each application quartile relative to the lowest quartile. Particularly when excluding Indian companies, the coefficients are negative and monotonically decreasing for larger applicants, such that small applicants have a higher degree of home bias. As shown in Figure B3, a stark exception are Indian companies, where large applicants have a home bias of almost 300 percentage points larger than smaller applicants. This is driven predominantly by the large Indian outsourcers whose business model is hiring computer scientists from India through the H-1B program. I also corroborate in column 3 that results hold when the dependent variable is in levels instead of logs, ruling out that results are driven by a mechanical correlation where large applicants have smaller log-differences.

The number of H-1B applications is positively correlated with the size of firms in the US as shown in Section B.4.1. Hence, the result of smaller applicants having a larger home bias 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 might be more useful for production. However, the correlation between firm size and number of applications is not close to one, but between 0.3 to 0.4. Therefore, a more precise interpretation of the results is that firms with higher levels of H-1B employment have lower home bias.

[14] I rank all firms in terms of their average visa applications for nonsource-country immigrants between 2001 and 2014. I exclude home-country immigrants when calculating total applications to have a measure that is independent of home bias and a better proxy for firm size. Including source-country immigrants does not change the results in any meaningful way.

Table B8: Home bias by application size quartile

Number of visa applications	(1)	(2)	(3)
	$Log(N_{j,o,t})$	$Log(N_{j,o,t})$	$N_{j,o,t}$
$\mathbb{1}(o = s)$	1.26^a	1.72^a	57.18^a
	(0.43)	(0.28)	(16.7)
$\mathbb{1}(o = s) \times \mathbb{1}(25th < visas < 50th)$	0.26	-0.65^a	-11.43^c
	(0.67)	(0.21)	(6.72)
$\mathbb{1}(o = s) \times \mathbb{1}(50th < visas < 75th)$	0.15	-0.83^a	-18.72^a
	(0.82)	(0.25)	(5.41)
$\mathbb{1}(o = s) \times \mathbb{1}(visas > 75th)$	-0.85	-1.46^a	-76.8^a
	(0.55)	(0.29)	(23.62)
N	38,032	37,424	37,424
Sample	All	All	All
Indian companies included	Yes	No	No

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions are at the firm-nationality-time level and control for source-industry-time fixed effects, nationality-industry-time fixed effects, and size quartile fixed effects. Standard errors are clustered at the nationality-source level. The dependent variable is the log number of visa petitions except for column 3 where the number of visa petitions is used. This table presents the estimates for γ_q taken from equation (16). Time period is 2001 to 2014. I calculate the average number of visas for nonsource-country workers across all years a firm is observed hiring and divide firms into quartiles, where quartile 1 includes the smaller applicants and quartile 4 includes the largest ones. Columns 2 and 3 exclude Indian companies from the analysis.

Finally, I estimate equation (17), to understand which source countries follow this aggregate pattern:

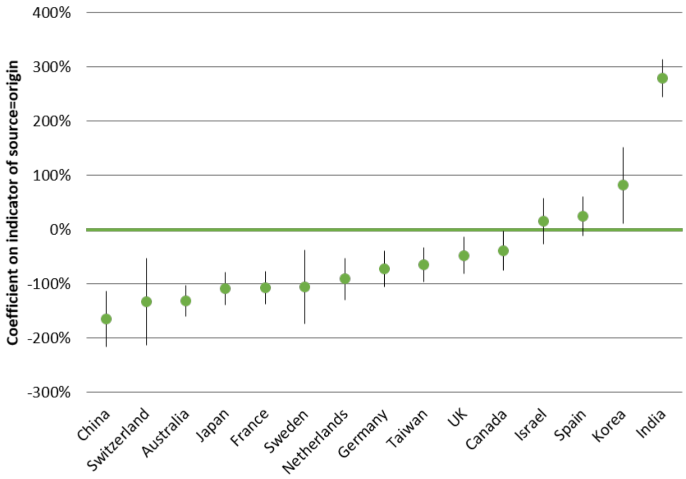
$$Log(N_{j,o,k,s,t}) = \gamma_0 + \sum_s \left(\gamma_s \mathbb{1}(o = s) + \gamma_s^{p50} \mathbb{1}(o = s) \times \mathbb{1}(\text{avg visas}_j > 50\text{th})\right) + \zeta X_{j,o,k,s,t} + \xi_{j,o,k,s,t}. \tag{17}$$

Equation (17) is equivalent to equation (16) but I group the top two and bottom two quartiles, such that coefficient γ_s^{p50} can be interpreted as the differential home bias for the applicants above the median relative to those below the median in terms of average visa applications. As shown in Figure B3, with the exception of India, Korea, Israel, and Spain, large visa applicants from all source countries have a lower degree of home bias than smaller applicants.

B.4.1 Number of applications and firm size relationship

As mentioned in Section 3.1, large visa applicants have a lower degree of home bias than small visa applicants. One possible interpretation is that the average number of visa applications is correlated with the size of the firm in the US, and smaller firms are more dependent on home-country workers as they might have a stronger need of communication with the parent company. Since I lack data on total US employment at the firm level, I cannot directly test for

Figure B3: Home bias difference for large applicants



The number of observations for all plots is 38,032. Standard errors are clustered at the origin-source-country level. All regressions control for source-industry-time, nationality-industry-time, and size quartile FEs. Figure B3 plots the interaction coefficients γ_s^{p50} and 95% confidence intervals estimated using regression (16). The estimates capture the differential home bias between applicants above and below the median number of applications. Only visas for nonsource-country workers are considered to measure the size of the applications.

this assumption.[15] However, I can use the available employment data to calculate the correlation between subsidiary employment and number of visas.

To do so I run two exercises. First, I use BEA data on employment and revenues of foreign MNEs in the US at the industry-source-year level. For each industry, I calculate the share of employees, share of revenues, and share of H-1B visas across MNE source countries. I then regress the share of employment/revenues on the share of visas and calculate the correlation which is shown in the left panel of Table B9. Second, I use the available data on US employment at the firm level from Orbis and correlate it with firm-level average visas. The results for this second analysis are presented in the right panel of Table B9. In both exercises, I use the total visas granted to nonsource-country workers to have the visa application measure not depend on home bias.

Overall, both sets of analyses indicate that there is a positive and significant correlation between the number of visas and firm size. However, the correlation is not close to one, and tends to be between 0.3 to 0.4. Therefore, while the application size measure can be used as a proxy of firm size, there are likely other components such as firm-level immigrant intensity or firm growth that might also be correlated with visa applications.

[15] Compustat provides consolidated employment at the firm level, which for foreign MNEs might not reflect the true size of the operations in the US. Orbis has some information on employment at the subsidiary level, and while it captures well the aggregate revenues at the industry-source-country level, it is somewhat incomplete when looking at individual firms and has limited coverage on subsidiary employment over time. For the firms in my sample that were matched to Orbis, only 40% have US employment data for at least one year.

Table B9: Correlation between number of applications and size

	Share employment	Share revenues		Firm-level employees	Firm-level employees	Firm-level employees
Share of visas	0.294^a	0.325^a	Number of visas	31.11^a	26.40^a	90.78^a
	(0.036)	(0.046)		(1.88)	(1.66)	(9.48)
N	628	596	N	2434	1990	444
R-sq	0.097	0.076	R-sq	0.10	0.11	0.17
Correlation	0.31	0.28	Correlation	0.32	0.34	0.42
			Source countries	All	US	Non-US

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. In the left panel, I regress the share of employment and share of revenues of each non-US source-country in a given industry against the share of H-1B visas of that source country in an industry. Total employment and revenues at the year-industry-source-country level are taken from the BEA. I group years into five time periods between 2001 and 2014. The right panel uses available data on firm-level employment from Orbis. I first regress firm-level employment and total H-1B visas on industry FEs. Then I regress the residual of the employment regression on the residual of the visa regression. In the last two columns, I separate the sample into US-based companies and foreign MNEs.

