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

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November 2018

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**Abstract**

The purpose of this paper is to quantify the effects of high-skill migration on the location of high-skill industries and multinational activity. To establish empirically the link between multinational enterprises (MNEs) and migration, I assemble a novel firm-level dataset on high-skill visa applications and show that there is a large home-bias effect, demonstrating that foreign MNEs in the US tend to hire more migrant workers from their home countries compared to US firms. To quantify the general equilibrium implications for production and welfare, I build a quantitative model that includes trade, MNE production, and the migration decisions of high-skill workers. I use the new dataset to structurally estimate the key elasticities of the model: the elasticity of labor supply and the elasticity of substitution between high-skill natives, home country workers, and other foreign workers. The estimated model is used to run two main counterfactual exercises. The first one evaluates the implications of a more restrictive immigration policy in the US in line with recent proposals whose aim is to reduce high-skill immigration. I find that a restriction on immigration to the US that decreases its total workforce by 2.1% would decrease by 3%-4% the US share of production in industries that rely heavily on high-skill migrants, such as IT and High-Tech manufacturing. This decline in US production would coincidently fuel IT sector growth predominantly in India (4.4%) and Canada (1.2%) and would decrease welfare for US workers by 0.98%. In the second counterfactual exercise I increase the barriers to MNE production to calculate the welfare gains generated by MNEs. I show that a model *not* incorporating migration would overestimate the MNE welfare gains for high-skill workers by 34% and underestimate welfare gains for low-skill workers by 7%.

*JEL:* F16, F22, F23, J61

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

*I would like to thank John Bound, Andrei Levchenko, Jagadeesh Sivadasan and Sebastian Sotelo for invaluable research advice. I would also like to thank Vanessa Alviarez, Dominick Bartelme, Charlie Brown, Javier Cravino, Catalina Franco, Amelia Hawkins, Gaurav Khanna, Mel Stephens, Gonzalo Vazquez-Bare and seminar participants at the University of Michigan, the Midwest International Trade Conference (Vanderbilt) and LACEA (Ecuador) for helpful comments and suggestions. I am grateful to the Alfred P. Sloan Foundation and the NBER Fellowship on High-Skill Immigration for generous research support.

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# 1 Introduction

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

In this paper, I quantify the impact that US restrictions to high-skill immigration would have on welfare, MNE activity, and total production in high-skill industries. To establish a link between MNEs, high-skill industries, and high-skill migration, I present stylized facts showing that foreign MNEs are more dependent on immigrant labor from their home countries than US companies and that across industries there is significant heterogeneity in the intensity of their migrant employment from different origins. Based on these stylized facts, I build and estimate a quantitative model with multiple industries and countries that incorporates high-skill migration, trade and MNE activity, and I use this model to run two main counterfactual exercises. First, I study the effects of restricting immigration into the US on welfare, production and MNE activity. Second, in order to quantify the welfare gains created by MNEs, I increase the barriers to MNE production and calculate the relevancy of incorporating migration for estimating the welfare gains from MNEs.

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

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

I document three stylized facts that relate immigration to MNEs activity and industrial composition. First, I show that foreign MNEs in the US have a large "home-bias", where on average, they hire 200% more foreign workers from their source-country than other foreign workers, compared with the number of workers from that source country hired by US companies and other foreign MNEs. There is heterogeneity in the magnitude of the home-bias across countries, and this effect is consistently large. Second, I show that across industries there is significant heterogeneity in their dependence on high-skill migrants, which correlates positively with the average skill intensity of the industry. Third, I show that workers from different origin countries select into migration to work for industries where their home country has a comparative advantage. Fact 1 suggests that when located in the US, foreign MNEs have a specific dependence on migrants from their source country. Facts 2 and 3 reinforce the idea that a restriction in immigration will predominantly affect high-skill intensive. Accounting for multiple industries and origin countries is shown to be relevant when quantitatively estimating the impact of immigration restrictions.

Guided by these facts I build a quantitative model that accounts for several channels through which immigration affects production. The production side of the model allows for trade and MNE activity across multiple industries, similar to the work of Ramondo and Rodriguez-Clare (2013) and Alviarez (2018). If German producers want to sell goods to the US, they will choose the production location that allows them to sell the goods at the lowest price. The model allows them to choose between producing the goods in Germany and shipping them to the US, paying a trade cost, or setting a plant in the US and selling their product domestically, and paying an MNE cost, or setting a plant in a third country and selling to the US, paying both trade and MNE costs. Such decisions are at the core of why a company relocates its production when migration restrictions are imposed; their marginal cost is increased causing them to move. The labor supply side of the model focuses on the decisions of college-educated workers in each country who choose which country to migrate to, industry to work in, and source technology to work with. For example, if a worker is employed by a company whose parent is headquartered in the US, he or she works with US source technology. Workers draw idiosyncratic productivities to work in each country-industry-source triplet, and they sort endogenously across triplets as explained in Roy (1951). If they choose to migrate, workers have to pay a non-pecuniary migration cost. I assume low-skill workers to be homogeneous and not mobile across countries.

In the model, immigrants affect firm-level production in two ways. First, as suggested by Peri and Sparber (2011) I allow for imperfect substitution between immigrants and natives in the production function. Second, I allow for workers from different countries of origin to have a comparative advantage in specific industries; this advantage will make migration more lucrative for some sectors than others. The link between MNE and migration appears through two separate channels. From the labor supply side, the migration cost is deemed to be lower if workers migrate to work at a company whose source technology is the same as that in the worker's home country. From the labor demand side, foreign MNEs treat workers from their source country as imperfect substitutes for domestic and other foreign workers; therefore they treat source country workers as distinct inputs for production.

I show that in order to measure the changes in welfare and production between the observed equilibrium and a counterfactual equilibrium, I only need four elasticities and data on observed migration shares, trade shares, MNE shares, and labor expenditure shares. I use the approach proposed by Dekle et al. (2008) and re-write the equilibrium in proportional changes from the observed equilibrium to a counterfactual equilibrium. This move allows me to significantly reduce the number of parameters to be estimated and to focus on four key elasticities that determine the magnitude of endogenous responses of the model to any given exogenous shock, such as an increase in cost of migration. I use my novel dataset to estimate structurally two of the elasticities that are not available in the literature: the labor supply elasticity and the elasticity of substitution between high-skill natives, source-country workers and other foreign workers. I use the observed dispersion of wages across industries, origin countries and source technologies to estimate the elasticity of labor supply [2]. Intuitively, if individuals face a larger dispersion in their ability-draws across options, their labor supply and migration choices will be less responsive to changes in wages or migration costs. For the elasticity of substitution between high-skill units of labor I use a new instrumental variables approach based on supply shifters that reduce the cost of migration to identify the slope of the relative demand for high-skill natives, source and other foreign workers.

I use this estimated model to run two main counterfactual exercises. In the first, I increase the costs of immigration into the US from all other countries to replicate the long-term effects of a recently debated policy that imposes a minimum wage on foreign high-skill workers hired in the US [3]. If the lower limit of a \$90,000 annual wage were to be imposed, it would decrease the long-term stock of inbound high skill immigrants by 70%, consistent with a 2.1% decrease in total US workforce. The decrease of high-skill immigrants would cause US production in high-skill intensive industries such as IT and high-tech manufacturing to decrease by 3.08% and 3.85% respectively. This decrease would be driven in part by foreign MNEs who respond disproportionately to the migration restrictions. This model predicts that US IT companies revenues would decrease by 2.94% while, for example, Indian companies US revenue will decrease by more than 35%. Other countries share in production is expected to increase as a response with the IT sector in India increasing by 4.4% and in Canada by 1.19%. Welfare for US low-skill workers would decrease by 2.01%. High-skill workers are complements in produc-

[2]This approach, using the observed wage dispersion to estimate the labor supply elasticity, has been previously used by Lagakos and Waugh (2013),Hsieh et al. (2018) and Lee (2017) among others.

[3]The "Protect and Grow American Jobs Act" bill introduced by Rep. Darrell Issa in January 2017 proposes among other things to set a minimum wage for H-1B recipients that "is equal to the lesser of \$135,000 or the mean wage for applicants occupation in their area (but subject to a floor of no less than \$90,000)". More details on the proposed bill can be found here.

tion to low-skill workers such that the decrease in immigration of high-skill workers lowers the demand for low-skill workers and decreases their wages. The increase in labor costs caused by immigration restrictions would also increase prices for US consumers, adding to the negative effect on the general welfare of US workers. On the other hand US high-skill workers would experience a gain of 1.13% in their welfare driven by an increase in the market wages caused by the lower competition from immigrants. Overall, the welfare of US workers decreases by 0.98% when immigration is restricted which in dollar terms would account for a total long-term loss of 21 billion USD for the US economy.

In the second counterfactual exercise, I increase the barriers to MNE production in order to calculate the welfare gains from MNE activity. Foreign MNEs bring more efficient technologies that lower the costs of production domestically and improve efficiency. Canonical papers in the MNE literature such as Ramondo and Rodriguez-Clare (2013) and Tintelnot (2017) have focused on quantifying the welfare gains of going from MNE "autarky" where MNE costs are prohibitive and MNE flows are zero to the observed equilibrium in which MNE flows are positive. I use my quantitative model to show that going from MNE autarky to the observed MNE flows would increase welfare for high and low skill native workers by 1.17% and 1.42% respectively. A model that does *not* incorporate migration would overstate the welfare gains for high-skill workers by 34.2% and understate the gains for low-skill workers by 7.9% since it would not account for the negative impact of immigration on high-skill natives nor the positive impact for low-skill workers. This result shows that the link between MNEs and immigration significantly affects the distributional welfare gains predicted by canonical MNE models that do not incorporate migration.

