The Global Race for Talent: Brain Drain, Knowledge Transfer, and Growth

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Abstract

How does inventors' migration affect international talent allocation, knowledge diffusion, and productivity growth? To answer this question, I build a novel two-country innovation-led endogenous growth model, where heterogeneous inventors produce innovations, learn from others and make dynamic migration and return decisions. Migrants interact with individuals at origin and destination, creating a network that diffuses knowledge within and across countries. To quantify this framework, I construct a micro-level dataset of migrant inventors on the US-EU corridor from patent data and document that (i) gross migration is asymmetric, with brain drain (net emigration) from the EU to the US; (ii) migrants increase their patenting by 42% per year after migration; (iii) migrants continue working with inventors at origin after moving, although less frequently; (iv) migrants' productivity gains spill over to their collaborators at origin, who increase patenting by 18% per year when a co-inventor emigrates. I calibrate the model to match the empirical results and study the impact of innovation and migration policy. A tax cut for foreigners and return migrants in the EU to eliminate the brain drain increases EU innovation but lowers US innovation and knowledge spillovers. The former effect dominates in the first 25 years, increasing EU productivity growth by 5%, but the latter dominates in the long-run, lowering growth by 6%. On the migration policy side, doubling the size of the US H1B visa program increases US and EU growth by 9% in the long run, because it sorts inventors to where they produce more innovations and knowledge spillovers.

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1 Introduction

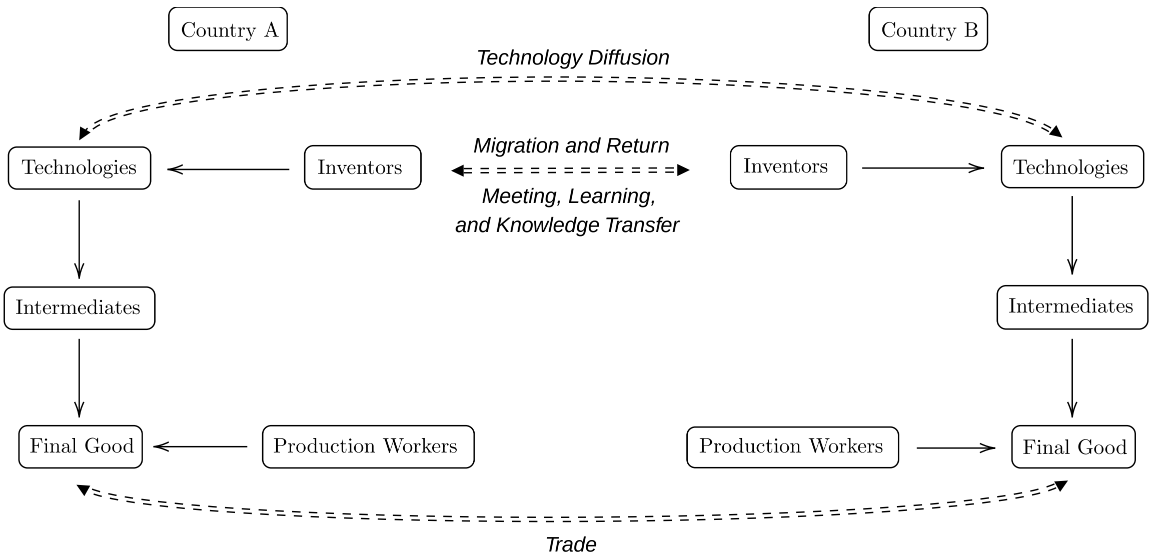
A prolific French inventor, Jean Calvignac, in 1998 moved to the Research Triangle Park in North Carolina, where he and his team initiated the IBM network processor activities. By then, he had filed over 40 patents at the European Patent Office (EPO) in France, with a network of over 100 collaborators. Most of them were French, but a handful were Americans. Calvignac's sojourn in the USA was likewise productive, with over 30 new patents filed in the EPO records. Even after moving to the US, he continued to work with some of his collaborators in France. In addition, over a hundred new collaborators benefitted from his knowledge and experience. About half of them worked in US labs, and half in French labs. Moving to North Carolina, Calvignac contributed to valuable innovation in the US, he expanded his network of co-inventors, and created collaboration bridges between the US and France. Each of those collaborators could then spread the acquired knowledge to their own network, creating a cascading effect of interactions and knowledge diffusion.

The migration of high-skilled knowledge workers remains an open and contentious topic of academic and policy debates because it creates various positive and negative effects on the economy, which are challenging to evaluate jointly. For the origin country, the fear of a "brain drain" is opposed by the benefit of cross-country knowledge transfers channeled by emigrants. On the other hand, for the host country, migrants bring valuable talent, but they might displace native workers. What are the aggregate implications of migration on the countries of origin and destination? Assessing the balance between positive and negative effects requires a framework that embeds micro-level migration decisions and interactions, mapping them into aggregate outcomes. What determines the decisions of individuals to migrate? How do individuals form their collaboration and interaction networks? How can we discipline this framework empirically? What is the quantitative importance of interactions for international knowledge diffusion? What is the role of policy in shaping these individual-level decisions and aggregate outcomes? The answers to these questions are central to policy debates concerning both sides of migration: brain drain and immigration.

This paper studies the impact of international migration on the allocation of talent, innovation, and knowledge transfer across countries, providing theoretical, empirical, and quantitative contributions. On the theoretical side, I develop a novel two-country model of innovation-based endogenous growth, with migration decisions and endogenous interaction networks, providing a micro-foundation for the cascading effects of international knowledge spillovers. On the empirical side, I link the model to micro-level data from the EPO, focusing on the migration corridor between the United States (US) and the European Union (EU). With these data, I document four new facts about the migration flows of inventors, the evolution of their productivity and interactions around the time of migration, and the change in productivity for their collaborators at the origin. I then use the empirical results to calibrate key parameters of the model. Finally, on the quantitative side, I use the calibrated model to quantify the various effects of migration and the impact of migration policies on the two economies.

In the theoretical section, the paper introduces a novel two-country general equilibrium model of innovation-based endogenous growth that highlights the role of international migration and knowledge diffusion in allocating scarce human capital. The model introduces two key novelties. First, migration decisions are micro-founded and shape migration flows, innovation, and talent allocation. Second, inventors accumulate human capital by learning from others within endogenous interaction networks which vary across countries.

Figure 1: Summary of the Model



The main elements of the models are summarized in Figure 1. In every period, inventors decide where to move, learn from others, and produce innovations, which improve goods quality and drive productivity growth. The size of innovations depends on inventors' heterogeneous talent and idiosyncratic country-specific productivity. Talent evolves endogenously due to learning from others. In particular, meeting probabilities are different for locals and immigrants and they depend on the distribution of inventors' types and a matrix of exogenous meeting frictions. This structure generates endogenous interaction networks that, in the quantitative section, match the empirical patent collaboration networks. Meetings across individuals in different countries generate international knowledge transfers, with cascading effects on the economy via the interactions system. Crucially, migrants continue to interact with locals in their origin country after migration, transferring knowledge and making locals more productive. Inventors then choose to migrate or return for three reasons: (i) innovations are more valuable in the country with higher TFP, (ii) learning opportunities differ across countries, and (iii) the idiosyncratic productivity component is country-specific. Individuals move in both directions due to the idiosyncratic country-specific productivity component. However, the most talented individuals tend to move to the country with the highest TFP and highest human capital and, upon moving, they learn more from the local interaction network, reinforcing the selection effect. Aggregate TFP increases as the result of local innovation and exogenous diffusion from the frontier.

The strength of this framework is that, by modeling migration decisions and interaction networks, it produces endogenous net and gross flows of migrants and knowledge spillovers that respond to economic conditions and policy. Existing models study either micro-level migration decisions, taking the macroeconomic environment as given, or macro effects of immigration on innovation, taking the flows of migrants as given. This model, instead, takes a global perspective on migration and is suitable to analyze the impact of policies on origin and destination countries jointly. I introduce two types of policies: taxes on inventors' profits and immigration restrictions. Policies have multiple effects. First, the direct effect is a change in net migration flows, affecting the number of inventors in each location. Three indirect effects then arise: (i) change in sorting patterns of inventors to the locations where they are most productive, (ii) change in international knowledge transfers, and (iii) change in technology diffusion from the innovation frontier. To quantify the effects of policy and discipline the framework empirically, I proceed to the empirical analysis.

The empirical section documents four novel results, which provide qualitative motivation for the new model ingredients and serve as quantitative targets to calibrate the key parameters. The empirical analysis of migration is challenging because it requires data that track individuals across countries and consistently measure their outcomes, which are very limited. To overcome this challenge, I build a new dataset of international migrants based on a recently developed panel of inventors from the EPO. Patent data offers a unique opportunity to observe (i) inventors' mobility, (ii) their output, measured by the number and quality of their patent applications, and (iii) their employers and co-inventors. I identify migrants from changes in the residential address of inventors registered in patent files, and I trace the entire network of co-inventors for migrants and locals. I focus on the migration corridor between the US and the EU, which accounts for most of my data. With this measure in hand, I document four main findings:

1. Migration flows between the EU and the US are asymmetric, with net immigration in the US (brain gain) and net emigration from the EU (brain drain).

2. After migration, EU and US migrants increase patent applications by 42% per year on average, relative to local inventors in their country of origin with similar observable characteristics who do not move.

3. Collaboration networks are heterogeneous for locals and migrants, as inventors are more likely to collaborate with individuals living in the same location or coming from the same origin. Nonetheless, migrants continue working with inventors at their origin after moving.

4. Local inventors increase their patent application by 18% per year on average after a co-inventor emigrates, relative to other local inventors who have a collaborator similar to the migrant who does not move.

Through the lens of the model, I interpret these findings as evidence that inventors tend to move to a place where they are more productive. In addition, migrants keep collaborating with inventors in their origin country and they diffuse knowledge internationally, making their collaborators at origin more productive.

In the quantitative section of the paper, I link the model to my data from the US and the EU by calibrating the parameters to match the empirical results. I then use the calibrated model to quantify the importance of knowledge spillovers and the effects of policy. I numerically solve for the Balanced Growth Path (BGP) equilibrium and the transitional dynamics of the model. To highlight the role of policy, I set the fundamental parameters of the productivity distribution and productivity shock processes to be the same across the two locations, and I let tax policy and migration barriers vary by location. I show that the calibrated model provides a good fit for targeted and non-targeted moments. Along the BGP, the two countries grow at the same rate, but the EU displays brain drain to the US, lower innovation, and lower aggregate productivity than the US. Nonetheless, the negative impact of brain drain on innovation is partly offset by international knowledge transfers. A counterfactual BGP simulation shows that shutting off international knowledge transfers exacerbates net emigration from the EU, which increases from 7% to 10%, and reduces innovation in the EU by 9%.

Concerns about the consequences of migration have motivated policy interventions both in the US and in European countries to manage migration flows. I study two two policy counterfactuals that replicate real-world policies : (i) a tax cut in the EU for foreigners and return migrants, and (ii) a change in visa caps in the US.

First, I simulate the transitional dynamics of the economy after a tax cut in the EU for foreigners and return migrants to eliminate the brain. As a result, innovation increases in the EU, but it declines in the US, lowering technology diffusion from the US to the EU. The former effect dominates in the short run, but the latter dominates in the long run. As a result, productivity growth in the EU increases by 5% in the first 25 years, but it declines by 6% in the new long-run equilibrium. I then decompose the impact of different forces to highlight the sizeable impact of knowledge transfers. By reducing migration flows, the tax cut also reduces international knowledge transfers, which account for a 10 percentage-points output decline in the long run.

Second, I study the impact of changes to the number of immigrants allowed to enter the US in every period, mimicking shifts to the H1B visa cap policy. Doubling the immigration cap exacerbates the brain drain from the EU. As a result, innovation declines in the EU, but it increases in the US, inducing more technology diffusion from the US to the EU. The former effect dominates in the short run, reducing EU productivity growth by 4%, but the latter dominates in the long run, increasing productivity growth by 9% for both the US and the EU in the new long-run equilibrium.

The results of this paper offer more general insight into high-skilled migration and raise new questions. The analysis focuses on inventors because of the unique availability of patent data. Nevertheless, the theoretical mechanisms illustrated in this paper apply to a broader category of high-skilled individuals such as students, engineers, scientists, STEM workers, and more general "knowledge workers". These individuals are motivated to migrate, at least in part, by the possibility of acquiring human capital, and they can generate knowledge spillovers with effects similar to the ones outlined in this paper. Additionally, the analysis focused on two main channels linked to emigration, talent allocation and knowledge transfer, which could be disciplined with the data at hand. Besides these channels, high-skilled emigration leads to other interesting effects, such as the impact on the demand side for talent by the private and public sectors or the impact on demographics and fertility, which await further research.

Related Literature. This paper relates to several strands of literature.

First, this paper builds on and contributes to the theoretical literature on endogenous growth. Unlike most papers in this literature that focus on the role of firms, this paper follows recent work which focuses on individuals (Lucas and Moll (2014), Akcigit et al. (2018), Akcigit et al. (2020)). Following Akcigit et al. (2018) and König et al. (2016), this paper combines elements of innovation-based growth models and diffusion-based growth models. As in classic innovation-based endogenous growth theories, in my model growth results from costly investment in innovation, which improves aggregate productivity (Romer (1990), Grossman and Helpman (1991a), Aghion and Howitt (1992), Jones (1995)). As in diffusion models (Kortum (1997), Lucas and Moll (2014), Perla and Tonetti (2014), Buera and Oberfield (2020), see Buera and Lucas (2018) for a review), agents in the economy can increase their productivity through interactions with others, which are typically described as draws from a specific exogenous or endogenous distribution. The contribution of this project is to introduce (i) endogenous international migration and (ii) endogenous interaction networks and knowledge spillovers within and across countries in a model of endogenous growth. Ehrlich and Kim (2015) study a model of endogenous migration and growth where skill-biased technological change drives high-skilled migration. Beine et al. (2001) connect migration and growth to educational choices. In my model, interactions shape incentives to migrate and provide a micro-foundation for knowledge transfer associated with migration. In this respect, this paper also relates to a literature on knowledge diffusion and imitation (Nelson and Phelps (1966),Cohen and Levinthal (1989), Kogut and Zander (1992), Acemoglu et al. (2006), Geroski (2000), Stoneman (2002), Eeckhout and Jovanovic (2002) and Comin and Mestieri (2014)). This paper also contributes to theories that connect economic growth and demography (Peretto (1998), Galor and Weil (2000), Jones (2022a), Acemoglu and Restrepo (2022), Greenwood et al. (2021)), by highlighting the connection between migration and growth.

Second, my paper also relates to work that studies the allocation of talent in the economy and how it influences economic growth. Talent is a scarce resource, thus allocating it efficiently is important to increase productivity. Hsieh et al. (2019), Cook and Kongcharoen (2010), and Buffington et al. (2016) document the importance of improving talent allocation across race and gender groups. Lagakos et al. (2018) and Porzio (2017) study cross-country differences in human capital accumulation and optimal allocation of talent and technology. Wuchty et al. (2007), Jones (2009), Jaravel et al. (2018), and Pearce (2020) study the importance of talent allocation in research teams. Jovanovic (2014)) and Akcigit et al. (2020) study the importance of education and occupational choice for talent allocation. This project contributes to this literature by studying the effect of migration on the allocation of individuals across countries.

Finally, this paper contributes to a large literature that studies the link between innovation, migration, and growth. Kerr (2007), Kerr (2008), and Foley and Kerr (2013) document the contribution of ethnic inventors to US technology formation, international technology diffusion, and multinational firm activity. Agrawal et al. (2006), Breschi and Lissoni (2009), Agrawal et al. (2011), Breschi et al. (2017), and Bernstein et al. (2018) use patent and citation data to document knowledge flows associated with migration. Iaria et al. (2018) show that international cooperation is important for knowledge diffusion. Recent work has documented the importance of immigrants for innovation in modern US (Bernstein et al. (2018)) and historical US (Akcigit et al. (2016), Arkolakis et al. (2019), Burchardi et al. (2020)). Ottaviano and Peri (2006) and Peri et al. (2015) document that immigrants generate positive spillovers on the wages of US natives. Moser et al. (2014) use historical evidence from Nazi Germany to document the impact of German scientists on US innovation. Parey et al. (2017) and Moser and San (2020) analyze the selection of migrants based on skills. A further review of the literature is provided by Kerr et al. (2016) and Kerr (2020). In this paper, high-skill immigrant flows can increase talent and the stock of ideas in the country of destination (as in Kerr and Lincoln (2010), Hunt and Gauthier-Loiselle (2010)), but they also displace local knowledge producers (as in Borjas and Doran (2012)). Although this body of work focuses on the effect of immigration on the receiving country, this paper makes a distinct contribution by additionally emphasizing the effect of emigration on the sending country. Additionally, this paper relates to recent work that documents the role of taxation in the mobility of superstar scientists and inventors (Akcigit et al. (2017), Moretti and Wilson (2017), Akcigit et al. (2022)) and studies the effect of taxation on long-run growth (Jaimovich and Rebelo (2017), Jones (2022b)).

The rest of the paper proceeds as follows. Section 2 describes the theory, starting with the environment and equilibrium, and then moving to the introduction of policies. Section 3 introduces the data and the empirical results. Section 4 presents the calibration of the model and the quantitative policy counterfactuals. Section 5 concludes.

2 Model

This section introduces an endogenous growth model that highlights the role of international migration and knowledge diffusion in allocating scarce human capital. Time is discrete, and two economies exist, labeled A and B. Each economy has a final-good sector, an intermediate-goods sector, and a technology sector. On the human capital side, individuals, at birth, are exogenously allocated to work as either production workers in the final good sector or as inventors in the technology sector. Inventors produce technologies that increase the quality of intermediate goods, driving productivity growth.

Inventors choose where to move, and they innovate and learn. They are born with heterogeneous talent and an idiosyncratic country-specific productivity shock. Talent increases over time due to learning from other inventors, whereas idiosyncratic country-specific productivity evolves stochastically. Interactions among inventors generate knowledge spillovers within and across countries. In every period, inventors choose where to move, subject to a moving cost and depending on their talent and country-specific productivity. At the aggregate level, when migration flows are asymmetric, the country with net emigration faces a "brain drain" and the other faces a "brain gain". Section 2.1 introduces two types of policies, taxes on inventors' profits and immigration restrictions. It also describes an application to the EU-US context, which is the benchmark for the quantitative analysis in Section 4.

The two economies are open to final-goods trade and capital markets, sharing a common exogenous interest rate r. By contrast, the technology sector is closed to trade, as in Grossman and Helpman (1991b).[1]

In this section, the analysis focuses on a BGP equilibrium where aggregate variables grow at a constant rate and talent distributions are stationary. I suppress the time index t in the model's description where it does not create confusion. The numerical analysis of transitional dynamics is presented in Section 4.

Innovation

The economies are populated by a unit mass of individuals of each nationality, A or B. Country-specific variables are indicated with c, for $c \in \{A, B\}$. Individuals survive to the following period with probability δ; when they exit the economy, they are replaced by a newborn individual. They have linear utility and discount factor β, and they spend their entire income on consumption of final-good in every period.

At birth, individuals are exogenously split into production workers or inventors. Let the mass of production workers in country c be denoted by L_c and the mass of inventors be denoted by I_c; then, the allocation of individuals across occupations implies that $L_c + I_c = 1$.

Inventors are allowed to move across countries. I use the term local inventors to denote those who live in their country of birth, and the term migrant inventors for those who live in a different country from where they are born in a given period. The mass of local inventors in country A is endogenous and denoted by μ_{AA}, where the first letter of the index indicates the country of origin and the second one the country of residence. Similarly, the mass of migrants from country A to B is endogenous and denoted by μ_{AB}. The endogenous masses of locals and migrants from country B are denoted respectively by μ_{BB} and μ_{BA}. The sum of locals and migrants thus equals the total number of inventors of each nationality, $\mu_{AA} + \mu_{AB} = I_A$, and similarly for B.

Inventors are born with heterogeneous talent z, drawn from an exogenous country-specific Pareto distribution, $\tilde{F}_c(z)$, with scale parameter equal to 1 and shape parameter θ_c. Additionally, they draw an idiosyncratic country-specific productivity differential ϵ from an exogenous distribution, $\Upsilon(\epsilon)$, with support on the real line.[2]

[1] Trading technologies and intermediate goods could allow innovations to instantly diffuse across countries. While this is not explicitly studied in this framework, the model captures this idea with an exogenous technology diffusion parameter σ, introduced later in this section. The speed of technology diffusion determines the relative productivity level across countries, which is a target moment in the quantitative section.

[2] In the quantitative section, the process for ϵ matches the average change in productivity for migrants after

Inventors produce technologies, or ideas. In every period t, an inventor with talent z_t and foreign productivity shock ϵ_t produces a bundle of technologies q_t with a linear production function:

$$q_t(z_t, \epsilon_t) = \begin{cases} z_t & \text{if local (living in the country of origin)} \\ \max\{z_t + \epsilon_t, 1\} & \text{if migrant (living abroad).} \end{cases}$$

Given that the talent distribution has support $z \geq 1$, it follows that $q \geq 1$, even if ϵ can take negative values. The foreign productivity differential captures idiosyncratic reasons why an inventor could be more productive abroad.[3]

For inventors of each type $j \in \{AA, AB, BB, BA\}$, I denote as $F_{j,t}(q)$ the endogenous distribution of innovation bundles produced by type j at time t.[4] I also denote the endogenous distribution of technology bundles produced in country $c \in \{A, B\}$ as F_c, which combines locals and immigrants.[5]

The evolution of talent, z, is endogenous due to interactions and learning, while the evolution of foreign productivity, ϵ, follows an exogenous mean-reverting process. In particular, ϵ evolves following an AR(1) stochastic process:

$$\epsilon_t = \rho\epsilon_{t-1} + v_t,$$

where $v_t \sim N(0, \omega^2)$. I denote by $\upsilon_{\epsilon_t|\epsilon_{t-1}}$ the CDF of ϵ_t, conditional on the $t-1$ value ϵ_{t-1}. I assume that, at birth, individuals draw the value ϵ from the stationary distribution of the AR(1) process, that is, the distribution Υ is a normal distribution with mean 0 and variance $\omega^2/(1-\rho^2)$.[6]

Next, I turn to the description of the endogenous evolution of talent as the result of interactions and learning.

Interactions and Learning

Inventors can improve their initial talent level, z, by learning from other inventors, as the result of random meetings. In every period, with probability λ an inventor has a meeting and her talent z increases; with probability $1 - \lambda$ an inventor has no meeting and her talent z remains unchanged.

A meeting results in learning for both inventors. When an inventor with talent z and innovation bundle q meets another inventor with talent $\hat{z}$ and innovation bundle $\hat{q}$, each of their talents evolves

migration. Notably, both EU and US migrants increase their patenting after moving. A model without country-specific productivity differential would not be able to match this result.

[3]For example, an inventor with expertise in a specific industry (e.g., automotive engineering) could be a good fit for a new project in a country where that industry is more developed (e.g. Germany). The productivity differential ϵ does not capture the network of inventors of a given country, which is instead explicitly modeled.

[4]The distribution $F_{j,t}(q)$ captures the joint density over ϵ and z.

[5]The endogenous distributions satisfy the following condition:

$$F_c(q) = \frac{\mu_{Ac}F_{Ac}(q) + \mu_{Bc}F_{Bc}(q)}{\mu_{Ac} + \mu_{Bc}}.$$

[6]Note that, under these assumptions, the distribution of ϵ in the population of individuals is equal to the stationary distribution of the AR(1) process.

according to the following learning function (regardless of their origin and residence):

$$z_t = z_{t-1}\hat{q}_{t-1}^{\eta} \qquad \text{and} \qquad \hat{z}_t = \hat{z}_{t-1}q_{t-1}^{\eta},$$

where $\eta \geq 0$. Given that $z, \hat{z}, q$ and $\hat{q}$ are weakly greater than one, an inventor's talent always increases after a meeting. The shape of the learning technology indicates that individuals with higher talent, z, learn relatively more from meeting an inventor with a large innovation, $\hat{q}$; formally: $\partial^2 z_t / \partial z_{t-1} \partial \hat{q}_{t-1} > 0$.[7]

The probability of meeting a specific inventor with bundle $\hat{q}$ depends on the interaction network and meeting frictions. Every inventor can meet any of the four types of inventors in the global economy: AA, AB, BA, BB. Conditional on having a meeting, the probability of an individual of type i meeting an individual of type j is denoted by $\psi_{i,j,t}$, for $i, j \in \{AA, AB, BA, BB\}$. The endogenous probability $\psi_{i,j,t}$ is the product of the endogenous relative frequency of type j in the economy multiplied by an exogenous meeting friction $\xi_{i,j}$, for $i \neq j$:

$$\psi_{i,j,t} = \frac{\mu_{j,t}}{\sum_{j' \in \mathcal{J}} \mu_{j',t}} \xi_{i,j}.$$

For the cases $i = j$, the values $\psi_{i,j,t}$ are derived from the condition that the probability of meeting any type must add up to 1: $\sum_{j \in \mathcal{J}} \psi_{i,j} = 1$ for all i.[8] The set of probabilities $\{\psi_{i,j}\}$ captures the endogenous interaction network in the global economy, where inventors meet within and across countries. The set of frictions $\{\xi_{i,j}\}$ captures meeting frictions across any two types.[9]

In general, locals and migrants meet a given type with different probabilities, as captured by the meeting frictions .[10] Thus, moving allows individuals to access different interaction networks and learning opportunities. Additionally, a migrant of origin c can still meet a local in origin country c after moving.[11] This type of meeting allows the migrant to create knowledge spillovers on locals at origin, who learn from their innovations and become more productive. Given that learning depends on the size of the innovation bundle, the meeting is particularly beneficial for locals because migrants produce larger innovations while abroad, due to the productivity differential ϵ.

