# THE GLOBAL RACE FOR TALENT: BRAIN DRAIN, KNOWLEDGE TRANSFER, AND GROWTH *

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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, diffusing knowledge within and across countries. To quantify this framework, I construct a micro-level data set of migrant inventors on the U.S.-EU corridor from patent data and document that (i) gross migration is asymmetric, with brain drain (net emigration) from the EU to the United States; (ii) migrants increase their patenting by 33% a 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 16% a year when a co-inventor emigrates. I calibrate the model to match the empirical results and study the effect of innovation and migration policy. A tax cut for foreigners and return migrants in the EU that eliminates the brain drain increases EU innovation but lowers U.S. innovation and knowledge spillovers. The former effect dominates in the first 25 years, increasing EU productivity growth by 3%, but the latter dominates in the long run, lowering growth by 3%. On the migration policy side, doubling the size of the U.S. H1B visa program increases U.S. and EU growth by 4% in the long run, because it sorts inventors to where they produce more innovations and knowledge spillovers. *JEL codes:* O3, O4, F22.

## I. Introduction

In 1998, a prolific French inventor, Jean Calvignac, moved to Research Triangle Park in North Carolina, where he and his team

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initiated the IBM network processor activities. By then, he had filed more than 40 patents at the European Patent Office (EPO), with a network of more than 100 collaborators. Most of them were French, but a handful were Americans. Calvignac's sojourn in the United States was likewise productive, with more than 30 new patents filed in the EPO records. After moving to the United States, he continued to work with some of his collaborators in France. In addition, over 100 new collaborators benefited from his knowledge and experience. About half of them worked in U.S. labs, and half in French labs. Calvignac contributed to valuable innovation in the United States; he expanded his network of co-inventors, and created collaboration bridges between the United States and France. Each collaborator could then spread the acquired knowledge to their own co-inventors, 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 counteracted by the benefit of cross-country knowledge transfers channeled by emigrants. 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 they 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 on both sides of migration: brain drain and immigration.

This article 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 interactions, providing a microfoundation for the cascading effects of international knowledge

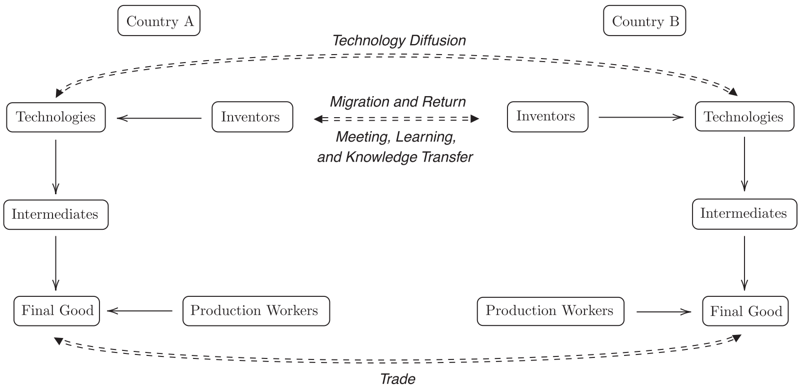



FIGURE I

Model Summary

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 and the European Union (EU). With these data, I document four new facts about inventors' migration flows, the evolution of their productivity and interactions around the time of migration, and the change in productivity for their collaborators in the origin country. I 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 effect of migration policies on the two economies.

In the theoretical section, the article 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 in endogenous interaction networks, which vary across countries.

The main elements of the models are summarized in Figure I. 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 because of 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 match the empirical patterns of collaboration in the patent data. Meetings between individuals in different countries generate international knowledge transfers, with cascading effects on the economy through interactions. 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 total factor productivity (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; after moving, they learn more from the local interaction network, reinforcing the selection effect. Aggregate TFP increases as a result of local innovation and exogenous diffusion from the frontier.

The strength of this framework is that by modeling migration decisions and interactions, 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. My model takes a global perspective on migration and is suitable for analyzing 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.

In the empirical section, I build a data set of international migrant inventors to document novel results on their migration and collaboration patterns, 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 data set of international migrants based on a recently developed panel of inventors from the EPO. Patent data offer a unique opportunity to observe inventors' mobility; their output, measured by the number and quality of their patent applications; and their employers and co-inventors. I identify migrants from changes in the residential address of inventors registered in patent files, and I trace the network of co-inventors for migrants and locals. I focus on the migration corridor between the United States and the European Union, which accounts for most of my data.

I document four main findings. First, migration flows between the EU and the United States are asymmetric, with net immigration in the United States (brain gain) and net emigration from the EU (brain drain). Second, after migration, EU and U.S. migrants increase patent applications by 33% a year on average, relative to local inventors in their country of origin with similar observable characteristics who do not move. Third, collaboration networks are heterogeneous for locals and migrants, as inventors are more likely to collaborate with others living in the same location or coming from the same origin. Nonetheless, migrants continue working with inventors in their origin country after moving. Fourth, local inventors increase their patent applications by 16% a 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, I link the model to the data from the United States and the EU by calibrating the parameters to match the empirical results. I 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 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 United States, lower innovation, and lower aggregate productivity than the United States. I highlight three main quantitative findings.