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

More broadly, several papers have used general equilibrium models to understand how high- and low-skill immigration affects wages and employment of native workers. Among others, Docquier et al. (2014), Bound, Khanna, and Morales (2018) and Burstein et al. (2018) look at the effects of immigration for native workers with different skills and occupations by focusing on the consequences for the recipient country and ignoring the implications of migration for the rest of the world. A second set of papers go beyond that and use multi-country models to study the consequences of migration in both receiving and sending countries. Such a global view on migration requires us to incorporate, to some extent, the possibility that production will relocate as a response to changes in immigration policy (Caliendo et al., 2018; Desmet et al., 2018; di Giovanni et al., 2015; Iranzo and Peri, 2009; Khanna and Morales, 2018). This paper contributes to this literature by including the channel of multinational production, which is key to understanding the effects that firms decisions to relocate production due to immigration policies have on welfare and productivity. I also incorporate additional features that are relevant for the quantitative exercise such as heterogeneity in abilities which is not considered by di Giovanni et al. (2015) and Khanna and Morales (2018) and heterogeneity across industries not incorporated by Caliendo et al. (2018) and Desmet et al. (2018).

A closely related strand of literature has used a reduced-form approach to establish a link between immigration and trade (Gould, 1994; Hiller, 2013), immigration and FDI activity (Glennon, 2018; Javorcik et al., 2011; Yeaple, 2018), and the interrelations between migration, trade and FDI, (Aubry et al., 2018). Perhaps the closest analog to my research question is Wang (2014), who uses a calibrated two-country model of the US and Canada that incorporates an imperfect substitution between migrants and natives within the MNE. I contribute to this literature by building and estimating a quantitative model that includes multiple countries, industries, endogenous migration, and labor supply decisions which allows me to properly quantify the aggregate implications of immigration for MNEs production and for welfare.

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

# 2 Context and Data

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

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

# 3 Stylized facts

In this section I show three stylized facts that help shed light on the link between high-skill immigration, MNE activity and industry composition and that motivate the model in section 4. In a first stage, I show that there is a strong link between MNEs and high-skill immigration captured by a "home-bias" measure that indicates foreign MNEs from a given source country are more likely to hire immigrants from that country than US companies and MNEs from other countries. In a second stage, I present two additional facts that uncover a significant degree of heterogeneity across industries in their dependence on immigrants. First, skill intensive industries are more intensive on high-skill immigrants than low-skill intensive industries. Second, workers from different origin countries select into migration to work in industries where they have a comparative advantage. Accounting for multiple industries and origin countries will be proven to be relevant for the quantitative welfare effects of changing migration policy.

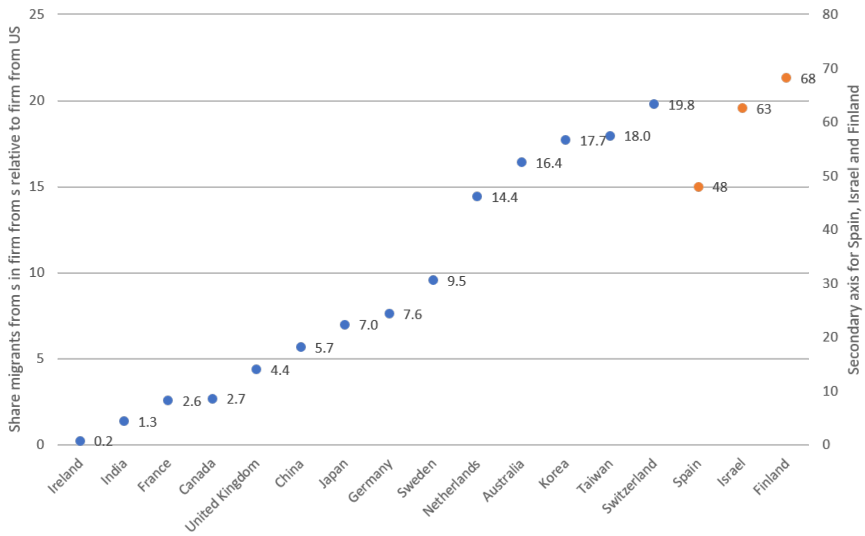
**Fact 1: Foreign MNE companies have a "home-bias" towards workers from their source country**

Foreign MNE companies have a "home-bias" towards recruiting workers from their source country when compared to US companies. This is relevant since we should expect foreign companies to respond more to a migration policy change than American companies, which in turn has further implications for changes to the industrial structure and welfare in the US. To find support for this in the H-1B and L-1 data, I plot the share of high-skill visas granted to firms from country $s$ that go to workers from $s$ relative to the share of high-skill visas granted to US firms that go to workers from $s$ as shown in equation 1.

$$\frac{\text{N visas to firm from } s\text{,worker from } s}{\text{N visas to firm from } s} \div \frac{\text{N visas to firm from US,worker from } s}{\text{N visas to firm from } US} \tag{1}$$

As shown in Figure 1 there is a large "home-bias" for most countries in the sample. With the exception of Ireland, all other countries seem to hire more source country workers relative to US companies. To interpret the numbers in Figure 1, the share of visas to Chinese companies that go to Chinese workers is 4.4 times larger than the share of visas to US companies that go to Chinese workers. For countries like Israel or Finland, the ratio is higher than 60.

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



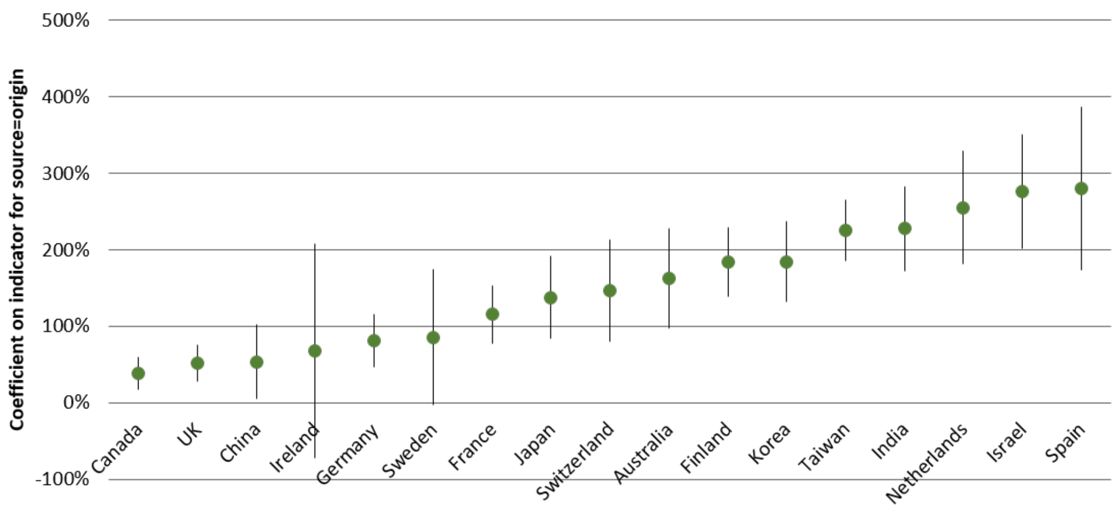

The figure plots the share of migrants from country $s$ among all migrants hired by firms from $s$ in the US relative to the share of migrants from country $s$ among all migrants hired by US firms in the US. The dataset only includes high-skill migrants to the US that arrived between 2012 and 2014 under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

For now, I will not take a stand on whether the home bias is driven by workers being more likely to find a job at a company headquartered in their origin country, or foreign companies having a greater need for workers from their source country. In the model and subsequent estimation in sections 4 and 5, I explicitly separate these two channels. The results in Figure 1 pool all industries together so they might be partly driven by a correlation in worker and source country comparative advantage in specific industries. To test whether home bias holds when controlling for this, I collapse the high-skill visa data to the origin ($o$) - source ($s$) - industry level ($k$) and proceed to run a regression as in equation 2. For example, one observation of the regression is German H-1B and L-1 recipients working for Japanese automotive companies located in the US.

$$Ln(N_{k,o,s}) = \gamma_0 + \sum_s \gamma_s \mathbb{1}(origin = s) + \delta_{k,o} + \delta_{k,s} + \epsilon_{k,o,s} \tag{2}$$

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

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




Appendix B explores further how do the regression results change when only using at H-1B visas, including source-origin pairs with 0 value and running the regression at the source-origin level. The finding of home-bias is very robust to these specifications.