Based on their talent, z, and productivity ϵ, inventors will compare expected values in country A and B to make their migration decision. These values capture learning prospects and returns to innovation. Before turning to migration decisions, I will describe the production of the final good, intermediate goods, and the market for ideas, which determine the returns for inventors.

[7] This learning technology induces highly talented individuals to move to the country with higher average talent. In equilibrium, this produces a sorting pattern that is consistent with the data, as illustrated in Figure 8 of Section 4.1. In Appendix A.8 I compare this learning function to the literature by introducing a general learning function, which nests equation (17) and several cases studied in the literature.

[8] The total number of meetings between individuals of type i and j is: $\mu_i \lambda \psi_{i,j} = \mu_j \lambda \psi_{j,i}$., which implies that $\xi_{i,j} = \xi_{j,i}$.

[9] Note that $\xi_{i,j} = 1$ for all i and j corresponds to the frictionless case; $\xi_{i,j} \neq 1$ for some i and j captures frictions in meetings. For example, frictions may indicate that two individuals are more likely to meet if they are in the same country or of the same type.

[10] In particular, this is the case whenever $\psi_{AA,j} \neq \psi_{AB,j}$ and $\psi_{BB,j} \neq \psi_{BA,j}$ for any $j \in \{AA, AB, BA, BB\}$.

[11] In particular, this is the case whenever $\psi_{AA,AB} \neq 0$ and $\psi_{BB,BA} \neq 0$.

Production of Goods

In each country $c \in \{A, B\}$, the final good $Y_{c,t}$ is competitively produced at time t using labor L_c and a continuum of intermediate goods $k_{j,c,t}$:

$$Y_{c,t} = \frac{1}{1-\alpha}(L_c)^{\alpha} \int_0^1 (A_{j,c,t})^{\alpha} (k_{j,c,t})^{1-\alpha} dj,$$

where $A_{j,c,t}$ is the quality of intermediate j at time t. The price of the final good is normalized to 1.[12] The final good optimization problem maximizes output minus payments to labor, $w_c L_c$, and to intermediate goods, $p_{j,c} k_{j,c}$. This problem delivers the following demand curve for intermediate input k_j:

$$P_{j,c} = (L_c)^{\alpha} (A_{j,c})^{\alpha} (k_{j,c})^{-\alpha}. \tag{1}$$

Each intermediate good is produced by a monopolist using the final good at marginal cost ψ. To simplify exposition, I assume $\psi = 1 - \alpha$.[13] Each monopolist maximizes profits subject to the demand curve coming from the final good:

$$\Pi_{j,c} = \max_{k_{j,c}, P_{j,c}} \left\{ P_{j,c} k_{j,c} - (1-\alpha) k_{j,c} \right\}, \qquad \text{subject to (1).}$$

The optimal profits for the intermediate-goods producer j are then given by $\Pi_{j,c} = \alpha L_c A_{j,c}$.

Aggregate productivity in economy c, $\bar{A}_c$, is defined as the average quality of intermediate goods: $\bar{A}_c \equiv \int_0^1 A_{j,c} dj$. It follows that the equilibrium workers' wage and aggregate output are linear in aggregate productivity and given by

$$w_c = \frac{\alpha}{1-\alpha} \bar{A}_c \tag{2}$$

$$Y_c = \frac{1}{1-\alpha} L_c \bar{A}_c. \tag{3}$$

Intermediate goods monopolists can purchase technologies to improve the quality of their goods. Next, I describe the production and transaction of technologies.

Market for Ideas

Intermediate-goods monopolists improve the quality of their product line in two ways. First, they purchase technologies from local inventors. Second, intermediates in the country with the lowest aggregate productivity (i.e., the laggard economy) benefit from exogenous technology diffusion from the country with the highest aggregate productivity (i.e., the frontier economy). I will describe each of these two processes in detail.

When an intermediate goods monopolist purchases a technology bundle q, the quality of the

[12] Note that the final good is traded, so its price is the same for the two countries.

[13] This assumption simplifies the solution in the goods market, but does not affect the main results.

product line increases by a step size $q\bar{A}$, i.e., quality $A_{j,c,t}$ will increase to $A_{j,c,t+1} = A_{j,c,t} + q\bar{A}_{c,t}$ after the purchase. Inventors and intermediate firms are matched in a country-level market for ideas.[14] When intermediate goods monopolists are matched to inventors, they pay a price $p_{j,c,t}(q)$ for the technology bundle q. In every period, the number of matches depends on the number of intermediate firms, IF_c, which is equal to 1, and the number of inventors residing in c, which is the sum of local inventors and migrant inventors. The number of matches is given by

$$x_{c,t} = (\mu_{Ac,t} + \mu_{Bc,t})^{\nu}(IF_c)^{1-\nu},$$

where μ_{Ac} are inventors of nationality A active in c, μ_{Bc} are inventors of nationality B active in c, and ν denotes the curvature of the matching technology. It follows that the technology-purchasing probability for firms and the technology-selling probability for inventors are respectively:

$$\frac{x_{c,t}}{IF_c} = (\mu_{Ac,t} + \mu_{Bc,t})^{\nu} \qquad \text{and} \qquad \frac{x_{c,t}}{\mu_{Ac,t} + \mu_{Bc,t}} = (\mu_{Ac,t} + \mu_{Bc,t})^{-(1-\nu)}.$$

The parameter ν governs crowding effects in the matches between firms and inventors. A value $\nu < 1$ indicates that a larger number of inventors in the economy leads to a lower matching rate per inventor, resulting in lower "realized" innovation per individual. Thus, immigration can crowd out innovation by locals by reducing the technology-selling probability for inventors.

The average bundle of ideas available in country c, defined as Q_c, is given by:

$$Q_{c,t} = \frac{\mu_{Ac,t}\int_1^{\infty} q dF_{Ac,t}(q) + \mu_{Bc,t}\int_1^{\infty} q dF_{Bc,t}(q)}{\mu_{Ac,t} + \mu_{Bc,t}}, \tag{4}$$

which is the weighted average of the technologies produced by locals and immigrants in c.

In addition to purchasing technologies, intermediate firms in the laggard country receive exogenous technology diffusion from the frontier economy at rate σ, at no cost. As a result, the quality of an intermediate firm will exogenously increase by the amount $\tilde{\sigma}_{c,t} = \sigma \max\{\bar{A}_{-c,t} - \bar{A}_{c,t}, 0\}$.[15]

Thus, the value of owning a product line with quality $A_{j,c,t}$, denoted by $J(A_{j,c,t}, t)$, is:

$$J(A_{j,c,t}, t) = \Pi_{j,c,t} + \frac{1}{1+r}\Bigg[x_{c,t}\Big(\int_1^{\infty}(J(A_{j,c,t} + \tilde{\sigma}_{c,t} + q\bar{A}_{c,t+1}, t+1) - p_{j,c,t+1}(q))dF_c(q)\Big) + (1 - x_{c,t})J(A_{j,c,t+1} + \tilde{\sigma}_{c,t}, t+1)\Bigg].$$

This value function has the following interpretation. On the right-hand side, the first term is the

[14] Intermediate monopolists cannot purchase technologies from foreign inventors. This assumption is meant to capture the local nature of "innovative labor services", as in Grossman and Helpman (1991b). That is, while inventors act as independent agents in this model, in the real world most inventors are employed by firms. Thus, they need to move to the country where a firm is located in order to sell their labor services to that given firm.

[15] Note that the size of the exogenous diffusion spillover is proportional to the productivity gap between the two economies. This structure guarantees the existence of a balanced growth path equilibrium where the two economies grow at the same rate. The parameter σ captures improvements in productivity of the laggard economy not driven by local innovation, such as technology diffusion driven by trade or foreign direct investment.

per-period profit $\Pi_{j,c,t,}$. The second term captures the change in firm value due to the purchase of technology, with probability $x_{c,t}$, which will increase quality by $q\bar{A}_{c,t+1}$, minus the cost of purchasing the idea. The probability of matching with a specific technology q depends on the distribution of bundles $F_c(q)$ in country c. The second term additionally captures the exogenous technology spillovers. I assume inventors appropriate all the surplus from the technology transaction. [16]

The profits of an inventor with talent z working in country c are given by the probability of matching with a firm multiplied by the revenues from selling technology q:

$$\pi_c(z,t) = (\mu_{Ac} + \mu_{Bc})^{\nu-1} p_{c,t}(q(z)). \tag{5}$$

Given their expected profits and learning opportunities in different countries, inventors make their migration decision, which I describe next.

Migration Decisions

In every period, inventors decide whether they want to move based on their idiosyncratic talent z, foreign productivity differential ϵ and the conditions of the global economy. Locals can emigrate subject to a fixed cost of migration $\kappa\bar{A}_{c,t}$. Migrants can return to their country of origin at no cost, and they can subsequently emigrate again.[17]

Let $V_{AA}(z,\epsilon,t)$ denote the value of a local inventor of nationality A, living in A, with talent z, and productivity abroad ϵ at time t. Similarly, let $V_{AB}(z,\epsilon,t)$ denote the value of a migrant born in A, living in B, with talent z, and productivity abroad ϵ at time t.

Let the value $W_{AA}(z,\epsilon,t)$ describe the migration problem for a local inventor in A, which satisfies the following Bellman equation for $j \in \{AA, AB, BB, BA\}$:

$$W_{AA}(z,\epsilon,t) = \max\{V_{AA}(z,\epsilon,t), V_{AB}(z,\epsilon,t) - \kappa\bar{A}_A(t)\}. \tag{6}$$

The interpretation of this value is the following. A local inventor in A makes a binary choice between the value of remaining a local, $V_{AA}(z,\epsilon,t)$, and the value of moving to B and becoming a migrant, $V_{AB}(z,\epsilon,t)$, minus the cost of migration $\kappa\bar{A}_A(t)$.

The value of a local inventor $V_{AA}(z,\epsilon,t)$ satisfies the following Bellman equation for $j \in \{AA, AB, BB, BA\}$:[18]

[16] This assumption implies $p_{j,c,t+1}(q) = \mathbb{E}[J(A_{j,c,t} + \tilde{\sigma}_{c,t} + q\bar{A}_{c,t+1}, t+1) - J(A_{j,c,t} + \tilde{\sigma}_{c,t}, t+1)$.The exact assignment of inventors to technologies does not matter for aggregate productivity growth along a BGP, because, as described in the next section, the value of a product line is linear in A_j, so that a certain technology produces the same improvement no matter which firm it is matched to.

[17] The assumption that migrants return for free is without loss of generality. Alternatively, an additional parameter for the cost of returning could be introduced into the model.

[18] This is the value of an inventor before being matched to an intermediate firm. The timing of events is the following: 1) inventors produce the technology bundle 2) if they meet a firm, they sell the bundle, 3) if the inventor survives, the following period starts 4) the new productivity differential ϵ' is realized 5) meetings occur 6) the inventor decides where to move.

$$
\begin{aligned}
V_{AA}(z,\epsilon,t) = \pi_A(z,t) + \beta\delta \int_{-\infty}^{\infty} \Bigg(\lambda \sum_j \psi_{AA,j,t} \int_1^{\infty} \left(W_{AA}(z\hat{q}^{\eta},\epsilon',t+1)\right) dF_{j,t}(\hat{q}) \\
+ (1-\lambda) W_{AA}(z,\epsilon',t+1) \Bigg) dv_{\epsilon'|\epsilon}.
\end{aligned}
$$

This value has the following interpretation. On the right-hand side, the first term indicates the current-period expected profits for the inventor, $\pi_A(z,t)$. The second term captures the continuation value, which is discounted by a factor β and survival probability δ. In period $t+1$, with probability λ, the inventor will have a successful meeting. If the meeting occurs, with probability $\psi_{AA,j}$, the inventor will meet an individual of group j and his talent will evolve to a value $z\hat{q}^{\eta}$, which depends on the distribution of bundles for inventors of type j. With probability $1-\lambda$, no meeting occurs and talent remains unchanged to z. Additionally, in $t+1$, idiosyncratic relative productivity term ϵ evolves to value ϵ'. After meetings occur, the inventor makes the migration decision, captured by the continuation value $W_{AA}(z,\epsilon,t)$.

The value $V_{AB}(z,\epsilon,t)$ of a migrant of nationality A and living in B takes the following form for $j \in \{AA, AB, BB, BA\}$:

$$
\begin{aligned}
V_{AB}(z,\epsilon,t) = \pi_B(z+\epsilon,t) + \beta\delta \int_{-\infty}^{\infty} \Bigg(\lambda \sum_j \psi_{AB,j,t} \int_1^{\infty} \left(W_{AB}(z\hat{q}^{\eta},\epsilon',t+1)\right) dF_{j,t}(\hat{q}) \\
+ (1-\lambda) W_{AB}(z,\epsilon',t+1) \Bigg) dv_{\epsilon'|\epsilon}.
\end{aligned}
$$

The value of a migrant $V_{AB}(z,\epsilon,t)$ has a similar interpretation to the value of a local $V_{AA}(z,\epsilon,t)$, with three important differences. First, current profits for a migrant, $\pi_B(z+\epsilon,t)$, depend on features of economy B. For example, if country B has higher aggregate productivity, all else equal, the same inventor will earn higher profits in B than in A. Second, while working in B, the migrant inventor will be subject to productivity differential ϵ, which could be positive or negative. Third, the migrant will interact with the various types of inventors with different probabilities than a local, governed by $\psi_{AB,j}$. These three differences correspond to three reasons why inventors choose to migrate in this model: (i) higher profits, (ii) idiosyncratic productivity gains, (iii) learning opportunities.

Finally, a migrant of type AB can choose to return to the country of origin, A, at no cost. The return problem for a migrant inventor born in A, living in B, with talent z, and productivity shock ϵ at time t is described by the continuation value W_{AB}:

$$
W_{AB}(z,\epsilon,t) = \max\{V_{AB}(z,\epsilon,t), V_{AA}(z,\epsilon,t)\}. \tag{7}
$$

The return decision depends on the evolution of the productivity differential ϵ. When ϵ falls to a sufficiently low value, the migrant decides to return to the country of origin, where innovation production only depends on talent z.

The migration and return problem for individuals of country B follow the same structure:

$$W_{BB}(z,\epsilon,t) = \max\{V_{BB}(z,\epsilon,t), V_{BA}(z,\epsilon,t) - \kappa \bar{A}_B(t)\} \tag{8}$$

$$W_{BA}(z,\epsilon,t) = \max\{V_{BA}(z,\epsilon,t), V_{BB}(z,\epsilon,t)\}. \tag{9}$$

where V_{BB} is the value of a local inventor born in B and living in B; V_{BA} is the value of a migrant inventor born in B and living in A. The values of inventors of origin B are specular of those of inventors of origin A, and are omitted for brevity.

The allocation of individuals across locations is central to aggregate productivity and the growth of each country, described in the next section.

Balanced Growth Path

In this section, I analyze a BGP equilibrium of the global economy where aggregate productivity grows at a constant rate in each country and talent distributions are stationary.[19] Definition 4 formally describes the BGP equilibrium concept.

I begin by describing the equilibrium in the market for ideas.

Proposition 1 *Along a BGP, technology is sold at per-unit price $p_{c,t}$, independent of j, as follows:*

$$p_{j,c,t} = p_{c,t} = \alpha \frac{1+r}{r} L_c \bar{A}_{c,t}. \tag{10}$$

Proof. See Appendix A. ■

After describing the equilibrium price of ideas, the next proposition describes the migration decisions in equilibrium.

Proposition 2 *Along a BGP, migration decisions are time-invariant.*

Proof. See Appendix A. ■

Next, I describe aggregate productivity growth in equilibrium. Define total innovation in country c as the probability that an intermediate firm is matched with an inventor times the expected quality of ideas available in country c, that is $\iota_c(t) \equiv x_c(t) Q_c(t)$. Additionally, let the productivity gap between economy A and B be defined as the ratio of their aggregate productivity; that is, $a(t) = \frac{\bar{A}_A(t)}{\bar{A}_B(t)}$. The following proposition describes the evolution of aggregate productivity in equilibrium.

Proposition 3 *Along a BGP, aggregate productivity grows at the same rate in each country:*

$$g_A = g_B = g = \max\{\iota_A, \iota_B\}, \tag{11}$$

[19] Appendix A presents a description of the law of motion for the distributions of talent and requirements for stationarity.

and the productivity gap is constant and equal to:

$$a = \begin{cases} \frac{\sigma}{\sigma+\iota_B-\iota_A} & \text{if } \iota_B > \iota_A \\ \frac{\sigma+\iota_A-\iota_B}{\sigma} & \text{if } \iota_B < \iota_A. \end{cases} \tag{12}$$

Proof. See Appendix A. ■

This result indicates that, even if innovation in the laggard economy declines, the two countries grow at the same rate, because the exogenous technology diffusion, governed by the parameter σ, is proportional to the TFP gap between the two economies. However, if innovation declines in the laggard economy, the TFP gap relative to the frontier will increase. Finally, if innovation in the frontier economy declines, the growth rate for both countries will decline.

Migration and interaction networks affect innovation and productivity through the mass of local and immigrant inventors (μ_j), and the average size of their innovations, which depends on the distributions F_j, as illustrated by equation (4). When an inventor relocates from the laggard to the frontier economy, it produces several effects. First, the mass of inventors decreases in the laggard economy but increases at the frontier. Second, the migrant produces larger innovations at the destination due to the productivity differential ϵ. Third, the migrant also transfers knowledge to the laggard economy by meeting local inventors at the origin. Finally, the laggard economy benefits from higher innovation at the frontier through the exogenous technology diffusion.

The next definition summarizes the characteristics of a BGP where aggregate productivity in each country grows at a constant rate and the productivity distributions are time-invariant.

Definition 4 ***Balanced Growth Path.*** *A BGP equilibrium consists of a constant growth rate g, a constant productivity gap a, and, for each country $c \in \{A, B\}$, paths for production workers wages $w_c(t)$, inventor profits $\pi_c(t)$, price of ideas $p_c(t)$, allocation of inventors across locations, $\mu_{AA}, \mu_{AB}, \mu_{BA}, \mu_{BA}$, productivity distributions $F_c(q)$ such that*

1. *The wage of production workers satisfies equation (2).*
2. *Profits of inventors satisfy equation (5).*
3. *Migration decisions are time invariant and solve equations (6),(7),(8), and (9).*
4. *The price of technology clears the market for ideas and satisfies equation (10).*
5. *The growth rate g and the productivity gap a satisfy equations (11) and (12).*
6. *Aggregate productivity $\bar{A}_c$ and aggregate output Y_c grow at rate g in each country.*
7. *The endogenous productivity distributions F_A and F_B are stationary, and the mass of individuals of each type $\mu_{AA}, \mu_{AB}, \mu_{BA}, \mu_{BA}$ is constant.*

2.1 Taxation and Migration Policies

In this section, I introduce two policies in the model: (i) taxes on inventors' profits, (ii) immigration caps. Inventors are subject to a country-specific tax rate τ_c. Thus, net profits are given by:

$$\pi_c(z,t) = (1-\tau_c)(\mu_{Ac}+\mu_{Bc})^{\nu-1} p_{c,t}(q(z)). \tag{13}$$

The government uses the tax revenues to fund a lump-sum transfer to production workers, balancing the budget in every period.[20]

Country A admits a free flow of foreign inventors, whereas country B enforces migration restrictions: every period, a mass of at most $\bar{\mu}$ inventors of nationality A is allowed to enter country B. If more than $\bar{\mu}$ inventors of nationality A want to move to B in a certain period, then $\bar{\mu}$ inventors are selected at random among those willing to move and allowed into country B.

Let $\mu^*_{AB,t}$ be the mass of local inventors of origin A who want to move to B at time t:

$$\mu^*_{AB,t} = \int\int \mathbf{1}\{V_{AB}(z,\epsilon,t) - \kappa \bar{A}_A(t) - V_{AA}(z,\epsilon,t) > 0\} g_{AA,t}(z,\epsilon) d\epsilon dz$$

where $g_{AA,t}(z,\epsilon)$ indicates the joint distribution over z and ϵ for locals in A. Then, the probability of being allowed to move, m_t, is given by the mass of people allowed to move over the mass of people who would like to move:

$$m_t = \min\left\{\frac{\bar{\mu}}{\mu^*_{AB,t}}, 1\right\}.$$

Thus, the continuation value $W_{AA}(z,\epsilon,t)$ for a local inventor born in A and living in A satisfies the following Bellman equation for $j \in \{AA, AB, BB, BA\}$:

$$W_{AA}(z,\epsilon,t) = \max\{V_{AA}(z,\epsilon,t), m_t\left(V_{AB}(z,\epsilon,t) - \kappa\bar{A}_A(t)\right) + (1-m_t)V_{AA}(z,\epsilon,t)\}. \tag{14}$$

I will next study the equilibrium of the model under a specific configuration of policies.

Application: Asymmetric Tax Rates

This model admits a variety of applications to different scenarios, depending on the configuration of the parameters. In the remainder of the paper, I consider an application to two countries with asymmetric tax policies, namely, $\tau_A < \tau_B$. In addition, countries have asymmetric migration policies, as previously outlined: country A has free immigration policy, whereas B admits no more than $\bar{\mu}$ inventors per period. I then assume that the talent structure is identical across countries, as outlined in Assumption 1. [21]

[20] Thus, total income for production workers is $w_c + T_c$ where T_c is the lump sum transfer from the government. To balance the budget, transfers must satisfy the following condition: $\tau_c(\mu_{Ac}+\mu_{Bc})^{\nu}\int p_{c,t}(q(z))dF_c(z) = T_c L_c$

[21] This structure mimics the migration corridor between the EU (country A) and the US (country B), which is analyzed in the Empirical Section 3 and in the Quantitative Section 4.1. A different application of this model could

Assumption 1 *The exogenous occupational allocation, talent distribution, and location preference process are identical across countries:* $I_A = I_B$ *and* $\theta_A = \theta_B$*.*

I also consider a particular structure for the meeting frictions, reflecting that individuals are more likely to meet others in the same location. Thus, a migrant inventor is more likely to meet individuals at the destination than at the origin. This structure is formalized in Assumption 2.[22]

Assumption 2 *Compared to locals in A, migrants of nationality A are*

(i) more likely to meet other migrants from A ($\xi_{AB,AB} > \xi_{AA,AB}$)*,*

(ii) more likely to meet locals in B ($\xi_{AB,BB} > \xi_{AA,BB}$)*, and*

(iii) less likely to meet migrants from B in A ($\xi_{AB,BA} < \xi_{AA,BA}$)*.*

Similarly, for country B, $\xi_{BA,BA} > \xi_{BB,BA}$*,* $\xi_{BA,AA} > \xi_{BA,AA}$*, and* $\xi_{BA,AB} < \xi_{BB,AB}$*.*

Under Assumptions 1 and 2, along a BGP, migration decisions take a threshold form. In particular, more talented individuals are more likely to move from A to B and less likely to move from B to A for any given value of their productivity shock ϵ. This characterization of migration decisions is formalized in Proposition 5.

Proposition 5 *Under Assumptions 1 and 2, along a BGP, there exist thresholds* $\bar{z}_{AA}(\epsilon)$*,* $\bar{z}_{AB}(\epsilon)$*,* $\bar{z}_{BB}(\epsilon)$*, and* $\bar{z}_{BA}(\epsilon)$ *such that individuals with state* (z, ϵ) *of type:*

- *AA move to B if* $z > \bar{z}_{AA}(\epsilon)$*, given* ϵ*; AB return to A if* $z < \bar{z}_{AB}(\epsilon)$*, given* ϵ*;*
- *BB move to A if* $z < \bar{z}_{BB}(\epsilon)$*, given* ϵ*; BA return to B if* $z > \bar{z}_{BA}(\epsilon)$*, given* ϵ*.*

Proof. See Appendix *A*. ■

The intuition for the threshold migration rules is the following. Profits are higher in B because of lower taxation, and they are linear in talent, z. Thus, given the fixed moving cost κ, individuals with higher talent gain relatively more from moving to B. The flow of talented individuals toward B endogenously increases average talent in B, due to interactions, despite the exogenous talent distributions being identical across countries. Higher average talent, in turn, attracts more talented inventors to B for two reasons. First, due to Assumption 2, inventors in country B are more likely to meet locals in B and immigrants, who have high talent. Second, the learning technology is linear in own talent, z; thus, more talented inventors gain more from an interaction network with a higher average talent. In equilibrium, country B has more numerous and talented inventors, resulting in higher innovation and aggregate productivity.

illustrate migration between a developed and a developing country. For instance, if $\theta_B > \theta_A$, the exogenous average talent is lower in A, representing a less developed education system.

[22]This structure is consistent with the observations on collaborations in the microdata, as discussed in Section 3. These data are used to calibrate meeting frictions in Section 4.

Why do migrant inventors ever return to their origin country? In this model, return decisions result from the evolution of the productivity shock, ϵ. For a given value of z, locals move when their productivity abroad, ϵ, is high enough. Once they are abroad, they decide to return if ϵ evolves to a sufficiently low value. This result is formalized in Proposition 6. Heterogeneity across ϵ also implies that not all individuals with the same talent z make the same decisions. Those with high enough ϵ choose to move abroad, whereas the others stay.