B.5 Changes in home bias overtime

As a second check, 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 (18):

$$Log(N_{j,o,k,s,t}) = \gamma_0 + \gamma \mathbb{1}(o = s) + \sum_{\bar{t}=2}^{\bar{T}} \gamma_{\bar{t}} \mathbb{1}(o = s) \times \mathbb{1}(t = \bar{t}) + \zeta X_{j,o,k,s,t} + \xi_{j,o,k,s,t}. \tag{18}$$

I interact the sourcing indicator with a series of dummies that distinguish how many periods ($\bar{t}$) was the firm observed applying for H-1B visas. As the H-1B data begins in 2001, I exclude companies that are observed hiring immigrants in the first period and focus only at those that are not observed hiring H-1Bs before 2003. While this limits the sample significantly, it is important to avoid pooling together new applicants with firms that might have been hiring H-1Bs for many years before the data begins. The control variables $X_{j,o,k,s,t}$ include source-industry-time fixed effects, origin-industry-time fixed effects, and indicators for number of periods since first application.

As shown in the right panel of Table B10, home bias in the first period is positive and significant, but it decreases in later periods. Such decreasing trend is particularly stronger if we exclude Indian companies and MNEs from countries with high-attrition in the sample. As shown in column 3, home bias decreases by half in years four to six, and almost disappears after year seven. 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 noisier results when including India, since when companies get bigger they seem to focus on recruiting a higher number of Indians.

Table B10: Home bias by time since first application

Time since first observed	(1)	(2)	(3)
	$Log(N_{j,o,t})$	$Log(N_{j,o,t})$	$Log(N_{j,o,t})$
$\mathbb{1}(o=s)$	0.52^a	0.81^a	0.95^a
	(0.18)	(0.14)	(0.14)
$\mathbb{1}(o=s) \times \mathbb{1}$(years 4 -6)	0.01	-0.31	-0.55^b
	(0.20)	(0.19)	(0.24)
$\mathbb{1}(o=s) \times \mathbb{1}$(years 7 -9)	0.04	-0.39	-0.78^a
	(0.25)	(0.24)	(0.18)
$\mathbb{1}(o=s) \times \mathbb{1}$(years 10 -12)	0.60	-0.15	-0.79^a
	(0.39)	(0.36)	(0.22)
N	11,229	11,071	10,924
Sample	All	All	Excluding high-attrition
Indian companies included	Yes	No	No

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions are at the firm-nationality-time level and control for source-industry-time, nationality-industry-time fixed, and years since first application fixed effects. Standard errors are clustered at the nationality-source level. The dependent variable is the log number of visa petitions. The table presents the estimates for $\gamma_{\bar{t}}$ taken from equation (18). Time period is 2004 to 2014. Sample is limited to firms that are first observed hiring H-1B workers in 2004 or later. The dummy interactions with the sourcing variable stand for the years since the firm is first 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.). Columns 2 and 3 exclude Indian companies from the analysis. Column 3 also excludes MNEs from source countries where companies tend to have high attrition (e.g., firms are likely to be seen hiring one year and never again). These high-attrition countries are Australia, China, Israel, Korea, and Spain.

B.6 Analysis on occupations

Finally, I estimate equation (19) to look at the role of occupations and check whether source-country immigrants are hired to perform specific tasks:

$$\text{Share in occ}_{j,o,k,s,t} = \gamma_0 + \gamma \mathbb{1}(o=s) + \varrho_{s,k,t} + \omega_{o,k,t} + \xi_{j,o,k,s,t}. \tag{19}$$

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 use as a dependent variable the fraction of workers from origin o in firm j who work in a given occupation. As shown in Table B11, source-country workers are 1.9 percent points more likely to be administrative professionals and 1.7 percent points more likely to be managers than nonsource-country immigrants relative to companies from other source countries. On the contrary, when looking at a less communication intensive occupation such as engineering, we see source-country workers being 4.7 percentage points less likely to work in those occupations. In the last column, I specifically distinguish high-wage engineers, since those who get paid higher wages are more likely to be involved in technology transfer which makes home-country workers more valuable. As shown in Table B11, the negative and significant result for engineers is driven mainly by lower paid engineers. For those engineers with the highest wages, the coefficient is weaker but the estimates relative to the baseline mean are similar. I also estimate equation (19) but add separate dummies for each source country, as shown in Figures B4a-B4c.

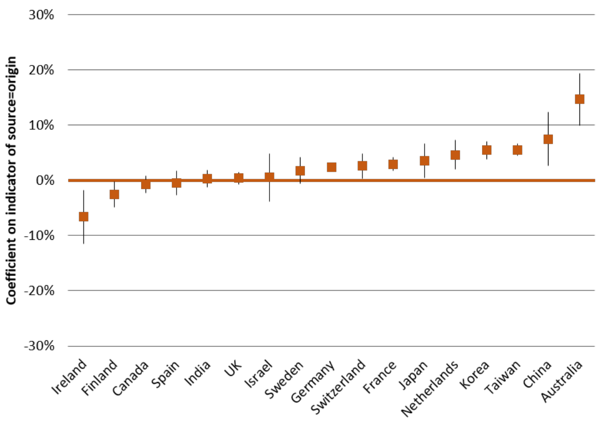
Table B11: Dependent variable: Share of immigrants from o in specific occupations

	Share of Admins	Share of Managers	Share of Engineers	Share of High-Wage Engineers
$\mathbb{1}(o = s)$	0.019^{a}	0.017^{a}	-0.047^{a}	-0.013^{c}
	(0.005)	(0.007)	(0.0135)	(0.007)
N obs	38,032	38,032	38,032	38,032
Mean outcome	0.023	0.052	0.136	0.038

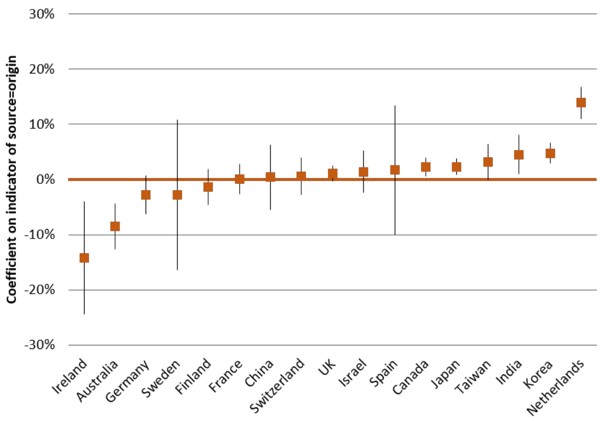
$a = p < 0.01, b = p < 0.05, c = p < 0.1$. All regressions control for firm-time and nationality-industry-time fixed effects. Regression is at the firm-nationality-time level. Dependent variable is the share by nationality in a given occupation (administrators, managers, engineers, and high-wage engineers). High-wage engineers are a subset of engineers who are in the top quartile in terms of wages. Standard errors clustered at the nationality-source level.