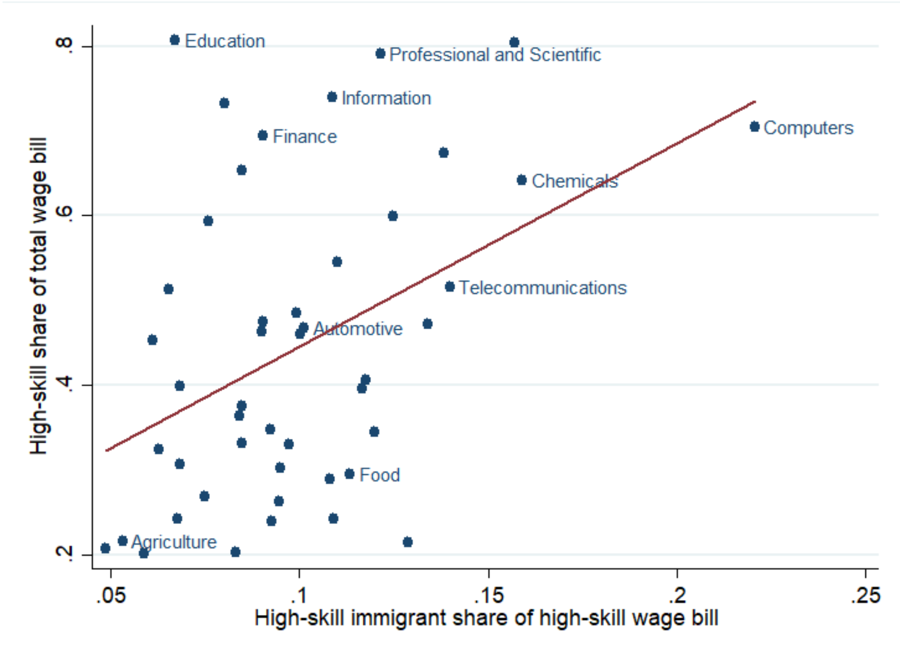
**Fact 2: Heterogeneity across industries in recruiting high-skill migrants.**

Facts 2 and 3 aim to highlight the relevance of accounting for multiple industries and origin-countries to quantify the effect of immigration restrictions on production. Beyond the channel of multinational companies, we should expect different responses across industries when restricting immigration. More specifically, high-skill industries are expected to be more affected than low skill industries. As shown in Figure 3 we can see that there is a large heterogeneity across industries regarding regarding the share of their college graduate wage bill spent on immigrants, where high-skill intensive industries such as computer manufacturing spend more than 20% of their high-skill wage bill on immigrants and chemicals and telecommunications employing around 15%. Figure 3 shows that high-skill intensive industries, measured through the share of the total wage bill that is spent in college graduates, have a greater need for skills that are harder to find in the local labor market, thus spending a greater share on immigrants than low-skill intensive industries.[4] It also highlights the importance of considering industry heterogeneity to

[4]The correlation between the skill-intensity of an industry and the share of the high-skill wage bill spent on immigrants is 42.14%. In Appendix B I show that the correlation is even stronger when only looking at tradable

understand the implications of migration policy, as different industries depend differently on high-skill migration. As will be shown in section E accounting for multiple industries will be relevant in the quantitative exercise.

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




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

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

The last fact I present is that it is also relevant to consider the origin of the immigrants to understand which industries they select into. While there are some industries that employ a larger share of immigrants, it is also true that immigrants from different origins are more likely to select into migration to work in industries in which their home country has a comparative advantage relative to the US. To show this pattern I run a regression at the origin-industry level of the log number of immigrants into the US from origin $o$ that work for industry $k$ on the comparative advantage of industry $k$ in country $o$ relative to the US. The regression is shown in equation 3.

$$Ln(\text{N employees from } o \text{ in } k) = \beta_0 + \beta_1 Ln\left(\frac{\tilde{T}_{o,k}}{\tilde{T}_{us,k}}\right) + \delta_k + \delta_o + \epsilon_{k,o} \tag{3}$$

As in the Ricardian literature, comparative advantage can be interpreted as the average pro-

industries (excluding health, education, government etc.) (56.9%) and manufacturing industries (79.1%).

ductivity of a given industry in country $o$ relative to the average productivity of industry $k$ in the US and is denoted by $\frac{\tilde{T}_{o,k}}{\tilde{T}_{us,k}}$[5]. The results in Table 1, Column 1 look at the stock of high-skill immigrants, and it is shown that if the comparative advantage of country $o$ in industry $k$ relative to the US increases by 1%, the number of migrants of that origin that work in industry $k$ in the US increases by 0.083%. The results hold for the H-1B and L-1 data from 2014 which can be considered as a flow of immigrants instead of the stock measured by the ACS, as shown in Column 2. Finally we can see that this correlation is not driven by foreign MNE companies, as the correlation is almost identical when only immigrants that work for American companies are considered (Column 3).

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

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

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

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

[5] I calculate this term using the gravity equation and the observed trade flows as in Eaton and Kortum (2002). Details on this estimation can be found in Appendix B. The $\tilde{T}$ used in this section come from a simpler model than the one used in section 4.2.1. As will become clear later, the $\tilde{T}$ are a combination of the productivities of local companies and foreign MNEs operating in each country.

Facts 1-3 aim to characterize the sorting patterns of immigrants across origins, industries, and source countries. To understand the implications of high-skill immigration policy we should expect different responses depending on the industry and source country of the company as well as the origin of the immigrants the company is more likely to hire. In this section, I presented evidence that high skill intensive industries depend more on immigration and workers from a given origin are more likely to select into migration to work in industries where their home country has a comparative advantage. Finally, within a given industry and origin country, foreign companies seem to depend more on migration than American companies, since they are more likely to recruit workers from their source country than workers from other origins.

# 4 Model

To understand the general equilibrium implications of changes to high-skill immigration policy in the US and guided by the stylized facts in section 3, I build a quantitative model to disentangle the different mechanisms through which immigration affects production, welfare and industry composition. The model consists of two main parts: a labor market for high-skill workers described in section 4.1 and a product market that includes trade and MNE activity described in section 4.2. The model is static, and consists of $O$ countries. Production can be carried out by local companies or by foreign companies that set up an affiliate outside of their home country.

## 4.1 Labor Market and Migration Choices

Each country $o$ is endowed with a number of low-skill ($\bar{L}_o$) and high-skill ($\bar{N}_o$) workers. Low skill workers are a homogeneous group who cannot migrate and receive wage $w_o$. On the other hand, high-skill workers have heterogeneous abilities and are able to choose the location $\ell$, industry $k$ and source technology $s$ they want to work with. Source technology refers to the country where the company they work for is headquartered. At the beginning of the period each worker $i$ at origin $o$ takes an ability draw $\eta^{i,o}_{k,\ell,s}$ to work at each triplet $z = k, \ell, s$ from a Frechet distribution as shown in equation 4:

$$F(\eta^{i,o}_{k,\ell,s}) = exp\left(-\sum_{z=1}^{Z} A_{k,o}\left(\eta^{i,o}_{z}\right)^{-\kappa}\right) \tag{4}$$

For expositional purposes the ability draws are assumed to be i.i.d. but in Appendix E I explore the implications of using correlated draws for my quantitative results[6]. The shape parameter of the distribution $\kappa$ is common across origin countries and governs the dispersion of abilities for each individual. Lower values of $\kappa$ imply that individuals are likely to have very different abilities across triplets $k, \ell, s$. As will be shown later, the parameter $\kappa$ 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 scale parameter, $A_{k,o}$, 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., 2018; Lagakos and Waugh, 2013; Lee, 2017), as well as both for internal (Bryan and Morten, 2018) and international migration (Liu, 2017). The parameter $A_{k,o}$ is directly related to Facts 2 and 3 presented in section 3. First, immigrants will tend to select into migration to work in industries where they have a comparative advantage as shown in Fact 3. Second, such selection into migration implies we will tend to see more foreign workers in some industries than in others as presented by Fact 2.

Each high-skilled worker, indexed by $i$ chooses the triplet $k, \ell, s$ that maximizes their utility as in equation 5:

$$max \quad _{k,\ell,s} \quad \{U^{i,o}_{k,\ell,s}\} = \eta^{i,o}_{k,\ell,s} \times \frac{w_{k,\ell,s}}{P_\ell} \times \frac{1}{\phi_{o,\ell,s}} \tag{5}$$

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

As $\phi_{o,\ell,s}$ is non-pecuniary, the wage that individuals actually receive in the labor market is $W^o_{k,\ell,s} = \eta^{i,o}_{k\ell,s} \times w_{k,\ell,s}$.

[6] The Frechet distribution when adding correlation among the draws for each individual ($\rho > 0$) would be $F(\eta^{i,o}_{k,\ell,s}) = exp\left(-\left(\sum_{z=1}^{Z}\left(A_{k,o}\left(\eta^{i,o}_{z}\right)^{-\kappa}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}\right)$.