First, I show that knowledge transfers are quantitatively important. For the EU, the negative effect of brain drain on innovation is partly offset by international knowledge transfers. A counterfactual BGP simulation shows that shutting off interactions, keeping the brain drain level similar to the baseline, would reduce the EU growth rate by 10% (or about 0.12 percentage points).

Second, I find that in the baseline BGP where the United States is the frontier economy with a brain drain of EU inventors to the United States, both the U.S. and EU growth rates are higher compared with a scenario in which EU inventors cannot move to the United States. A counterfactual BGP simulation shows that shutting off international migration would reduce both the EU and the U.S. growth rate by 6% (or about 0.07 percentage points). This result is due to three main forces. First, because of learning complementarities, inventors benefit from interactions with other highly productive inventors. Because migrants toward the frontier economy are positively selected on talent, they expand the pool of productive interactions at the destination, increasing frontier human capital and innovation. Second, the benefit of immigration at the frontier through learning is partly offset by crowding effects, which imply that immigrants might crowd out local inventors; however, this force is quantitatively small. Third, due to exogenous technology diffusion, technologies produced at the frontier are eventually available for production and consumption in the laggard economy, which benefits from higher frontier innovation.

Next I turn to the quantitative analysis of policy counterfactuals. Concerns about the consequences of migration have motivated policy interventions in the United States and European countries to manage migration flows. I study the BGP and transitional dynamics of 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 United States.

A third main result is that the effect of the policies depends on the resulting inventors' talent allocation and varies at different time horizons. In particular, an EU tax cut for foreigners and return migrants reallocates inventors toward the EU and leads to a permanent increase in EU innovation and a short-run increase in output. The long-run effects, however, depend on the overall talent allocation and migration level. On the one hand, a relatively small tax cut that eliminates the brain drain from the EU to the United States but increases the dispersion of inventors across the two locations reduces the long-run growth rate by 3% (about 0.04 percentage points), because it reduces learning opportunities and technology diffusion. Although the reduction in long-run growth is the result of multiple forces with opposite effects, the decline in knowledge transfers, which is the mechanism at the center of this article, accounts for about 50% of the total decrease in the long-run growth rate. On the other hand, a more extreme EU tax cut that could induce a brain drain of inventors from the United States to the EU would lead the EU to become the frontier economy and increase long-run growth, reversing the role of frontier and laggard for the two economies. Finally, considering the current situation of the United States as the frontier economy and the limited evidence on crowding-out effects by immigrants on local inventors, relaxing the visa cap in the United States by doubling the inflow of EU inventors would increase long-run growth by 4% for both the EU and United States, but at the cost of lower EU innovation and temporarily lower TFP level in the EU.

The results of this study 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 here 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 here. In addition, 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.

### I.A. Related Literature

This article relates to several strands of literature. First, I build on and contribute to the theoretical literature on endogenous growth. Unlike most studies in this literature that focus on the role of firms, this article follows recent work that focuses on individuals (Lucas and Moll 2014; Akcigit et al. 2018; Akcigit, Pearce, and Prato forthcoming). Following Akcigit et al. (2018) and König et al. (2016), this article 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 1991b; Aghion and Howitt 1992; Jones 1995). As in diffusion models (Kortum 1997; Eaton and Kortum 2001; Lucas and Moll 2014; Perla and Tonetti 2014; Buera and Oberfield 2020), 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 interactions and knowledge spillovers within and across countries in a model of endogenous growth. The model of Braun (1993) (see Barro and Sala-i-Martin 2004, chap. 9) studies endogenous migration decisions in the context of the neoclassical growth model, deriving a positive relationship between the responsiveness of the migration rate to differentials in per capita product and the speed of convergence for per capita output. Beine, Docquier, and Rapoport (2001) connect migration and growth to educational choices. Ehrlich and Kim (2015) study a model of endogenous migration and growth where skill-biased technological change drives high-skilled migration. In my model, interactions shape incentives to migrate and provide a micro-foundation for knowledge transfer associated with migration. In this respect, this study also relates to a literature on knowledge diffusion and imitation (Nelson and Phelps 1966; Cohen and Levinthal 1989; Kogut and Zander 1992; Geroski 2000; Stoneman 2001; Eeckhout and Jovanovic 2002; Acemoglu, Aghion, and Zilibotti 2006; Griffith, Lee, and Van Reenen 2011; Comin and Mestieri 2014), and particularly to a literature that studies knowledge spillovers from trade (Santacreu 2015; Sampson 2016; Cai, Li, and Santacreu 2022; Hsieh, Klenow, and Nath 2023; Lind and Ramondo 2023;

Ayerst et al. 2023). See Barro and Sala-i-Martin (2004), chap. 8, and Buera and Lucas (2018) for a review. This article also contributes to theories that connect economic growth and demography (Peretto 1998; Galor and Weil 2000; Jones 2022b; Acemoglu and Restrepo 2022; Greenwood, Guner, and Marto 2023), by highlighting the connection between migration and growth.

Second, my article 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, Jones, and Uzzi (2007), Jones (2009), Jaravel, Petkova, and Bell (2018), and Pearce (2020) study the importance of talent allocation in research teams. Jovanovic (2014) and Akcigit, Pearce, and Prato (forthcoming) 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.