Figure B4: Home bias robustness: occupations

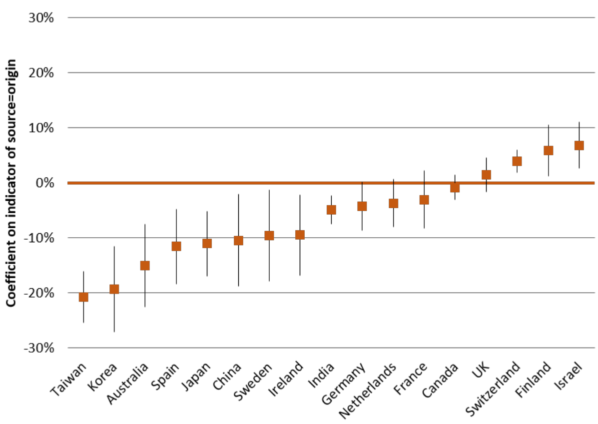
(a) Administrators



(b) Managers



(c) Engineers



The number of observations for all plots is 38,032. Standard errors are clustered at the origin-source-country level. All regressions control for firm-time and nationality-industry-time FEs. Figures B4a-B4c plot the coefficient (γ_s) by country from a regression like equation (19), but with source-country separate dummies.

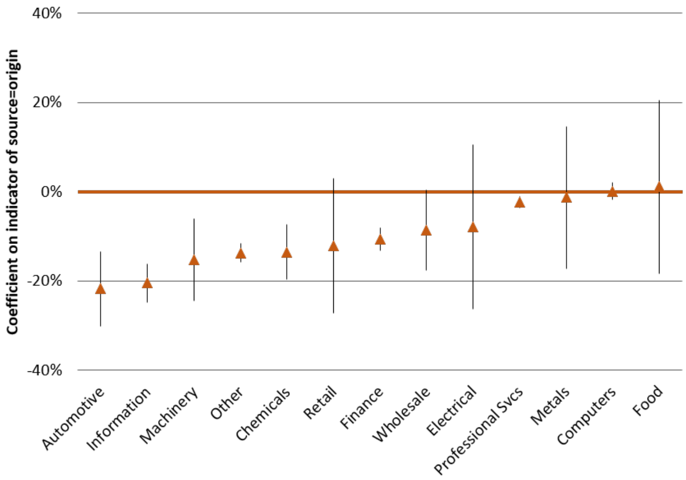
B.7 Home bias and wages - additional analysis

To complement the wage results in Section 3.2, I replicate some of the analysis done in Section 3.1 for the employment home bias but using average wages as the dependent variable. I begin by estimating equation (20):

$$Log(\bar{w}_{i,o,k,s,t}) = \beta_0 + \sum_k \beta_k \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \zeta X_{i,o,k,s,t} + \xi_{i,o,k,s,t}. \tag{20}$$

The coefficient β_k measures what is the wage difference that foreign MNEs in industry k pay their source-country workers relative to their non-source workers, when compared to other companies. As shown in Figure B5, a majority of industries pay lower wages to source-country workers relative to nonsource-workers. Manufacturing industries like automotive, machinery, chemicals, and automotive pay significantly lower wages to their source-country workers. Companies in service sectors such as information or finance also pay significant penalties to source-country workers.

Figure B5: Estimated coefficient (β_k) by industry



The dependent variable is the log of average wages $Log(\bar{w}_{j,o,k,s,t})$. I plot the coefficients β_k and 95% confidence intervals estimated using regression (20). The number of observations is 1,727,197. Standard errors are clustered at the origin-source-country level.

Finally, I reproduce the exercise done to compute the correlations in Table 1 but using equation (21) to compute the wage difference coefficients:

$$Log(\bar{w}_{i,o,k,s,t}) = \beta_0 + \sum_k \sum_s \beta_{s,k} \mathbb{1}(o = s) + \varrho_{s,k,t} + \omega_{o,k,t} + \zeta X_{i,o,k,s,t} + \xi_{i,o,k,s,t}. \qquad (21)$$

I then correlate the estimates of $\hat{\beta}_{s,k}$ with observable characteristics at the source-country and industry level, and present the estimates in Table B12. Overall, the correlations are weaker than those observed for employment but one number stands out. There is a negative correlation between being an MNE from an nonEnglish-speaking country and the wage difference between source- and nonsource-workers. This makes sense since, as shown in Figure 2, countries like the Australia, India, and Ireland had a positive wage difference, while most of the other countries presented a wage penalty for source-country workers. A possible explanation for this pattern is that home-country MNEs provide a greater reduction in the migration cost to the US when the country does not have English as a native language. If so, low ability workers from such countries who migrate to the US would disproportionately work for home-country MNEs and receive lower wages.

Table B12: Pairwise correlation between source-nonsource wage difference and observables

Source country characteristics (s)		**Industry characteristics** (k)	
GDP per worker at s	0.11	Share of college grads in k	0.06
Country s in non-English speaking	-0.34^a	Average college grads wage in k	0.07
Distance from s to US	-0.12	Employment share in US	-0.11
Source-Industry characteristics (s,k)			
Industry GDP at s	-0.20	US Employment MNEs from s in k	-0.14
Share of US imports from s in k	-0.05	US Employment growth MNEs from s in k	0.04
Comparative advantage of s in k	0.06		

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. Subscript s source country, k industry. Coefficients $\beta_{s,k}$ are estimated using regression (21). I run pairwise correlations between the coefficients and industry-source characteristics. All characteristics are measured at year 2014. MNE employment growth is measured between 2005 and 2014. "Share of college graduates," "Average college graduate wage," and "Employment share in US" are calculated for the US at the industry level using the American Community Survey. GDP per capita comes from the World Bank. Language and distance taken from CEPII. Industry GDP, the share of imports, and comparative advantage come from WIOT. Comparative advantage is measured as the share of global exports from country s in industry k relative to the overall share of global exports from country s. Employment of MNEs in the US comes from the BEA.

C Equilibrium details

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

1. MNE shares - the share of production in ℓ in industry k that is done by MNEs from country s as in equation (22), where there is one equation for each $\{k, \ell, s\}$ triplet:

$$\pi^{mne}_{k,\ell,s} = \frac{T_{k,s}\left(c_{k,\ell,s} \times \varphi_{k,\ell,s}\right)^{-\theta}}{\sum_{s'} T_{k,s'}\left(c_{k,\ell,s'} \times \varphi_{k,\ell,s'}\right)^{-\theta}} \tag{22}$$

2. Effective technology in country ℓ - one for each $\{k, \ell\}$ pair is shown in equation (23).

$$\tilde{T}_{k,\ell} = \sum_s T_{k,s}\left(c_{k,\ell,s} \times \varphi_{k,\ell,s}\right)^{-\theta} \tag{23}$$

The technology composite $\tilde{T}_{k,\ell}$ 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_z and the MNE iceberg cost $\varphi_{k,\ell,s}$.

3. Trade shares - one for each $\{k, \ell, n\}$ triplet.

$$\pi^{trade}_{k,\ell,n} = \frac{(\tau_{k,\ell,n})^{-\theta}\tilde{T}_{k,\ell}}{\sum_{\ell'}(\tau_{k,\ell',n})^{-\theta}\tilde{T}_{k,\ell'}} \tag{24}$$

Consumers choose the pair ℓ, s from which to buy each variety within each industry. Given the properties of the Fréchet distribution, it is possible to write the share of goods bought from pair ℓ, s by consumers in n as in equation (24). 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, $\tilde{T}_{k,\ell}$.