## 4.2 Production, Trade and MNE activity

I lay out the consumer problem in two stages. First, individuals take ability draws and choose a triplet $k, \ell, s$ as explained in sub section 4.1. Second, conditional on their choice and the wage they receive, they maximize their consumption utility as an individual living in $\ell$ who has Cobb-Douglas preferences over $K$ industries as in equation 6

$$U_\ell = \Pi_{k=1}^{K} Q_{k,\ell}^{\gamma_{k,\ell}} \tag{6}$$

Each $Q_{k,\ell}$ can be written as a continuum of varieties indexed by $j$, and aggregated CES as in equation 7:

$$Q_{k,\ell} = \left( \int q_{k,\ell}^{j \frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} \tag{7}$$

Each variety $q^j_{k,\ell,s}$ is produced using a Cobb-Douglas aggregate of intermediate inputs from each industry $K$ and a composite of low and high skilled labor as in equation 8.

$$q_{k,\ell} = \epsilon_{k,\ell} \prod_{k'=1}^{K} Q_{\ell,k,k'}^{\gamma_{\ell,k,k'}} \left( \psi_{k,\ell}^{l} l_{k,\ell}^{\frac{\alpha-1}{\alpha}} + \psi_{k,\ell}^{h} h_{k,\ell}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}(1-\sum_{k'} \gamma_{\ell,k,k'})} \tag{8}$$

$\alpha$ represents the elasticity of substitution between low $(l_{k,\ell})$ and high skill $(h_{k,\ell})$ units of labor and $\gamma_{\ell,k,k'}$ is the expenditure share for industry $k$ in country $\ell$ on intermediates from industry $k'$. Each producer has an idiosyncratic productivity $\epsilon^j_{k,\ell}$. While I omit index $j$ in equations 8 and 9, both equations are at the producer level. I assume high-skill labor $h_{k,\ell}$ is a composite of effective units from the domestic country $h^d_{k,\ell}$, source country $h^s_{k,\ell}$ and other foreign countries $h^f_{k,\ell}$. That is, if the producer uses a source technology in a location $\ell \neq s$ then the aggregate $h_{k,\ell}$ can be written as in equation 9: [7]

$$h_{k,\ell,s} = \left( \underbrace{\psi_{k,\ell,s}^{d} \left( h_{k,\ell,s}^{d} \right)^{\frac{\lambda-1}{\lambda}}}_{\text{local workers}} + \underbrace{\psi_{k,\ell,s}^{s} \left( h_{k,\ell,s}^{s} \right)^{\frac{\lambda-1}{\lambda}}}_{\text{source country}} + \underbrace{\psi_{k,\ell,s}^{f} \left( h_{k,\ell,s}^{f} \right)^{\frac{\lambda-1}{\lambda}}}_{\text{other foreign}} \right)^{\frac{\lambda}{\lambda-1}} \tag{9}$$

The parameter $\lambda$ governs the substitution between effective units of the domestic country, source country and other foreign workers. Having foreign and native workers be imperfect substitutes is consistent with the findings of Peri and Sparber (2011) who find that immigrants tend to specialize in different tasks than natives. At the same time, having source country

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

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. I allow the share parameters $\psi^d_{k,\ell,s}, \psi^s_{k,\ell,s}, \psi^f_{k,\ell,s}$ to depend on source country and particularly, on industry. This is an additional channel through which the heterogeneity in hiring migrants across industries discussed in Fact 2 in Section 3 appears, as some industries will be more immigrant intensive than others.

### 4.2.1 International trade and MNE

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

Producers of each variety $j$ in source country $s$ take a productivity draw $\epsilon^j_{k,\ell,s}$ to produce variety $j$ in each possible location $\ell$. Such productivity is drawn from a Frechet distribution as in equation 10:

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

Once again, the shape parameter $\theta$ governs the productivity dispersion across production locations for a given producer. If $\theta$ is low, then there are large gains to MNE production, as a producer might have low productivity in their source country but high productivity at some alternative location. A producer of variety $j$, in industry $k$, with source technology $s$ who chooses to locate production at location $\ell$ and sell their products to destination country $n$ would charge a price as in equation 11:

$$p^{j,k}_{s,\ell,n} = \frac{c^k_{s,\ell}\tau^k_{\ell,n}\delta^k_{s,\ell}}{\epsilon^j_{k,s,\ell}} \tag{11}$$

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

Consumers end up buying each variety from the cheapest producer such that: $min_{s,\ell}\{p^{j,k}_{s,\ell,n}\}$.

### 4.3 Equilibrium

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

The fraction of workers from origin $o$ who choose to migrate to location $\ell$ and work for industry $k$ with source technology $s$ can be written as in equation 12:

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

Equation 12 implies that the probability of migration from origin $o$ to triplet $k, \ell, s$ depends on the comparative advantage of origin $o$ in industry $k$ $(A_{o,k})$, the real wage per effective unit in triplet $k, \ell, s$ $\left(\frac{w_{k,\ell,s}}{P_\ell}\right)$, the migration cost from $o$ to $\ell, s$ $(\phi_{o,\ell,s})$ and a combination of these terms for all other triplets, captured by the denominator in equation 12.

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

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

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

Finally, it is possible to write the share of production in $\ell$ in industry $k$ that is done by MNEs from country $s$ as in equation 14:

$$\pi^{mne}_{k,s,\ell} = \frac{\left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta}}{\sum_{s'} \left(c^k_{\ell,s'} \times \delta^k_{\ell,s'}\right)^{-\theta}} \tag{14}$$

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

To solve for the equilibrium in the model, I use the approach suggested by Dekle et al. (2008) and solve the model in proportional changes. This method, also called the exact hat-algebra method, allows me to re-write the equilibrium equations as changes between the real and the counterfactual scenarios. That is, I can re-write each variable $x$ as $\hat{x} = \frac{x'}{x}$ where $x$ is the variable under the real scenario and $x'$ is the value of the variable under the counterfactual. A key advantage of this method is that it allows me to understand more transparently how an exogenous change in for example, migration costs to the US $\hat{\phi}_{o,US,s} > 1$, affect other endogenous variables of the model. I re-write all equilibrium equations in proportional changes in Appendix C.1. As an example, it is possible to re-write the migration share (equation 12) as in equation 15:

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

As shown by equation 15, this approach allows me to classify each object of the equilibrium into four categories: Endogenous variables such as $\hat{w}_{k,\ell,s}$, $\hat{P}_\ell$, fundamental parameters such as $\kappa$, exogenous parameters such as $\hat{\phi}_{o,\ell,s}$ and $\hat{A}_{o,k}$, and data on observed allocations $\pi^{mig}_{o,k,\ell,s}$. The model includes many exogenous parameters such as migration costs $\hat{\phi}_{o,\ell,s}$, trade costs $\tau_{k,\ell,n}$, MNE costs $\delta_{k,s,\ell}$, fundamental technologies $T_{s,k}$, worker comparative advantages $A_{k,o}$ and labor shares $\psi_{k,\ell,s}$ but there are assumed to stay constant between the real and the counterfactual such that $\hat{x} = 1$. The counterfactual scenario involves changing just some of the exogenous parameters and evaluating how the endogenous variables respond. This strategy helps me avoid having to calibrate all parameters and just focus on four key elasticities that govern the responses of the endogenous variables: $\kappa$ the elasticity of migration and labor supply, $\lambda$ the elasticity of substitution between high-skill effective units of labor, $\alpha$ the elasticity of substitution between college and non-college workers and $\theta$ the trade and MNE elasticity. Those elasticities together with data on observed allocations are enough to compute the changes in the endogenous variables of the model. While I also need data on the observed migration, trade shares, MNE shares and labor allocations, I do not need to take a stand on any other parameters of the model which greatly reduces the number of parameters to be estimated.

## 4.4 Intuition

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

Using the simplified version of equation 12 and taking logs of the ratio between the migration share of Indians going to the US relative to Indians staying in India, we get an expression like in equation 16:

$$Ln(\hat{\pi}^{mig}_{in,us}) - Ln(\hat{\pi}^{mig}_{in,in}) = \kappa Ln\left(\frac{\hat{w}_{us}}{\hat{P}_{us}}\right) - \kappa Ln\left(\frac{\hat{w}_{in}}{\hat{P}_{in}}\right) - \kappa Ln(\hat{\phi}_{in,us}) \tag{16}$$

An increase in the migration cost from India to the US will decrease the number of Indians in the US relative to the Indians that stay in India. The magnitude of the decrease is quantified by $\kappa$ which also determines the dispersion of abilities across options for each individual. High values of $\kappa$ imply that the abilities across triplets will be very concentrated and that small changes in the migration cost or the wages will generate large responses in the number of workers who migrate, since the ability they have to work in the US will be close to the ability to work elsewhere.

A decrease in the number of foreign workers in the US will rise the wage paid for foreign effective units of labor $\hat{w}^f_{us} > 1$. The effect of such increase on marginal cost will depend on the elasticities $\lambda$ and $\alpha$. To see this, we know from equation 9 that the unit cost of high skill labor can be written as in equation 17:

$$\hat{cost}_{h,us} = \left(\hat{\psi}^{\lambda}_{d}\hat{w}^{1-\lambda}_{d,us} + \hat{\psi}^{\lambda}_{f}\hat{w}^{1-\lambda}_{f,us}\right)^{\frac{1}{1-\lambda}} \tag{17}$$

The higher the $\lambda$, the higher the substitutability between effective units of foreign and domestic high skill labor, such that the marginal cost of high-skill labor will respond less to an increase in $\hat{w}_{f,us}$. $\lambda$ will quantify the response of high-skill marginal cost to a change in the migration cost $\hat{\phi}_{in,us}$. Following a similar intuition, if the elasticity of substitution between low and high skill workers $\alpha$ is high, low and high skill effective units are highly substitutable. If the cost for high-skill units increases as a response to the migration cost increase, the firm could simply substitute high for low skill units keeping the overall marginal cost lower, as shown in equation 18.

$$\hat{cost}_{us} = \left(\hat{\psi}_L^{\alpha}\hat{w}_{L,us}^{1-\alpha} + \hat{\psi}_H^{\alpha}\hat{cost}_{h,us}^{1-\alpha}\right)^{\frac{1}{1-\alpha}} \tag{18}$$