Proposition 6 *Along a BGP, there exist thresholds $\bar{\epsilon}_{AA}(z)$, $\bar{\epsilon}_{AB}(z)$, $\bar{\epsilon}_{BB}(z)$, and $\bar{\epsilon}_{BA}(z)$ such that individuals with state (z, ϵ) of type:*

- *AA move to B if $\epsilon > \bar{\epsilon}_{AA}(z)$, given z; AB return to A if $\epsilon < \bar{\epsilon}_{AB}(z)$, given z;*
- *BB move to A if $\epsilon > \bar{\epsilon}_{BB}(z)$, given z; BA return to B if $\epsilon < \bar{\epsilon}_{BA}(z)$, given z.*

Proof. See Appendix *A*. ■

The equilibrium of the model is solved numerically in Section 4, which also provides a visualization of the migration thresholds and stationary talent distributions. First, I turn to the description of the empirical results.

3 Data, Measurement, and Empirical Findings

This section documents empirical results on migration flows, migrants' productivity, interaction networks, and spillovers on local inventors. I begin with a description of the data and then proceed to the empirical strategy and results.

3.1 Data

Two primary sources of data on patents and inventors are used for the empirical analysis: the data on migratory patterns of inventors by Miguelez and Fink (2013), and the disambiguated inventor data by Coffano and Tarasconi (2014).

Patent data have unique features for studying international migration. The empirical study of international migration is challenging because of the limited availability of data that track individuals across countries and consistently measure their output. Patent documents contain rich information on patent assignees (who own property rights on the patent and can be a firm, an individual, or other types of institutions), the individual inventors who worked on the innovation, and a description of the innovation itself. Importantly, patent documents allow for inventors to be tracked over time and for their addresses to be recorded, which is helpful to identify migrants, as I detail below. As a result, patent data provide (i) a measure of individual-level mobility, tracking inventors across countries when they move, (ii) a consistent measure of inventors' output and productivity, as measured by patent applications, and (iii) information on collaborations, given by the list of individuals appearing as co-inventors on each patent.

The data on migratory patterns of inventors by Miguelez and Fink (2013) is extracted from information included in patent applications filed under the Patent Cooperation Treaty (PCT). The PCT is an international treaty administered by the World Intellectual Property Organization (WIPO), which facilitates the route for seeking international patent protection. The PCT data cover about 54 % of all international patent applications. Individuals can file a PCT application only if they are nationals or residents of a PCT member country. Thus, PCT applications have the unique feature of recording both the residence and nationality of inventors for most patents to verify the applicants' eligibility. A migrant is defined as someone who lives in a country other than the country of nationality. Due to records on nationality, these data offer a comprehensive measure of migration that I use to quantify aggregate migration flows. Nevertheless, the migratory patterns of inventors by Miguelez and Fink (2013) are only available at the country level and do not allow observation of individual patents. For this reason, I turn to the data by Coffano and Tarasconi (2014) to enrich the analysis with individual-level observations.

The disambiguated inventor data by Coffano and Tarasconi (2014) cover inventors who filed patents with the EPO in the period 1978-2016. They include the patent number, the name, and address of all inventors who contributed to the patent, the name and address of the assignee who owns property rights on the patent, the technology class of the patents, and all citations to prior work listed on the patents. Notably, the disambiguated data identify the same inventor over time in different patent applications, even across different addresses.

Measuring Individual-Level Migration

The disambiguated EPO data do not provide information on the nationality of inventors. Thus, I develop a procedure to identify international migrants. The inventor's address provides information on the country of residence and reveals when an individual migrates to a different country. I identify migration as a change of address across different countries over time. I measure the time of migration as the date of the first patent application in the new country. This procedure allows the observation of rich information on migrants before and after migration, including the number of patent applications, the firm they work for, and the individuals they work with. This procedure also has shortcomings. First, only individuals with at least two patents can be categorized into migrants and non-migrants, because the procedure compares addresses in different patent applications. Second, individuals who migrate before ever filing a patent will not be categorized as migrants with this procedure. Thus, this procedure tends to undercount migrants. For this reason, I rely on PCT as a source for aggregate flows.

The result of this procedure is a new dataset that records the mobility of inventors. Nonetheless, observing an inventor moving from a specific origin to a destination does not imply that the place of origin coincides with the individual's nationality. I thus complement the dataset with an analysis of the ethnic origin of names using the commercial software "Namsor".[23] The software takes as

[23]See Kerr (2008) and Breschi and Lissoni (2013) for a similar approach to the analysis of ethnic origin of inventors' names.

inputs the first and last name and country of residence and returns the most likely country of origin, based on an algorithmic search of administrative databases. Then, I use this information to infer the most likely country of origin of the international migrants in my dataset.[24]

The EPO data contain records of 4,029,289 unique inventors, of which 1,293,431 file more than one patent and can be classified into migrants and non-migrants. I identify 12,743 unique migrants. For individuals who file at least three patents, I can also define "Return Migrants" as those migrants who return to their first country after filing patents in another country for a certain period. I identify 2,371 return migrants in the data. The EU and the US are the two most prominent geographical locations covered in the dataset, accounting for 66% of total inventors and 76% of all migrants. For this reason, in the calibration of the model, I set the EU to be location A and the US to be country B (see section 4.1), and thus, the empirical results will focus on migration between the US and the EU. Summary statistics on inventors and migrants in the EPO data are reported in Table B.1.

The PCT data and the EPO data provide complementary information on migration. The PCT provides systematic information on aggregate migration flows. The EPO data provides rich micro-level data on migrants. Together, the two datasets offer a comprehensive view of the migration of inventors.

Measuring Productivity and Interactions

The empirical analysis sheds light on key channels of the model, particularly on how migration is connected with changes in productivity and interaction networks of inventors. In this section, I describe the measurement of individuals' productivity and interactions in the patent data, following the literature on innovation (most closely, Akcigit et al. (2018)).

My benchmark measure of the innovative output of an inventor is the number of patent applications submitted by individual i in year t, denoted by $p_{i,t}$. Other measures of productivity commonly used in the innovation literature are based on the number of forward citations. I produce two additional measures of an inventor's productivity: (i) total citations per year, given by the sum of all citations received by all patents submitted in year t by inventor i; and (ii) truncated citations per year, given by the sum of citations in a three-year window after application for all patents submitted in year t by inventor i, to account for the issue of truncation of citations.[25] The literature commonly considers forward citations as a measure of patent quality. However, for EPO and PCT, the procedure to collect citations can differ across regions and across patent filing procedures (see OECD (2009)).[26] As a result, using citations to assess the productivity of a mi-

[24] Further details on sample construction are provided in Appendix B.

[25] The issue of truncations in the citations indicates that older patents tend to have more citations because they have had more years to accumulate them, as described in Hall et al. (2001).

[26] The literature on innovation and citations is mostly based on data from the United States Patents and Trademarks Office (USPTO). Applicants at the USPTO are legally required to include a full list of the prior art known or believed to be relevant, and failure to do so can result in patent litigation and penalties. Such a requirement does not exist at EPO, where citing prior art is optional, and examiners add most citations. See OECD (2009) for further details.

grant across different locations can be misleading because citations could be collected differently in different locations. This issue is evident Panel B of Table B.1, presenting the average value of a set of variables in the full sample, EU sample, and US sample. All variables take similar values across the EU sample and US sample except for citation measures, which are substantially lower in the US sample. Due to this issue, I use patent count as the main measure of productivity and use citations for robustness checks.

To measure interactions, I rely on records of co-inventors, that is, inventors listed on the same patents. In particular, I define the co-inventors of individual i in year t as all inventors who are listed on patent applications submitted by i in year t.

3.2 Empirical Findings

In this section, I present the empirical results, which document four main findings:

(i) Migration flows between the EU and the US are asymmetric: the US exhibits net immigration (brain gain), and the EU net emigration (brain drain).

(ii) Migrants tend to become more productive after migration.

(iii) Collaboration networks are heterogeneous for locals and migrants and migrants continue working with inventors at origin after moving.

(iv) Local inventors tend to become more productive after a co-inventor emigrates.

These results inform important channels of the model, and I use them to calibrate key parameters, as detailed in Section 4.1.

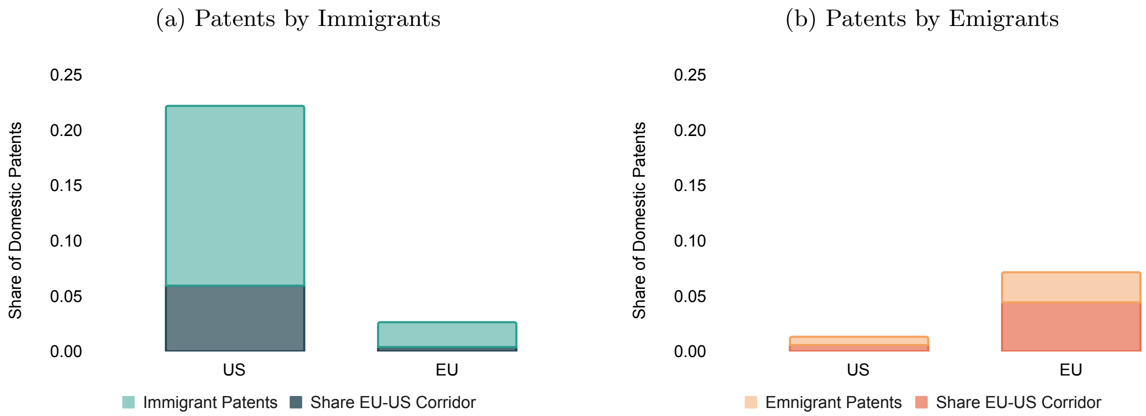
Migration Flows between the EU and the US

Migration flows for the EU and the US are depicted in Figure 2, based on PCT data. Panel (a) shows patents filed by immigrants as a share of all patents filed by US locals. Over the period 2000-2010, patents filed by immigrants in the US accounted for about 22% of patents filed by locals in the US under the PCT. EU immigrants accounted for about 27% of all patents filed by immigrants in the US.[27] By contrast, in the EU, patents filed by immigrants accounted for only about 3% of patents filed by EU locals. US immigrants in the EU accounted for about 15% of all patents filed by immigrants.

Panel (b) shows patents filed by emigrants as a share of domestic patents in the location of origin. The magnitude of flows across locations is now reversed. Patents filed by US emigrants account for only about 1% of patents filed by locals in the US; 40% of emigrant patents are accounted for by US emigrants to the EU. On the other hand, patents filed by EU emigrants are about 7% of patents filed by local Europeans, and emigrants to the US account for 62% of all emigrants' patents.

[27] The EU is the largest origin of immigrant inventors to the US, followed by China and India.

Figure 2: Immigration and Emigration of Inventors in US and EU, 2000-2010



Note: Panel (a) illustrates the patents filed by immigrants as a share of patents filed by nationals in the US and EU. Panel (b) illustrates the patents filed by US and EU emigrants in foreign countries as a share of patents filed by US and EU nationals in the home country. The figures also highlight the share of patents accounted for by the migrants in the EU-US corridor for each group. Source: PCT Dataset.

Migration flows are thus largely asymmetric. The US attracts many foreign immigrants and exports relatively few emigrants, thus experiencing a "brain gain". On the other hand, more emigrants are leaving the EU than the immigrants are arriving, resulting in a "brain drain". This asymmetry is true both when considering the US-EU migration corridor, as well as when considering broader migration flows with the rest of the world.

After documenting aggregate migration flows, I turn to individual-level data, to document results about individual migrants and their co-inventors. In particular, I will explore whether the aggregate migration flows are accompanied by indirect effects along two dimensions:(i) whether migrants become more productive after moving and (ii) whether migrants generate positive spillovers on locals.

Evolution of Productivity of Migrants

The previous section documented large and asymmetric migration flows. A potential positive consequence of migration, at the individual level, is that individuals might relocate to a place where they are more productive, thus producing more innovation. This motif for migration is consistent with the model, where individuals make migration decisions based on location-specific productivity shocks. This section describes how patenting activity evolves for migrants before and after they move. Migration decisions are endogenous to productivity outcomes. Thus, this section does not aim to identify the causal effect of migration on innovative activity; but, rather, it documents the dynamics of patenting productivity around the time of migration.

The evolution of innovative activity for migrants is documented with an event study centered around the time of migration, using a difference-in-differences design. A potential concern is that inventors' productivity may follow a different trajectory than the general population of inventors.

To address this concern, I compare migrants with a "placebo" control group of local inventors who appear similar to migrants before migration, never moved internationally, and are not co-inventors of migrants, following Jaravel et al. (2018). To build the control group, I use a one-to-one exact matching procedure on the country of origin, the first year in the sample, the cumulative number of patent applications at the time of migration, and experience at migration. [28] Additionally, I require individuals in the control group to file for a patent in the first year after the migration, consistently with the sample construction of actual migrants. Using this procedure, 955 out of 1,057 migrants from the EU to the US find an exact match, and 504 out of 518 migrants from the US to the EU find an exact match. Thus, the matching procedure results in a total of 2,917 individuals, which I use for the analysis. Tables B.2 and B.3 in Appendix B present the summary statistics before and after matching for individuals of EU and US origin, respectively.

Panel A of Figure 3 shows the path of mean patent applications per year for migrants (solid line) and the placebo control group (dashed line) around the year of migration. This figure shows that the patent activity of migrants is on a similar trajectory as the placebo control group before the time of migration, but it increases after. Notice that the construction of the control group is such that migrant and placebo inventors have the same cumulative stock of patent applications by the time of migration, but the dynamic trajectory is not matched. The raw means for migrant and placebo inventors offer a transparent depiction of the data and bolster credibility of the empirical exercise, but cannot control for potential individual, year, or age-profile fixed effects nor for potential mechanical effects due to the construction of the sample. To address these concerns, I turn to a regression framework.

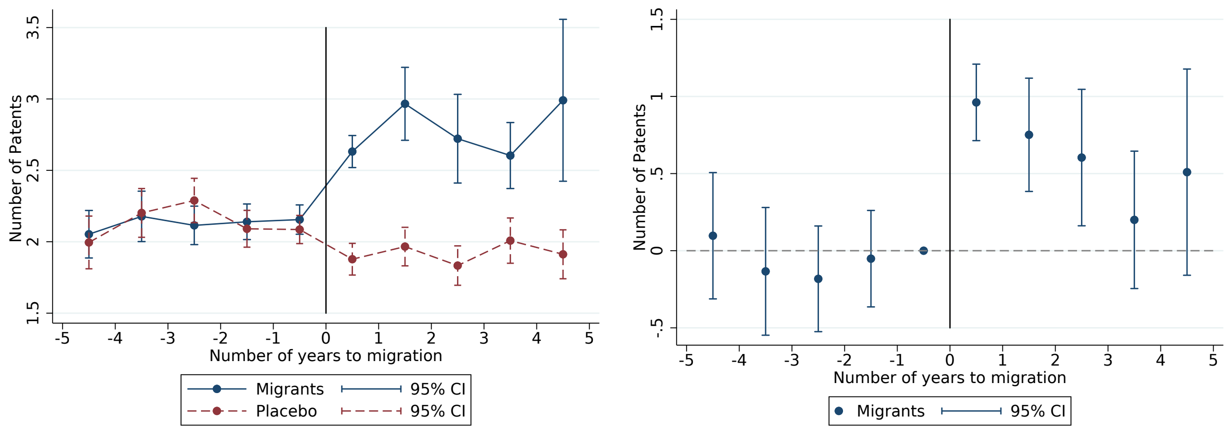
To study the dynamics of productivity around the time of migration, I implement an OLS specification that includes the following elements. First, I include a set of leads and lags around migration time for migrants (L_{it}^{Mig}) associated with the coefficients $\{\beta_\tau^{Mig}\}_{\tau=-5}^{5}$, where τ denotes time relative to the year of migration. Second, I include a set of leads and lags around the time of migration that is common to both the migrants and the controls (L_{it}^{All}) associated with the coefficients $\{\beta_\tau^{All}\}_{\tau=-5}^{5}$. In addition, I include individual fixed effects (α_i), year fixed effects (α_t), and experience fixed effects (α_e). The resulting OLS specification is the following:

$$x_{it} = \sum_{\tau=-5}^{5} \beta_\tau^{Mig}\ \mathbf{1}[L_{it}^{Mig} = \tau] + \sum_{\tau=-5}^{\tau=5} \beta_\tau^{All} \mathbf{1}[L_{it}^{All} = \tau] + \alpha_i + \alpha_t + \alpha_e + \epsilon_{it}. \tag{15}$$

The main outcome variable of interest, x_{it}, will be the number of patent applications per year. The coefficients of interests are $\{\beta_\tau^{Mig}\}_{\tau=-5}^{5}$, which denote the differential productivity of migrants. The individual fixed effects control for permanent individual characteristics, whereas the lags and leads common to all (L_{it}^{All}) control for joint dynamics around the time of migration.

[28] When more than one exact match is made, ties are broken at random. When individuals migrate more than once, I consider the time of the first migration. Matching on additional variables such as the cumulative number of citations at the time of migration or technology field is possible, but it reduces the number of exact matches substantially.

Figure 3: Patenting Activity by Migrant Inventors around Time of Migration



Note: The figure displays changes in migrants' productivity around migration time realtive to the placebo control group. Panel (a) displays the raw means. Panel (b) displays the estimated coefficients from the regression specification in equation (15). Unbalanced panel. EU migrants: 5,976 obs. US migrants: 2,907 observations. EU placebo: 5,189 observations. US placebo: 2,474 observations. SE clustered at inventor level.

To summarize the results, I use a more parsimonious specification, with a dummy turning to 1 after the time of migration for migrants ($AfterMigration_{it}^{Mig}$) and another dummy turning to 1 after migration for all ($AfterMigration_{it}^{All}$). The specification is the following:

$$x_{it} = \beta^{Mig} AfterMigration_{it}^{Mig} + \beta^{All} AfterMigration_{it}^{All} + \alpha_i + \alpha_t + \alpha_e + \epsilon_{it}. \tag{16}$$

Panel B of Figure 3 reports the estimates and 95 % confidence intervals for the coefficients β_τ^{Mig} from specification (15). [29] The figure indicates that migration is associated with an increase in patent applications per year for migrants, compared to the placebo control group. The increase in productivity accrues immediately upon migration and then declines over time. The figure also shows no pre-trends before migration, bolstering the credibility of the empirical exercise.

To summarize the results, I implement specification (16). The results are reported in column (1) of Table 3. The estimated coefficient for β^{Mig} indicates that migrants apply for 0.86 more patents per year than the locals in the placebo control group after migration on average, with a standard error of 0.09. The coefficient is statistically significant at the 1% confidence level, and the magnitude is economically large: it indicates that patent applications for migrants after migration increase by about 43% relative to the sample average (equal to about two patent applications per year for individuals in the event study sample).

I use the same specification to investigate the heterogeneity of this result. In columns (2) and (3), I explore whether the effect is different for the subsample of migrants of EU and US origin

[29] The point estimate on the lag in the year before migration is normalized to 1.

respectively. The point estimates indicate that the average increase in patents relative to the locals per year after migration is 0.89 for Europeans and 0.84 for Americans. These estimates correspond to an increase in patent applications per year after migration of about 42% relative to the sample average (which is 2.1 patent applications per year for Europeans and 2 for Americans).[30]

Table 1: Patenting Activity of Migrants around the Time of Migration

	Number of Patent Applications per Year		
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Migration	0.8592***	0.8861***	0.8353***
	(0.0945)	(0.1067)	(0.2071)
Obs	16546	11165	5381
R2	0.390	0.438	0.344
Inventor FE	X	X	X
Year FE	X	X	X

Notes: The table displays the estimated change in migrants' productivity around migration time realtive to the placebo control group from the regression specification in equation (16). Column (1) displays the benchmark regression results for all migrants along the US-EU corridor. Column (2) includes only the sample of migrants of EU origin. Column (3) includes only the sample of migrants of US origin. Standard errors clustered at inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Appendix B reports a series of additional robustness checks. A recent literature highlights limitations of the two-way fixed-effects regressions model as in equation (15). I show that results are similar when using different estimators. An additional concern is that many migrants remain employed for a foreign subsidiary of the same company after moving. The observed change in patenting could then be the consequence of a reorganization at the firm level, which involves the reallocation of individuals and increases in productivity. To rule out this possibility, I show that the effects are robust for migrants that switch companies. Finally, I show robustness across a range of citation-based measures.

Overall, these finding suggests that migrants tend to become more productive after migration, consistently with the model. This result helps inform the calibration of the expected increase in productivity for a migrant relative to a local inventor. Next, I turn to productivity dynamics for local inventors.

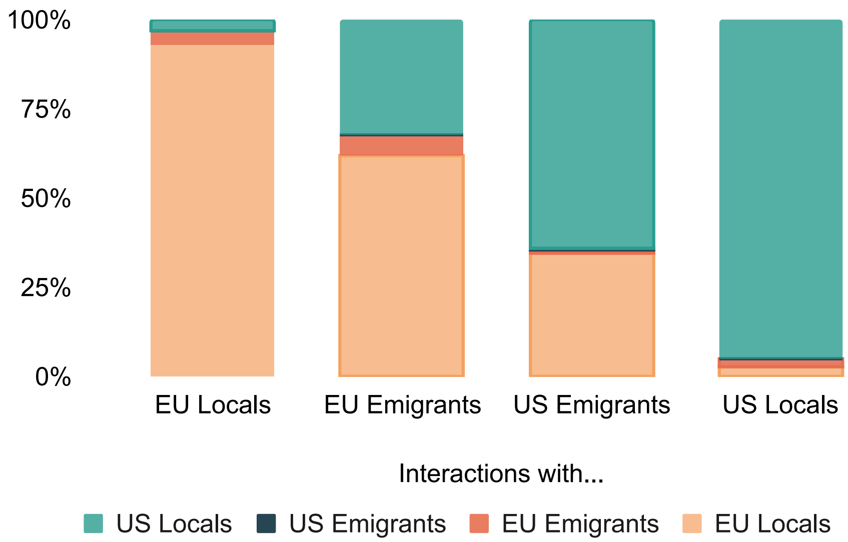
Interaction networks.

In the model, collaboration networks are different for locals and migrants. Nonetheless, migrants continue interacting with inventors at their origin after migration. To discipline interaction networks in the data, I explore the network of co-inventors of locals and migrants, as a measure of their interactions.

[30]Dynamic event studies for the EU and US samples are reported in Appendix B.

I consider four groups of inventors in the data: EU locals, EU emigrants (i.e., migrants from the EU to the US), US locals, US emigrants (i.e., migrants from the US to the EU). For each inventor, I collect the set of all their collaborations, that is, the list of all of their co-inventors. [31] Then, for inventors in each group, I compute the share of co-inventors who belong to the same group, or each of the other three groups. The results are displayed in Figure 4.

Figure 4: Interaction Networks



Note: Figure based on the inventor-coinventor pairs in the EPO dataset. Inventors are grouped into four categories: EU locals, EU migrants, US migrants and US locals. For each cateogry, the co-inventors are also grouped into the same four categories. The figure displays the share of co-inventorship relationships belonging to each category.

The figure shows that locals co-invent mostly with other locals in the same location. In particular, for EU locals, the share of EU local co-inventors is 93%, while EU emigrants account for 4% of their collaborations, US locals for 3%, and US emigrants only 0.2%. For US locals, the share of US local co-inventors is 95%, while US emigrants account for 0.3% of collaborations, EU locals for 3%, and EU migrants for 2%. Co-inventors are more heterogeneous for migrants. In particular, for EU emigrants, 62% of co-inventors are EU locals, 6% are other EU emigrants, 32% are US locals, and only 0.1% are US emigrants. For US emigrants, 62% of interactions are with US locals, 4% with other US emigrants, 33% with EU locals, and 1% with EU emigrants.

Figure 4 provides evidence that migrants have a different interaction network than locals. However, it does not reveal whether the interaction network changes for migrants after migration, or whether migrants already had a different pattern of interaction than the average local before moving. To explore the dynamics of the migrants' interactions, I implement the regression model described in equation (16) on the sample of migrant inventors and placebo control group. The results are displayed in Table 2. The outcomes of interest are the share of migrants' co-inventors who are locals

[31]If two inventors co-patent more than one time, I include the pair multiple times. Results are similar when including a unique observation per pair.

Table 2: Interactions of migrants around the time of migration

-Panel A: Share of Local Co-Inventors at Origin-			
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Migration	-0.1327***	-0.1381***	-0.1207***
	(0.0100)	(0.0120)	(0.0182)
Obs	15237	10172	5065
R2	0.739	0.716	0.772
Inventor FE	X	X	X
Year FE	X	X	X

-Panel B: Share of Local Co-Inventors at Destination-			
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Migration	0.1232***	0.1270***	0.1164***
	(0.0091)	(0.0107)	(0.0170)
Obs	15237	10172	5065
R2	0.721	0.697	0.752
Inventor FE	X	X	X
Year FE	X	X	X

Notes: The table describes the change in the share of local co-inventors at origin (Panel A) and destination (Panel (B) for migrants after migration relative to the placebo control group. Column (1) displays the estimates for the full sample. Column (2) displays the estimates for invetors of EU origin. Column (3) displays the estimates for inventors of US origin. Standard Errors clustered at inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

in the place of origin (Panel A) and locals at the destination (Panel B). Column (1) of Panel (A) indicates that the migrants' share of local co-inventors at origins declines by 13 percentage-points on average after migration relative to the control group. Column (1) of Panel (B) indicates that the migrants' share of local co-inventors at destination increases by 23 percentage-points on average after migration relative to the control group. The results are similar for migrants of EU origin (column (2)) and US origin (column (3)).[32] These results provide evidence that migrants access different interaction networks after migration but, importantly, they also keep collaborating with inventors at origin after moving.

Local inventors and interactions with emigrants.