Third, this article contributes to a large literature that studies the link between innovation, migration, and growth. Kerr (2007, 2008) and Foley and Kerr (2013) document the contribution of ethnic inventors to U.S. technology formation, international technology diffusion, and multinational firm activity. Agrawal, Cockburn, and McHale (2006), Breschi and Lissoni (2009), Agrawal et al. (2011), Breschi, Lissoni, and Miguelez (2017), and Bernstein et al. (2018) use patent and citation data to document knowledge flows associated with migration. Docquier and Rapoport (2012) offer a review of the literature on the connection between brain drain and economic growth. Iaria, Schwarz, and Waldinger (2018) show that international cooperation is important for knowledge diffusion. Recent work has documented the importance of immigrants for innovation in the modern United States (Bernstein et al. 2018) and the historical United States (Akcigit, Baslandze, and Stantcheva 2016; Arkolakis, Peters, and Lee 2019; Burchardi et al. 2020). Bahar and Rapoport (2018), Bahar, Choudhury, and Rapoport (2020), and Bahar et al. (2022) provide evidence that inventors' migration is a key source of knowledge diffusion across countries. Griffith, Harrison, and Van

Reenen (2006) and Coluccia and Dossi (2023) show evidence of knowledge diffusion between the United States and the United Kingdom channeled by inventors using modern and historical data, respectively. Ottaviano and Peri (2006) and Peri, Shih, and Sparber (2015) document that immigrants generate positive spillovers on wages of U.S. natives; however, there could be heterogeneous effects on different categories of workers (Morales 2023; Mahajan 2024). Mayda et al. (2023) show that restricting high-skilled immigration to the United States would harm U.S. firms. Mayda, Orefice, and Santoni (2022) show that high-skilled immigrants have a positive effect on French firms' innovation through task specialization. Moser, Voena, and Waldinger (2014) use historical evidence from Nazi Germany to document the impact of German scientists on U.S. 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 article, high-skill immigrant flows can increase talent and the stock of ideas in the country of destination, as in Kerr and Lincoln (2010) and 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 article 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 effect of taxation on the mobility of superstar scientists and inventors (Akcigit, Grigsby, and Nicholas 2017; Moretti and Wilson 2017; Akcigit et al. 2022) and studies the effect of taxation on long-run growth (Jaimovich and Rebelo 2017; Jones 2022a).

The rest of the article proceeds as follows. Section II describes the theory, starting with the environment and equilibrium, then moving to the policies. Section III introduces the data and the empirical results. Section IV presents the calibration of the model and the quantitative policy counterfactuals. Section V concludes.

## II. Model

I introduce an endogenous growth model that highlights the role of international migration and knowledge diffusion in allocating scarce human capital.

For ease of exposition, I first introduce in Section II.A the environment and growth process in a closed economy with no migration. Time is discrete, and the economy consists of 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' ability to produce technologies depends on their own talent, which increases over time due to learning from other inventors.

Then in Section II.B I turn to an environment with two economies, $A$ and $B$. Inventors are allowed to move across countries and they draw an idiosyncratic country-specific productivity shock, which evolves stochastically over time. In addition, inventors interact and learn from other domestic, foreign, and migrant inventors, subject to meeting frictions. 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."

Finally, in Section II.C I introduce two types of policies, taxes on inventors' profits and immigration restrictions. I also describe an application to the EU–U.S. context, which is the benchmark for the quantitative analysis in Section IV.

There are no aggregate shocks in the model, so 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 IV.

### *II.A. Innovation, Interactions, and Growth in a Closed Economy*

1. *Inventors, Interactions, and Learning.* I begin with the description of the environment of a single closed economy without migration.

The economy in country $c$ is populated by a unit mass of individuals. Individuals survive to the following period with probability $\delta$; when they exit the economy, they are replaced by a newborn individual. They have linear utility and discount factor $\beta$, and they spend their whole income on consumption of the final good in every period.

At birth, people are exogenously split into production workers or inventors. Let the mass of production workers 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 born with heterogeneous talent $z$, drawn from an exogenous Pareto distribution, $\tilde{F}_c(z)$, with scale parameter equal to one and shape parameter $\theta_c$. They produce technologies, or ideas. In every period $t$, an inventor with talent $z_t$ produces a bundle of technologies $q_t$ with the linear production function $q_t(z_t) = z_t$. The evolution of talent, $z$, is endogenous due to interactions and learning, so I denote as $F_{c,t}(q)$ the endogenous distribution of innovation bundles produced at time $t$.

Inventors can improve their initial talent level, $z$, by learning from other inventors as the result of random meetings. In every period, with probability $\lambda$ 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. When an inventor with talent $z$ and innovation bundle $q$ meets another inventor with talent $\hat{z}$ and innovation bundle $\hat{q}$, her talent evolves according to the following learning function:

$$z_t = z_{t-1}\hat{q}_{t-1}^{\eta}, \tag{1}$$

where $\eta \geqslant 0$.[1] 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: $\frac{\partial^2 z_t}{\partial z_{t-1} \partial \hat{q}_{t-1}} > 0$.[2] The probability of meeting an inventor with an innovation $q$ is given by $F_{c,t}(q)$.