Finally, the parameter $\theta$ quantifies how much does an increase in the marginal cost for US firms changes the demand for goods produced in the US. $\theta$ governs the dispersion of productivities across production locations. High values of $\theta$ mean that productivity is more concentrated across locations. If an increase in migration cost increases marginal cost for companies in the US, we should expect a larger change in the share of goods other countries buy from the US, as productivities abroad are similar to those in the US and a small change in marginal cost can have significant implications for the location of production. This can be shown by re-working the gravity equation by taking the ratio of the share of goods the US buys from India relative to the share of goods the US buys from itself as shown in equation 19:

$$Ln(\hat{\pi}_{us,in}^{cons}) - Ln(\hat{\pi}_{us,us}^{cons}) = Ln\left(\frac{\hat{T}_{in}}{\hat{T}_{us}}\right) - \theta\left(Ln(\hat{cost}_{in}) - Ln(\hat{cost}_{us})\right) - \theta Ln(\hat{\tau}_{us,in}) \tag{19}$$

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

# 5 Estimation

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

### 5.1 Labor supply elasticity $\kappa$

In the model presented in section 4 the shape parameter of the ability distribution, $\kappa$, has two main interpretations. First, it governs the dispersion of productivities, with lower values of $\kappa$ implying higher dispersion between draws. 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. I will use the dispersion property to estimate $\kappa$ using the observed distribution of wages for high-skill migrants. Similar approaches have been used in the EK-Roy literature to estimate the supply elasticity such as in Lagakos and Waugh (2013), Hsieh et al. (2018) and Lee (2017). While this approach relies on the distributional assumptions for the ability draws, the Frechet distribution has been shown to provide a good approximation of the observed wage distribution (Burstein et al., 2018). Before proceeding to the estimation I will present two results based on the Frechet properties.

**Proposition 1** *If productivity draws $\eta$ are distributed Frechet with shape parameter $\kappa$, the observed market wages paid to employees $W^{i,o}_{k,\ell,s} = \eta^{i,o}_{k,\ell,s} w_{k,\ell,s}$ are also distributed Frechet with parameter $\kappa$.*

**Proposition 2** *If a random variable $W$ is distributed Frechet with shape parameter $\kappa$ 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 $\Gamma$ is the Gamma function. Proposition 1 indicates that observed market wages are also distributed Frechet with shape parameter $\kappa$ which means that the parameter $\kappa$ is related to the dispersion of observed wages, conditional on individuals choosing the triplet $k, \ell, s$. This proposition indicates that the observed dispersion of wages can be used to make inference on the value of $\kappa$. 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 $\kappa$.

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 20 and estimate the parameter $\kappa$ by GMM, choosing a value of $\kappa$ that minimizes the distance between the empirical moments and the moments from proposition 2.

$$\left(\frac{Var(W^o_{k,\ell,s})}{\left(\overline{W}^o_{k,\ell,s}\right)^2}\right) = \frac{\Gamma\left(1-\frac{2}{\kappa}\right)}{\left(\Gamma\left(1-\frac{1}{\kappa}\right)^2\right)} - 1 \qquad (20)$$

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

Table 2: Estimates for $\kappa$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Elasticity of Supply ($\kappa$) | 5.95*** | 6.41*** | 6.58*** | 6.99*** |
| | (0.535) | (0 .45) | (0 .56) | (0.49) |
| | 697 | 1202 | 1078 | 1624 |
| Industry | NAICS 2-dig | NAICS 2-dig | NAICS 3-dig | NAICS 3-dig |
| N origin countries | 18 | 63 | 18 | 63 |

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

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

Table 3: $\kappa$ estimates ACS vs H-1B

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

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

## 5.2 Elasticity of substitution of high-skill effective units $\lambda$

The elasticity of substitution between domestic, source country and other foreign effective units can be interpreted as the relative demand elasticity for migrants. It is possible to re-work the first order conditions of the components in equation 9 to get to equation 21:

$$Ln\left(\frac{\text{wage bill}^s_{k,\ell,s}}{\text{wage bill}^f_{k,\ell,s}}\right) = (1-\lambda)Ln\left(\frac{w^s_{k,\ell,s}}{w^f_{k,\ell,s}}\right) + \lambda Ln\left(\frac{\psi^s_s}{\psi^f_s}\right) \tag{21}$$

Equation 9 implies that for an MNE from source $s$, the ratio of the wage bill spent on source country workers relative to the wage bill spent on other foreign workers is a function of the ratio of effective wage paid to source country workers relative to the effective wage paid to other foreign workers.[8] If one were to run this regression by OLS, two main issues would arise. First, the effective wage ratio $Ln\left(\frac{w^s_{k,\ell,s}}{w^f_{k,\ell,s}}\right)$ 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 $\kappa$ 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 $\lambda$.

Using the the properties of the Frechet distribution, we can write the observed average wages for each group as in equation 22:

[8]For estimation purposes, parameters $\psi^s_s$ and $\psi^f_s$ are simplified from those in equation 9. They no longer include a country sub-index $\ell$ since I will only use US data for estimation nor an industry sub-index $k$. Results will be robust to adding industry fixed effects to capture industry heterogeneity.

$$\overline{wage}^{o}_{k,\ell,s} = w^{x}_{k,\ell,s}\pi_{o,k,\ell,s}^{-\frac{1}{\kappa}}A_{i,o}^{\frac{1}{\kappa}}\bar{\Gamma} \tag{22}$$

Where $\overline{wage}^{o}_{k,\ell,s}$ is the average wage for those from origin $o$ that migrate to triplet $k,\ell,s$, conditional on choosing $k,\ell,s$. $w^{x}_{k,\ell,s}$ is the equilibrium wage per effective unit paid to those who choose triplet $k,\ell,s$ and the superscript $x$ indicates whether the workers are hired by an MNE with $s = o$ or if they are hired just as other foreign workers. $\pi_{o,k,\ell,s} = \frac{N^{o}_{k,\ell,s}}{N^{o}}$ is the fraction of workers from $o$, who migrate to $k,\ell,s$ and $A_{k,o}$ is the comparative advantage of workers from $o$ in industry $k$. Finally, $\bar{\Gamma}$ is the Gamma function. Equation 22 summarizes how selection works in terms of comparative advantages. When the share of workers from $o$ that choose triplet $k,\ell,s$ increases, average wages of workers from $o$ in $k,\ell,s$ are expected to decrease, since those switching to $k,\ell,s$ have on average, lower abilities in $k,\ell,s$ than those who were already there.

By taking the ratio between $\overline{wage}^{o=s}_{k,\ell,s}$ and $\overline{wage}^{o\neq s}_{k,\ell,s}$, taking logs and re-arranging terms, it is possible to get to equation 23:

$$\underbrace{Ln\left(\frac{\overline{wage}^{s}_{k,\ell,s}}{\overline{wage}^{o}_{k,\ell,s}}\right) + \frac{1}{\kappa}Ln\left(\frac{N^{s}_{k,\ell,s}}{N^{o}_{k,\ell,s}}\right)}_{\text{Data}} = \underbrace{Ln\left(\frac{w^{s}_{k,\ell,s}}{w^{f}_{k,\ell,s}}\right) + \frac{1}{\kappa}Ln(N_{s}A_{k,s})}_{Source-IndustryFE} - \underbrace{\frac{1}{\kappa}Ln(N_{o}A_{k,o})}_{Origin-IndustryFE} \tag{23}$$

Equation 23 shows that it is possible to run a regression at the source-origin-industry level using the H-1B data for average wages ($\overline{wage}^{o=s}_{k,\ell,s}$ and $\overline{wage}^{o\neq s}_{k,\ell,s}$) and number of employees by group ($N^{s}_{k,\ell,s}$, $N^{o}_{k,\ell,s}$) together with the estimated value of $\kappa$, 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 $Ln\left(\frac{w^{s}_{k,\ell,s}}{w^{f}_{k,\ell,s}}\right)$ which is our object of interest.

I proceed to estimate equation 21, by using the foreign MNEs in my H-1B data and run a firm level regression, using the log ratio of the wage bills of source and foreign workers as the dependent variable, and the log ratio of the effective wages estimated in equation 23 as an explanatory variable. The term $Ln\left(\frac{\psi^{s}_{s}}{\psi^{f}_{s}}\right)$ can be captured by a source fixed effect. Since adding a fixed effect for each source would limit the power of the regression, I only add a fixed effect that takes the value of 1 when the company is from India, as Indian companies have a different recruitment process of migrants than other foreign companies. To consistently estimate equation 21, I need an instrument that shifts supply but is uncorrelated with unobserved demand shocks in order to identify the demand parameter $1 - \lambda$. I choose as an instrument the average wage paid in country $s$. This is a valid instrument because the wage in the origin country is one of the main predictors of migration flows as shown by Grogger and Hanson

(2011) and Docquier et al. (2014), thus a change in the wage level in the origin country is a good predictor of the migration cost. The migration cost is directly related to the supply curve but is not correlated with demand shocks in the US that affect the ratio of effective wages between source and other foreign workers which makes it a good instrument for the relative effective wages in the US.

The OLS and 2SLS results of equation 21 can be found in table 4 and results are coherent with what we would expect. OLS results are upward biased, since they predict a $\lambda$ lower than one and not significant. When instrumenting for the effective wages, the estimated $\lambda$ is 12.89, which is consistent with the estimates of Ottaviano and Peri (2012) who found an elasticity of substitution between native and immigrant college graduates of 12.89, and Burstein et al. (2018) who found an aggregate elasticity of 10.