The previous result documented that migrants become more productive after migration and that they keep collaborating with inventors at their origin. A potential positive spillover from the brain drain is that emigrants could be a vector of knowledge transfer from their host countries to the locals in their place of origin, especially if, after moving, emigrants continue to collaborate with

[32] The dynamic specifications are described in Appendix B.

inventors in the country of origin. This section investigates the productivity dynamics of local co-inventors of migrants in the country of origin.

To document changes in productivity for co-inventors of migrants, I build the network of co-inventors in the country of origin for each of the migrant and placebo control inventors from the previous section. I exclude co-inventors who are themselves migrants. Whenever a local inventor is associated with multiple migrants, I consider the time of migration of the first migrant. I also exclude co-inventors associated both with a migrant and a placebo inventor. This procedure yields 16,890 co-inventors of EU migrants, 5,580 co-inventors of US migrants, 23,784 co-inventors of EU placebo, and 9,295 co-inventors of US placebo. Tables B.6 and B.7 in Appendix B present the summary statistics for co-inventors of migrants and placebo inventors of EU and US origin respectively.

I then explore the productivity dynamics of local co-inventors after their migrant collaborator moves away, using a similar empirical setup to the one in the previous section. In particular, I implement event studies for locals and set the event's time equal to zero (i.e., $\tau = 0$) when the emigrant leaves. I then compare the productivity of co-inventors of migrants to co-inventors of placebo inventors. In principle, the departure of a migrant could either benefit or damage local inventors' productivity. Benefits could derive, for example, from knowledge spillovers. On the other hand, distance and reduced interactions with the migrant could decrease the local inventor's productivity.

Panel A of Figure 5 shows the path of mean patent applications per year for co-inventors around the year of migration of their associated migrant or placebo inventor. The figure shows that patenting for co-inventors of migrants is on a similar trajectory to the placebos before the time of migration, but it increases after. The similarity in the raw mean of patent applications per year before migration is remarkable because the two groups of co-inventors are not matched on any variable. After observing patterns in the raw data, I turn to a regression framework.

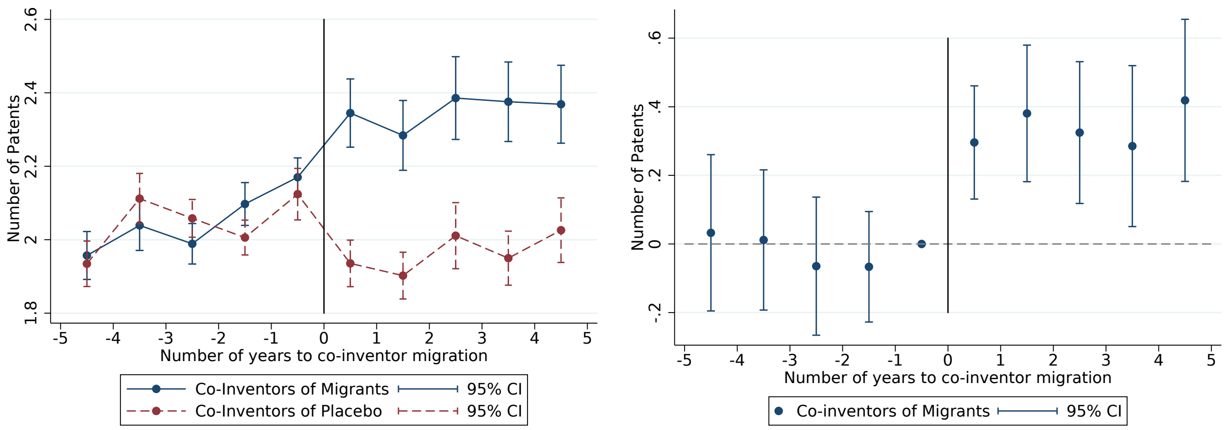
I repeat the same OLS specification as in equation (15) on the sample of co-inventors of migrants and placebos, who never migrate. The relative time in this event study, denoted by τ, now indicates the number of years relative to the year of migration of the associated emigrant. Panel B of Figure 5 shows the estimated coefficients and 95% confidence intervals for β_τ^{Mig} from specification (2) run on the sample of co-inventors. The figure confirms no pre-trends in the patenting activity of co-inventors of migrants relative to the co-inventors of placebos before the year of migration, bolstering credibility that the observed effect is not driven by differential trends. After migration, co-inventors of migrants file more patents per year than the co-inventors of placebos, and the effect is persistent up to five years after the time of migration.[33]

To summarize the results, I implement specification (16) on the sample of co-inventors, where time is relative to the year of migration of the associated co-inventor. Table 3 reports the results. Column (1) indicates that co-inventors of migrants file 0.36 more patents per year than co-inventors

[33] In this setup, there may be serial correlation in an inventor's outcomes over time and the outcomes of local co-inventors associated to the same migrant may be correlated. To account for both forms of correlation, I cluster standard errors at the level of the associated migrant inventor (see Jaravel et al. (2018)).

Figure 5: Patenting Activity by Co-inventors of Migrants around Time of Migration

(a) Raw means for local co-inventors of emigrants (b) Coefficients β_τ^{Mig} for co-inventors of emigrants



Note: The figure displays changes in the productivity of local co-inventors of migrants in the country of origin around migration time realtive to the co-inventors of the placebo control group. Panel (a) displays the raw means. Panel (b) displays the estimated coefficients from the regression specification in equation (15). Unbalanced panel. EU co-inventors of migrants: 28,661 observations; US co-inventors of migrants: 11,879 observations; EU co-inventors of placebo: 23,967 observations; US co-inventors of placebo: 13,147 observations. Standard errors clustered at the associated migrant inventor level.

of placebo in the five years after the migration of their associated inventors on average. This effect is statistically significant at the 1% confidence level. The magnitude of the estimated coefficients corresponds to an 18% increase in patenting relative to the sample mean.

Table 3: Patenting Activity of Co-inventors of Migrants around the Time of Migration

	Number of Patent Applications per Year		
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Migration	0.3597***	0.3382***	0.3895***
	(0.0610)	(0.0752)	(0.1049)
Obs	77654	52628	25026
R2	0.496	0.509	0.464
Inventor FE	X	X	X
Year FE	X	X	X

Notes: The table displays the estimated coefficients for the changes in the productivity of local co-inventors of migrants in the country of origin around migration time realtive to the co-inventors of the placebo control group. Panel (a) displays the raw means from the regression specification in equation (16). Column (1) displays the benchmark regression results for co-inventors of migrants at origin. Column (2) includes only the sample of co-inventors of EU origin. Column (3) includes only the sample of co-inventors of US origin. Standard errors clustered at the associated migrant inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Columns (2) and (3) show the results for the subsamples of inventors of EU and US origin respectively. The estimated coefficients are positive and statistically significant in both cases. The point estimates are 0.34 for EU inventors and 0.39 for US inventors, corresponding to an average increase in patenting of about 17% and 19% per year respectively, relative to the sample mean.[34]

Appendix B presents additional results and robustness checks. I document that the increase in productivity is more pronounced for local co-inventors that continue to co-invent with the migrant after she moves away.[35] Additionally, I show that results are robust for co-inventors of migrants that switch firms upon migration and co-inventors of return migrants. I also show that results are robust when excluding patents that are co-invented with migrants.

The results of this section show that individuals tend to become more productive when they are exposed to the migration of a co-inventor. This finding is consistent with the model, where local inventors become more productive after interacting with migrants, because migrants are more productive on average. These results help quantify the magnitude of the knowledge-transfer channel.

After describing the empirical results, I next turn to the quantitative analysis, which combines the model and the data.

4 Quantitative Analysis

This section quantifies the effects of migration and knowledge transfers on innovation and productivity and studies the effects of counterfactual taxation and immigration policy. To do this, I calibrate the model from Section 2 to match the empirical results from Section 3. I then show that the calibrated model closely fits the data for both targeted and non-targeted moments, and I use it to study counterfactual policy exercises.

4.1 Calibration

I calibrate the model along a BGP equilibrium to match features of the EU-US migration corridor, setting the EU to be country A and the US to be country B. The benchmark calibration aims at studying the role of policies on equilibrium migration, innovation, and allocation of talent. To highlight the role of policy, I set the parameters for the distribution of talent and share of inventors to be the same across locations; that is, $\theta_A = \theta_B$, and $I_A = I_B$.[36]

Given this restriction, 22 parameters remain to be calibrated, described in Table 4: $\{\beta, r, \delta, \alpha, \nu, \tau_A, \tau_B, I_A, \bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega\}$ and six free parameters in the set of $\{\psi_{i,j}\}$ for $i, j \in \{AA, AB, BA, BB\}$ (discussed in further detail below).

The calibration proceeds in three steps. First, eight parameters are calibrated to match existing results in the literature ($\beta, r, \delta, \alpha, \nu, \tau_A, \tau_B, I_A$). Second, six parameters are directly matched to the microdata on interactions of inventors ($\xi_{AB,AA}, \xi_{AB,BB}, \xi_{BB,AA}, \xi_{BA,AA}, \xi_{BA,AB}$, and $\xi_{BA,BB}$). Third, the remaining eight parameters are jointly calibrated using the simulated method of moments (SMM) to match important features of the microdata ($\bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega$).

[34]Dynamic event studies for the EU and US samples are reported in Appendix B.

[35]About 9% of local co-inventors at origin continue to co-invent with the associated migrant after migration.

[36]The quantitative results are robust across different specifications. See Appendix C.

Table 4: Parameter Values

Parameter	Description	Value
	— Panel A. External Calibration —	
β	Discount Rate	0.97
r	Interest Rate	0.03
δ	Survival Rate	0.95
α	Final Good Production	0.11
ν	Inventor-Firm match rate	1.00
τ_A	Tax Rate EU	0.40
τ_B	Tax Rate US	0.30
I_A	Share R&D workers	0.01
	— Panel B. Direct Match to Data —	
$\xi_{AB,AA}$	Meeting Frictions	1.31
$\xi_{AB,BB}$	Meeting Frictions	0.65
$\xi_{BB,AA}$	Meeting Frictions	0.06
$\xi_{BA,AA}$	Meeting Frictions	0.71
$\xi_{BA,AB}$	Meeting Frictions	0.32
$\xi_{BA,BB}$	Meeting Frictions	1.24
	— Panel C. SMM Calibration —	
$\bar{\mu}$	Migration cap to US (Share of Inventors)	0.01
κ	Cost of Migration	0.10
λ	Meeting Intensity HH	0.10
η	Learning Technology	0.34
σ	Technology Absorption	0.02
θ_A	Talent CDF H	15.00
ρ	Location Shock Persistence H	0.89
ω	Location Shock SD H	0.20

Note: List of model parameters and calibrated values. For the SMM calibration (Panel C), all parameters are calibrated jointly.

External Calibration

In the model, production and preferences are similar to the existing literature. The key innovation in the framework is how individuals interact and make migration decisions. Therefore, the parameters for preferences and production are externally calibrated to closely follow the literature. I set $\alpha = 0.11$ (Akcigit and Kerr (2018)), $\beta = 0.97$, $r = 0.03$, $\delta = 0.95$, and $I_A = 0.01$ (Akcigit et al. (2020)). The parameter ν governs the matches between firms and inventors. A value $\nu < 1$ indicates that a larger number of inventors in the economy leads to a lower matching rate per inventor, resulting in lower "realized" innovation per individual. Thus, immigration can crowd out innovation by locals by reducing the technology-selling probability for inventors. Kerr and Lincoln (2010) and Hunt and Gauthier-Loiselle (2010) study the effects of immigration on innovation and find no evidence of displacement of locals and, if anything, evidence of crowding in. Therefore, I set the baseline value of $\nu = 1$. On the other hand, Borjas and Doran (2012) find evidence that Soviet mathematicians who immigrated to the US displaced US scientists working in the same field. To account for contrasting evidence, in Appendix C, I explore robustness to different values of ν. Finally, I set $\tau_A = 0.4$ and $\tau_B = 0.3$. Although the tax system cannot be thoroughly summarized with one parameter, these values approximate the different taxation of labor income, which is higher in the EU than in the US (OECD (2021a)). The parameters are summarized in Panel A of Table 4.

Direct Match to Microdata

The parameters for the meeting frictions are calibrated to directly match the microdata on co-inventors, presented in Figure 4. This figure displays, for any group of inventors, the share of co-inventors that are EU locals, US locals, EU migrants, or US migrants. Thus, each block in this figure corresponds to a model object $\psi_{i,j}$ for some $i, j \in \{AA, AB, BB, BA\}$. Mapping the data to the model requires accounting for some additional restrictions. First, the total number of matches between individuals of groups i and j must satisfy the following condition: $\mu_i \lambda \psi_{i,j} = \mu_j \lambda \psi_{j,i}$. Second, for every i, the probabilities of meeting each group in the economy must add up to 1; that is, $\sum_{j \in \mathcal{J}} \psi_{i,j} = 1$. Thus, six free parameters remain to be matched directly to the data, $\psi_{AB,AA}, \psi_{AB,BB}, \psi_{BB,AA}, \psi_{BA,AA}, \psi_{BA,AB}$, and $\psi_{BA,BB}$, summarized in Panel B of Table 4.

Internal Calibration Using SMM

For the remaining eight parameters $\{\bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega\}$, I select eight informative moments from the data and empirical results in Section 3. I then compute the corresponding moments in the model by simulating the behavior of the economy along a BGP equilibrium and simulating a sample of inventors, their migration decision, their interactions, and their resulting productivity. I then implement the SMM, minimizing the squared percent distance between the model-simulated moments, $M(\Theta)$, and their empirical counterparts, M^E, by searching over the parameter space Θ, using a simulated annealing algorithm:

$$\min_{\Theta} \sum_{i=1}^{8} \left(\frac{M_i^E - M_i(\Theta)}{0.5(M_i^E + M_i(\Theta))} \right)^2.$$

Even though the parameters are jointly calibrated, below I provide a heuristic discussion of the most relevant moment for each parameter.

Share Migrants EU-US. The share of inventors with nationality from one of the 28 EU countries who patented from a US address was, on average, 6% of local Europeans in the years 2000-2010 in the PCT data (Figure 2). This moment primarily informs the mass of inventors allowed to enter

Table 5: Moments

Moment	Data	Model
Share Migrants EU-US	6.00	6.83
Share Migrants US-EU (% domestic inventors)	0.40	0.39
Share Return Migrants (% migrants)	0.13	0.10
Δ productivity migrants EU-US (%)	0.28	0.32
Δ productivity co-inventors of migrants EU (%)	0.17	0.16
Δ productivity co-inventors of migrants US (%)	0.19	0.18
Growth rate (%)	1.50	1.39
TFP gap	0.90	0.90

Note: List of target moments for the calibration with SMM technique. The table presents the value of moments in the data and in the calibrated model.

country B in every period, $\bar{\mu}$. [37]

Share Migrants US-EU. The share of inventors with US nationality who patented from an EU address was, on average, 0.4% of local Americans in the years 2000-2010 in the PCT data (Figure 2). This moment primarily informs the cost of migration, κ.

Share Return Migrants. The share of inventors who return to their original country in any given year, as a fraction of active migrants, is 0.13, on average, in the EPO data. This moment primarily informs the persistence of productivity shocks, ρ, because, in the model, inventors choose to return to their country of origin when they are affected by a negative enough productivity shock abroad.

Δ *productivity migrants EU-US.* I target the average change in productivity after migration for migrant inventors in the EU-US corridor. I replicate an event study equivalent to Figure 3 using data generated from the model. In particular, I simulate the steady state of the model and collect a sample of migrants. I then match every migrant with a local individual with the same location of origin, and the same level of productivity (z), and experience (years since birth) in the year before migration, obtaining a control group of "placebo migrants". Then, I run the following regression from the simulated data:

$$q_{it} = \sum_{\tau=-5}^{5} \beta_\tau^{Mig}\, \mathbf{1}[L_{it}^{Mig} = \tau] + \sum_{\tau=-5}^{\tau=5} \beta_\tau^{All} \mathbf{1}[L_{it}^{All} = \tau], + \epsilon_{it}$$

where i indexes the simulated inventors and t the simulated periods. The variable q is the bundle of technologies produced by the simulated inventors, according to the model. I then take the average value of coefficients β_τ^{Mig} for five periods after migration. I transform it into percentage change

[37] The migration restriction to country B is modeled to represent features of the H1B visa program for high-skilled immigrants into the US.

by dividing it by the average number of patents (in the data) or bundle q (in the model-simulated data) per year for migrants in the sample before migration. I obtain a target value of 0.28. In the model, the productivity of migrants, after they move, is boosted by the productivity shock ϵ. Thus, this moment primarily informs the standard deviation of the productivity shock, ω.

Δ *productivity co-inventors of migrants EU.* I target the average change in productivity for locals in the EU after they interact with an EU emigrant in the US, as reported in column (2) of Table 3. I produce an event study using data generated from the model. In particular, given the simulated migrants and control group described above, I collect all the local individuals who interact with them in the simulated sample. I then run an event study on the group of locals who interact with migrants versus locals who interact with a "placebo". Time 0 in the event study corresponds to the first interaction of the local with a migrant (or placebo). I then match the coefficient from the model-simulated event study to the coefficient in the empirical event study. I transform it into percentage change by dividing it by the average number of patents per year for locals in the sample before interaction with migrants, obtaining a target value of 0.17. In the model, locals can boost their productivity as they learn from interactions. Thus, this moment, together with the equivalent coefficient for US locals, primarily informs the parameters that govern the learning process, η and λ.

Δ *productivity co-inventors of migrants US.* I target the average change in productivity for locals in the US after they interact with an American emigrant in the EU, as reported in column (3) of Table 3. The description of the moment is analogous to the one for EU locals. The target percentage change in productivity is 0.19.

Growth Rate. I target a growth rate of 1.5%. In the model, the growth rate is tightly connected to the distribution of talent in the economy. Thus, this moment primarily informs the shape of the exogenous talent distribution, θ_A.

TFP gap. In the model, the parameter σ governs the average productivity gap between the two locations (see Equation 12). To obtain a similar counterpart in the data, I rely on the indicator of the GDP per hour worked built by the OECD (OECD (2021b)) and compare the average productivity gap between the US and the EU in the years 2000-2010.

4.2 Results

Calibrated Parameters and Targeted Moments

Panel C of Table 4 describes the value of the calibrated parameters with the SMM. The calibrated value of $\bar{\mu} = 0.01$ indicates that the flow of immigrant inventors allowed into the US amounts to 1% of local US inventors. The calibrated meeting intensity indicates that, in the model, inventors have about a 10% probability of meeting other inventors in every period. The parameter $\eta =$

0.34 indicates that inventors can learn substantially from interactions. Finally, the calibrated productivity process is quite persistent, with $\rho = 0.89$ and $\omega = 0.20$.

Table 5 reports the target moments from the data and the corresponding values obtained in the calibrated model. The calibration provides a close fit for the targeted moments. Overall, the model predicts important features of migration and interactions. In particular, the model is able to replicate the asymmetric migration flows of inventors between the US and the EU. The model also predicts that about 10% of migrants return to their country of origin in every period, similar to what is observed in the data. Finally, the model generates an increase in productivity for migrants after migration, as well as knowledge transfer thanks to interactions between migrants and locals.

Non-targeted Moments

Next, I discuss the goodness of fit of the calibrated model for some non-targeted moments.

Figure 6 shows the event studies for migrants and co-inventors in the data and in the model, as described in the previous section. The crosses represent the point estimates from Figures 3 and 5. The circles represent the event studies generated from model-simulated data. Even if I only target the average effect after the event, the model provides a good fit for the dynamic pattern.

Panel (a) documents the change in migrants' productivity. In the data, this does not represent the causal effect of migration. Instead, it describes dynamics around migration time, because individuals move in response to endogenous changes to opportunities abroad, which affect their productivity. Importantly, this mechanism is also present in the model, where individuals move in response to changes to their productivity differential abroad (ϵ), which results in a jump in productivity after moving. After the initial jump, productivity declines due to the mean-reverting nature of the process for ϵ.

Panel (b) documents the change in productivity for local co-inventors of migrants in the origin country. In the model, the observed increase in productivity occurs because locals can meet emigrants abroad. These meetings increase the productivity of locals substantially, because they can learn from the innovations of emigrants, which on average are sizeable due to the foreign productivity differential ϵ.

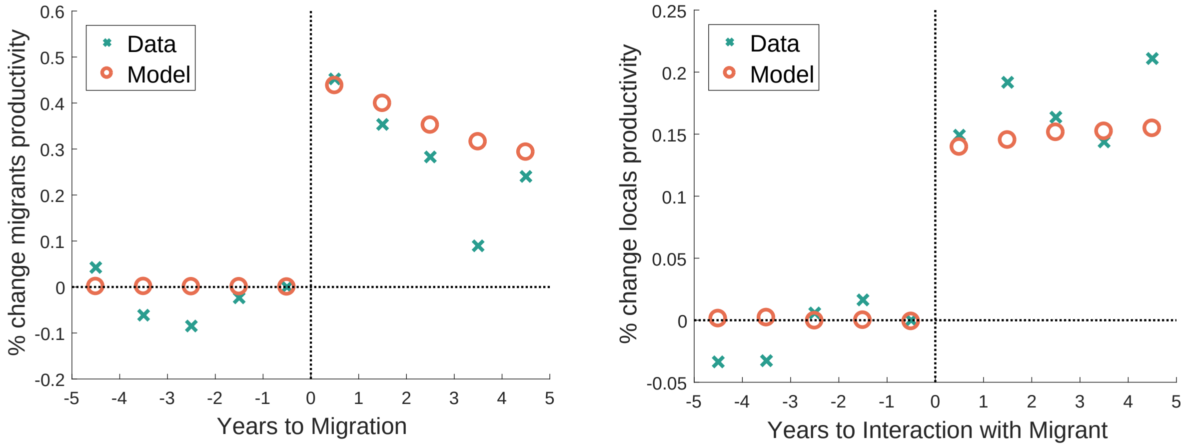
The model also replicates important qualitative features of the data. Panel (a) of Figure 7 displays a histogram of the number of years of experience (i.e., years since the first patent) of migrants at the time of their first migration, from the EPO data. Most migrants in the sample migrate early in their careers; as the experience at first migration increases, the frequency in the sample declines. Panel (b) shows that the calibrated model replicates this qualitative aspect of migration data.

Another relevant qualitative feature of this framework is the self-selection of migrants based on their talent, displayed in Figure 8. In the model, inventors from location A have more incentive to move to location B if they are more talented (i.e., higher z). The reason is twofold: (i) more talented inventors gain more from moving to a location with higher TFP (formally, the cross derivative of inventors' profits with respect to talent and TFP is positive), and (ii) more talented inventors

Figure 6: Event Studies on Productivity of Migrants and Locals: Data vs. Model

(a) Migrants around Time of Migration

(b) Locals around Interaction with Migrant

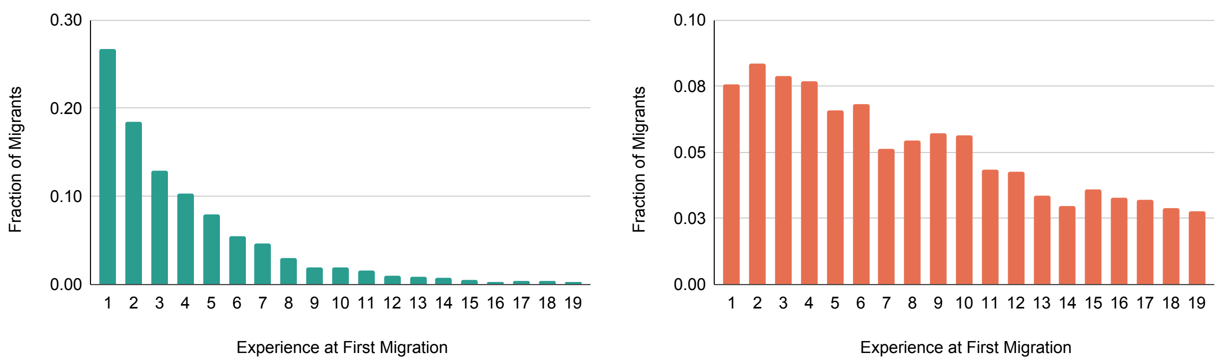


Note: The figure describes event studies for changes in productivity of migrants (panel (a)) and local co-inventors of migrants in the country of origin (panel (b)) around migration time. The circle markers indicate estimates from a model-simulated sample. The cross markers indicate estimates from the data, corresponding to Figures 3 and 5.

Figure 7: Experience at First Migration: Data vs. Model

(a) Data

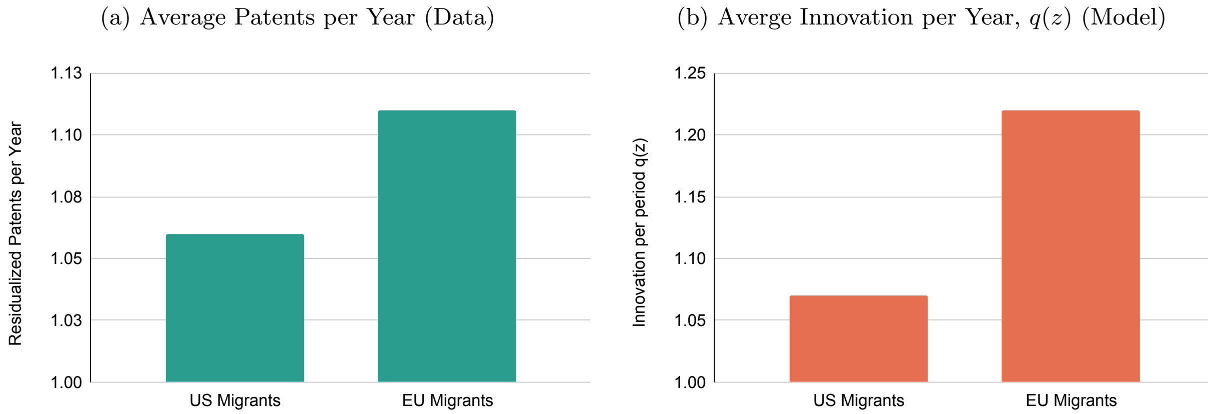
(b) Model



Note: The figure displays histograms of the number of years of experience for migrants at migration time, in the data (panel (a)) and the model (panel (b)). Experience indicates the number of years since the first patent application.

gain more from interactions with a more talented network. The same two reasons disincentivize migration of highly talented individuals from B to A, because they lose more from leaving a location with higher TFP and better learning opportunities. As a result, in the model, migrants from the EU to the US tend to be more talented, before migration, than migrants from the US to the EU. This finding is also true in the data, as confirmed by Panel (a) of Figure 8: US migrants to the EU file, on average, 1.06 patents per year before migration, versus 1.11 for EU migrants to the EU, after controlling for calendar time and experience. Panel (b) verifies this result for the simulated sample of inventors from the model: the innovation bundle ($q(z)$) of US migrants to the EU before migration is 1.07 on average, versus 1.22 for EU migrants to the US.