4. Domestic price index - one for each $\{k, n\}$ pair:

$$P_{k,n} = \bar{\Gamma} \left(\sum_{\ell} (\tau_{k,\ell,n})^{-\theta} \tilde{T}_{k,\ell} \right)^{-\frac{1}{\theta}}, \tag{25}$$

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

5. Unit cost in country ℓ, industry k, source technology s (triplet $z = \{k, \ell, s\}$):

$$c_z = \bar{C} \prod_{k'=1}^{K} P_{k',\ell}^{\chi_{z,k'}} \left((\psi_z^l)^\alpha (w_{L,\ell})^{1-\alpha} + (\psi_z^h)^\alpha (c_z^h)^{1-\alpha} \right)^{\frac{1}{1-\alpha}(1-\bar{\chi}_z)}, \tag{26}$$

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

$$c_z^h = \left((\psi_z^d)^\lambda (w_z^d)^{1-\lambda} + (\psi_z^{fs})^\lambda (c_z^{fs})^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \tag{27}$$

$$c_z^{fs} = \left((\psi_z^s)^\iota (w_z^s)^{1-\iota} + (\psi_z^f)^\iota (w_z^f)^{1-\iota} \right)^{\frac{1}{1-\iota}} \tag{28}$$

6. Share of noncollege (Θ_z^L), college (Θ_z^L) - one for each $z = \{k, \ell, s\}$ triplet:

$$\Theta_z^L = \frac{(\psi_z^l)^\alpha (w_{L,\ell})^{1-\alpha}}{(\psi_z^l)^\alpha (w_{L,\ell})^{1-\alpha} + (\psi_z^h)^\alpha (c_z^h)^{1-\alpha}} \quad \Theta_z^H = \frac{(\psi_z^h)^\alpha (c_z^h)^{1-\alpha}}{(\psi_z^l)^\alpha (w_{L,\ell})^{1-\alpha} + (\psi_z^h)^\alpha (c_z^h)^{1-\alpha}} \tag{29}$$

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

$$\Theta_z^d = \frac{(\psi_z^d)^\lambda (w_z^d)^{1-\lambda}}{\sum_{x'} (\psi_z^{x'})^\lambda (w_z^{x'})^{1-\lambda}} \quad \text{for x'=\{d,sf\}} \quad \Theta_z^x = \frac{(\psi_z^x)^\iota (w_z^x)^{1-\iota}}{\sum_{x'} (\psi_z^{x'})^\iota (w_z^{x'})^{1-\iota}} \quad \text{for x,x'=\{s,f\}} \tag{30}$$

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

$$w_{L,\ell}L_z = (1-\bar{\chi}_z)\Theta_z^L \pi_z^{mne} I_{\ell,k} \tag{31}$$

$$w_{x,\ell}H_z^x = (1-\bar{\chi}_z)\Theta_z^H \Theta_z^x \pi_z^{mne} I_{\ell,k} \quad \text{with } x = d,s,f \tag{32}$$

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; and $\bar{L}_\ell$ total low-skill labor supply:

$$I_{\ell,k} = \sum_n \pi_{k,\ell,n}^{trade} \times \chi_{k,n} \times X_n \tag{33}$$

$$X_n = w_{L,\ell}\bar{L}_\ell + \sum_{z,x} w_z^x H_z^x \quad \text{with } x = d,s,f \tag{34}$$

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

$$\sum_{k,s} w_{L,\ell}L_z = w_{L,\ell}\bar{L}_\ell \tag{35}$$

11. Migration shares - one for each $\{o,z\}$ with $z = \{k,\ell,s\}$ group:

$$\pi_{o,z}^{mig} = \frac{A_{o,k}\left(\frac{w_z}{P_\ell}\varepsilon_{o,z}\right)^\kappa \phi_{o,\ell,s}^{-\kappa}}{\sum_{z'} A_{o,k'}\left(\frac{w_{z'}}{P_{\ell'}}\varepsilon_{o,z'}\right)^\kappa \phi_{o,\ell',s'}^{-\kappa}} \tag{36}$$

Equation (36) captures the fraction of workers from origin o who choose to migrate to location ℓ and work for industry k with source technology s. The probability of migration from origin o to triplet $z = \{k,\ell,s\}$ depends on the comparative advantage of origin o in industry k ($A_{o,k}$); the real wage per effective unit in triplet z $\left(\frac{w_z}{P_\ell}\right)$; the migration cost from o to ℓ, s ($\phi_{o,\ell,s}$); the random origin-specific term $\varepsilon_{o,z}$, and a combination of these terms for all other triplets, captured by the denominator in equation (36).

12. High-skill market clearing, domestic (d), source (s), other foreign (f) - one for each $z = \{k,\ell,s\}$ triplet. N_o is the total number of workers born in o:

$$w_z^d H_z^d = w_z^d \varepsilon_{o=\ell,z}(\pi_{o,k,\ell=o,s}^{mig})^{\frac{\kappa-1}{\kappa}} N_\ell A_{k,\ell}^{\frac{1}{\kappa}} \Gamma\left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{37}$$

$$w_z^s H_z^s = w_z^s \varepsilon_{o=s,z}(\pi_{o,k,\ell\neq o,s=o}^{mig})^{\frac{\kappa-1}{\kappa}} N_s A_{k,s}^{\frac{1}{\kappa}} \Gamma\left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{38}$$

$$w_z^s H_z^s = \sum_{o\neq\{\ell,s\}} w_z^f \varepsilon_{o,z}(\pi_{o,k,\ell\neq o,s\neq o}^{mig})^{\frac{\kappa-1}{\kappa}} N_o A_{k,o}^{\frac{1}{\kappa}} \Gamma\left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{39}$$

C.1 Writing the equilibrium in proportional changes

Following Dekle et al. (2008), I rewrite all equilibrium equations in proportional changes. That is, I can rewrite each variable y as $\hat{y} = \frac{y'}{y}$; where y is the variable under the real scenario; and y' is the value of the variable under the counterfactual. In the remainder of this section, I show how this approach allows me to distinguish four 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 31, 32, 37, and 38 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:

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

2. Trade shares/ Domestic price index:

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

3. Unit cost / high-skill unit cost:

$$\hat{c}_z = \prod_{k'=1}^{K} \hat{P}_{k',\ell}^{\chi_{z,k'}} \left((\hat{\psi}_z^l)^{\alpha} \hat{w}_{L,\ell}^{1-\alpha} \Theta_z^L + (\hat{\psi}_z^h)^{\alpha} (\hat{c}_z^h)^{1-\alpha} \Theta_z^H\right)^{\frac{1}{1-\alpha}(1-\bar{\chi}_z)}$$

$$\hat{c}_z^h = \left((\hat{\psi}_z^d)^{\lambda} (\hat{w}_z^d)^{1-\lambda} \Theta_z^d + (\hat{\psi}_z^{fs})^{\lambda} (\hat{c}_z^{fs})^{1-\lambda} \Theta_z^{fs}\right)^{\frac{1}{1-\lambda}}$$

$$\hat{c}_z^{fs} = \left((\hat{\psi}_z^s)^{\iota} (\hat{w}_z^s)^{1-\iota} \Theta_z^s + (\hat{\psi}_z^f)^{\iota} (\hat{w}_z^f)^{1-\iota} \Theta_z^f\right)^{\frac{1}{1-\iota}}$$

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

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

5. Low-skill market clearing / Migration share:

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

6. Other-foreign market clearing:

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

The equations above imply that the change in the endogenous variables can be computed as long as I have estimates of the five key elasticities (θ, α, λ, ι,and κ); the Cobb-Douglas share on intermediate inputs $\chi_{z,k'}$; and data on the following equilibrium allocations: Trade shares ($\pi_{k,\ell,n}^{trade}$); MNE shares (π_z^{mne}); Migration shares ($\pi_{o,z}^{mig}$); Share of wage bill spent in low-skill (Θ_z^L) and high-skill (Θ_z^H) for each triplet $z = \{k, \ell, s\}$; Share of high-skill wage bill spent on natives (Θ_z^d), source workers (Θ_z^s), and other foreign workers (Θ_z^f); Share of low-skill in total labor income (Λ_ℓ^L); Share of high-skill type $x = \{d, s, f\}$ in z in total labor income (Λ_z^x); Share of low-skill employed in z (Λ_z^L); Share of wage bill of z on migrants from $o \neq \{\ell, s\}$ ($\Lambda_{o,z}$) 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 ($\varphi_{k,\ell,s}$); producer comparative advantage ($T_{k,s}$); trade costs ($\tau_{k,\ell,n}$); production function labor shares (ψ_z^l, ψ_z^h, ψ_z^d, ψ_z^s, ψ_z^f, ψ_z^{fs}); Total low-skill ($\bar{L}_\ell$) and high-skill (N_ℓ) labor born in ℓ; individual ability comparative advantage ($A_{o,k}$); origin-specific productivity ($\varepsilon_{o,z}$); 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 6.1 and 6.2 will compute how the equilibrium changes after an exogenous change of the MNE cost in all countries $\varphi_{k,\ell,s}$ or the migration cost to the US $\phi_{o,\ell=US,s}$.