Table 4: Estimating equation for $\lambda$

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

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

## 5.3 Implementation

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

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

I set $\theta = 4$, $\alpha = 1.7$, $\kappa = 5.95$ and $\lambda = 12.89$ consistent with the baseline parameters estimated in section 5. Finally, the estimation of the model requires me to use data on observed trade shares by industry, MNE shares by industry, migration shares from each origin $o$ to each triplet $k, \ell, s$ and skill shares for domestic, source country and other foreign workers for each triplet $k, \ell, s$. In Appendix D I explain how I construct the dataset to run the counterfactual exercises. While the data on migration and skill shares for the US can be constructed using a combination of the ACS and my H-1B dataset, the data availability for migration in Canada and Europe is limited. In Appendix D I also explain how I impute some of the data for those regions using the US data together with additional datasets on global migration and industry employment.

Finally to calculate the equilibrium I need to impose a normalization. I follow Allen et al. (2018) and impose that World output stays constant as in equation 24. This normalization implies that the output results should be interpreted as how do the endogenous variables change as a share of total World output.

$$X_{us} + X_{in} + X_{ca} + X_{eu} + X_{ch} + X_{oth} = \bar{X} \tag{24}$$

# 6 Counterfactual exercises

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

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

As a first counterfactual exercise, I study how the location of high-skill industries and welfare would change in the long term if the US implements a more restrictive migration policy. To put my results into context, I explore the long term implications of a recent policy discussed in the US regarding high-skill migration and the H-1B program. The "Protect and Grow American Jobs Act" bill introduced by Rep. Darrell Issa in January 2017, proposes among other things to set a minimum wage for H-1B recipients that "is equal to the lesser of $135,000 or the mean wage for applicants occupation in their area (but subject to a floor of no less than $90,000)"[9]. The proposal aims to reduce total high-skill migration while still allowing those migrants with the highest abilities to come to the US. American high-skill workers would presumably benefit from the lower competition for high-skill jobs.[10].

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

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

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

[9] More details on the proposed bill can be found here.

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

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.

Table 5: Percent Change in production relative to World output

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

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

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

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

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

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

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

While the drop in production is a relevant channel through which migration restrictions affect welfare for US natives, there are some workers who gain from such restrictions. As shown in table 7 high-skill workers would experience an increase of 1.39% in their welfare due to the migration restriction. When there are fewer migrants firms substitute the missing foreign workers with natives pushing up the US native wage. Low skill workers on the other hand would see their welfare decreased by 2.01% given their complementarity with high-skill workers. Aggregating across skill types, total welfare for US workers would decrease by 0.98% when migration is restricted. Welfare is calculated as the average wage for each group divided by the price index. A restriction in migration affects welfare predominantly through changes in wages as shown in column 2 of table 7.

Table 7: Welfare and Wages for US natives

| | Welfare (percent change) | Effective Wages (percent change) | Compensating Variation ($ billions) |
|---|---|---|---|
| Welfare high-skill natives | 1.39% | 2.09% | -39 |
| Welfare low-skill natives | -2.01% | -1.34% | 60 |
| Welfare US natives | -0.98% | -0.30% | 21 |

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

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. The losses for low-skill workers amount to 60 billion dollars while the gains for high-skill workers amount to 39 billion dollars.

### 6.1.1 Mechanisms and Robustness

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

The stylized facts in section 3 motivated three main additions to the model. Fact 1 highlighted the link between foreign MNE production and migrant intensity, motivating the specific treatment of foreign MNEs in the model. Fact 2 showed that there was significant heterogeneity across industries in their intensity to hire migrants which motivated incorporating multiple industries into the model. Finally, Fact 3 suggested that migrants from different origins are likely to have a different comparative advantage across different industries, motivating to incorporate multiple origin countries into the analysis. In table 8 I compare the welfare effects of the baseline model with alternative models that remove each channel to understand how they drive the baseline result. Columns 2-3 compare the baseline with a model that does not include MNE production. Such model is equivalent to an multi-country, multi-industry Eaton and Kortum (2002) model that allows for migration. The data used assumes all companies producing in the US are domestic companies, so their intensity in hiring migrants is the one observed for US companies. The model without MNE production understates the welfare losses by 5.4% since it no longer accounts for the specific productivity derived by foreign MNEs from source-country migrants. The MNE channel is not as big when looking at the aggregate effects since MNEs account for a fairly small share of total production in high-skill industries and the estimated elasticity of substitution between natives, source-country workers and other foreign workers is high. However, as shown in section 6.2 the migration channel does have a large impact in the welfare gains that stem from allowing MNE production.

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

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

Table 8: Understanding mechanisms - modeling assumptions

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

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

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

Table 9: Understanding mechanisms - elasticities

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

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

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

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

Restrictions to migration have big consequences on the activity of MNEs in the receiving country. To understand the aggregate implications of such result, I explore how do the welfare gains from MNE activity are affected by incorporating migration into the model. A vast literature in international economics has used quantitative models to measure the welfare gains from trade by looking at the change in welfare when going from autarky, where trade costs are assumed to be very large such that trade is prohibitive, to the observed trade flows in equilibrium. Similarly, for MNEs, the welfare gains from MNE production is the welfare change when going from an equilibrium where MNE costs are very large (MNE autarky) to an equilibrium where MNE flows are as in the data. Given my estimated model, a contribution of this paper is to show that incorporating high-skill migration as an additional mechanism into a quantitative MNE model has significant implications for the distributional welfare gains across workers with different skills.

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

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

Table 10: Welfare gains from MNE production

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

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

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

# 7 Conclusion

This paper presents evidence of a strong link between high-skill immigration, the location of high-skill industries and MNE activity in the United States. Using a novel dataset constructed from visas of high-skilled workers and linked to firms global ownership, I document the stylized fact that foreign MNEs have a "home-bias" towards hiring immigrants from their home countries compared to US firms. I build a quantitative model that includes migration decisions of high-skill workers, trade and MNE activity and incorporates the main channels through which immigration affects production. I use my novel dataset to structurally estimate the key elasticities of the model and run two counterfactual exercises. First, I simulate the long-term implications of restricting high-skill immigration to the US in light of recent policy discussions concerning the curtailing of high-skill immigration. I increase the cost of immigration into the US such that it decreases the stock of immigrants by 70%, consistent with a 2.1% decrease in total US workforce. The quantitative estimates indicate that production in IT and High-tech manufacturing in the US would decrease by 2.98%-3.34%, disproportionately driven by a drop in foreign MNE activity in the US. Welfare for native US workers would decrease by 0.98%, but there are distributional consequences. High-skill workers gain from the reduced labor-market competition by 1.39% while low-skill workers lose by 2.01%. In a second counterfactual exercise, I use my model to calculate the welfare gains of MNE production, by calculating the welfare gains of going from MNE "autarky" to the observed MNE flows. Given the strong connection between MNEs and high-skill migration, I show that a model that doesn't consider immigration would overestimate the MNE welfare gains for high-skill workers by 34% and underestimate the MNE gains for low-skill workers by 7.9%. This finding suggests that immigration is a relevant channel to quantify the distributional welfare gains of MNEs.

The results presented in this paper have useful implications for immigration policy in the United States. While a restriction on high-skill immigration that reduces the number of immigrants by 70% might be extreme, restrictions that reduce the number of immigrants to a lesser degree will also have negative consequences for low skill workers and positive consequences for native high-skill workers. A reduction of 10% in the stock of migrants would cause a total loss of 3 billion USD for the US economy, driven by an 8 billion loss for low skill workers and a 5 billion gain for high-skill workers. The interrelation between MNEs activities and immigration is a feature to consider when designing policies that aim to attract FDI into the country since restrictions in immigration will be likely to mitigate the inflows of MNE activity.

While this paper focuses on high-skill migration, an important policy question is how the results would change if I was to incorporate low-skill migration as well. Restricting low-skill immigration is expected to have effects that mirror the results in this paper, lowering welfare for low-skill natives and raising welfare for high-skill natives. The net welfare resulting from the restriction of both types of migration is hard to predict *a priori* without data on low skill immigration and the appropriate elasticities of supply and substitution, which might be different for low-skill workers. The effects of immigration on MNE activity on the other hand, are expected to be different for low and high skill immigration. As shown by Cho (2018), Korean MNEs disproportionately predominantly hire Korean migrants only for managerial occupations, which are high-skill intensive. Hence, the entry of MNEs is likely to have a stronger link to high-skill immigration than low-skill immigration.

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

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

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

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

Table 11: Sample matched to Orbis

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

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

# B Empirical facts details

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

The first fact in section 3 shows that there is a strong home-bias effect, where foreign MNEs hire more migrant workers from their source country $s$ than other companies in the US. In this section I present additional results that confirm the result holds under different specifications. For expositional simplicity, I present the robustness results with a pooled regression as in equation 25, that presents the average home-bias effect across different source countries.

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

Where $Ln(N_{k,o,s})$ is the log number of migrants in $k, o, s$. $\delta_{k,o}$ is an industry-origin fixed effect and $\delta_{k,s}$ is a source-industry fixed effect. The key coefficient of interest is $\gamma$ which measures how much more likely it is that a company from source $s$ will hire someone from $o = s$ relative to $o \neq s$ when compared to all other companies from other source countries.