1. In a closed economy without migration, it holds that $q_t = z_t$ and $\hat{q} = z$, so that the learning function could be expressed as a function of talent only. However, in the economy with migration, the inventor's talent and the innovation bundle are not always equal, so I introduce a general learning function that holds in both environments with and without migration.

2. The literature has studied a range of different learning functions. In Online Appendix A.10, I introduce a general learning function, which nests equation (1) and allows a comparison to several cases studied in the literature. The choice of a learning technology with complementarity in talent generates positive selection of migrants, which could not be obtained, for example, from the learning technology in Lucas and Moll (2014), commonly used in the literature. The positive selection is an important feature of the data, as I document in Online Appendix Table B.1, and I discuss it in more detail in Sections II.B and II.C. Assessing the strength

An inventor's value function depends on their talent, learning prospects, and returns to innovation. To determine the returns for inventors, I describe the production of the final good, intermediate goods, and the market for ideas.

2. *Production of Goods.* The final good $Y_{c,t}$ is competitively produced at time $t$ using labor $L_c$ and a continuum of intermediate goods $k_{j,c,t}$:

$$Y_{c,t} = \frac{1}{1-\alpha}(L_c)^\alpha \int_0^1 (A_{j,c,t})^\alpha (k_{j,c,t})^{1-\alpha} dj, \tag{2}$$

where $A_{j,c,t}$ is the quality of intermediate $j$ at time $t$.[3] The price of the final good is normalized to one. 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 demand curve for intermediate input $k_j$:

$$P_{j,c} = (L_c)^\alpha (A_{j,c})^\alpha (k_{j,c})^{-\alpha}. \tag{3}$$

Each intermediate good is produced by a monopolist using the final good at marginal cost $\psi$. Each monopolist maximizes profits subject to the demand curve coming from the final good:

$$\Pi_{j,c} = \max_{k_{j,c}, P_{j,c}} \left\{ P_{j,c} k_{j,c} - \psi k_{j,c} \right\}, \qquad \text{subject to equation (3).}$$

The optimal profits for the intermediate-goods producer $j$ are then given by $\Pi_{j,c} = \alpha \left(\frac{1-\alpha}{\psi}\right)^{\frac{1-\alpha}{\alpha}} L_c A_{j,c}$. In line with the literature (Akcigit and Kerr 2018), I assume that $\psi = 1 - \alpha$.[4]

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 are given by

of learning complementarity, and thus the value of the parameter $\eta$, is central to the calibration in Section IV.A. I also use the calibrated model to compare the predictions on migrants' selection in the model and in data in Section IV.B.

3. The choice of this production function implies that aggregate productivity, inventors' values, and firms' values are linear in the average intermediate quality, improving the tractability of the model. In addition, given that the main novelties of the framework are migration decisions and interactions, I keep the production side of the model as close as possible to the existing literature both in the theory and in the calibration.

4. This assumption does not affect the structure and the results of the model, and it is introduced because a combination of $\alpha$ and $\psi$ can be used to target profits.

$$w_c = \frac{\alpha}{1-\alpha}\bar{A}_c \tag{4}$$

$$Y_c = \frac{1}{1-\alpha}L_c\bar{A}_c. \tag{5}$$

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

3. *The Market for Ideas.* Intermediate goods monopolists improve the quality of their product line by purchasing technologies from local inventors. When an intermediate goods monopolist purchases a technology bundle $q$, the quality of the product line increases by a step size $q\bar{A}$, that is, 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.[5]

Inventors and intermediate firms are matched in a country-level market for ideas. 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, $N_c$, equal to one, and the number of inventors, which is $I_c$. The number of matches is given by

$$x_c = (I_c)^{\nu}(N_c)^{1-\nu},$$

where $\nu \in [0, 1]$ 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:

$$\frac{x_c}{N_c} = (I_c)^{\nu} \qquad \text{and} \qquad \frac{x_c}{I_c} = (I_c)^{-(1-\nu)}.$$

The parameter $\nu$ 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.

5. Note that the step size is proportional to the current level of aggregate productivity, capturing the idea that new technologies are "standing on the shoulders of giants." The step size is thus increasing over time, generating sustained endogenous growth, as explained in more detail below.

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

$$J(A_{j,c,t}, t) = \Pi_{j,c,t} + \frac{1}{1+r}\Bigg[x_{c,t+1}\Big(\int_1^{\infty} (J(A_{j,c,t} + q\bar{A}_{c,t+1}, t+1) - p_{j,c,t+1}(q))dF_{c,t+1}(q)\Big) + (1 - x_{c,t+1})J(A_{j,c,t}, t+1)\Bigg]. \quad (6)$$

This value function has the following interpretation. On the right side, the first term is the per period profit $\Pi_{j,c,t}$. The second term captures the discounted change in firm value due to the purchase of technology, with probability $x_{c,t}$, which will increase quality by a step size $q\bar{A}_{c,t+1}$, minus the cost of purchasing the idea. The discount factor depends on the exogenous interest rate, $r$.[6] The probability of matching with a specific technology $q$ depends on the distribution of bundles $F_{c,t}(q)$. I assume inventors appropriate all the surplus from the technology transaction.[7]

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

$$\pi_c(z, t) = (I_c)^{\nu-1} p_{c,t}(q(z)). \quad (7)$$

It follows that the value of an inventor with talent $z$, $V(z, t)$ satisfies the following Bellman equation:[8]

$$V(z, t) = \pi_c(z, t) + \beta\delta\Big(\lambda \int_1^{\infty} V(z\hat{q}^{\eta}, t+1)dF_{c,t}(\hat{q}) + (1-\lambda)V(z, t+1)\Big).$$

6. The interest rate is exogenous for consistency with Section II.B, where the two small open economies share a common exogenous interest rate.