C.2 Assumptions and limitations of the model

Before proceeding to the estimation of the model, it is important to discuss its assumptions and limitations. In the empirical facts presented in Section 3, most of the analysis was at the firm level, as firms can be identified in the H-1B data and it is a natural setup to document the observed home bias patterns and its mechanisms. The quantitative model in Section 4, however, distinguishes producers primarily at the industry-location-source level (a triplet $\{k, \ell, s\}$). Within a given triplet, firm boundaries are indeterminate and the model assumes that there is a representative firm that makes hiring decisions, where the producers within a triplet pay the same wages and employ the same shares of each type of labor, regardless of their productivity.

Part of the reason to look into the aggregate effects at the $\{k, \ell, s\}$ level, as opposed to individual firms, is related to the available data. While the H-1B data is at the firm level, data on MNE outcomes and information on total employment across skill groups within the firm is not easily available. The BEA provides publicly available data at the source-country-industry level for the US, and I leverage that level of aggregation to estimate the model. However, an emerging literature started by Abowd et al. (1999) has used employer-employee matched data to identify a firm "wage premium" and establish that firm and worker sorting are important to explain phenomena like changes in wage inequality (Card et al., 2013), the direct and indirect effects of foreign MNEs on domestic workers (Setzler and Tintelnot, 2021), and the wage gap evolution between natives and immigrants (Dostie et al., 2023), among many other applications. The EK-Roy setup in this paper will not capture the dynamics on how high-ability workers sort into high-productivity firms.

The current model, however, is well suited to quantify the *aggregate* effects of immigration into the US and its relationship with MNEs. The home bias in employment and wages presented in Section 3.1 is captured through differing migration costs and through having source-country workers as a specific input in production. The decreasing selectivity channel generated by the EK-Roy structure, where as more immigrants from a given origin come into the country, the newcomers would be of lower ability than those already in the country, is consistent with the findings of McKenzie and Rapoport (2010) and the facts shown in Figure 3. Overall, the quantitative model is useful to study the counterfactuals in this paper such as how the economy adjusts to an influx of immigrants, as well as how MNE production across industries and source countries expands and relocates when immigration changes. There are other counterfactuals where allowing for firm-worker sorting might significantly change the aggregate predictions of the model. For example, a technology shock that shifts productivity for a group of firms could lead to such firms matching with better workers. However, productivity shocks are not the focus of my analysis.

When studying the H-1B program, the feature of the model where workers who migrate are positively selected relative to those who stay behind (driven by abilities being distributed Fréchet) might seem at odds with the rationing feature of the US immigration system. The total number of H-1B visas is rationed through a cap and visas are assigned through a lottery, where those who win the lottery might not be of higher ability than those who lose. 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 an application fee 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 nonlottery-subject company. Third, even if the worker loses the lottery, employers can apply for a new visa again in subsequent years. Fourth, workers who receive graduate degrees in the US have a higher likelihood of getting accepted in the lottery. Finally, given that the lottery is random, as long as the motives for immigration are consistent with positive selection, the lottery would only add noise to the sorting on abilities. Overall, such features suggest that if the number of immigrants were to be reduced, those still migrating would be positively selected.

Finally, I ignore the role of noncollege-educated migrants in the model. Given the complementarities between low- and high-skill workers, an increase in high-skill immigrants would push up the wage for low-skill workers, which in turn, would increase immigration of low-skill immigrants. Such relationships are not present in the current model for two main reasons. First, as shown by Cho (2018), Korean MNEs only seem to have a home bias for high-skill immigrants, with little employment levels of home-country, low-skill immigrants. Second, as mentioned above, the model implies that those who choose to migrate will have a higher ability than those who don't. In the context of the US immigration system, this is not as obvious for low-skill workers, who primarily come to the US either through family reunification or as undocumented immigrants. Hence, the EK-Roy model might not be the best to capture low-skill immigration patterns into the US.

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 among 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 Fréchet distribution, it is possible to write the conditional expectation of abilities as in equation (40).

$$E\left(\eta_{i,o,z}|i \text{ chooses } z\right) = A_{o,k}^{\frac{1}{\kappa}}\left(\pi_{o,z}^{mig}\right)^{-\frac{1}{\kappa}}\bar{\Gamma}. \tag{40}$$

The Gamma function, denoted by $\bar{\Gamma}$ is evaluated in $1-\frac{1}{\kappa(1-\rho)}$. Equation (40) 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. 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: $W_{i,o,z}=w_z^x\varepsilon_{o,z}\eta_{i,o,z}$; where w_z^x is the equilibrium wage per effective unit paid to those who choose triplet z, and the superscript x indicates whether the workers are hired by an MNE with $s=o$ or if they are hired just as "other" foreign workers. The wage also depends on $\varepsilon_{o,z}$, which 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 (40), it is possible to calculate average wages as in equation (41):

$$E\left(W_{i,o,z}|i \text{ chooses } z\right) = w_z^x \varepsilon_{o,z} A_{o,k}^{\frac{1}{\kappa}} \left(\pi_{o,z}^{mig}\right)^{-\frac{1}{\kappa}} \bar{\Gamma}. \tag{41}$$

By taking logs and reorganizing terms, we get estimating equation (42):

$$Ln\left(\overline{W}_{o,z,t}\right) = \underbrace{Ln\left(w_{z,t}^x\right)}_{k\text{-}s\text{-}t\text{-}x \text{ FE}} - \frac{1}{\kappa} Ln\left(N_{o,z,t}\right) + \underbrace{\frac{1}{\kappa}\left(Ln\left(A_{o,k,t}\right) Ln\left(N_{o,t}\right)\right)}_{o\text{-}k\text{-}t \text{ FE}} + \underbrace{Ln\left(\varepsilon_{o,z,t}\right)}_{\text{error term}}. \tag{42}$$

Using the US H-1B data, it is possible to estimate equation (42) by using data on average wages and employment at the industry-source-origin-time level and controlling for k-s-t-x fixed effects and o-k-t fixed effects.[16]

Estimating equation (42) 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 necessary to construct a demand shifter for workers from o employed at companies from triplet z that is uncorrelated with the choices of workers from o at time t. To do so, I draw from the literature on trade shocks started by Autor et al. (2013), and construct an instrument as described in equation (43):

$$\text{Instrument}_{o,z,t} = \pi_{o,z,2001}^{mig} \times \left(\frac{\text{Exports of } k \text{ from } s \text{ to } \ell \neq US \text{ in } t}{\text{Exports of } k \text{ to } \ell \neq US \text{ in } t}\right), \tag{43}$$

where the instrument consists of the interaction between 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. The intuition for the instrument is as follows: the share of imports in industry k from non-US countries that come from country s 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.[17] Importantly, if an immigrant is employed by a multinational from their source country ($o = s$), those observations are fully captured by fixed effect k-s-t-x, such that only immigrants who work for nonsource-country companies help identify parameter $-\frac{1}{\kappa}$. This helps with identification as shocks to a given country can be correlated with migration decisions of workers from that country. Excluding those workers helps isolate demand variation that is likely independent from worker migration choices. The

[16] Since I will use time variation for estimation, I add a time subscript t. I drop $\bar{\Gamma}$ for exposition purposes. Indicator 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 $\pi_{o,z}^{mig} = \frac{N_{o,z,t}}{N_{o,t}}$.