As in the disaggregated regression in section 3 the magnitude of the home bias is large. As shown in Table 12, columns 1-3, controlling for worker and source country fixed effects is relevant to isolate the home-bias effect. Interpreting the result shown in the 3rd column, companies from country $s$ in industry $k$ are 125.6% more likely to hire someone from country $s$ than any other country when compared to companies not from $s$. Column 4 shows that the result holds and it is even larger when only using the H-1B data. The estimation in section 5 uses data on wages which is only available for H-1Bs so it is reassuring that results hold when excluding L-1 visas. Column 5 shows these results are robust to running the regression at the origin-source level, by aggregating the data across all industries. The aggregate home-bias is a bit larger when not considering industries which is in line with having a positive correlation between origin-industry and source-industry comparative advantages. Finally column 6 shows the results are robust to including source-origin pairs for which the data shows 0 observations. To handle zero values, I estimate the parameters using a Poison Pseudo Maximum Likelihood (PPML) to include zero observations as suggested by Santos Silva and Tenreyro (2006).

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

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

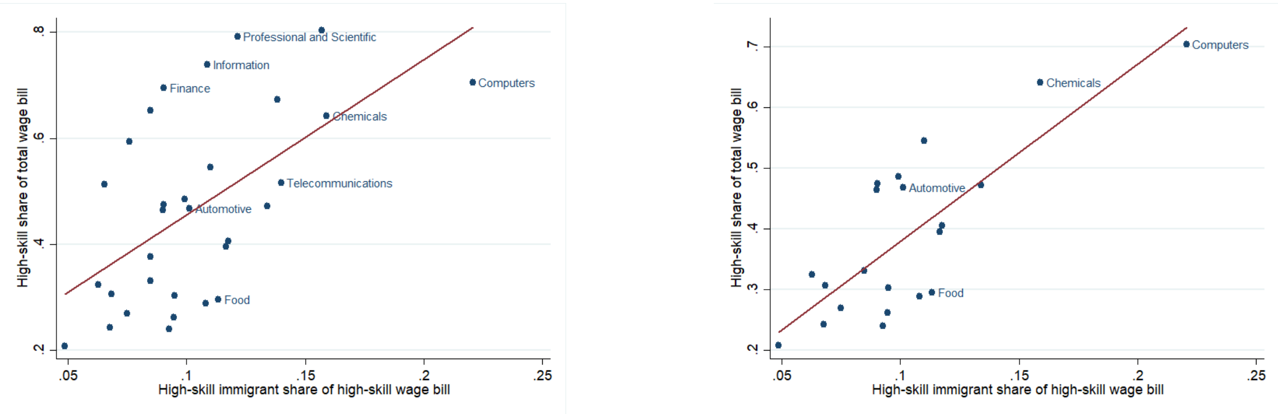
$*p < 0.1, **p < 0.05, ***p < 0.01$, SE clustered at the source-nationality level. Visas for new employment filed in 2012, 2013 and 2014.

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

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

Figure 4: Skill and migrant intensity

(a) Tradable industries (b) Manufacturing industries




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

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

The final fact in section 3 shows that workers from different origins have a different comparative advantage across industries. The comparative advantage of the origin country in each industry relative to the US is used as a proxy for the comparative advantage of the workers from each origin across industries. To calculate the relative comparative advantage term I follow the methodology proposed by Eaton and Kortum (2002) (EK) and extended to a multi-industry setting as in Levchenko and Zhang (2016). Using the gravity equation of a multi sector EK model together with data on the bilateral trade flows and wages it is possible to back out the comparative advantage term for each country and industry.[11] From EK we know that the share of goods bought by country $n$ from country $\ell$ relative to the share of goods country $n$ buys from itself can be written as in equation 26:

$$\frac{\pi^k_{n,\ell}}{\pi^k_{n,n}} = \frac{\tilde{T}^k_\ell (c^k_\ell \tau^k_{n,\ell})^{-\theta}}{\tilde{T}^k_n (c^k_n)^{-\theta}} \tag{26}$$

Where $\tilde{T}^k_\ell$, $\tilde{T}^k_n$ are the comparative advantage terms for $\ell$ and $n$ in industry $k$. $c^k_\ell$ and $c^k_n$ are the unit costs for $\ell$ and $n$ in industry $k$ and $\tau^k_{n,\ell}$ is the iceberg trade costs of selling goods from $\ell$ to $n$. As a first step I approximate log trade costs using a bilateral measure of distance ($d^k_{n,\ell}$), common language indicator ($b^k_{n,\ell}$), common currency union indicator ($CU^k_{n,\ell}$), regional trade agreement indicator ($RTA^k_{n,\ell}$), an importer fixed effect ($im^k_{n,\ell}$) and an error term ($v^k_{n,\ell}$) as in Eaton and Kortum (2002) presented in

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

equation 27.

$$log(\tau^k_{n,\ell}) = d^k_{n,\ell} + b^k_{n,\ell} + CU^k_{n,\ell} + RTA^k_{n,\ell} + im_{n,\ell} + v^k_{n,\ell} \tag{27}$$

By taking logs on equation 26 and using the trade cost specification in equation 27, I run an bilateral pair level regression to back out the convolution of relative productivities and relative unit costs between country $\ell$ and the US for each industry as in equation 28:

$$\underbrace{Ln\left(\frac{\pi^k_{n,\ell}}{\pi^k_{n,n}}\right)}_{\text{Observed trade flows}} = \underbrace{Ln(\tilde{T}^k_\ell(c^k_\ell)^{-\theta})}_{\text{Exporter FE}} - \underbrace{Ln(\tilde{T}^k_n(c^k_n)^{-\theta}) - \theta im_{n,\ell}}_{\text{Importer FE}} \underbrace{-\theta d^k_{n,\ell} - \theta b^k_{n,\ell} - \theta CU^k_{n,\ell} - \theta RTA^k_{n,\ell}}_{\text{Trade costs approximation}} + \underbrace{v^k_{n,\ell}}_{\text{Error term}} \tag{28}$$

After estimating equation 28, the exporter fixed effect gives us for each country an estimate for $Ln(\tilde{T}^k_\ell(c^k_\ell)^{-\theta})$ relative to the omitted country (US). In the homogeneous single factor model, the unit cost $(c^k_\ell)$ is the wage, so using relative wages between each country $\ell$ and the US, and $\theta = 4$ following Simonovska and Waugh (2014) it is possible to back out the relative technologies in industry $k$ between each country $\ell$ and the US.

# C Equilibrium details

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

1. MNE shares - one for each $s$-$k$-$\ell$ triplet

$$\pi^{mne}_{k,s,\ell} = \frac{\left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta}}{\sum_{s'}\left(c^k_{\ell,s'} \times \delta^k_{\ell,s'}\right)^{-\theta}} \tag{29}$$

2. Effective technology in country $\ell$ - one for each $k$-$\ell$ pair:

$$\tilde{T}^k_\ell = \sum_s T^k_s\left(c^k_{\ell,s} \times \delta^k_{\ell,s}\right)^{-\theta} \tag{30}$$

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

$$\pi^{trade}_{k,\ell,n} = \frac{(\tau^k_{\ell,n})^{-\theta}\tilde{T}^k_\ell}{\sum_{\ell'}(\tau^k_{\ell',n})^{-\theta}\tilde{T}^k_{\ell'}} \tag{31}$$

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

$$P_{k,n} = \bar{\Gamma} \left( \sum_{\ell} (\tau_{\ell,n}^{k})^{-\theta} \tilde{T}_{\ell}^{k} \right)^{-\frac{1}{\theta}} \tag{32}$$

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

5. Unit cost in country $\ell$ industry $k$, source technology $s$

$$c_{\ell,s}^{k} = \bar{\gamma} \prod_{k'=1}^{K} P_{k',\ell}^{\gamma_{\ell,k,k'}} \left( (\psi_{k,\ell}^{l})^{\alpha} w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^{h})^{\alpha} (c_{k,\ell,s}^{h})^{1-\alpha} \right)^{\frac{1}{1-\alpha}(1-\sum_{k'} \gamma_{\ell,k,k'})} \tag{33}$$

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

$$c_{k,\ell,s}^{h} = \left( (\psi_{k,\ell,s}^{d})^{\lambda} (w_{k,\ell,s}^{d})^{1-\lambda} + (\psi_{k,\ell,s}^{s})^{\lambda} (w_{k,\ell,s}^{s})^{1-\lambda} + (\psi_{k,\ell,s}^{f})^{\lambda} (w_{k,\ell,s}^{f})^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \tag{34}$$

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

$$\Theta_{k,\ell,s}^{L} = \frac{(\psi_{k,\ell}^{l})^{\alpha} w_{L,\ell}^{1-\alpha}}{(\psi_{k,\ell}^{l})^{\alpha} w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^{h})^{\alpha} (c_{k,\ell,s}^{h})^{1-\alpha}} \quad \Theta_{k,\ell,s}^{H} = \frac{(\psi_{k,\ell}^{h})^{\alpha} (c_{k,\ell,s}^{h})^{1-\alpha}}{(\psi_{k,\ell}^{l})^{\alpha} w_{L,\ell}^{1-\alpha} + (\psi_{k,\ell}^{h})^{\alpha} (c_{k,\ell,s}^{h})^{1-\alpha}} \tag{35}$$