7. This assumption implies $p_{j,c,t+1}(q) = \mathbb{E}[J(A_{j,c,t} + q\bar{A}_{c,t+1}, t+1)] - J(A_{j,c,t}, t+1)$. 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 a certain technology produces the same improvement no matter which firm it is matched to.

8. This is the value of an inventor before being matched to an intermediate firm. The timing of events is the following: (i) inventors produce the technology bundle; (ii) if they meet a firm, they sell the bundle; (iii) if the inventor survives, the following period starts; (iv) meetings occur and the inventors' productivity is updated. Note that in a closed economy without migration, inventors are not making any decisions.

This value has the following interpretation. On the right side, the first term indicates the current-period expected profits for the inventor, $\pi_c(z, t)$. The second term captures the continuation value, which is discounted by a factor $\beta$ and survival probability $\delta$. In period $t+1$, with probability $\lambda$, the inventor will have a successful meeting. If the meeting occurs, with probability $F_{c,t}(\hat{q})$, the inventor will meet an individual with productivity $\hat{q}$ and her talent will evolve to a value $z\hat{q}^{\eta}$. With probability $1-\lambda$, no meeting occurs and talent remains unchanged at $z$.

I turn to the description of a BGP equilibrium in a closed economy without migration.

4. *BGP Equilibrium in a Closed Economy with No Migration.* I describe the BGP equilibrium of a closed economy with no migration where aggregate productivity grows at a constant rate and the talent distribution is stationary.

The following proposition describes 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:

$$p_{j,c,t} = p_{c,t} = \alpha \frac{1+r}{r} L_c \bar{A}_{c,t}. \tag{8}$$

*Proof.* See Online Appendix A.

In equilibrium, the per unit price of technology is increasing in the market size $L_c$, in aggregate productivity $\bar{A}_{c,t}$, and in the contribution of intermediate quality to final good production ($\alpha$), while it is decreasing in the interest rate $r$. Note that along a BGP, the technology price is equal across all product lines, because the value of owning a product line, $J(A_{j,c})$, is linear in equilibrium, as shown in Online Appendix A.

I describe the aggregate productivity growth rate in equilibrium. The change in aggregate productivity in country $c$ is given by the increase in quality of each intermediate product, which depends on the probability of firm-inventor matching and the size of bundles purchased from inventors. Define the average bundle of ideas available in country $c$ as $Q_{c,t} = \int_1^{\infty} q dF_{c,t}(q)$, which is the weighted average of the technology bundles produced by inventors. Then define the 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,

$\iota_c(t) \equiv I_c^{\nu} Q_c(t)$. The following proposition describes the evolution of aggregate productivity in equilibrium.

PROPOSITION 2. Along a BGP, the aggregate productivity growth rate, $g_c$, is equal to the total innovation in country $c$: $g_c = \iota_c = I_c^{\nu} \int_1^{\infty} q dF_c(q)$.

*Proof.* See Online Appendix A.

In the closed economy, sustained long-run growth is driven by innovation, which increases the quality of intermediates, following innovation-based endogenous growth theories (Grossman and Helpman 1991b; Aghion and Howitt 1992). As in these theories, the step-size increase in productivity from innovation is proportional to the current level of productivity (see equation (6)), capturing the idea that new technologies are "standing on the shoulders of giants." The step size is then increasing over time, enabling endogenous growth. Total innovation depends on the number of inventors and the average size of the technology bundles they produce, which in turn depends on inventors' talent and their interactions with others, as in diffusion models (Lucas and Moll 2014; Perla and Tonetti 2014).

## II.B. *Two Economies Setup: Knowledge Diffusion, Migration, and Growth*

I turn to the description of an environment consisting of two economies that allow for the migration of inventors. In this setup, the growth rate still depends on the number of inventors and the average size of the technology bundles, but both terms are affected by migration, interactions, and technology diffusion across countries. Country-specific variables are indexed with $c$, for $c \in \{A, B\}$. The economies are populated by a unit mass of individuals of each nationality, A or B. The two economies are open to final-good 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 (1991a).[9]

9. Trading technologies and intermediate goods could allow innovations to instantly diffuse across countries. While this type of trade is not explicitly studied in this framework, the model captures it with an exogenous technology diffusion parameter $\sigma$, 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.

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, in a given period, live in a different country from where they are born. The mass of local inventors in country $A$ is endogenous and denoted by $\mu_{AA}$, where the first letter of the index indicates the country of origin and the second one is the country of residence. Similarly, the mass of migrants from country A to B is endogenous and denoted by $\mu_{AB}$. The endogenous masses of locals and migrants from country $B$ are denoted, respectively, by $\mu_{BB}$ and $\mu_{BA}$. 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 $B$.