[17] 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.

initial share, $\pi^{mig}_{o,z,2001}$, re-weights the shock across origin countries according to the historical employment of immigrants from o in companies from k, s in the US.

As shown in Table D13, 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 Section 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.[18]

Table D13: Estimates of equation (42)

	OLS	2SLS		$Ln\left(N_{o,k,s,t}\right)$
$Ln\left(N_{o,k,s,t}\right)$	-0.031^a	-0.162^a	Instrument$_{o,z,t}$	21.40^a
	(0.0068)	(0.053)		(4.78)
N obs	2,534	2,534	N obs	2,534
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 five visa petitions were dropped. Standard errors are clustered at the year, industry and source country. First stage is included in right panel.

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 Fréchet 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 equation (42) 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 Fréchet properties.

Proposition 1 *If productivity draws η are distributed Fréchet with shape parameter κ, the observed market wages paid to employees $W_{i,o,z} = \eta_{i,o,z} w_z$ are also distributed Fréchet with parameter κ.*

[18] 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).

Proposition 2 *If a random variable W is distributed Fréchet 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, σ is the population standard deviation, and μ is the population mean. Proposition 1 indicates that observed market wages are also distributed Fréchet with shape parameter κ, which means that the parameter κ is related to the dispersion of observed wages, conditional on individuals choosing the triplet $z = \{k, \ell, s\}$. 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 (44) 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:

$$\left(\frac{Var(W_{i,o,z})}{\left(\overline{W}_{o,z}\right)^2}\right) = \frac{\Gamma\left(1-\frac{2}{\kappa}\right)}{\left(\Gamma\left(1-\frac{1}{\kappa}\right)^2\right)} - 1 \tag{44}$$

I present the baseline results using the H-1B data in Column (1) of Table D14. An alternative strategy is to use the estimate of $\kappa = 6.17$ from equation (42) together with equation (44), replacing κ by $\kappa(1-\rho)$. Table D14 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 D14: Estimates for κ using dispersion of wages

	Only using dispersion	Using trade shock and dispersion
κ	8.28^a	6.17^a
	(0.138)	(2.03)
$\tilde{\kappa}$	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 rework the first-order conditions of the components in equation (9) to get to equation (45):

$$Ln\left(\frac{\text{wage bill}^s_{z,t}}{\text{wage bill}^f_{z,t}}\right) = (1-\iota)Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right) + \iota Ln\left(\frac{\psi^s_{z,t}}{\psi^f_{z,t}}\right). \tag{45}$$

Equation (9) implies that for an MNE from source s, the ratio of the wage bill spent on source-country workers relative to other foreign workers is a function of the ratio of effective wage paid to source-country workers relative to other foreign workers.[19] 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 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 (41) 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 Fréchet distribution, we can write the observed average wages for each group as in equation (46):

$$\overline{wage}_{o,z,t} = w^x_{z,t}\pi_{o,z,t}^{-\frac{1}{\kappa}}A_{k,o,t}^{\frac{1}{\kappa}}\bar{\Gamma}\varepsilon_{o,z,t}, \tag{46}$$

where $\overline{wage}_{o,z,t}$ is the average wage for those from origin o that migrate to triplet $z = \{k, \ell, s\}$ at time t, conditional on choosing z. The equilibrium wage per effective unit paid to those who choose triplet z is denoted by $w^x_{z,t}$, where 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. The fraction of workers from o who migrate to z is denoted by $\pi_{o,z,t} = \frac{N_{o,z,t}}{N_{o,t}}$ 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 $\overline{wage}_{o=s,z,t}$ and $\overline{wage}_{o\neq s,z,t}$, taking logs, and rearranging terms, it is possible to get to equation (47):

$$\underbrace{Ln\left(\frac{\overline{wage}_{o=s,z,t}}{\overline{wage}_{o\neq s,z,t}}\right) + \frac{1}{\kappa}Ln\left(\frac{N_{o=s,z,t}}{N_{o\neq s,z,t}}\right)}_{\text{Data}} = \underbrace{Ln\left(\frac{w^s_{z,t}}{w^f_{z,t}}\right) + \frac{1}{\kappa}Ln(N_{s,t}A_{k,s,t})}_{\text{Source-Industry-Time FE}} - \underbrace{\frac{1}{\kappa}Ln(N_{o,t}A_{k,o,t})}_{\text{Origin-Industry-Time FE}} + \underbrace{Ln\left(\frac{\varepsilon_{s,z,t}}{\varepsilon_{o,z,t}}\right)}_{\text{Error term}}. \tag{47}$$

[19] Once again I add time-subscript t since I will use multiple years of data for estimation.

Equation (47) shows that it is possible to run a regression at the source-origin-industry-time 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 ($N_{o=s,z,t}$, $N_{o\neq s,z,t}$) 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 (45) by using the foreign MNEs in my H-1B data and running a firm-time level regression. I use the log ratio of the wage bills between source and foreign workers as the dependent variable, and the log ratio of the effective wages estimated in equation (47) as an explanatory variable. The term $Ln\left(\frac{\psi^s_{z,t}}{\psi^f_{z,t}}\right)$ 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 (45). The instrument should shift the relative supply of source to nonsource workers 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 construct a supply-push instrument that captures inflows of immigrants from country s in industry k as shown in equation (48), 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:

$$\text{Supply Push}_{s,k,t} = \underbrace{\frac{\text{N immig}_{o=s,k,2001}}{\text{N immig}_{o=s,2001}}}_{\text{Initial Share}} \times \underbrace{(\text{N immig from s, going to US firms, } k' \neq k,\ t)}_{\text{time shifter}}. \quad (48)$$

The instrument consists of the interaction between the distribution of immigrants from country s across industries k in 2001 and the number of immigrants from source country s who come work for US companies in other industries ($k' \neq k$). The intuition is that the number of immigrants from s going to US companies in other industries, captures supply-driven increases of immigrants from s that are independent of demand shocks that affect firms from s in the US. I reweight the stock of migrants by the initial distribution across industries which is assumed to be uncorrelated with future shocks that affect the employment and wage ratio of source- to nonsource-country immigrants. Importantly, I am instrumenting the *ratio* of effective wages between source- and nonsource-country immigrants for a given source-industry pair. Hence, it is still fine if the instrument is correlated with aggregate demand shocks, as long as they increase demand for both source- and nonsource-country immigrants in the same proportion. The identification assumption relies on the instrument being independent from shocks that change the *relative* demand between source- and nonsource-country workers.

Second, I use as an instrument 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. (2014b), 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 (45) can be found in Table D15, 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 supply-push instrument, 6.84 using the log of the gdp per worker, and 3.75 using both instruments together. I will use $\iota = 3.75$ as my baseline value, which is roughly in between the estimates of the two instruments.