Figure 8: Average Productivity of Migrants Before Migration: Data vs. Model



Note: Panel (a) depicts the average residualized patent applications per year for US and EU migrants before migration in the data, after controlling for year and experience fixed effects. Panel (b) shows the average innovation per year in the model (q) for US and EU migrants before migration.

4.3 Quantitative Exercises

The previous section showed that the calibrated model provides a good fit to the data for both targeted and non-targeted moments. Thus, the model is well-suited to study counterfactual exercises. First, I will quantify the importance of international knowledge transfers. Second, I will assess the impact of counterfactual policy exercises that resemble real-world policies implemented to manage migration flows. From the point of view of the EU, I consider a reduction in the tax rate for foreigners and return migrants to eliminate the brain drain. For the US, I study changes in the immigration cap. [38]

Quantifying the Importance of Knowledge Transfers

How important are international knowledge transfers for developing human capital and innovation? To answer this question, I shut off interactions across different groups of inventors; i.e., I set $\xi_{i,j} = 0$ for all $i \neq j$. The interpretation of this restriction is that local Europeans can only interact with other local Europeans, and similarly for all other groups. Table 6 shows the results from this exercise.

Panel A describes the effect of innovation, which declines by about 9% in the EU and increases by 6.5 % in the US. This result is the combination of quantity effects and quality effects on the allocation of talent. On the quantity side, Panel B shows the implications for migration flows.

[38] The baseline economy is inefficient because inventors do not internalize the effect of their migration decisions on innovation, knowledge spillovers and output growth. The solution of the efficient allocation or planning problem is outside of the scope of this paper and is left for future research.

Table 6: Shutting Down International Knowledge Transfers

	Baseline	New	% Change
—Panel A. Innovation and Growth —			
Innovation EU	1.19%	1.08%	-9.2%
Innovation US	1.39%	1.48%	6.5%
Growth Rate	1.39%	1.48%	6.5%
TFP Gap	0.90	0.83	-8.2%
—Panel B. Migration Flows —			
EU-US Migrants	0.07	0.10	54.5%
US-EU Migrants	0.00	0.00	-100.0%
Return Share	0.10	0.03	-65.4%
—Panel C. Talent Allocation —			
Avg. Talent EU Locals	1.21	1.20	-1.1%
Avg. Talent EU Migrants	1.35	1.98	47.2%
Avg. Talent US Locals	1.28	1.28	0.4%
Avg. Talent US Migrants	1.02		-100.0%

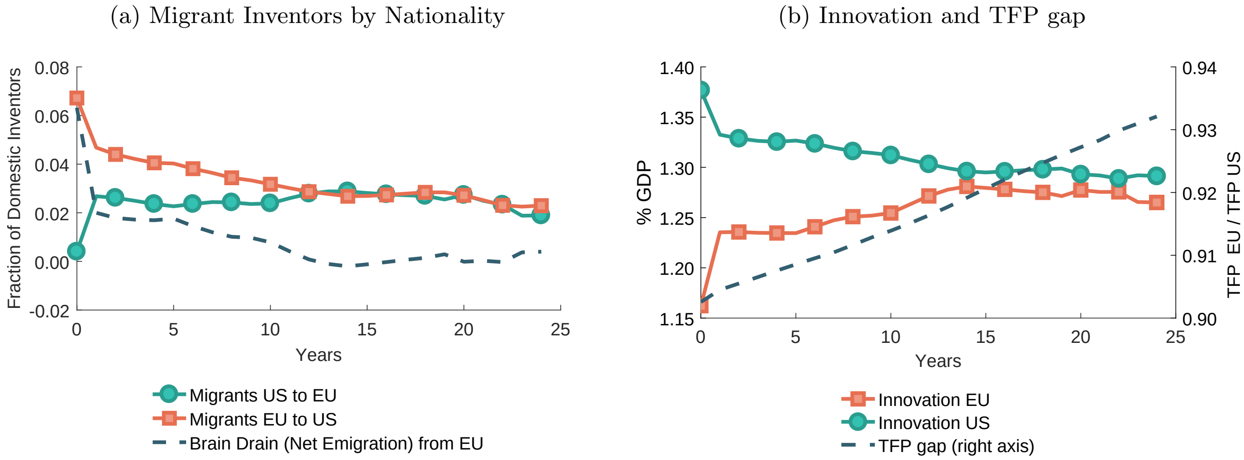
Note: The table shows the BGP equlibrium results from a counterfactual exercise of shutting off interactions across different groups of inventors, that is, setting $\xi_{i,j} = 0$ for all $i \neq j$.

The share of migrants from the EU to the US increases from 6.5% to 10%. The value of being a migrant increases substantially in this exercise, because it provides the opportunity to have high-quality interactions. As a result, the average talent of EU migrants increases by almost 50%, as described in Panel C. At the same time, fewer European migrants want to return to the EU, because they anticipate that they will no longer be able to learn from other migrants. In fact, the share of returning migrants declines by almost two-thirds. By contrast, the share of US migrants declines to 0, because of the declining quality of interactions for them. Thus, innovation in the EU declines because of (i) a large increase in emigration and (ii) a slight decline in the average talent of locals. Innovation in the US increases because of (i) a large increase in the quantity and quality of immigrants and (ii) a slight increase in the average talent of locals. Overall, this exercise indicates that international knowledge transfers partly offset the negative impact of brain drain on innovation in the EU. Shutting off international knowledge transfers exacerbates net emigration from the EU, which increases by more than 50%, and reduces innovation in the EU by 9%.

Policy Exercise: Tax Cut for Foreign Inventors and Return Migrants in the EU

The fear of a brain drain has motivated policy interventions in European countries to reduce the outflow of talented individuals. In this section, I analyze the consequences of a reduction in the EU tax rate (τ_A) for foreign inventors and return migrants. This exercise replicates the scope of policies to "revert the brain drain", implemented in several EU countries, including the Netherlands, Denmark, Italy, France, Spain, and Ireland. I study the transition from an initial BGP with a tax rate of 0.4 for all inventors in the EU to a new BGP with an EU tax rate of 0.3 for foreign inventors and return migrants. This rate approximates the actual preferential tax schemes for foreigners implemented in several EU countries.[39] The goal of this exercise is to quantify the effect of this policy intervention on migration, innovation, knowledge spillovers, and output.

Figure 9: Tax Cut for Foreigners and Return Migrants in the EU: Migration and Innovation.



Notes: The figures display transitional dynamics upon the implementation of a counterfactual tax cut for foreing inventors and return migrants in the EU from 0.4 to 0.3. Panel (a) shows the equilibirum stock of EU emigrants (square markers), US emigrants (circle markers), and net emigration from the EU (dashed line). Panel (b) shows aggregate innovation in the EU (square markers) and in the US (circle markers), as well as the productivity gap (dashed line).

Panel (a) of Figure 10 plots the evolution of the mass of EU migrants (square markers) and US migrants (circles markers) along the transition.[40] The tax cut immediately attracts US immigrants to the EU, whose stock (circle markers) jumps significantly upon the implementation of the policy, accounting for up to 3% of local US inventors. Additionally, the tax cut has two effects on the stock of EU migrants. First, it increases the value of migration for Europeans, who anticipate lower taxes if they migrate and then return to the EU. Thus, a larger mass of Europeans would like to move, but they are constrained by the immigration cap in the US, so that the flow of migrants from the EU to the US remains unchanged (see Figure C.4, panel (a)). Second, the return intensity for EU migrants increases, thanks to the lower tax rate upon return (see Figure C.4, panel (b)). As a result, the stock of EU migrants (square markers) to the US decreases over time, from 6%

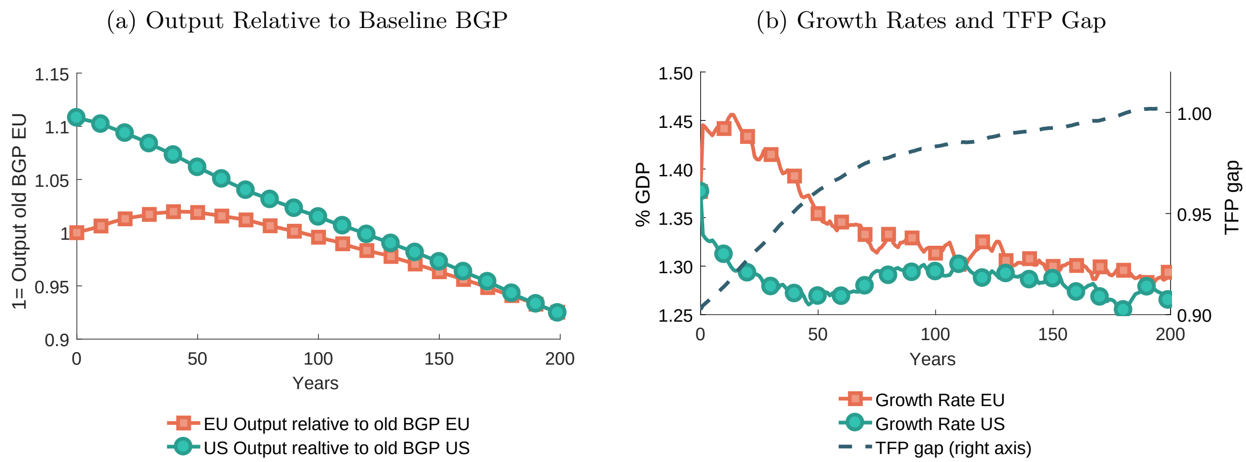
[39]For example, in 1992, Denmark implemented a preferential tax scheme for foreign researchers and high-income foreigners in all other professions, who sign contracts for employment in Denmark after June 1, 1991. Foreigners would pay a flat tax of 25 % instead of the regular progressive income tax. In Spain, a special tax scheme was passed in 2005 (Royal Decree 687/2005), applicable to foreign workers moving to Spain after January 1, 2004. The special tax scheme is a flat tax of 24 % in lieu of the regular progressive income tax with a top rate of 45 % when the law was passed). See Kleven, Landais and Saez (2013).

[40]Figure C.3 in Appendix C describes the BGP equilibrium values of migration and innovation for different values of the tax cut.

to 3% of domestic EU inventors over 25 years. Thus, brain drain from the EU (or net emigration, depicted by the dashed line) declines to 0. While the elasticity of migration to the tax rate is not targeted in the calibration, the model produces an elasticity in line with empirical estimates in the literature.[41]

Panel (b) displays the evolution of EU innovation (square markers), US innovation (circle markers), and the productivity gap (dashed line). After 25 years since the policy implementation, innovation increases by 9% in the EU and declines by 6% in the US, due to the reallocation of inventors across countries. As a result of these two effects, aggregate productivity in the EU, relative to the US, increases by up to 3% in the span of 25 years, as predicted by equation (12).

Figure 10: Tax Cut for Foreigners and Return Migrants in the EU: Output and Growth.



Notes: The figures display transitional dynamics upon the implementation of a counterfactual tax cut for foreign inventors and return migrants in the EU from 0.4 to 0.3. Panel (a) shows the path for aggregate output realitve to the old GDP for the EU (square markers), and the US (circle markers). Panel (b) shows the growth rate in the EU (square markers) and in the US (circle markers), as well as the productivity gap (dashed line).

What are the effects of the tax cut on aggregate productivity and output? Figure 10 displays, in panel (a), the path of output for the EU (square markers) and the US (circle markers), relative to the output path along the baseline BGP. Output in the US declines due to lower US innovation. Output in the EU increases in the first 40 years since policy implementation, but then it declines due to the interaction of different forces, which are described in Table 7.

The first column of Table 7 illustrates that, after 25 years since the tax cut, the direct reallocation effect increases output by 2.63%. The direct effect captures the change in the number of local and migrant inventors, if they maintained the same level of productivity as in the old BGP. However, those Europeans who were migrants in the baseline BGP but are locals in the

[41]The elasticity of the number of domestic inventors to the tax rate in this exercise is 0.12. In comparison, Akcigit et al. (2016) estimate elasticities to the net marginal tax rate of the number of domestic superstar inventors in the range of 0.02-0.7.

Table 7: Tax Cut for Foreigners and Return Migrants in the EU: Effects on EU Output

Channel	**Change in EU Output**	
	After 25 years	After 200 Years
Direct Reallocation Effect	+2.63	+32.50
Change in Migrants' Productivity	-0.36	-4.69
Migrants' Selection	+0.65	+ 8.26
Change in Diffusion from US	-0.87	-33.77
Knowledge Spillovers	-0.57	-9.77
Net Effect	+ 1.48	-7.40%

Notes: The table illustrates the change in EU output after 25 years and 200 years since a cut in the tax rate for foreigners and return migrants in the EU from 0.4 to 0.3. The table documents the seprate impact of different channels and their net effect.

new equilibrium are on average less productive in the EU, because of the productivity differential ϵ. This channel reduces the direct effect by 0.36 percentage-points. On the other hand, selection forces imply that returning EU migrants and US immigrants have higher talent, increasing output by 0.65 percentage-points. In addition, lower innovation in the US reduces the exogenous diffusion of technologies to the EU, reducing output by -0.87 percentage-points. Finally, local EU inventors are less productive in the new equilibrium due to smaller knowledge spillovers, since the mass of EU emigrants is smaller. The change in spillovers additionally reduces output by 0.57 percentage-points.[42] The net effect of these different forces leads to an increase in EU output by 1.48% after 25 years. While EU output initially increases, the negative effects increase over time, eventually reducing output relative to the old BGP path, as illustrated in the second column of Table 7. In particular, while the direct effect and change diffusion are the dominant forces, the decline in knowledge spillovers also has a sizable effect on output in the long run, accounting for a -9.77 percentage-points reduction in GDP.

Panel (b) of Figure 10 displays the effects on the growth rates. The US growth rate declines over time, down by 8% (or 0.11 percentage-points) in the new long-run equilibrium. As a result of the different forces previously described, productivity growth in the EU increases by 5% (or 0.07 percentage-points) in the first 25 years. However, it declines by 6% (or 0.08 percentage-points) in the new long-run equilibrium.

Finally, I compute the welfare effects of the policy change along the transitional dynamics of the economy, discounting future periods since policy implementation by the discount factor β multiplied by the survival probability δ.[43] The weighted average of welfare for EU individuals (including inventors and workers) increases by 1.87%. This result is driven by the initial increase in output, because the discounting implies that agents put close to zero weight on the distant future when output will decline. On the other hand, welfare for US individuals decreases by -1.92%, due

[42]Figure C.5 illustrates the change in interaction networks between the baseline BGP and the new long-run equilibrium. Due to changes in migration flows, the interaction networks change, affecting the magnitude of knowledge spillovers.

[43]Appendix A describes the measure and computation of welfare.

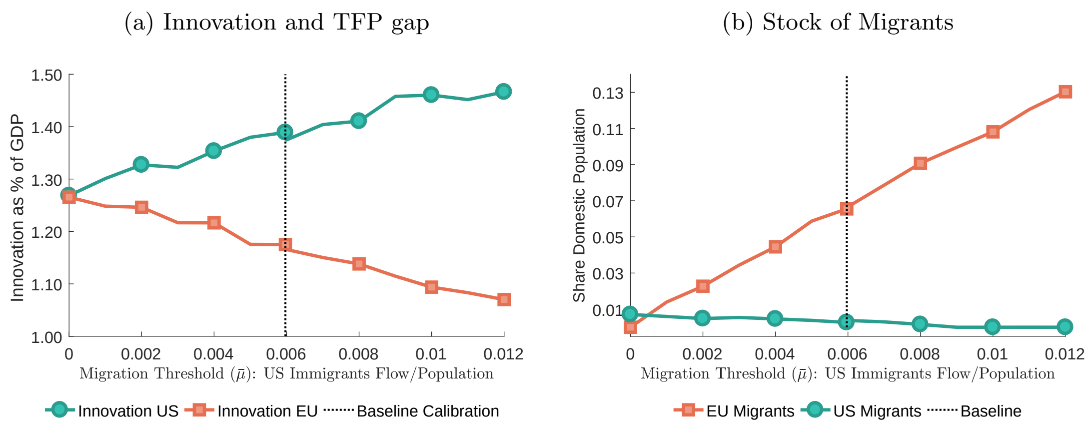
to declining output.

The overarching message from this exercise is that the effectiveness of a tax cut for foreigners and return migrants in the EU, aimed at eliminating the brain drain, depends on the time horizon of the policymaker.[44] In the short run, this policy attracts foreign inventors and return migrants to the EU and boosts EU innovation, aggregate productivity, and wages. However, in the long run, it reduces the growth rate of the global economy as well as knowledge spillovers and technology diffusion to the EU, reducing both EU and US productivity.

Policy Exercise: Changing Migration Limit in US

What are the implications of changing the number of immigrants allowed to flow into the US ($\bar{\mu}$)? This exercise mimics changes to the H1B visa program, which regulates the immigration of high-skill workers in the US.

Figure 11: Counterfactual Change to US Immigration Threshold ($\bar{\mu}$): BGP Comparison



Notes: The figures compare counterfactual BGP equilibria for different values of the immigration threshold to the US. Panel (a) shows equilibirum aggregate innovation in the EU (square markers) and in the US (circle markers). Panel (b) shows equilibirum migration of EU inventors (square markers) and US inventors (circle markers).

Figure 11 describes the BGP equilibrium of the model for different values of the migration threshold $\bar{\mu}$, plotted on the horizontal axis. Panel (a) describes the effects on innovation: as the threshold $\bar{\mu}$ increases (i.e., more individuals are allowed to enter the US in every period), innovation increases in the US and declines in the EU. This effect is mainly explained by the change in the mass of migrants of each nationality, depicted in panel (b). The increase in the migration threshold is accompanied by an increase in the mass of EU migrants and a decline in the mass of US migrants. The mass of EU migrants increases with the threshold because the migration threshold is binding in

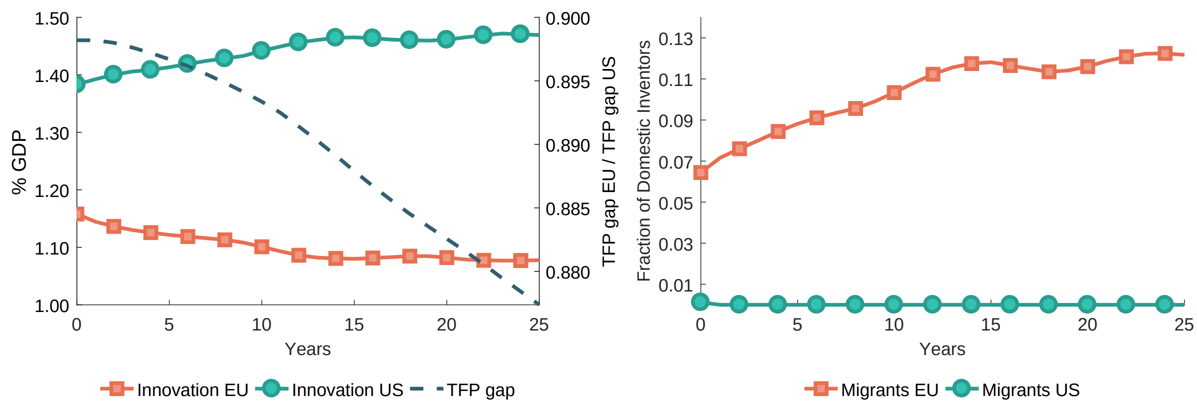
[44]Note that a tax cut of a different magnitude would imply a different change in migration and inventors allocation, as depicted in Figure C.3, and may increase EU output in the long run.

the initial BGP.[45] The mass of US migrants declines with the threshold because higher innovation in the US implies higher aggregate productivity and profits for domestic inventors, increasing the opportunity cost of moving to the EU. Changes in migration flows of both Europeans and Americans increase the number of inventors active in the US in equilibrium, resulting in higher US innovation.[46]

Figure 12: Counterfactual Increase of US Migration Threshold: Transitional Dynamics.

(a) Innovation and TFP Gap

(b) Stock of Migrants by Nationality



Notes: The figures display transitional dynamics upon the implementation of a counterfactual increase of the migration threshold in the US from 0.006% to 0.012% of domestic inventors per year. Panel (a) shows aggregate innovation in the EU (square markers) and in the US (circle markers), as well as the productivity gap (dashed line). Panel (b) shows equilibirum migration of EU inventors (square markers) and US inventors (circle markers).

After comparing the BGP at different thresholds, I analyze the dynamic evolution of the economies upon a doubling of the immigration threshold in the US from 0.006 to 0.012, displayed in Figure 12. This exercise mimics an increase in the issuance of H1B visas for skilled immigrants to the US.

Panel (a) displays the evolution of innovation in the two economies and the productivity gap. Innovation increases monotonically in the US, up by about 7% after 25 years. At the same time, innovation decreases by about 2% in the EU. These two effects increase the productivity gap between the US and the EU by about 2%. Panel (b) plots the evolution of the mass of migrants of each nationality. The threshold reduction leads to an increase in the stock of immigrants in the US by about 50% after 25 years. The mass of US migrants declines slightly; thus, the net brain drain from the EU increases.

The change in migration policy affects output and productivity. Figure 13 displays, in panel (a), the path of output for the EU (square markers) and the US (circle markers), relative to the

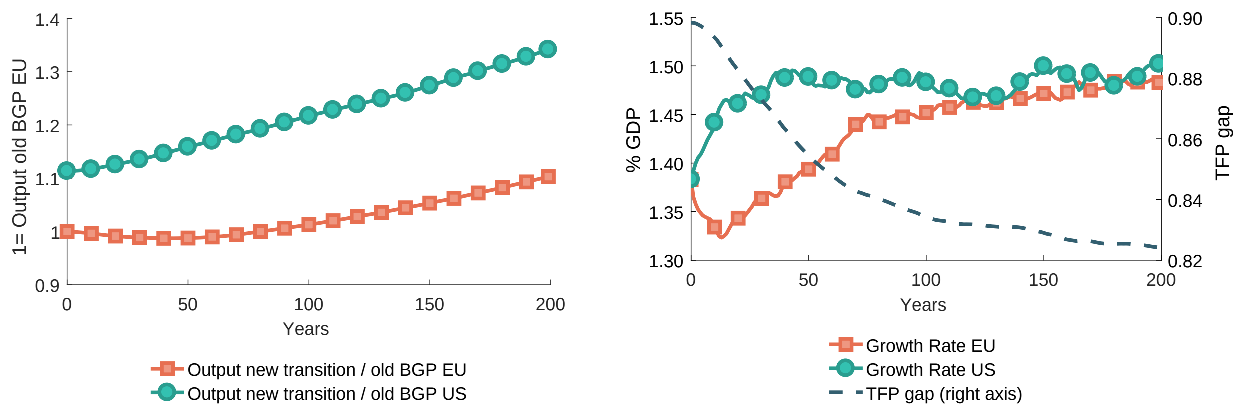
[45] In BGPs with a migration limit $\bar{\mu}$ larger than 15% of domestic investors, the threshold is no longer binding.

[46] In fact, in the baseline calibration, the value of $\nu = 1$ implies that immigrants do not crowd out local inventors, so that more immigration results in more innovation, as explained in Section 4.1.

Figure 13: Counterfactual Increase of US Migration Threshold: Transitional Dynamics.

(a) Output Relative to Baseline BGP

(b) Growth Rates and TFP Gap



Notes: The figures display transitional dynamics upon the implementation of a counterfactual increase of the migration threshold in the US from 0.006% to 0.012% of domestic inventors per year. Panel (a) shows the path for aggregate output realitve to the old GDP for the EU (square markers), and the US (circle markers). Panel (b) shows the growth rate in the EU (square markers) and in the US (circle markers), as well as the productivity gap (dashed line).

output path along the baseline BGP. US output increases monotonically relative to the baseline BGP, following the increase in US innovation. EU output declines by 1% in the first 50 years since the policy change due to lower EU innovation. After that, EU output increases due to higher knowledge spillovers and technology diffusion from the US. Panel (b) displays the effects on the growth rate. The US growth rate increases over time, up by 9% (or 0.12 percentage-points) in the new long-run equilibrium. Productivity growth in the EU decreases by 4% (or 0.05 percentage-points) in the first 15 years. However, it increases by 9% (or 0.12 percentage-points) in the new long-run equilibrium.

Overall this policy increases welfare in the global economy by 0.6%. The sorting of inventors to the US increases innovation in the US, which is the frontier economy, benefitting both the US and EU economies. In the latter, the short-term decline in productivity due to lower EU innovation is compensated by long-term productivity gains due to more significant knowledge spillovers and technology diffusion from the US.