1. *Inventors' Productivity and Interactions across Countries.* As in the closed economy case, inventors are born with heterogeneous talent $z$, drawn from an exogenous country-specific Pareto distribution, $\tilde{F}_c(z)$, with scale parameter equal to one and shape parameter $\theta_c$. In addition, they draw an idiosyncratic country-specific productivity differential $\epsilon$ from an exogenous distribution, $\Upsilon_c(\epsilon)$, with support on the real line.[10]

In every period $t$, an inventor with talent $z_t$ and foreign productivity shock $\epsilon_t$ 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 $z \geqslant 1$, it follows that $q \geqslant 1$, even if $\epsilon$ can take negative values.[11] The foreign productivity differential captures idiosyncratic reasons why an inventor could be more productive abroad.[12]

10. In the quantitative section, the process for $\epsilon$ matches the average change in productivity for migrants after migration. Notably, both EU and U.S. migrants increase their patenting after moving. A model without the country-specific productivity differential would not be able to match this result.

11. The assumption that $q_t$ is bounded below by one implies that inventors' talent is weakly increasing after a meeting. In addition, it guarantees that migrants' productivity is always positive, even if they draw a negative value of the foreign productivity shock such that $z_t + \epsilon_t < 0$.

12. 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 $\epsilon$ does not capture the network of inventors of a given country, which is instead explicitly modeled.

I denote as $F_{j,t}(q)$ the endogenous distribution of innovation bundles produced by type $j$ at time $t$.[13] I also denote the endogenous distribution of technology bundles produced in country $c \in \{A, B\}$ as $F_c$, which combines locals and immigrants.[14]

The evolution of foreign productivity, $\epsilon$, for an inventor born in $c$, follows an exogenous mean-reverting process. In particular, $\epsilon$ evolves following an AR(1) stochastic process:

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

where $v_t \sim N(0, \omega_c^2)$. I denote by $\upsilon_{c,\epsilon_t|\epsilon_{t-1}}$ the cumulative distribution function of $\epsilon_t$, conditional on the $t-1$ value $\epsilon_{t-1}$. I assume that at birth, individuals draw the value $\epsilon$ from the stationary distribution of the AR(1) process, that is, the distribution $\Upsilon_c$ is a normal distribution with mean zero and variance $\frac{\omega_c^2}{1-\rho^2}$.[15]

The evolution of talent, $z$, is endogenous due to interactions and learning. In this environment, every inventor can meet and learn from any of the four types of inventors in the global economy: $AA, AB, BA, BB$. The probability of meeting a specific inventor with bundle $\hat{q}$ depends on meeting frictions, based on inventors' location of birth and residence. 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 $i$.[16] The set of probabilities $\{\psi_{i,j}\}$ captures the endogenous interactions in the global economy, where

13. The distribution $F_{j,t}(q)$ captures the joint density over $\epsilon$ and $z$.

14. The endogenous distributions satisfy the following condition:

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

15. Note that under these assumptions, the distribution of $\epsilon$ in the population of individuals is equal to the stationary distribution of the AR(1) process.

16. The 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 $\xi_{i,j} = \xi_{j,i}$.

inventors meet within and across countries. The set of frictions $\{\xi_{i,j}\}$ captures meeting frictions across any two types.[17]

In general, locals and migrants meet a given type with different probabilities, as captured by the meeting frictions.[18] Thus, moving allows individuals to access different interaction networks and learning opportunities. In addition, a migrant of origin $c$ can still meet a local in origin country $c$ after moving.[19] This type of meeting allows the migrant to generate knowledge spillovers onto locals at origin, who learn from migrants' innovations and become more productive. Given that learning depends on the size of the innovation bundle, meeting a migrant is particularly beneficial for locals because migrants produce larger innovations while abroad, due to the productivity differential $\epsilon$.

Based on their talent, $z$, and productivity $\epsilon$, 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 describe the production of the final good, intermediate goods, and the market for ideas, which determine the returns for inventors.

2. *Production, the Market for Ideas, and Technology Diffusion.* The production side in each economy follows the same structure as in the closed economy setup, described in Section II.A.

Each economy produces the final good, $Y_{c,t}$, at time $t$ using local labor and a continuum of local intermediate goods as in equation (2). The final good is traded, so the price is the same for the two countries. In each country, each intermediate good is produced by a monopolist using the local final good at marginal cost $1 - \alpha$, subject to the demand curve expressed in equation (3). The resulting equilibrium workers' wage and aggregate output are given by equations (4) and (5).

In the open economies environment, intermediate goods monopolists improve the quality of their product line in two ways.

17. 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. Online Appendix C.2.4 describes an extension with a richer model of network formation.

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

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

First, they purchase technologies from local inventors,[20] as in the closed economy. 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 describe each process in detail.