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

$$\Theta_{k,\ell,s}^{x} = \frac{(\psi_{k,\ell,s}^{x})^{\lambda} (w_{k,\ell,s}^{x})^{1-\lambda}}{\sum_{x'} (\psi_{k,\ell,s}^{x'})^{\lambda} (w_{k,\ell,s}^{x'})^{1-\lambda}} \quad \text{for x,x'=\{d,s,f\}} \tag{36}$$

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

$$w_{L,\ell} L_{k,\ell,s} = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta_{k,\ell,s}^{L} \pi_{k,s,\ell}^{mne} I_{\ell,k} \tag{37}$$

$$w_{x,\ell} H_{k,\ell,s}^{x} = (1 - \sum_{k'} \gamma_{\ell,k,k'}) \Theta_{k,\ell,s}^{H} \Theta_{k,\ell,s}^{x} \pi_{k,s,\ell}^{mne} I_{\ell,k} \quad \text{with } x = d, s, f \tag{38}$$

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

$$I_{\ell,k} = \sum_n \pi^{trade}_{k,\ell,n} \gamma_{k,n} X_n \tag{39}$$

$$X_n = w_{L,\ell} \bar{L}_\ell + \sum_{k,\ell,s,x} w^x_{k,\ell,s} H^x_{k,\ell,s} \quad \text{with } x = d, s, f \tag{40}$$

10. Low-skill market clearing - one for each $\ell$

$$\sum_{k,s} w_{L,\ell} L_{k,\ell,s} = w_{L,\ell} \bar{L}_\ell \tag{41}$$

11. Migration shares - one for each $o$-$k$-$\ell$-$s$ group

$$\pi^{mig}_{o,k,\ell,s} = \frac{A_{o,k} \left(\frac{w_{k,\ell,s}}{P_\ell}\right)^\kappa \phi^{-\kappa}_{o,\ell,s}}{\sum_{\ell',s',k'} A_{o,k'} \left(\frac{w_{i',\ell',s'}}{P_{\ell'}}\right)^\kappa \phi^{-\kappa}_{o',\ell',s'}} \tag{42}$$

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

$$w^d_{k,\ell,s} H^d_{k,\ell,s} = w^d_{k,\ell,s} (\pi^{mig}_{o,k,\ell=o,s=o})^{\frac{\kappa-1}{\kappa}} N_\ell A^{\frac{1}{\kappa}}_{k,\ell} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{43}$$

$$w^s_{k,\ell,s} H^s_{k,\ell,s} = w^s_{k,\ell,s} (\pi^{mig}_{o,k,\ell\neq o,s=o})^{\frac{\kappa-1}{\kappa}} N_s A^{\frac{1}{\kappa}}_{k,s} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{44}$$

$$w^s_{k,\ell,s} H^s_{k,\ell,s} = \sum_{o\neq\{\ell,s\}} w^f_{k,\ell,s} (\pi^{mig}_{o,k,\ell\neq o,s\neq o})^{\frac{\kappa-1}{\kappa}} N_o A^{\frac{1}{\kappa}}_{k,o} \Gamma \left(1 - \frac{1}{\kappa(1-\rho)}\right) \tag{45}$$

## C.1 Writing the equilibrium in proportional changes

Following Dekle et al. (2008), I re-write all equilibrium equations in proportional changes. That is, I can re-write each variable $x$ as $\hat{x} = \frac{x'}{x}$ where $x$ is the variable under the real scenario and $x'$ is the value of the variable under the counterfactual. In the remainder of this section, I show how this approach allows me to distinguish 4 components needed to estimate the model: parameters needed for estimation, endogenous variables, parameters not needed for estimation and data. I use the color scheme together with the equilibrium equations to clearly see how the different components affect the estimation of the model. Equations 37, 38, 43 and 44 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 $\ell$

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

2. Trade shares/ Domestic price index

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

3. Unit cost / high-skill unit cost

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

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

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

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

5. Low-skill market clearing / Migration share

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

6. Other-foreign market clearing

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

The equations above imply that the change in the endogenous variables can be computed as long as I have estimates of the 4 key elasticities ($\theta$, $\alpha$, $\lambda$ and $\kappa$), the Cobb-Douglas share on intermediate inputs $\gamma_{\ell,k,k'}$ and data on the following equilibrium allocations: Trade shares ($\pi^{trade}_{k,\ell,n}$); MNE shares ($\pi^{mne}_{k,s,\ell}$);

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

One of the advantages of the exact hat algebra procedure is that several parameters do not change between the real and the counterfactual so they do not need to be explicitly solved for. These parameters are MNE costs ($\delta^k_{\ell,s}$), producer comparative advantage ($T^k_s$), trade costs ($\tau^k_{\ell,n}$), production function labor shares ($\psi^l_{k,\ell}$, $\psi^h_{k,\ell}$, $\psi^d_{k,\ell,s}$, $\psi^s_{k,\ell,s}$, $\psi^f_{k,\ell,s}$), Total low-skill ($\bar{L}_\ell$) and high-skill ($N_\ell$) labor born in $\ell$, individual ability comparative advantage ($A_{o,k}$) and the migration costs ($\phi_{o,\ell,s}$). The hat-algebra approach makes it easier to calculate the counterfactuals. For example, the counterfactuals computed in sections 6.2 and 6.1 will compute how the equilibrium changes after an exogenous change of the MNE cost in all countries $\delta^k_{\ell,s}$ or the migration cost to the US $\phi_{o,us,s}$.

# D Dataset for counterfactual

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

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

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

**Migration shares and labor allocations ($\pi^{mig}_{o,k,\ell,s}$):** Migrant and native counts by origin country and industry in the US are taken from the 2012 American Community Survey (ACS) and for Canada from IPUMS International for the year 2011. For Europe, not all countries have micro data available so I use the surveys for France, Ireland and Spain in IPUMS international to calculate the distribution of migrants across industries. Total migrant counts for Europe are taken from the IAB brain-drain data (Brucker et al., 2013). A key piece of information that is not available in any survey is whether workers are employed by a domestic or foreign company. To impute such data, I use the FOIA dataset on H-1B and L-1 to back out the proportion of native, source-country and other foreign workers in the US by MNE source. As a first step, I compute the total ratio of foreign workers employed by firms from source $s$ relative to US firms using the FOIA data. Second, from the BEA data used to calculate MNE shares, I calculate the relative size of MNEs with source technology $s$ in industry k relative the size of US firms in industry $k$. These two ratios allow me to back out the likelihood of firms from $s$ to employ foreign workers relative to US firms. I then use the FOIA data to calculate how many source vs other foreign workers are employed by non-US MNEs in each industry. Since the FOIA data is just for the US, I impute the ratio of foreign to native college graduates for Europe and Canada. The ratios of Canadian firms in the US are used for US firms abroad. The results are robust to alternative imputation methods.

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

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

# E Counterfactual 1: A more restrictive migration policy

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

Table 13: Percent changes in employment shares

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

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

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

Table 14: Percent point changes in US trade shares

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

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

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

Table 15: Contribution of MNEs to output drop

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

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

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

Table 16: Welfare implications for alternative counterfactuals

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

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

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

Table 17: Robustness for ability dispersion and correlation

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

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

# F Counterfactual 2: Welfare gains of MNE production

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

Table 18: Welfare gains of MNE production by country

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

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

The literature on welfare gains of MNEs has generally looked at the relationship between MNE gains and gains from trade. To understand how the migration channel affects this relationship, I run two alternative counterfactuals that relate trade to MNE. First I look at what happens if MNE production is as in the observed equilibrium but trade costs are doubled. Results shown in Columns 1-3 in table 19 show the welfare gains from going from a situation with double trade costs to the observed equilibrium. At first glance, it is possible to see that opening trade has very different effect for migration than opening MNE activity since migration is a substitute for trade while it is a complement for MNE. Lowering trade costs generates a 51% decrease in migration in the US. The welfare gains from the no-migration model underestimate the gains for high-skill workers by 39% and overestimate the gains for low skill workers by a very large 5031%. When adding the high-skill migration channel, the large drop in migrants generated by opening up trade affects low skill workers negatively and offsets the positive effects from opening up trade. Such effects are muted when looking at both a decrease in trade costs and MNE costs in columns 4-6, but the trade impact is larger.

Table 19: Welfare of opening trade and MNE

| | Double trade costs | | | Double trade costs and prohibitive MNE costs | | |
|---|---|---|---|---|---|---|
| | Baseline | No migration | Relative to baseline | Baseline | No migration | Relative to baseline |
| Welfare high-skill natives US | 4.20% | 2.54% | -39% | 5.41% | 4.39% | -18.85% |
| Welfare low-skill natives US | -0.05% | 2.32% | 5031% | 2.04% | 3.87% | 89.74% |
| Total welfare US | 1.21% | 2.39% | 98% | 3.04% | 4.02% | 32.39% |
| | | | | | | |
| Migrants in US | -50.84% | | | -41.15% | | |

Columns 1-3: percent changes in welfare of going from double trade costs to the observed equilibrium. Double trade costs is the case where trade iceberg costs $\tau^k_{s,\ell}$ are doubled. Columns 4-6: percent changes in welfare of going from double trade costs AND MNE autarky to the observed equilibrium. Columns 3 and 6 show the welfare change in the no migration setting relative to the welfare change in the baseline model with migration.