Table D15: Estimating equation for ι

		Second Stages		
	OLS	2SLS	2SLS	2SLS
Log wage effective units ratio	-0.002	-1.84^a	-5.84^b	-2.75^a
	(0.20)	(0.66)	(1.40)	(0.76)
N obs	1,750	1,750	1,750	1,750
Implied λ	1.00	2.84	6.84	3.75
1st stage F-stat		16.0	23.36	12.25
		First Stages		
Supply push		-0.0002^a		-0.0002^a
		(0.00005)		(0.00008)
GDP per worker			0.145^a	0.054
			(0.03)	(0.05)
N obs		1,750	1,750	1,750
Instruments		Supply push	GDP per worker	Both

$a = p < 0.01, b = p < 0.05, c = p < 0.1$. The dependent variable of the second stage is the term on the left in equation (47). Controlling for time-industry fixed effects. Standard errors are bootstrapped with 200 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 counterfactuals

This section describes how the dataset needed to compute the model is constructed. The description is based on the simplifications explained in Section 5.1 and the data needed as outlined in Appendix C.1. I construct the database for six regions of the world. This includes the 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 (RoW) that includes a set of twenty-one countries and an aggregate for the RoW as available in the World Input-Output Tables (WIOT). Industries are grouped into four 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," including NAICS 325 (Chemicals), 333 (Machinery), 334 (Computer and Electronic), 335 (Electrical Equipment, Appliance and Components), and 336 (Transportation Equipment); and "Financial Services," which includes NAICS 52 (Finance and Insurance). All other industries are grouped into "Other."

Trade Shares ($\pi^{trade}_{k,\ell,n}$), production shares ($\Lambda_{k,n,\ell}$), and intermediate input shares ($\chi_{z,k'}$): I use WIOT for year 2012 which contains bilateral trade flows and total output statistics by country-pairs and NAICS industries. For the intermediate input shares, $\chi_{z,k'}$, I assume that within a location-industry pair (ℓ, k), companies from all source countries s have the same input share ($\chi_{z,k'} = \chi_{k,\ell,k'}$).

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 in 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 proceed to make some simplifications. First, I assume that the share or college- and non-college workers only varies by location ℓ and industry k. This means that all source countries have the same skill-intensity within (ℓ, k). Second, I allow companies across triplets $z = \{k, \ell, s\}$ to have different intensities across domestic, source, and other foreign workers. I use the FOIA data 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. First, 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. Total high- and low-skill worker counts for China-Taiwan and the Rest of the World 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 (Θ_z^L, Θ_z^H, Θ_z^d, Θ_z^s, Θ_z^f, Λ_ℓ^L, Λ_z^x, Λ_z^L, $\Lambda_{o,z}$): 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 RoW 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 2, foreign MNEs in the US respond more in terms of revenues than US companies. Table F16 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 15.49% while only accounting for 4.51% of production in IT. Similarly, foreign companies in high-skill manufacturing contribute 26.25% of the output drop while only accounting for 24.32% of production. Foreign companies in the financial sector contribute 40.1% of the output drop while only accounting for 15.18% of total production.

Table F16: Contribution of MNEs to output drop

	IT and Professional Services	High-Skill Manufacturing	Financial Services
Decomposition of change in revenues by MNE origin			
US	-0.32%	-0.31%	-0.22%
Foreign	-0.06%	-0.11%	-0.15%
Total	-0.38%	-0.41%	-0.37%
Contribution of Foreign MNEs in output drop	15.49%	26.25%	40.10%
Share in total production by MNE source			
US	95.49%	75.68%	84.82%
India	0.27%	0.06%	0.04%
Western Europe	4.06%	22.81%	12.57%
Canada	0.18%	1.29%	2.50%
China-Taiwan	0.00%	0.16%	0.08%
Foreign - total	4.51%	24.32%	15.18%

The top panel shows percent changes in revenues by industry and source country from increasing migration cost such that the total stock of migrants decreases by 10%. The rows "US" and "Foreign" show the contribution to output drop by US companies and foreign MNEs separately. Bottom panel presents the share of production in the US by Industry and MNE source.

In Table F17, 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 natives, who can even lose from restricting immigration. 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 get quite muted when working with a higher elasticity of substitution. The model with $\alpha = 3$ would lower the gains for high-skill workers, as firms find it easier to substitute low- for high-skill labor when the latter becomes more expensive. Negative effects for low-skill natives are also reduced, as low-skill natives become closer to substitutes with immigrants. Finally, I study how the results change for different values of κ. First, I recompute the model for $\kappa = 2$ as calibrated in other papers using an EK-Roy setup such as Hsieh et al. (2019). A lower κ implies that abilities are more dispersed, and workers are less sensitive to wage changes. The results are also more muted when κ is lower as workers are less mobile across sectors and native high-skill workers gain less from switching to immigrant jobs. To bound the impact of an alternative κ, I also recompute the model for $\kappa = 8.28$ 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. As such, their real wages increase more than in the baseline. On the other hand, low-skill workers lose more, since firms find it easier to find natives to replace the immigrants. For this specific counterfactual, alternative values of θ and ι yield very similar results to the baseline, so I omit the robustness analysis.

Table F17: Understanding mechanisms - elasticities

	Baseline	$\lambda = 7$	$\lambda = 2$	$\alpha = 3$	$\kappa = 2$	$\kappa = 8.28$
High-skill natives	0.17%	0.12%	-0.17%	0.07%	0.10%	0.18%
Low-skill natives	-0.26%	-0.26%	-0.27%	-0.15%	-0.16%	-0.27%
Total US natives	-0.13%	-0.15%	-0.24%	-0.08%	-0.08%	-0.14%

Percent changes from increasing migration cost such that the total stock of migrants decreases by 10%. Column 1: baseline results $\lambda = 13.25$, $\kappa = 6.17$, and $\alpha = 1.7$. The rest of the columns change only one parameter at a time and leave all others as in the baseline.

F.1 Immigrants lower barriers to MNE activity and trade

The literature on the relationship between immigration, trade, and MNE activity suggests that immigrants lower information barriers, which facilitates production and trade across countries (Burchardi et al., 2019; Ottaviano and Peri, 2018). If immigrants embody knowledge that is specific to their home countries, they can help transfer technology and information across borders. While part of such effect is likely driven by immigrants employed within the firm, most of the literature has taken a broader approach by allowing trade and MNE costs to depend on the number of immigrants from a given origin working in the labor market. The reasoning for this approach is that immigrants might share information of local business opportunities with companies located in their home country, as well as help new immigrants assimilate faster. Such channels can encourage MNE activity and trade even if the MNE or exporting company itself does not hire the immigrants who lower the information frictions.

In this paper, the main channel through which technology transfer happens is through the employment of home-country immigrants within the firm. As shown in equation (9), source-country immigrants are imperfect substitutes with other immigrants, meaning they are a specific input in production. While the model does not take a stand on what underlying characteristics make source and nonsource-country immigrants different, the analysis in Section 3.1 suggests that they might facilitate communication between the US affiliate and the parent company. In Appendix F.2, I corroborate quantitatively that the employment of MNEs disproportionately responds to immigration from their home country. The baseline model predicts that a 10% increase in immigration from a country o increases MNE employment of companies from $s = o$ by 0.18%.

To evaluate how the results would change when allowing for a broader impact of immigrants in reducing MNE costs, I expand the model to allow for all immigrants in the labor market to reduce MNE barriers. I rewrite the iceberg MNE cost $\varphi_{k,\ell,s}$ to depend on the number of immigrants from s who work in location ℓ. The MNE cost can be written as in equation (49):

$$\varphi_{k,\ell,s} = \bar{\varphi}_{k,\ell,s} \left(N_{o=s,\ell}\right)^{-\nu}, \tag{49}$$

where $\bar{\varphi}_{k,\ell,s}$ is a baseline MNE iceberg cost; and $N_{o=s,\ell}$ is the number of migrants from $o = s$ that work in ℓ. The relevance of this mechanism is determined by parameter ν. I assume that firms are sufficiently small to consider the stock of immigrants at the national level ($N_{o=s,\ell}$) 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 largest employers for immigrants, it is reasonable that MNEs see the stock of immigrants at the national level as exogenous to their own hiring decisions.