The country-level market for ideas and the innovation step size are the same as in the closed economy. The only difference is that the number of inventors residing in $c$ is the sum of local inventors and migrant inventors. The number of matches is then given by:

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

where $\mu_{Ac}$ are inventors of nationality $A$ active in $c$, $\mu_{Bc}$ are inventors of nationality $B$ active in $c$, and $N_c$ is the number of intermediate firms, which is equal to one. The parameter $\nu$ now captures the idea that immigration can crowd out innovation by locals, by reducing the technology-selling probability for inventors. It follows that the technology-purchasing probability for firms and the technology-selling probability for inventors are, respectively:

$$\frac{x_{c,t}}{N_c} = \left(\mu_{Ac,t} + \mu_{Bc,t}\right)^{\nu} \quad \text{and} \quad \frac{x_{c,t}}{\mu_{Ac,t} + \mu_{Bc,t}} = \left(\mu_{Ac,t} + \mu_{Bc,t}\right)^{-(1-\nu)}.$$

In addition to purchasing technologies, intermediate firms in the laggard country receive exogenous technology diffusion from the frontier economy at rate $\sigma$, at no cost. As a result, the quality of an intermediate firm will exogenously increase by the amount $\tilde{\sigma}_{c,t} = \sigma \max\{\bar{A}_{-c,t} - \bar{A}_{c,t}, 0\}$.[21]

20. 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 (1991a). 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 to sell their labor services to that firm.

21. 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 $\sigma$ captures improvements in productivity of the laggard economy not due to local innovation, such as technology diffusion driven by trade or foreign direct investment. There is a large literature studying the role of technology diffusion, starting from Nelson and Phelps (1966), and including Grossman and Helpman (1991c), Eaton and Kortum (2001), Santacreu (2015), Sampson (2016), Buera and Oberfield (2020), Cai, Li, and Santacreu (2022),

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

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

$$-p_{j,c,t+1}(q))dF_{c,t+1}(q)\Big) + (1-x_{c,t+1})J(A_{j,c,t+1}+\tilde{\sigma}_{c,t},t+1)\Big].$$

Compared with the closed economy setup, the second term also captures the exogenous technology spillovers.

Finally, the profits of an inventor with talent $z$ working in country $c$ now also depend on migration through the endogenous number of locals and immigrants and are given by the probability of matching with a firm multiplied by the revenues from selling technology $q$:

$$\pi_c(z,t) = (\mu_{Ac}+\mu_{Bc})^{\nu-1}p_{c,t}(q(z)). \tag{9}$$

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

3. *Migration Decisions.* In every period, inventors decide whether they want to move based on their idiosyncratic talent $z$, foreign productivity differential $\epsilon$, 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 later emigrate again.[22]

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 $\epsilon$ 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 $\epsilon$ 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

Hsieh, Klenow, and Nath (2023), Ayerst et al. (2023), and Lind and Ramondo (2023). For a review, see Barro and Sala-i-Martin (2004), chap. 8, or Buera and Lucas (2018).

22. The main cost of migration in this setup involves familiarizing oneself with and adapting to a new environment in a new country (e.g. learning a new language, adapting to new customs). Arguably, this cost is small for return migrants, who go back to their origin country that they already know, especially if they have not been abroad for too long, which motivates the assumption that they can return at no cost. This assumption is not necessary to solve the model. Alternatively, an additional parameter for the cost of returning could be introduced into the model.

equation for $j \in \{AA, AB, BB, BA\}$:

$$W_{AA}(z, \epsilon, t) = \max\{V_{AA}(z, \epsilon, t), V_{AB}(z, \epsilon, t) - \kappa \bar{A}_A(t)\}. \tag{10}$$

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 $j \in \{AA, AB, BB, BA\}$:[23]

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

This value has the following interpretation. On the right 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 $\beta$ and survival probability $\delta$. In period $t+1$, with probability $\lambda$, 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 at $z$. In addition, in $t+1$, the idiosyncratic relative productivity term $\epsilon$ evolves to value $\epsilon'$. After meetings occur, the inventor makes the migration decision, captured by the continuation value $W_{AA}(z, \epsilon, t)$.

23. This is the value of an inventor before being matched to an intermediate firm. The timing of events is the following: (i) inventors produce the technology bundle; (ii) if they meet a firm, they sell the bundle; (iii) if the inventor survives, the following period starts; (iv) the new productivity differential $\epsilon'$ is realized; (v) meetings occur; (vi) the inventor decides where to move.

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

$$V_{AB}(z, \epsilon, t) = \pi_B(z + \epsilon, t) + \beta\delta \int_{-\infty}^{\infty} \Bigg( \lambda \sum_j \psi_{AB,j,t} \times \int_1^{\infty} \big( W_{AB}(z\hat{q}^{\eta}, \epsilon', t+1) \big) \, dF_{j,t}(\hat{q}) + (1-\lambda) W_{AB}(z, \epsilon', t+1) \Bigg) d\upsilon_{\epsilon'|\epsilon}.$$

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 a productivity differential $\epsilon$, 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 inventors choose to migrate in this model: (i) higher profits, (ii) idiosyncratic productivity gains, and (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 $\epsilon$ at time $t$ is described by the continuation value $W_{AB}$:

$$W_{AB}(z, \epsilon, t) = \max\{V_{AB}(z, \epsilon, t), V_{AA}(z, \epsilon, t)\}. \tag{11}$$

The return decision depends on the evolution of the productivity differential $\epsilon$. When $\epsilon$ 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:

$$W_{BB}(z, \epsilon, t) = \max\{V_{BB}(z, \epsilon, t), V_{BA}(z, \epsilon, t) - \kappa \bar{A}_B(t)\} \tag{12}$$

$$W_{BA}(z, \epsilon, t) = \max\{V_{BA}(z, \epsilon, t), V_{BB}(z, \epsilon, t)\}, \tag{13}$$

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 next.