5 Conclusion

Inventors' migration has positive and negative effects on the allocation of talent and innovation of origin and destination countries. Migrants bring valuable talent and spread knowledge, but they can create a brain drain in the country of origin and displace native workers at the destination. To capture these multiple effects, this paper builds an innovation-based endogenous model that microfounds migration decisions, interaction networks, and knowledge spillovers. One of the key contributions is to bring a general equilibrium macroeconomic model to a largely empirical literature.

This new framework is apt for studying the global effects of migration. To do so, I link the model to a novel dataset of migrants, which I build from patent data. The empirical results show that migrants move to the place where they are most productive and facilitate cross-country collaborations, spreading knowledge. The quantitative model maps the empirical results to implications for the economy's innovative capacity. I study a tax cut for foreigners and return migrants in the EU, aimed at reverting the brain drain. The effectiveness of this policy depends on the time horizon of the policymaker: in the short run, this policy can attract foreign inventors and return migrants to the EU and boost EU innovation, aggregate productivity, and wages. However, in the long run, it reduces the growth rate of the global economy as well as knowledge spillovers and technology diffusion to the EU, reducing both EU and US productivity. On the migration policy side, increasing the size of the US H1B visa program increases productivity in the US and in the EU, because it sorts inventors to where they are most productive and can learn most, increasing knowledge spillovers to other countries.

This paper paves the way for a new research agenda on the macroeconomic effects of migration for long-run growth. I discuss two compelling areas for future research. First, in this model, individuals are exogenously split between production workers and inventors. A fruitful extension would be to endogenize occupational choice and study how migration interacts with the sorting of individuals between production and research. Second, the results of this paper highlight that migration policy has heterogeneous effects across different categories of workers. In future research, this framework can be applied to study the interaction between migration and inequality.

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Appendix

A Theoretical Derivations

A.1 Proof of Proposition 1.

Proof. The assumption that inventors appropriate the surplus implies that:

$$\mathbb{E}(J(A_{j,c,t}+\tilde{\sigma}_t q\bar{A}_{c,t+1},t+1)-p_{j,c,t+1}(q)-J(A_{j,c,t}+\tilde{\sigma}_t,t+1)=0.$$

Plugging this expression into the value function, the following expression results:

$$J(A_{j,c,t},t)=\Pi_{j,c,t}+\frac{1}{1+r}J(A_{j,c,t+1}+\tilde{\sigma}_t,t+1)$$

Along a BGP, the exogenous imitation rate takes the following form:

$$\begin{aligned}\tilde{\sigma}_{A,t}&=\sigma\bar{A}_{A,t}\max\{1/a-1,0\}\\ \tilde{\sigma}_{B,t}&=\sigma\bar{A}_{B,t}\max\{a-1,0\}\end{aligned}$$

Conjecture that the value takes the form $J(A_{j,c,t},t)=v_{1,c}A_{j,c,t}+v_{2,c}\bar{A}_{c,t}$ for some constants $v_1,v_2\in\mathbb{R}$. Plugging the guess into the value function and collecting terms we obtain:

$$\begin{aligned}v_{1,c}&=\frac{1+r}{r}\alpha L_c\\ v_{2,A}&=\frac{1+g_A}{r-g_A}v_{1,A}\sigma\max\{1/a-1,0\}\\ v_{2,B}&=\frac{1+g_B}{r-g_B}v_{1,B}\sigma\max\{a-1,0\}\end{aligned}$$

which verifies the conjecture. This implies that the price of the technology is:

$$p_{j,c,t+1}(q)=J(A_{j,c,t}+\tilde{\sigma}_{c,t}+q\bar{A}_{c,t+1},t+1)-J(A_{j,c,t}+\tilde{\sigma}_{c,t},t+1)=v_{1,c}q\bar{A}_{c,t+1}.$$

As a result, technology is sold at per-unit price $p_{c,t}=\frac{1+r}{r}\alpha L_c\bar{A}_{c,t}$. ■

A.2 Proof of Proposition 2

Conjecture that, along a BGP, the values of migrants and locals are linear in aggregate productivity and depend on time only through aggregate productivity, i.e. there exists constants v_{AA},v_{AB},v_{BB}, and v_{BA} such that $V_{AA}(z,\epsilon,t)=v_{AA}(z,\epsilon)\bar{A}_A(t)$, $V_{AB}(z,\epsilon,t)=v_{AB}(z,\epsilon)\bar{A}_B(t)$, $V_{BB}(z,\epsilon,t)=v_{BB}(z,\epsilon)\bar{A}_B(t)$, $V_{BA}(z,\epsilon,t)=v_{BA}(z,\epsilon)\bar{A}_A(t)$. The the continuation value for a local inventor in B

in equation (8) becomes:

$$\begin{aligned} W_{BB}(z,\epsilon,t) &= \max\{V_{BB}(z,\epsilon,t), V_{BA}(z,\epsilon,t) - \kappa\bar{A}_A(t)\} \\ &= \bar{A}_B(t)\max\{v_{BB}(z,\epsilon), (v_{BA}(z,\epsilon)-\kappa)a\} \\ &= \bar{A}_B(t) w_{BB}(z,\epsilon). \end{aligned}$$

where $w_{BB}(z,\epsilon) \equiv \max\{v_{BB}(z,\epsilon), v_{BA}(z,\epsilon)-\kappa\}$ is constant relative to time.

Then, the value of a local inventor in B becomes:

$$\begin{aligned} v_{BB}(z,\epsilon)\bar{A}_B(t) =& (1-\tau_c)(\mu_{Ac}+\mu_{Bc})^{\nu-1} z\frac{1+r}{r}\alpha L_B \bar{A}_B(t) + \\ & \beta\delta\left(\lambda\sum_j \psi_{BB,j}\mathbb{E}\left[w_{BB}(z',\epsilon')\bar{A}_B(t)|z,\epsilon\right] + (1-\lambda)\mathbb{E}[w_{BB}(z,\epsilon')\bar{A}_B(t)|\epsilon]\right) \end{aligned}$$

Canceling $\bar{A}_B(t)$ on both sides, the equation becomes:

$$\begin{aligned} v_{BB}(z,\epsilon) =& (1-\tau_c)(\mu_{Ac}+\mu_{Bc})^{\nu-1} z\frac{1+r}{r}\alpha L_B \\ & + \beta\delta\left(\lambda\sum_j \psi_{BB,j}\mathbb{E}\left[w_{BB}(z',\epsilon')|z,\epsilon\right] + (1-\lambda)\mathbb{E}[w_{BB}(z,\epsilon')|\epsilon]\right) \end{aligned}$$

The right hand-side of this equation is constant relative to time because w_{BB}, distributions of talent, mass of individuals of each type, and the growth rate are constant along a BGP. This proves the conjecture that $V_{BB}(z,\epsilon,t) = v_{BB}(z,\epsilon)\bar{A}_B(t)$. A similar reasoning holds for the remaining values.

Since $W_{BB}(z,\epsilon,t) = w_{BB}(z,\epsilon)\bar{A}_B(t)$, the migration decision for a local in country B with talent z and productivity shock ϵ is time invariant. To see this, consider a local (z,ϵ) in B that would choose to migrate at time t, i.e. such that $V_{BA}(z,\epsilon,t) - \kappa\bar{A}_A(t) - V_{BB}(z,\epsilon,t) > 0$. Then after a time interval δ:

$$\begin{aligned} & V_{BA}(z,\epsilon,t+\delta) - \kappa\bar{A}_A(t+\delta) - V_{BB}(z,\epsilon,t+\delta) = \\ & \bar{A}_B(t+\delta)w_{BA}(z,\epsilon) = \\ & \bar{A}_B(t)(1+g)^{\delta} w_{BA}(z,\epsilon) = \\ & (1+g)^{\delta}(V_{BA}(z,\epsilon,t) - \kappa\bar{A}_A(t) - V_{BB}(z,\epsilon,t)) > 0 \end{aligned}$$

proving that the individual (z,ϵ) would still choose to migrate at time $t+\delta$. A similar reasoning holds for the remaining migration and return decisions.

A.3 Proof of Proposition 3

Proof. The change in aggregate productivity in country c is given by:

$$\begin{aligned}\bar{A}_c(t+1) &= \int_0^1 \left(A_j(t) + x_c(t)Q_c(t)\bar{A}^c(t) + \sigma \max\{(\bar{A}_{-c}(t) - \bar{A}_c(t)), 0\}\right) dj \\ &= \bar{A}_c(t) + \iota_c(t)\bar{A}_c(t) + \sigma \max\{(\bar{A}_{-c}(t) - \bar{A}_c(t)), 0\}\end{aligned}$$

Then the growth rate of each economy is given by:

$$\begin{aligned}g_A(t) &= \frac{\bar{A}_A(t+1) - \bar{A}_A(t)}{\bar{A}_A(t)} = \iota_A(t) + \sigma \max\left\{\frac{\bar{A}_B(t)}{\bar{A}_A(t)} - 1, 0\right\} \\ g_B(t) &= \frac{\bar{A}_B(t+1) - \bar{A}_B(t)}{\bar{A}_B(t)} = \iota_B(t) + \sigma \max\left\{\frac{\bar{A}_A(t)}{\bar{A}_B(t)} - 1, 0\right\}\end{aligned}$$

Given that the distributions of talent are constant, along a BGP ι_A and ι_B are constant. In order for g_A and g_B to be constant, it must be the case that the TFP gap $a(t) = \frac{\bar{A}_A(t)}{\bar{A}_B(t)}$ is constant, i.e. $a(t) = a(t+1)$. The evolution of the TFP gap satisfies the following equation:

$$\begin{aligned}a(t+1) - a(t) &= \frac{\bar{A}_A(t+1)}{\bar{A}_B(t+1)} - \frac{\bar{A}_A(t)}{\bar{A}_B(t)} \\ &= \frac{\bar{A}_A(t)}{\bar{A}_B(t)}\left(\frac{1 + \iota_A + \sigma \max\{1/a - 1, 0\}}{1 + \iota_B + \sigma \max\{a - 1, 0\}} - 1\right) \\ &= \frac{\bar{A}_A(t)}{\bar{A}_B(t)}\left(\frac{\iota_A - \iota_B + \sigma(\max\{1/a(t) - 1, 0\} - \max\{a(t) - 1, 0\})}{1 + \iota_B + \sigma \max\{a - 1, 0\}}\right)\end{aligned}$$

Setting $a(t+1) = a(t)$ we obtain:

$$a = \begin{cases} \frac{\sigma}{\sigma + \iota_B - \iota_A} & \text{if } \iota_B > \iota_A \\ \frac{\sigma + \iota_A - \iota_B}{\sigma} & \text{if } \iota_B < \iota_A \end{cases}$$

This expression implies that, along a BGP, if $\iota_B > \iota_A$, then $a < 1$ and $\bar{A}_A(t) < \bar{A}_B(t)$, and viceversa. Without loss of generality, suppose that $\iota_B > \iota_A$. Then $g_b = \iota_B$ and the growth rate of the economy A can be re-written as:

$$\begin{aligned}g_A &= \iota_A + \sigma(1/a - 1) \\ &= \iota_A + \sigma\frac{\sigma + g_B - \iota_A - \sigma}{\sigma} = g_B,\end{aligned}$$

proving that, along a BGP, the two economies grow at the same rate g. Additionally, $g = \max\{\iota_A, \iota_B\}$.

■

A.4 Proof of Proposition 5.

To characterize migration decisions along a BGP, consider the time-independent values $v_j(z,\epsilon)$ for $j \in \{AA, AB, BA, BB\}$ defined in section A.2.

Observe that inventors' profits, described in equation (5), are increasing in z. The learning technology is also increasing in z. Thus, $v_j(z,\epsilon)$ is increasing in z for all j.

Next, we need to determine the slope of $v_j(z,\epsilon)$ as function of z, for a fixed value of ϵ. There are two components that determine the slope: (i) inventors' profits and (ii) learning opportunities. Suppose that, in equilibrium, aggregate productivity is higher in B, i.e., $a < 1$. Then, under assumption 1, since $\tau_B < \tau_A$, profits are higher in B, for any given value of z. Next, suppose that average bundle is highest for the A migrants, followed by B locals, A locals and B migrants, i.e., $\int_1^\infty q dF_{AB}(q) \geq \int_1^\infty q dF_{BB}(q) > \int_1^\infty q dF_{AA}(q) > \int_1^\infty q dF_{BA}(q)$. Under assumption 2, inventors in B interact more frequently with groups BB and BA. Thus, learning opportunities are higher in B.

Consider an individual of origin A. Given that profits and learning opportunities are higher in B, it follows that, $\frac{\partial v_{AA}(z,\epsilon)}{\partial z} < a\frac{\partial v_{AB}(z,\epsilon)}{\partial z}$. Thus, considering the migration problem of an individual of type AA, there are two possible cases. In the first case, $av_{AB}(1,\epsilon) - v_{AA}(1,\epsilon) - a\kappa > 0$. Then all individuals of type AA and productivity shock ϵ want to move to B, so the threshold is $\bar{z}_{AA}(\epsilon) = 1$. In the second case, $av_{AB}(1,\epsilon) - v_{AA}(1,\epsilon) - a\kappa \leq 0$. Then, since $\frac{\partial v_{AA}(z,\epsilon)}{\partial z} < a\frac{\partial v_{AB}(z,\epsilon)}{\partial z}$, there exists a value $\bar{z}_{AA}(\epsilon)$ such that $av_{AB}(\bar{z}_{AA}(\epsilon),\epsilon) - v_{AA}(\bar{z}_{AA}(\epsilon),\epsilon) - a\kappa = 0$. Thus, in both cases, we have defined a threshold $\bar{z}_{AA}(\epsilon)$ such that all individuals of origin A and productivity shock ϵ want to move to B if their value of z is above the threshold. A similar reasoning holds for the other thresholds, with the difference that movements from B to A occur when individuals are below a given threshold.

The threshold behavior indicates that the right tail of the distribution of locals in A moves to B, while the left tail of the distribution of locals in B moves to A. Similarly, the left tail of A migrants returns to A, while the right tail of B migrants returns to B. Additionally, under assumption 1, the distribution of individuals across shocks ϵ is symmetric across countries. As, a results, the working assumption that $\int_1^\infty q dF_{AB}(q) \geq \int_1^\infty q dF_{BB}(q) > \int_1^\infty q dF_{AA}(q) > \int_1^\infty q dF_{BA}(q)$. Under assumption 2 is confirmed. This, in turn, implies that innovation is higher in B, confirming that $a < 1$.

A.5 Proof of Proposition 6.

Note that the value of a migrant inventor is monotonically increasing in the idiosyncratic productivity shock ϵ, which has unbounded support. Thus, it simply follows that, for a given value of z, a local inventor chooses to move abroad for a high enough value of ϵ. The opposite is true for return decisions.

A.6 Law of Motion of Talent Distributions

In this section, I describe the law of motion for the bundle distributions for inventors of each type $j \in \{AA, AB, BB, BA\}$, $F_{j,t}(q)$. For ease of exposition, I introduce the cumulative distribution function of individuals of type j with talent no greater than z and location productivity shock equal to ϵ, denoted as $G_j(z, \epsilon, t)$. Lower case letters f and g indicate the corresponding probability distribution functions. I additionally define the CDF of newborn individuals of nationality A with talent no greater than z and shock ϵ as $\tilde{G}(z, \epsilon)$.

Consider first the CDF of local individuals of nationality B, denoted as $G_{BB}(z, \epsilon, t)$. The law of motion for this distribution satisfies the following equation:

$$\begin{aligned} g_{BB}(z,\epsilon,t+1) &= \delta g_{BB}(z,\epsilon,t) v_{\epsilon|\epsilon}(1-\lambda) \\ &+ \int_{-\infty}^{\infty}\int_{1}^{\infty} \delta g_{BB}(z',\epsilon',t) v_{\epsilon|\epsilon'}(\lambda \sum_{j\in\mathcal{J}} \psi_{BB,j} f_{j,t}((z/z')^{1/\eta})) dz' d\epsilon' \\ &+ \int_{-\infty}^{\infty}\int_{1}^{\infty} (1-\delta)\tilde{g}_{BB}(z',\epsilon,t)(\lambda \sum_{j\in\mathcal{J}} \psi_{BB,j} f_{j,t}((z/z')^{1/\eta})) dz' d\epsilon' \\ &+ \int_{-\infty}^{\infty}\int_{1}^{\infty} \delta g_{BA}(z',\epsilon',t) v_{\epsilon|\epsilon'}(\lambda \sum_{j\in\mathcal{J}} \psi_{BA,j} f_{j,t}((z/z')^{1/\eta})) \mathbf{1}_{BA}(z,\epsilon) dz' d\epsilon' \end{aligned}$$

where $\mathbf{1}_{BA}(z, \epsilon)$ is an indicator function that turns to 1 if individuals of type BA with productivity z and shock ϵ choose to return to B:

$$\mathbf{1}_{BA}(z,\epsilon) \equiv \mathbf{1}\{v_{BB}(z,\epsilon) - v_{BA}(z,\epsilon) > 0\}.$$

The equation for the law of motion has the following interpretation. At period $t+1$, the mass of individuals of type BB who has productivity equal to z and shock equal to ϵ is equal to the sum of (i) mass of type BB individuals that have productivity no greater than z and shock ϵ at time t, survive, remain at the same shock value ϵ, and have no meetings (first line) (ii) mass of individuals of type BB that start from values (z', ϵ'), survive, transition to ϵ and meet someone with bundle $q = (z/z')^{1/\eta}$ which brings them to talent level z (second line) (iii) newborn individuals of nationality B that start from values (z', ϵ), transition to ϵ and meet someone with bundle $q = (z/z')^{1/\eta}$ which brings them to talent level z (third line) (iv) mass of individuals of type BA that start from values (z', ϵ'), survive, transition to ϵ, meet someone with bundle $q = (z/z')^{1/\eta}$ which brings them to talent level z, and, once they are at values (z, ϵ), choose to return to B (fourth line). Along a BGP, I require that the talent distribution is stationary, i.e. $g_{BB}(z, \epsilon, t+1) = g_{BB}(z, \epsilon, t)$. The law of motion for the other types BA, AA, AB follow similar equations and interpretations. [47]

[47] Note that the law of motion for type AA must additionally account for the probability that an individual is allowed to move, m_t.

A.7 Welfare

In this section, I describe a measure of welfare along a BGP. In this model, utility is linear and there is no saving technology, thus individuals' consumption is equal to their income in every period. Thus, individuals' welfare is equal to the discounted stream of future profits.

Consider an initial time $t = 0$ and initial level of productivities for each economy $\bar{A}_{A,0}$ and $\bar{A}_{B,0}$. For an inventor of type $j \in \{AA, AB, BA, BB\}$, talent z and productivity shock, welfare $W_j(z, \epsilon, 0)$ is equal to the value $V_j(z, \epsilon, t)$. I then compute the average welfare of individuals of type z, labeled $W_j(0)$ as the average weighted by the distribution $G_j(z, \epsilon)$ of talent and productivity differential for type j :

$$W_j(0, \bar{A}_{A,0}, \bar{A}_{B,0}) = \int_{-\infty}^{\infty} \int_{1}^{\infty} V_j(z, \epsilon, 0) g_j(z, \epsilon) dz d\epsilon$$

The welfare of production workers in country c, $W_{P,c}(0)$, is equivalent to the discounted sum of future wages and tax rebates:

$$W_{P,c}(0, \bar{A}_{A,0}, \bar{A}_{B,0}) = \int_{0}^{\infty} (\beta\delta)^t (w_t + T_t) dt.$$

The weighted average of welfare for individuals of nationality c, labeled $W_c(0, \bar{A}_{A,0}, \bar{A}_{B,0})$, is given by:

$$W_c(0, \bar{A}_{A,0}, \bar{A}_{B,0}) = \mu_{cA} W_{cA}(0, \bar{A}_{A,0}, \bar{A}_{B,0}) + \mu_{cB} W_{cB}(0, \bar{A}_{A,0}, \bar{A}_{B,0}) + L_c W_{P,c}(0, \bar{A}_{A,0}, \bar{A}_{B,0}).$$

The tax rebate in country c must be such that the government balances the budget in every period. Tax revenues from group j, labeled $TR_{j,c}(t)$, are equal to:

$$TR_{j,c}(t) = \int_{1}^{\infty} \tau_{c,j} (\mu_{Ac} + \mu_{Bc})^{\nu-1} \frac{1+r}{r} \alpha L_c q dF_j(q) \bar{A}_c(t)$$

Total tax revenues in country c, labeled $TR_c(t)$ are equal to the weighted sum of revenues from each group od inventors: $TR_c(t) = \mu_{Ac}(t) TR_{Ac,c}(t) + \mu_{Bc}(t) TR_{Bc,c}(t)$. Thus the tax rebate is equal to :

$$T_A(t) = (\mu_{AA} + \mu_{BA})^{\nu-1} \frac{1+r}{r} \alpha \left(\tau_{A,AA} \int_{1}^{\infty} q dF_{AA}(q) + \tau_{A,BA} \int_{1}^{\infty} q dF_{BA}(q) \right) \bar{A}_A(t).$$

A.8 Learning Technology

The learning technology introduced in the main text implies that the expected evolution talent for an inventor of type i, before meetings are realized, is given by:

$$\mathbb{E}(z_t | z_{t-1}, i) = \lambda \sum_{j \in \mathcal{J}} \psi_{i,j} \int_{1}^{\infty} z_t \hat{q}_{t-1}^{\eta} dF_{j,t-1}(q_{t-1}) + (1-\lambda) z_{t-1}. \tag{17}$$

The literature on diffusion has introduced a range of different learning functions. Here, I introduce a generalized learning technology that nests equation (17) and several cases in the literature as special cases.

Consider the following law of motion for the evolution of talent, z, for an individual of type i:

$$\mathbb{E}(z_t|z_{t-1}, i) = \lambda \sum_{j\in\mathcal{J}} \psi_{i,j} \Bigg(\Big(F_{j,t-1}(\bar{k}z_{t-1}) - F_{j,t-1}(\underline{k}z) \Big)^{\gamma-1} \int_{\underline{k}z_{t-1}}^{\bar{k}z_{t-1}} (z_{t-1})^{\eta_1} (\hat{q}_{t-1})^{\eta_2} dF_{j,t-1}(\hat{q}_{t-1})$$
$$+ z_{t-1}\Big(1 - (F_{j,t-1}(\bar{k}z_{t-1}) + F_{j,t-1}(\underline{k}z_{t-1}))^{\gamma}\Big) \Bigg) + (1-\lambda)z_{t-1}$$

where $\underline{k} \in (-\infty, 1)$, $\bar{k} \in (1, +\infty)$ are "learning bounds", in the sense that the inventor can only learn when meeting someone inside the given bounds. The parameters $\eta_1 \geq 0$, $\eta_2 \geq 0$ determine how important is the initial level of productivity of each inventor for learning. Finally parameter $\gamma \in [0, 1]$ determines the direction of draw, in the sense that when $\gamma = 1$ the draw is completely random and the inventor might not learn from the meeting, whereas when $\gamma = 0$ the inventor always meets someone within the learning bounds. The general learning function nests several special cases that have been discussed in the literature. For example the case $\underline{k} = 1$, $\underline{k} = +\infty$, $\eta_1 = 0$, $\eta_2 = 1$, $\gamma = 1$ is equivalent to the learning function of Lucas and Moll (2014), Perla and Tonetti (2014), Akcigit et al. (2018). Lucas and Moll (2014) also introduced the idea of a learning bounds. Buera and Oberfield (2020) presents a learning function where the productivity of both parties in the meeting matters for learning. Finally, the case where $\underline{k} = -\infty$, $\underline{k} = +\infty$,$\eta_1 =$,$\gamma = 1$ corresponds to equation 17.

B Empirical Appendix

In this section, I present additional results and robustness to complement the empirical analysis presented in Section 3.

B.1 Additional Details on Sample Construction

Table B.1: Summary Statistics

Panel A: Number of Unique Observations						
	Full Sample		EU Origin		US Origin	
Unique Inventors	4,029,289		1,639,331		1,034,769	
w/ more than 1 patent	1,293,431		593,328		344,938	
Migrants	12,743		7,299		2,433	
Return Migrants	2,371		1,350		475	
Panel B: Averages per Individual × Year						
	Full Sample		EU Origin		US Origin	
	Locals	Migrants	Locals	Migrants	Locals	Migrants
Patents per year	1.83	2.74	1.83	2.77	1.85	2.60
Citations per year	4.10	7.69	4.25	8.84	3.15	4.69
3-year Citations	0.42	0.82	0.42	0.97	0.29	0.45
Experience	3.22	4.71	3.69	5.05	3.03	4.19
Co-Inventors per year	6.34	10.31	5.84	10.36	7.07	10.14

Notes: Panel A describes the number of observations in various sub-samples of the EPO dataset. Panel B presents the mean value for a set of variables across various sub-samples of EPO data. See text for a description of the variables.

Inventors' Addresses. A potential concern in measuring individual-level migration from changes in inventors' addresses is that individuals might report a fictitious address without actually changing their residence. To address this concern, I analyze the address reported by inventors in my data. I find that some inventors file the same patent application (i.e., same application number) at different patent offices using different addresses on the same day. This happens for 1,384 observations. I exclude these observations from the sample of migrants and drop them from the analysis.