Burchardi et al. (2019) study the relationship between foreign ancestry and FDI activity in the US. They estimate that a 10% increase in the number of residents in a US county who report ancestry from origin o increases local employment at subsidiaries of foreign firms by 0.73%. I use their estimates and calibrate a value of $\nu = 0.021$ that replicates these magnitudes in my model. This addition makes MNE employment more responsive to an increase in immigration than in the baseline model where the response is 0.18% as shown in Appendix F.2.[20]

In Table F18, the real wage losses from restricting immigration are slightly larger when allowing for the spillover channel. The reason is that foreign MNEs decrease production more when immigration decreases, making production less efficient and lowering wages for both high- and low-skill workers.

As a final channel, I explore how results change when allowing immigrants to reduce trade costs. The literature on the impact of immigration on trade costs is more extensive than with MNEs, but the literature has not reached a consensus. On one hand, Burchardi et al. (2019) find no effect of immigration on trade. On the other hand, other papers have found a positive relationship between trade and immigration (Gould, 1994; Hiller, 2013; Ottaviano and Peri, 2018). To explore the quantitative implications of this channel, I rewrite trade costs as shown in equation (50):

$$\tau_{k,\ell,n} = \bar{\tau}_{k,\ell,n} \left(N_{o=n,\ell}\right)^{-\varsigma}, \tag{50}$$

where the trade costs to export from country ℓ to country n depend on a baseline trade cost ($\bar{\tau}_{k,\ell,n}$) and the number of immigrants from country n working at country ℓ. The elasticity ς regulates the maginitude of the trade spillover. To calibrate ς, I use the estimates of Ottaviano and Peri (2018), who find that a 10% rise in the immigrant population from a given country increases services exports from the UK to that country by 2.5%. Using this magnitude, I calibrate $\varsigma = 0.075$. As shown in column 3 of Table F18, the presence of the trade spillover amplifies the real wage losses from restricting immigration by 27.5% (-0.13% vs -0.17%) with respect to the baseline scenario.

[20]The estimates of Burchardi et al. (2019) apply to a somewhat different context than this paper. Their concept of ancestry includes second generation immigrants and noncollege graduates who are not considered as immigrants in this paper. They also focus on all industries, while I focus on high-skill industries for MNE activity. Such differences imply that the information advantage estimated by Burchardi et al. (2019) is likely a lower bound for the real elasticity in my context.

Table F18: Changes in real wages for different values of the spillover parameter

	Baseline	MNE cost spillover	Trade cost spillover
High-skill natives	0.17%	0.16%	0.13%
Low-skill natives	-0.26%	-0.27%	-0.29%
Total US natives	-0.13%	-0.14%	-0.17%

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. The model with "MNE cost spillover" defines the MNE iceberg cost as in equation (49). The model with "trade cost spillover" defines the trade iceberg cost as in equation (50).

F.2 The role of source-country immigrants

Source-country immigrants are a specific production input within the firm, such that an increase in immigration of workers from a specific origin is expected to disproportionately affect MNEs from such origin. I use the model to compute how the employment of MNEs changes across source countries, in response to a 10% increase in the total stock of immigrants from a each origin in the US. As shown in Table F19, an increase of immigrants from a given origin disproportionately increases MNE employment from that country. For example, a 10% increase in the number of European immigrants in the US increases MNE employment of European MNEs by 0.16%, while increasing MNE employment of other source countries by less than half of that. Canada is an exception, where Canadian MNEs don't seem to respond differently to an increase in Canadian immigrants in the US than MNEs from other source countries, partly driven by the lower home bias of Canadian companies.

Table F19: Employment response to a change in immigrants across origin countries

	10% increase in immigrants from:			
Employment response of companies from:	India	Europe	Canada	China
India	**2.52%**	0.08%	0.06%	0.03%
Europe	0.16%	**0.16%**	0.03%	0.05%
Canada	0.14%	0.01%	**0.02%**	0.03%
China	0.32%	0.09%	0.02%	**0.35%**
US	0.19%	0.01%	0.01%	0.02%

The rows indicate source countries of MNEs in the US. Columns indicate origin countries of immigrants. I change migration costs by origin, one at a time, to increase the stock of immigrants from origin o in the US by 10%, while leaving the migration costs from other origins unchanged. I then compute the change in total employment for MNEs of each source country in the US.

I then quantify how much, on average, subsidiaries of country s increase their employment when there is a 10% increase in the stock of immigrants from $o = s$. I compare these average responses between my baseline model and the model with the spillover lowering MNE barriers. As shown in Table F20, the model with the spillover has an elasticity of 0.73%, by construction, to replicate the estimates of Burchardi et al. (2019). The baseline model without the spillover has an elasticity of 0.18%. As such, the baseline model can explain up to 25% of the total response estimated by the literature.

Table F20: Employment responses with and without spillover

	with spillover	without spillover	MNE employment share
India	3.14%	2.52%	1.11%
Europe	0.71%	0.16%	90.17%
Canada	0.64%	0.02%	8.20%
China	0.99%	0.35%	0.52%
Weighted average	0.73%	0.18%	

The rows indicate source countries of MNEs in the US. I present how MNEs from country s increase their US employment in response to a 10% increase in immigrants from s. The bottom row calculates the weighted average using total MNE employment by source as the weights. The results with spillover have an average response of 0.73%, by construction, to match the results in Burchardi et al. (2019). Column without spillover presents the responses for the baseline model ($\nu = 0$).

G Counterfactual 2: Gains of MNE production

Table G21, presents the MNE gains analysis for different values of the key elasticities. The results for MNE welfare gains with and without migration presented in Section 6.2 only looked at the gains for the US. Table G22 shows the welfare gains of MNE for the baseline model with migration and an alternative model without migration for the full set of regions in the model.

Table G21: Robustness to key elasticities

	$\alpha = 3$		$\lambda = 7$		$\theta = 8.28$		$\kappa = 8.28$	
	Baseline	No migration	Baseline	No migration	Baseline	No migration	Baseline	No migration
High-skill natives	1.51%	2.09%	1.44%	2.02%	0.73%	1.33%	1.35%	1.90%
Low-skill natives	1.63%	1.54%	1.74%	1.65%	0.96%	0.96%	1.66%	1.59%
Total US natives	1.60%	1.71%	1.65%	1.76%	0.89%	1.07%	1.57%	1.68%
Migrants in US	3.20%	0.00%	3.58%	0.00%	2.42%	0.00%	3.18%	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 $\varphi_{k,\ell,s}$ are very high such that MNE is prohibitive.

Table G22: Real wage gains of MNE production by country

		Baseline	No migration	Relative to baseline
US	High-Skill	1.46%	2.02%	38%
	Low-Skill	1.73%	1.65%	-4%
	All	1.65%	1.76%	7%
Western Europe	High-Skill	2.50%	2.58%	3%
	Low-Skill	1.92%	1.83%	-5%
	All	2.08%	2.03%	-2%
Canada	High-Skill	4.49%	5.48%	22%
	Low-Skill	5.30%	5.07%	-4%
	All	5.12%	5.16%	1%
India	High-Skill	1.03%	1.26%	22%
	Low-Skill	0.71%	0.66%	-7%
	All	0.73%	0.70%	-4%
China-Taiwan	High-Skill	0.53%	0.36%	-32%
	Low-Skill	0.41%	0.46%	13%
	All	0.42%	0.45%	8%

Percent changes in real wages of going from MNE autarky to the observed equilibrium. MNE autarky is the case where MNE iceberg costs $\varphi_{k,\ell,s}$ 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.