Country of origin and nationality. The EPO database does not report the country of nationality of inventors. To infer the most likely nationality, I analyze the ethnic origin of names using the commercial software "Namsor". The software takes as inputs the first and last name and country of residence of an individual. It then returns the ten most likely countries of origin, based on an algorithmic search of administrative databases. I implement this procedure for all the migrants and placebo control inventors in my dataset (see Section 3). Then, I compare this information to the country of origin in my dataset, where the first patent was filed. If the country of the first patent does not coincide with any of the countries of origin predicted by Namsor, then there are two possibilities. i) At least one of Namsor's predictions corresponds to the country of destination in my dataset; this is the case for 480 individuals. ii) None of Namsor's predictions corresponds to the country of destination; this is the case for 810 individuals. I flag observations corresponding to these two cases and explore robustness in the sections below.

B.2 Migrant Inventors

Table B.2: Summary Statistics Before and After Matching, Inventors of EU origin

	-Panel A: Before Matching -							
	EU Migrants				All EU Inventors			
	N	Mean	Median	SD	N	Mean	Median	SD
First Year in Sample	1057	1999	2000	8.04	4087243	1999	2000	9.23
Experience	1057	2.49	1	3.47	4087243	3.37	1	4.64
Patent Stock	1057	8.67	4	17.71	4087243	3.88	2	9.22
Co-Inventors Stock	1057	13.38	7	17.49	4087243	5.59	3	10.46
Citations Stock	1057	2.25	0	7.29	4087243	0.92	0	3.30
	-Panel B: After Matching -							
	Matched EU Migrants				Control Group (Placebo)			
	N	Mean	Median	SD	N	Mean	Median	SD
First Year in Sample	955	1999	2000	7.95	955	1999	2000	7.95
Experience	955	2.05	1	2.94	955	2.05	1	2.94
Patent Stock	955	5.52	3	6.71	955	5.52	3	6.71
Co-Inventors Stock	955	10.45	6	12.18	955	6.45	4	7.93
Citations Stock	955	2.02	0	7.09	955	1.45	0	6.45

Notes: This table reports summary statistics for EU inventors. The statistics for the full sample are computed using data from 1978 to 2016. Thus, each inventor appears multiple times. For the migrants and the control group, the statistics are computed using the year before migration. Thus, each inventor appears only one time.

Table B.2 presents the summary statistics for the sample of inventors of EU origin. Panel A compares migrants of EU origin to the full sample of EU inventors. The statistics for the full sample are computed using data from 1978 to 2016. Thus, each inventor appears multiple times. For the migrants and the control group, the statistics are computed using the year before migration. Thus, each inventor appears only one time. Migrants have less experience than the full population because they are measured before migrating, thus early in their careers. Nonetheless, they have cumulated more patents, co-inventors, and citations on average. Panel B presents the summary statistics after matching. The matching procedure looks for an exact correspondence based on country of origin, the first year in the sample, experience, and patent stock at the time of migration. Thus, the first three rows of Panel B are identical across the migrants and the control group. The procedure also results in similar average citations stock across the two groups, while migrants have more cumulated co-inventors than the control group.

Similar results hold for the sample of inventors of US origin, displayed in Table B.3.

Table B.3: Summary Statistics Before and After Matching, Inventors of US origin

	-Panel A: Before Matching -							
	US Migrants				All US Inventors			
	N	Mean	Median	SD	N	Mean	Median	SD
First Year in Sample	518	2000	2001	7.30	2150521	1999	2000	8.86
Experience	518	1.85	0	3.33	2150521	2.63	1	4.11
Patent Stock	518	5.16	2	7.72	2150521	3.32	1	6.40
Co-Inventors Stock	518	8.54	5	10.02	2150521	6.13	3	9.24
Citations Stock	518	0.98	0	3.71	2150521	0.64	0	2.56
	-Panel B: After Matching -							
	Matched US Migrants				Control Group (Placebo)			
	N	Mean	Median	SD	N	Mean	Median	SD
First Year in Sample	504	2001	2001	7.21	504	2001	2001	7.21
Experience	504	1.75	0	3.15	504	1.75	0	3.15
Patent Stock	504	4.45	2	5.72	504	4.45	2	5.72
Co-Inventors Stock	504	8.04	5	8.96	504	7.58	4	9.35
Citations Stock	504	1.00	0	3.75	504	0.66	0	2.20

Notes: This table reports summary statistics for US inventors. The statistics for the full sample are computed using data from 1978 to 2016. Thus, each inventor appears multiple times. For the migrants and the control group, the statistics are computed using the year before migration. Thus, each inventor appears only one time.

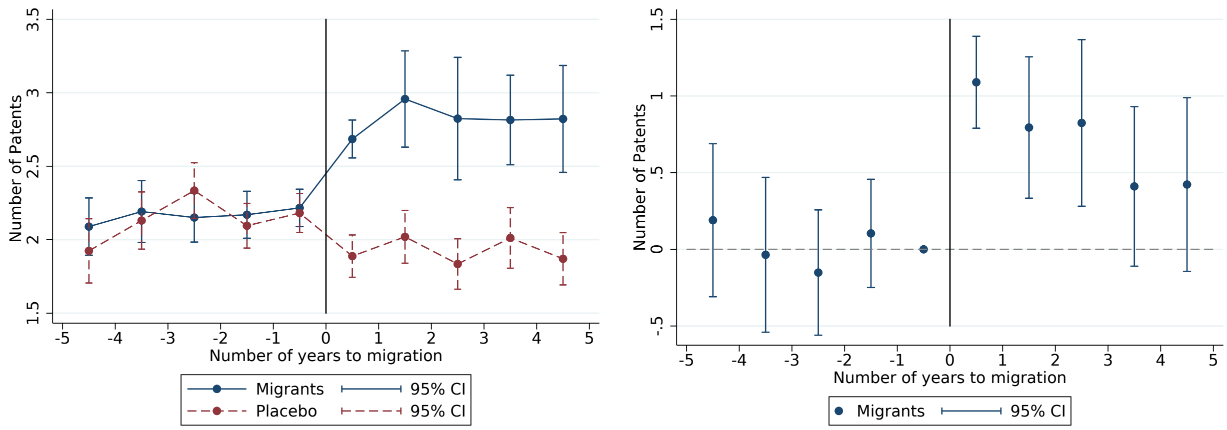
Next, I present robustness for the evolution of productivity of migrants. Figures B.2 and B.1 replicates the results of Figure 3 for the samples of EU inventors and US inventors separately. The results are more noisy, because the sample size is getting significantly smaller. Nonetheless, the dynamic pattern and the magnitudes are similar, consistently with the results of Table 1, which documented that the effects for the US sample and EU sample are not significantly different.

A recent literature has highlighted limitations of the two-way fixed-effects regressions model as in equation 15. Here I document that the results presented in the main text are robust to alternative specifications. Figure B.3 presents two alternative specifications. Panel (a) presents a specification without individual and experience fixed effects, thus using only time fixed effects. Panel (b) augments specification 15 adding all leads and lags. In both cases, there is no significant pre-trend and productivity increases after migration, by a magnitude similar to the results in Figure 3.

A potential concern is that many migrants remain employed by a foreign subsidiary of the

Figure B.1: Patenting activity by EU migrants around time of migration

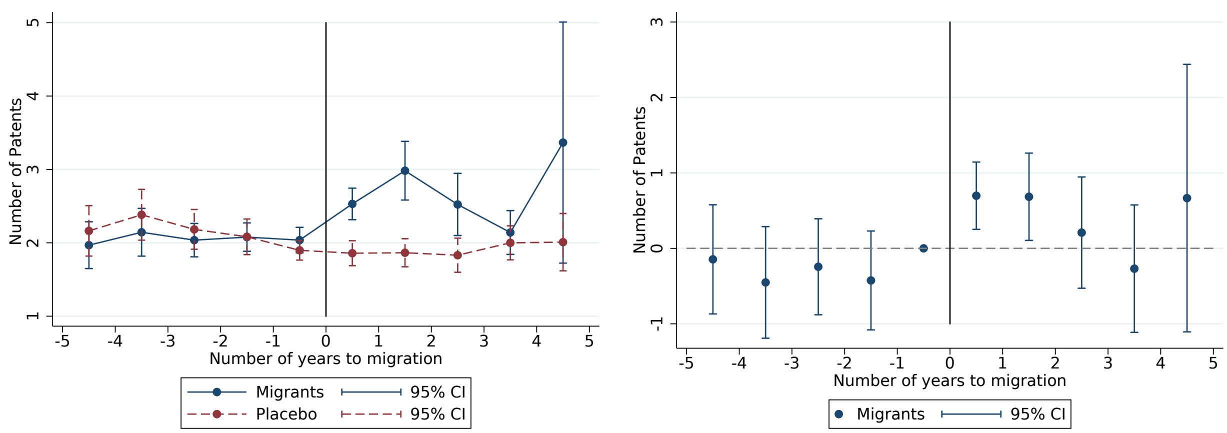
(a) Raw Means (b) Coefficients β_τ^{Mig} for migrants



Note: Unbalanced Panel. EU Migrants: 5,976 obs. EU Placebo: 5,189 observations. SE clustered at inventor level.

Figure B.2: Patenting activity by US migrants around time of migration

(a) Raw Means (b) Coefficients β_τ^{Mig} for migrants

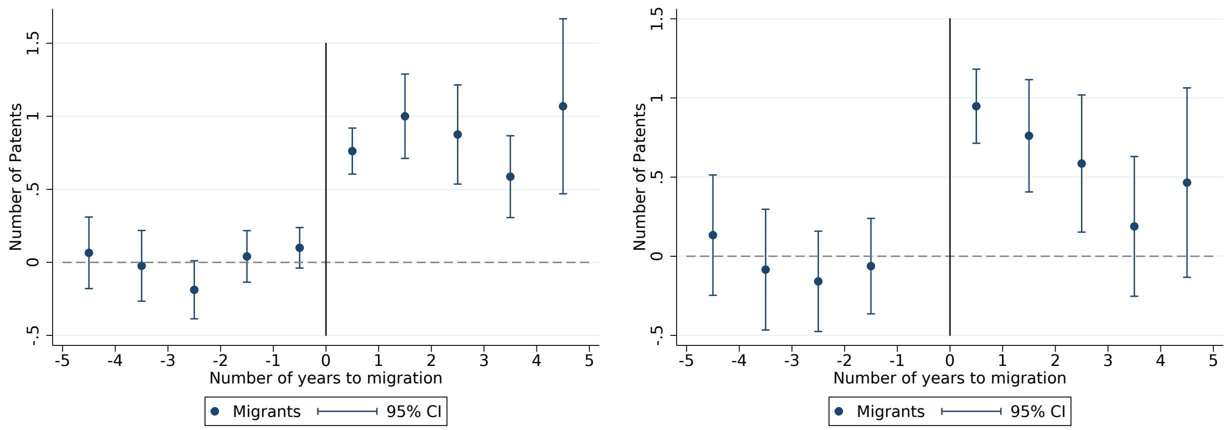


Note: Unbalanced Panel. US Migrants: 2,907 observations. US Placebo: 2,474 observations. SE clustered at inventor level.

same company after moving. The observed change in patenting could then be the consequence of a re-organization at the firm level, which involves the reallocation of individuals and increases in productivity. To rule this out, I show that the effects are robust for migrants that switch companies. Table B.4, in column (1), reports the results for specification (16) for the subsample of migrants that migrate within the same multinational company. Column (2) displays the results for migrants that change firm when they move. Importantly, the effect remains significant and sizeable for migrants that switch firms. The remaining columns document the results using the citation-based measure discussed in the main text. Results are not statistically significant, but point estimates

Figure B.3: Patenting activity by migrants around time of migration

(a) Only Time F.E. (b) All leads and lags



Note: Unbalanced Panel. EU Migrants: 5,976 obs. US Migrants: 2,907 observations. EU Placebo: 5,189 observations. US Placebo: 2,474 observations. SE clustered at inventor level.

confirm positive coefficients for the innovative output of migrants after migration.

Table B.4: Patenting activity of migrants around the time of migration: Robustness

	(1)	(2)	(3)	(4)
Outcome	Pat.	Pat.	Cit.	Cit. 3 -yr
Sample	Same Firm	Diff. Firm	All	All
Post Mig.	0.8209***	1.0262***	0.2502	0.0970
	(0.1060)	(0.2200)	(0.7386)	(0.0975)
Obs	13353	3182	14548	14548
R2	0.380	0.455	0.459	0.355
Inventor FE	X	X	X	X
Year FE	X	X	X	X

Notes: Column (1) displays the benchmark regression for the sub-sample of migrants who move to a different branch of the same multinational firm. Column (2) uses the sub-sample of migrants who move to a different firm. Column (3) uses forward citations as outcome variable. Column (4) uses forward citations in a 3-years window as outcome variable. Standard Errors clustered at inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Finally, in table B.5 I repeat the main analysis with the sample of migrants classified by Namsor. In particular, I drop those individuals for whom the country of nationality predicted by Namsor does not coincide with the country of origin in my sample, as explained at the beginning of this section. The results are consistent with the main findings displayed in Table 1.

B.3 Local Inventors

Table B.6 presents the summary statistics for the co-inventors of European migrants and placebo at the origin. The statistics are computed using the year before the migration of the corresponding

Table B.5: Patenting activity of migrants: Robustness with Name Ethnicity

	Number of Patent Applications per Year		
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Mig.	0.8925***	0.9185***	0.8608***
	(0.0984)	(0.1148)	(0.2467)
Obs	15312	9946	4136
R2	0.387	0.436	0.335
Inventor FE	X	X	X
Year FE	X	X	X

Notes: Sample of individuals for whom the country of origin in the EPO data corresponds to the conutry of nationality predicted by Namsor. Column (1) displays the benchmark regression results for the full sample. Column (2) displays the results for EU origin. Column (3) displays the results for US origin. Standard Errors clustered at inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.6: Summary Statistics Co-Inventors of Migrants and Placebo, EU origin

	Co-Inv. of EU Migrants in EU				Co-Inv. of EU Placebo in EU			
	N	Mean	Med.	SD	N	Mean	Med.	SD
First Year in Sample	16890	1999	2000	8.18	23784	2000	2002	7.83
Experience	16890	3.74	2	4.48	23784	3.31	2	4.18
Patent Stock	16890	5.50	3	8.27	23784	4.82	2	7.35
Co-Inventors Stock	16890	10.08	7	10.36	23784	7.48	5	8.10
Citations Stock	16890	1.73	0	4.84	23784	1.05	0	3.55

Notes: This table reports summary statistics for European co-inventors of European migrants and placebo. The statistics are computed using the year before migration of the corresponding migrant. Thus, each inventor appears only once.

Table B.7: Summary Statistics Co-Inventors of Migrants and Placebo, US origin

	Co-Inv. of US Migrants in US				Co-Inv. of US Placebo in US			
	N	Mean	Med.	SD	N	Mean	Med.	SD
First Year in Sample	5580	2000	2000	7.41	9295	2000	2001	7.27
Experience	5580	3.40	2	4.33	9295	2.95	1	4.02
Patent Stock	5580	5.23	3	7.41	9295	4.82	2	6.76
Co-Inventors Stock	5580	11.41	8	11.28	9295	10.25	7	10.80
Citations Stock	5580	1.06	0	4.23	9295	0.77	0	3.33

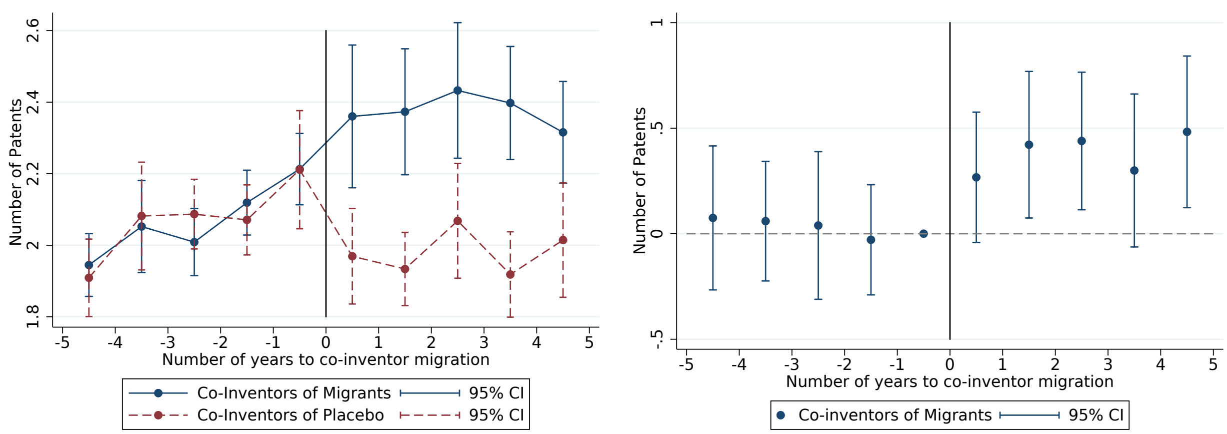
Notes: Notes: This table reports summary statistics for American co-inventors of American migrants and placebo. The statistics are computed using the year before migration of the corresponding migrant. Thus, each inventor appears only once.

migrant. Thus, each inventor appears once. Note that, while migrants and placebo are matched on observables, their co-inventors are not. Nonetheless, the table reveals that the two groups have similar values for the first year in the sample, experience, patent, and citation stock. These similarities bolster the credibility of the empirical exercise.

Similar results hold for the sample of co-inventors of migrants and placebo of US origin, displayed in Table B.7.

Next, I present robustness for the evolution of productivity of local co-inventors. Figures B.4 and B.5 replicates the results of Figure 5 for the samples of EU inventors and US inventors separately. The results are noisier, because the sample size is getting significantly smaller, but the dynamic pattern and the magnitudes are similar.

Figure B.4: Patenting activity by co-inventors of migrants around time of migration, EU.

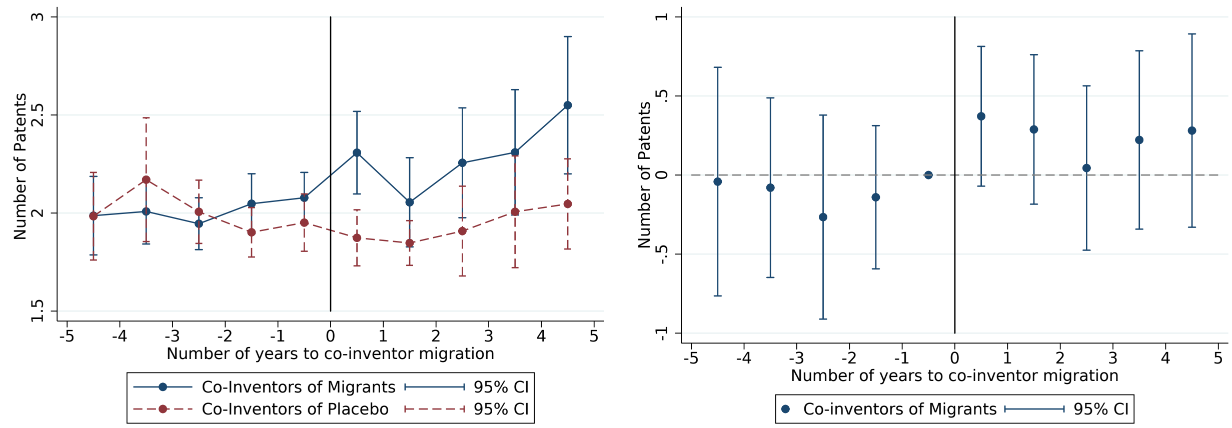


Note: Unbalanced Panel. EU Migrants: 28,661 observations; EU Placebo: 23,967 observations. Standard Errors clustered at the associated migrant inventor level.

Table B.8 presents robustness analysis for the result in table 3. Panel (a) includes all co-inventors of migrants at the origin. The first two columns separate the sub-sample of co-inventors of migrants who move abroad within the same firm (column (1)) and co-inventors of migrants who switch firms (column (2)). The point estimates are large for both, but the result in the second column is not statistically significant due to a much smaller sample size. The following columns separate the sub-sample of co-inventors of return migrants (column (3)) and co-inventors of permanent migrants (column (4)). The point estimates are large for both, but the result in the third column, with a smaller sample size, is not statistically significant. Column (5) displays the estimate for the full sample using three-year citations as an outcome variable. The estimated coefficient is positive but not statistically significant.

Panel (b) separates the local co-inventors at origin who no longer work with the migrant after migration (column (1)) and those who continue to patent with the migrant after migration (remaining columns). Column (1) shows that the estimated coefficient is positive and significant even for those who no longer work with migrants. However, the effect is much larger for locals who continue

Figure B.5: Patenting activity by co-inventors of migrants around time of migration, US.



Note: Unbalanced Panel. US Migrants: 11,879 observations; US placebo: 13,147 observations. Standard Errors clustered at the associated migrant inventor level.

to work with migrants (column (2)), even if the migrant switches to a different firm (column (3)), and even more so if the migrant returns (column (4)). Finally, even the coefficient for three-year citations becomes larger and significant at 10% confidence level for those locals who continue to work with migrants.

Another potential concern is that the observed increased in patenting for co-inventors of migrants at origin is exclusively driven by patents that are co-invented with migrants. To address this issue, I repeat the main analysis in table 3 excluding patents that are co-invented with migrants. The results are displayed in Table B.9. Although the estimated coefficients are smaller, the results are still positive and statistically significant.

Finally, in table B.10, I drop the co-inventors of migrants for whom the country of nationality predicted by Namsor does not coincide with the country of origin in my sample, as explained at the beginning of this section. The results are consistent with the main findings displayed in Table 3.

B.4 Interaction Network

Figure B.6 documents the dynamic evolution of co-inventors of migrants before and after migration, relative to the placebo control group. In Panels (a) and (b) the outcome is the share of local co-inventors at the destination for migrants. Panel (a) compares the raw means for the migrants and the placebo. Panel (b) shows the results of the regression specification from equation (15). The figures indicate that migrants have more foreign co-inventors than placebos before migration, but, importantly, they are on parallel trends. After migration, the share of foreign co-inventors for migrants increases from about 10% to about 40%, while for placebos it remains flat at around 2%.

In Panels (c) and (d) the outcome is the share of local co-inventors at the origin for migrants. Panel (a) compares the raw means for the migrants and the placebo. Panel (b) shows the results of

Table B.8: Patenting activity of co-inventors of migrants: Robustness

	(1)	(2)	(3)	(4)	(5)
Panel A: All local co-inventors at origin					
Outcome	Pat.	Pat.	Pat.	Pat.	Cit. 3 -yr
Sample	Non-Switch	Switch	Ret.	Non-Ret.	All
Post Co-Inv. Mig.	0.3718***	0.2737	0.3246	0.3828***	0.0588
	(0.0879)	(0.1967)	(0.1980)	(0.0905)	(0.0865)
Obs	70149	7599	15877	61871	77748
R2	0.500	0.493	0.483	0.505	0.436
Inventor FE	X	X	X	X	X
Year FE	X	X	X	X	X
Panel B: Co-inventors at origin patenting with migrant after migration					
	(1)	(2)	(3)	(4)	(5)
	Pat.	Pat.	Pat.	Pat.	Cit. 3-yr
Post Co-Inv. Mig.	0.2895***	0.8706***	0.4614**	0.9906**	0.2769*
	(0.0912)	(0.1865)	(0.2259)	(0.4217)	(0.1613)
Obs	46922	13260	1245	2912	13260
R2	0.488	0.458	0.508	0.456	0.407
Inventor FE	X	X	X	X	X
Year FE	X	X	X	X	X
Only Migrant Switchers			X		
Only Return Migrants				X	
Only Co-Inventors after Migration		X	X	X	X

Notes: This table shows the results of specification 16 comparing the local co-inventors of migrants at origin to the co-inventors of the placebo group. Different columns use different sub-samples. Panel (a) includes all co-inventors of migrants at origin. Column (1) uses the sub-sample of co-inventors of migrants who move abroad within the same firm. Column (2) uses the sub-sample of co-inventors of migrants who switch firms. Column (3) uses the sub-sample of co-inventors of return migrants. Column (4) uses the sub-sample of co-inventors of permanent migrants. Column (5) displays the estimate for the full sample using 3-years citations as an outcome variable.
Panel (b) displays, in column (1) the local co-inventors at origin who no longer work with the migrant after migration. Column (2) uses the co-inventors who continue to patent with the migrant after migration. Column (3) uses the same restriction as (2), additionally restricting to co-inventors of migrants who switch firm after migration. Column (4) uses the same restriction as (2), additionally restricting to co-inventors of return migrants. Column (5) uses the same restriction as (2), and displays the estimate using 3-years citations as an outcome variable. Standard Errors clustered at associated migrant inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

the regression specification from equation (15). The figures indicate that migrants have fewer local co-inventors than placebos before migration, but, importantly, they are on parallel trends. After migration, the share of foreign co-inventors for migrants decreases from about 80% to about 60%, while for placebos it remains flat at around 95%.

Table B.9: Patenting of co-inventors of migrants: exclude patents co-invented with migrants

	Number of Patent Applications per Year		
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Co-Inventor Migration	0.2450***	0.2218***	0.2902***
	(0.0566)	(0.0677)	(0.1047)
Obs	58989	40359	18630
R2	0.177	0.177	0.181
Inventor FE	X	X	X
Year FE	X	X	X

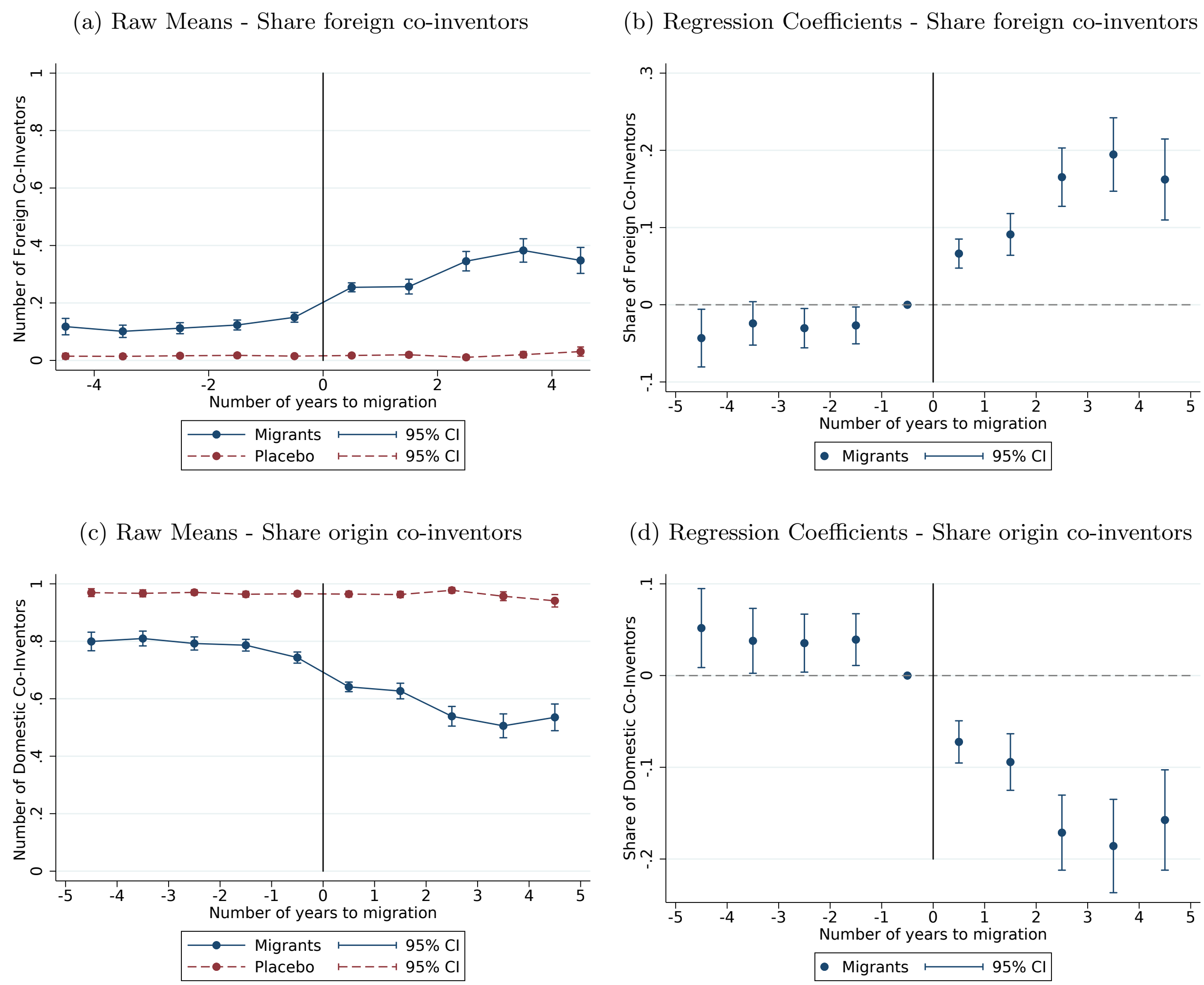
Notes: Outcome is number of patents per year excluding patents co-invented with migrants. Column (1) displays the benchmark regression results for the full sample. Column (2) displays the results for EU origin. Column (3) displays the results for US origin. Standard Errors clustered at the associated migrant inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.10: Patenting activity of co-inventors of migrants: name ethnicity robustness

	Number of Patent Applications per Year		
	(1)	(2)	(3)
	All	EU Origin	US Origin
Post Co-Inv. Mig.	0.3571***	0.3431***	0.4501***
	(0.0644)	(0.0778)	(0.1201)
Obs	70688	50086	20602
R2	0.497	0.510	0.456
Inventor FE	X	X	X
Year FE	X	X	X

Notes: Sample of individuals for whom the country of origin in the EPO data corresponds to the conutry of nationality predicted by Namsor. Column (1) displays the benchmark regression results for the full sample. Column (2) displays the results for EU origin. Column (3) displays the results for US origin. Standard Errors clustered at the associated migrant inventor level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure B.6: Interactions of migrants around time of migration



Note: Unbalanced Panel. EU Migrants: 5,761 obs. US Migrants: 2,801 observations. EU Placebo: 4,411 observations. US Placebo: 2,264 observations. SE clustered at inventor level.

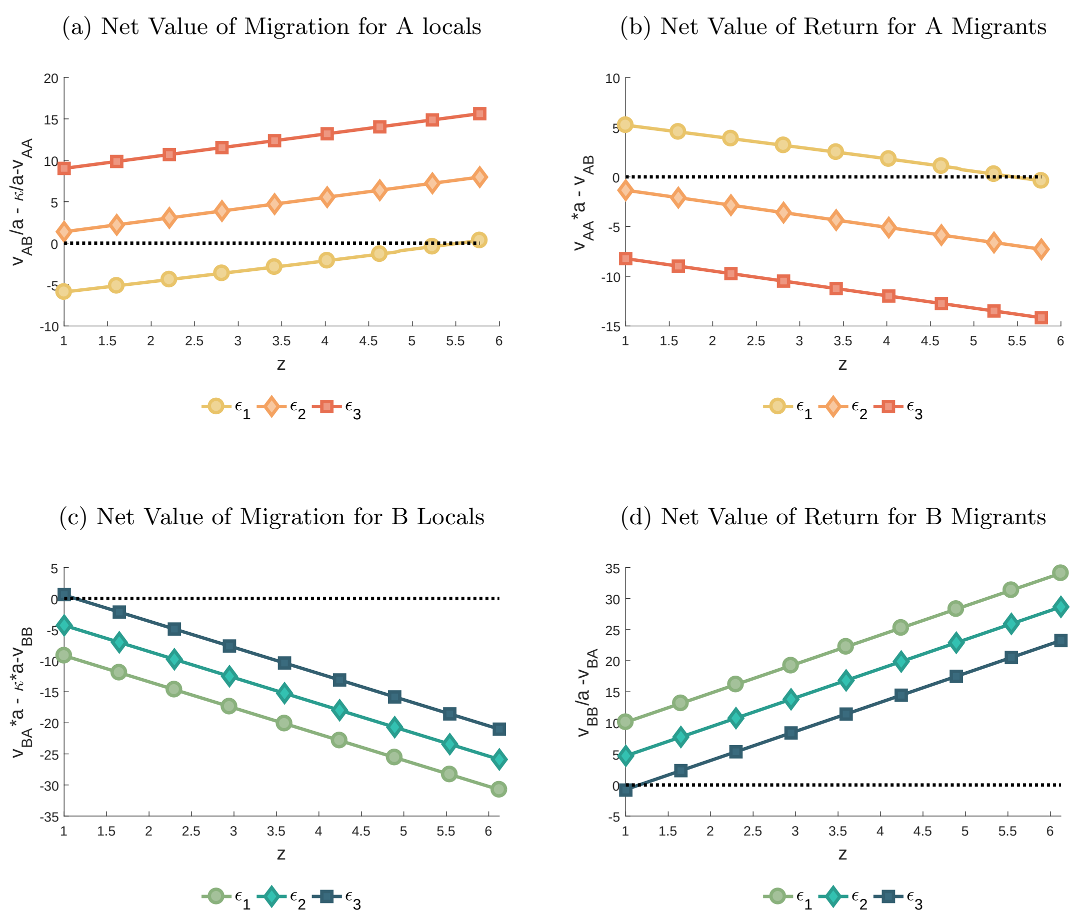
C Quantitative Appendix

C.1 Characterization of the Economy

In this section, I describe the migration decisions and the stationary talent distributions along a BGP in the calibrated model.

Figure C.1 displays migration and return decisions as a function of talent, z, plotted on the x-axis. In all panels, three lines correspond to the net value of moving for three different values of the productivity shock, $\epsilon_1 < \epsilon_2 < \epsilon_3$, indicated by circle, diamond, and square markers, respectively. The net value of moving is equal to the value of moving, minus the cost of migration, minus the cost of staying. Individuals move (i.e., migrate or return), when the net value of moving is positive.

Figure C.1: BGP Equilibrium: Migration and Return Decisions



Note: The figure displays the net moving value for each type of inventor in the model. In all panels, three lines correspond to the net value of migration for three different values of the productivity shock, $\epsilon_1 < \epsilon_2 < \epsilon_3$, indicated by circle, diamond, and square markers, respectively. Panel (a) displays the net value of migration for locals in A. Panel (b) displays the net value of returning for migrants of origin A. Panel (c) displays the net value of migration for locals in B. Panel (b) displays the net value of returning for migrants of origin B.

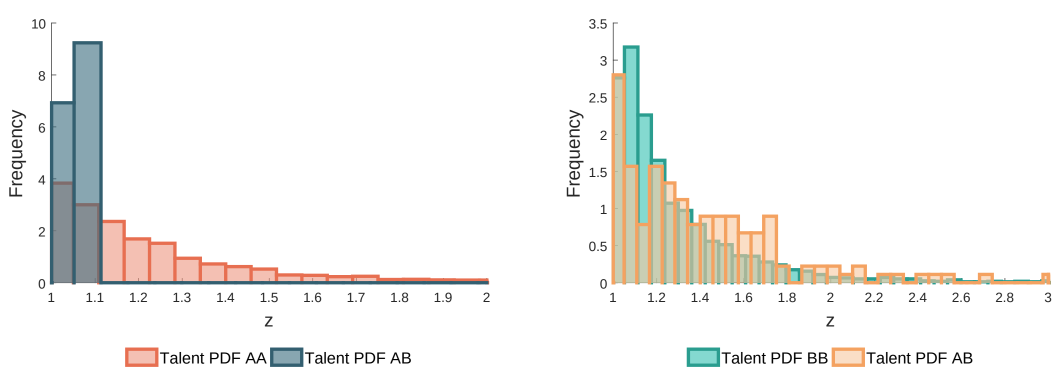
Panel (a) plots the net value of migration for a local in A. The net value of migration is increasing as a function of talent, z, because more talented inventors gain relatively more from moving to B, which, in equilibrium, has higher aggregate productivity, lower taxes, and better learning opportunities because of higher average talent. As a result, individuals move according to the threshold decision rules presented in Proposition 5, which are given by either (i) the intersection of each line with the zero line or (ii) the minimum value of the support, equal to 1. For productivity shock levels ϵ_2 and ϵ_3, the threshold is equal to 1: all individuals with these values of ϵ choose to move. This result corresponds to Proposition 6: for a given value of talent, z, individuals decide to move at a sufficiently high level of the productivity shock ϵ.

Panel (b) plots the net value of returning for a migrant of origin A. The net value is now negatively sloped because more talented individuals give up relatively more profits and learning opportunities when they move back to A. In fact, they are willing to do so only when the productivity shock is low enough. For example, when the productivity shock is equal to ϵ_2 or ϵ_3, no migrant wants to return, not even at the lowest value of z.

Panels (c) and (d) display the net value of migrating and returning for individuals of origin B, with similar interpretations. Again, the net values are negatively sloped when moving from B to A and positively sloped from A to B.

Figure C.2: BGP Equilibrium: Endogenous Talent Distributions

(a) Talent distributions in country A (b) Talent distributinos in country B



Note: The figure displays the endogenous stationary talent distributions for each type of inventor in the calibrated BGP. Panel (a) shows the distributions of individuals present in A: locals of origin A and migrants of origin B. Panel (b) shows the distributions of individuals present in B: locals of origin B and migrants of origin A.

Figure C.2 displays the endogenous stationary talent distributions for each type of inventor in the economy. Panel (a) shows the distributions of individuals present in A: locals of origin A and migrants of origin B. Panel (b) shows the distributions of individuals present in B: locals of origin B and migrants of origin A. The threshold decision rules imply that migrants from B come from the left tail of the distribution of talent at origin, whereas migrants from A come from the right tail. Given that the exogenous talent distribution is identical across countries, the result is that migrants from B on average have lower talent than locals in A and B. By contrast, migrants from A have higher talent than both types of locals on average. Figure 8 illustrates that the difference in average talent is confirmed in the micro-data.

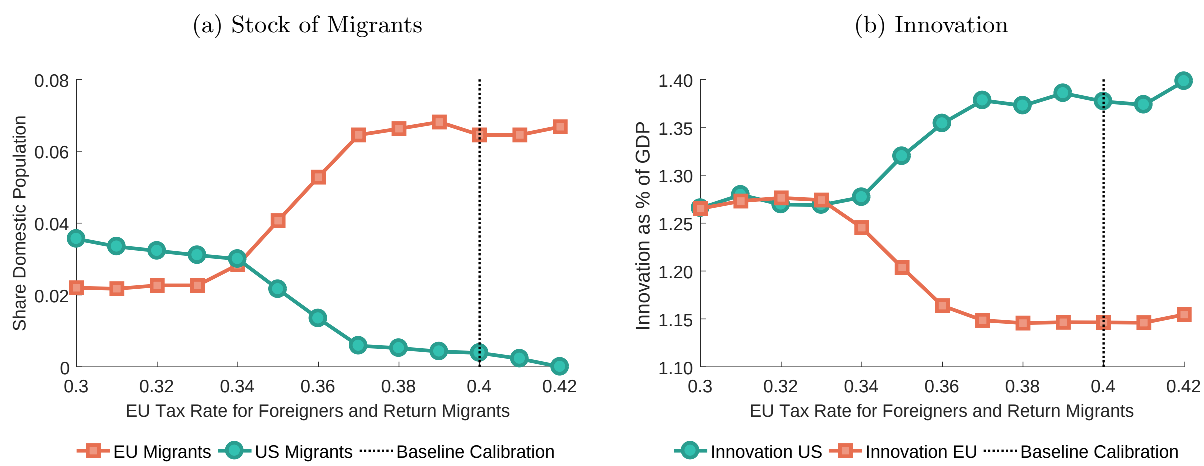
C.2 Tax Cut for Foreigners and Return Migrants in the EU

This section presents additional results for the counterfactual policy exercise of reducing the tax rate for foreigners and return migrants in the EU, presented in Section 4.

Figure C.3 describes the counterfactual BGP equilibrium of the model for different values of the tax rate τ_A for return migrants and US immigrants, plotted on the horizontal axis. Panel (a) plots the mass of migrants of each nationality along the BGP for different tax rates. A tax cut attracts US immigrants to the EU. Additionally, it has two effects on the stock of EU migrants. First, it increases the value of migration for Europeans, who anticipate lower taxes if they migrate and then return to the EU. Thus, a larger mass of Europeans would like to move, but they are constrained by the immigration cap in the US, so that the flow of migrants from the EU to the US remains unchanged (see Figure C.4, panel (a)). Second, the return intensity for EU migrants increases, thanks to the lower tax rate upon return (see Figure C.4, panel (b)). As a result, the stock of EU migrants declines in the BGP with a lower tax rate for return migrants.

Panel (b) shows that a tax cut, and the associated changes in migration and talent allocation, result in lower innovation in the US and higher innovation in the EU.

Figure C.3: Tax Cut for Foreigners and Return Migrants in the EU: BGP Comparison.

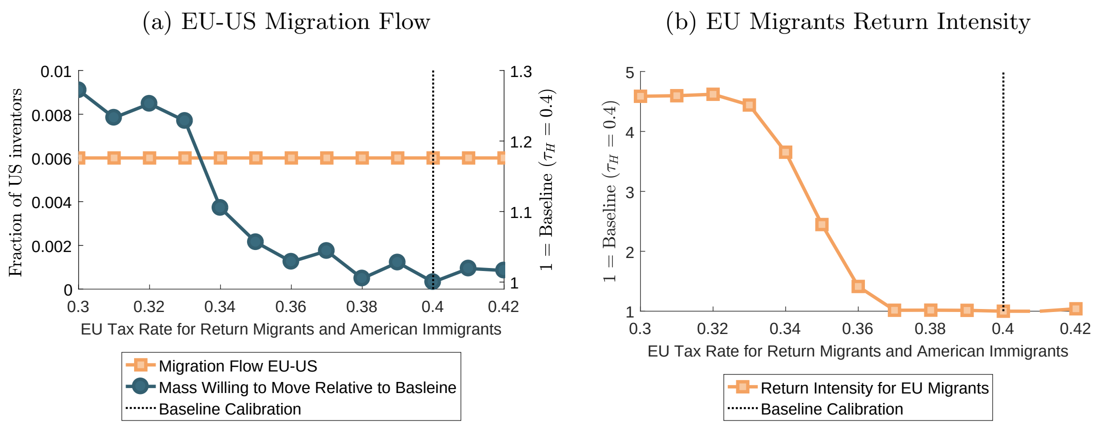


Notes: The figures compare counterfactual BGP equilibria for different values of the tax rate for foreign inventors nad return migrants in the EU. Panel (a) shows equilibirum migration of EU inventors (square markers) and US inventors (circle markers). Panel (b) shows equilibirum aggregate innovation in the EU (square markers) and in the US (circle markers).

Figure C.4 compares counterfactual BGP equilibria for different values of the tax rate for foreign inventors and return migrants in the EU. Panel (a) shows the flow of migrants from the EU to the

US (square markers) and the mass of European inventors willing to move (circle markers). The mass of individuals willing to move increases at lower tax rates, but migration to the US is constrained by the immigration thresholds; thus, the immigration flow remains constant across different tax rates. Panel (b) shows the equilibrium return intensity for European migrants relative to the baseline calibration. At lower tax rates, migration intensity increases, as more migrants return to the EU to take advantage of the lower tax rate.

Figure C.4: Counterfactual Tax Cut For Foreign and Return Inventors in the EU: BGP Comparison



Note: The figures compare counterfactual BGP equilibria for different values of the tax rate for foreign inventors and return migrants in the EU. Panel (a) shows the flow of migrants from the EU to the US (square markers) and the mass of European inventors willing to move (circle markers). Panel (b) shows the equilibirum return intensity for European migrants relative to the baseline calibration.

Figure C.5 illustrates the change in the interaction networks in the baseline BGP (columns labeled "Base") and in the new BGP after a cut in the tax rate for foreign inventors in the EU from 0.40 to 0.30 (columns labeled "New"). As migration flows change, the interaction networks endogenously adjust to reflect the different probability of meeting various types of inventors.

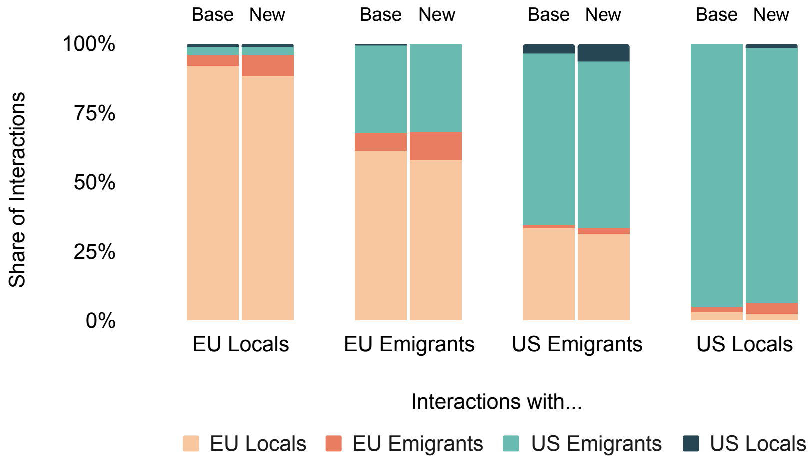
C.3 Robustness

In this section, I document the robustness of the quantitative exercise for alternative calibration and targets.

C.3.1 Heterogeneous Researcher Population

In the baseline calibration, I set the share of R&D workers to be equal across countries, $I_A = I_B = 0.01$. Here, I explore the robustness of results when the share of R&D workers is unequal across countries. The OECD researcher indicator collects data on professionals engaged in the conception or creation of new knowledge, products, processes, methods and systems, as well as in the management of the projects concerned. According to this measure, R&D workers account for

Figure C.5: Counterfactual Tax Cut for Foreign Inventors in the EU: Interaction Networks.



Notes: The figure shows the model-generated interaction network in the baseline BGP (columns labeled "Base") and in the new BGP after a cut in the tax rate for foreign inventors in the EU from 0.40 to 0.30 (columns labeled "New").

0.008 of the population in the US and 0.005 of the population in the EU between 2001-2010 on average. Thus, I set $I_A = 0.005$ and $I_B = 0.008$.

Table C.1 compares the main quantitative results in the baseline calibration and the new specification. The first two columns compare the change in BGP innovation when $I_A = I_B$ and $I_A \neq I_B$ when the EU tax rate for foreigners and return migrants is reduced from 0.4 to 0.3. The last two columns compare the change in BGP innovation when the US immigration threshold increases from 0.006 and 0.012. The results are similar across the two specifications, although the magnitude of the change in US innovation is smaller when $I_A \neq I_B$.

Table C.1: Robustness with Heterogeneous Researcher Population: BGP Comparison

Channel	**EU Tax Cut** from 0.4 to 0.3		**US Immigration Cap** from 0.006 to 0.012	
	$I_A = I_B$	$I_A \neq I_B$	$I_A = I_B$	$I_A \neq I_B$
Change EU Innovation	+10.5	+11.4%	-6.8%	-8.5%
Change US Innovation	-8.6%	-4.4%	+8.6%	+4.5%

Note: The first two columns compare the change in BGP innovation for the calibrations with $\nu = 1$ and $\nu = 0.9$ when the EU tax rate for foreigners and return migrants is reduced from 0.4 to 0.3. The last two columns compare the change in BGP innovation for the calibrations with $nu = 1$ and $\nu = 0.9$ when the US immigration threshold increases from 0.006 and 0.012.

C.3.2 Crowding in Market for Ideas

The parameter ν governs the matches between firms and inventors. A value $\nu < 1$ indicates that a larger number of inventors in the economy leads to a lower matching rate per inventor, resulting in lower "realized" innovation per individual. Thus, immigration can crowd out innovation by locals by reducing the technology-selling probability for inventors. In the baseline calibration, I set the value of $\nu = 1$. Here, I propose an alternative calibration for a value of $\nu = 0.9$, which creates crowding effects in the market for ideas: a 1% increase in the mass of inventors would reduce the technology-selling probability by 0.1%.

I repeat the SMM calibration for a value of $\nu = 0.9$. Table C.2 reports the calibrated parameters and table C.3 reports the resulting model-simulated moments.

Table C.2: Parameter Values for $\nu = 0.9$

Parameter	Description	Value
	— Panel B. Direct Match to Data —	
$\xi_{AB,AA}$	Meeting Frictions	1.31
$\xi_{AB,BB}$	Meeting Frictions	0.65
$\xi_{BB,AA}$	Meeting Frictions	0.06
$\xi_{BA,AA}$	Meeting Frictions	0.71
$\xi_{BA,AB}$	Meeting Frictions	0.32
$\xi_{BA,BB}$	Meeting Frictions	1.24
	— Panel C. SMM Calibration —	
$\bar{\mu}$	Migration cap to US (Share of Inventors)	0.01
κ	Cost of Migration	0.09
λ	Meeting Intensity HH	0.11
η	Learning Technology	0.29
σ	Technology Absorption	0.02
θ_A	Talent CDF H	14.78
ρ_A	Location Shock Persistence H	0.88
ω_A	Location Shock SD H	0.23

Note: List of model parameters and calibrated values for the SMM calibration when $\nu = 0.9$. All parameters are calibrated jointly.

Table C.4 compares the main quantitative results in the baseline calibration and the new specification. The first two columns compare the change in BGP innovation for the calibrations with $nu = 1$ and $\nu = 0.9$ when the EU tax rate for foreigners and return migrants is reduced from 0.4 to 0.3. The last two columns compare the change in BGP innovation for the calibrations with $nu = 1$ and $\nu = 0.9$ when the US immigration threshold increases from 0.006 and 0.012. The results indicated that, in the presence of crowding effects in the market for ideas, the absolute value of the change in EU and US innovation declines. In fact, crowding effects partially undo the brain drain or gain effect. For example, the tax cut increases the EU inventors' mass, but the realized

Table C.3: Moments

Moment	**Data**	**Model**
Share Migrants EU-US	6.00	4.97
Share Migrants US-EU (% domestic inventors)	0.40	0.22
Share Return Migrants (% migrants)	0.13	0.13
Δ productivity migrants EU-US (%)	0.28	0.42
Δ productivity co-inventors of migrants EU (%)	0.17	0.13
Δ productivity co-inventors of migrants US (%)	0.19	0.17
Growth rate (%)	1.50	2.00
TFP gap	0.90	0.89

Note: List of target moments for the calibration with SMM technique. The table presents the value of moments in the data and in the calibrated model.

innovation per inventor declines due to the congestion in the market for ideas.

Table C.4: Robustness with Crowding Effects: BGP Comparison

Channel	**EU Tax Cut** from 0.4 to 0.3		**US Immigration Cap** from 0.006 to 0.012	
	$\nu = 1$	$\nu = 0.9$	$\nu = 1$	$\nu = 0.9$
Change EU Innovation	+10.5	+9.7%	-6.8%	-5.7%
Change US Innovation	-8.6%	-7.0%	+8.6%	+6.9%

Note: The first two columns compare the change in BGP innovation for the calibrations with $nu = 1$ and $\nu = 0.9$ when the EU tax rate for foreigners and return migrants is reduced from 0.4 to 0.3. The last two columns compare the change in BGP innovation for the calibrations with $nu = 1$ and $\nu = 0.9$ when the US immigration threshold increases from 0.006 and 0.012.