4. *BGP.* 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.[24] Definiton 1 formally describes the BGP equilibrium concept.

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

PROPOSITION 3. Along a BGP, technology is sold at per unit price $p_{c,t}$, independent of $j$, as follows:

$$p_{j,c,t} = p_{c,t} = \alpha \frac{1+r}{r} L_c \bar{A}_{c,t}. \tag{14}$$

*Proof.* See Online Appendix A.

Note that the price in the market for ideas follows the same expression as in the closed economy setup (see equation (8)) and is not affected by migration rates. Inventors' profits and firm values still depend on migration rates, which determine the matching rate $x_{c,t}$ between firms and inventors.

The next proposition describes the migration decisions in equilibrium.

PROPOSITION 4. Along a BGP, migration decisions are time-invariant.

*Proof.* See Online Appendix A.

Along a BGP, both countries grow at the same rate and distributions are stationary, so inventors' values in each location also grow at the same rate, resulting in a constant flow of migrants.

I describe aggregate productivity growth in equilibrium. The change in aggregate productivity in country $c$ is given by the increase in quality of each intermediate product, which depends on the probability of matching and the size of bundles purchased from inventors. The average bundle of ideas available in country $c$, defined as $Q_c$, is now given by the weighted average of the

24. Online Appendix A presents a description of the law of motion for the distributions of talent and requirements for stationarity.

technologies produced by locals and immigrants in $c$:

$$Q_{c,t} = \frac{\mu_{Ac,t} \int_1^\infty q dF_{Ac,t}(q) + \mu_{Bc,t} \int_1^\infty q dF_{Bc,t}(q)}{\mu_{Ac,t} + \mu_{Bc,t}}. \tag{15}$$

Recall that total innovation in country $c$ is the probability that an intermediate firm is matched with an inventor multiplied by the expected quality of ideas available in country $c$, that is

$$\begin{aligned} \iota_c(t) &\equiv x_c(t) Q_c(t) \\ &= \left(\mu_{Ac,t} + \mu_{Bc,t}\right)^{(\nu-1)} \left[\mu_{Ac,t} \int_1^\infty q dF_{Ac,t}(q) + \mu_{Bc,t} \int_1^\infty q dF_{Bc,t}(q)\right]. \end{aligned}$$

Total innovation is affected by migration both through the number of inventors in the economy, which depends on the number of locals and immigrants, and through the average size of the bundle of ideas, which depends on the realized country-specific productivity shocks of migrants, interactions, and knowledge transfers across countries.

In addition, 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 5. Along a BGP, aggregate productivity grows at the same rate in each country:

$$g_A = g_B = g = \max\{\iota_A, \iota_B\}, \tag{16}$$

and the productivity gap is constant and equal to:

$$a = \begin{cases} \frac{\sigma}{\sigma + \iota_B - \iota_A} & \text{if } \iota_B > \iota_A \\ \frac{\sigma + \iota_A - \iota_B}{\sigma} & \text{if } \iota_B < \iota_A. \end{cases} \tag{17}$$

*Proof.* See Online Appendix A.

The two countries grow at the same constant rate, which is determined by total innovation in the frontier economy, while innovation in the laggard economy determines the productivity gap.

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 $\sigma$, 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 interactions affect innovation and productivity through the mass of local and immigrant inventors and the average size of their innovations, which depends on the distributions $F_j$, illustrated by equation (15). 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 $\epsilon$. 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.

Definition 1 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 1. *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, $\mu_{AA}, \mu_{AB}, \mu_{BA}, \mu_{BA}$, and productivity distributions $F_c(q)$ such that

(i) The wage of production workers satisfies equation (4).
(ii) Profits of inventors satisfy equation (9).
(iii) Migration decisions are time-invariant and solve equations (10), (11), (12), and (13).
(iv) The price of technology clears the market for ideas and satisfies equation (14).
(v) The growth rate $g$ and the productivity gap $a$ satisfy equations (16) and (17).
(vi) Aggregate productivity $\bar{A}_c$ and aggregate output $Y_c$ grow at rate $g$ in each country.
(vii) 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.

### II.C. Taxation and Migration Policies

I introduce two policies in the model: taxes on inventors' profits, and immigration caps. Inventors are subject to a country-specific tax rate $\tau_c$, as net profits are

$$\pi_c(z,t) = (1-\tau_c)(\mu_{Ac}+\mu_{Bc})^{\nu-1} p_{c,t}(q(z)). \tag{18}$$

The government uses the tax revenues to fund a lump-sum transfer to production workers, balancing the budget in every period.[25]

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 are 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 $t$:

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

where $g_{AA,t}(z,\epsilon)$ indicates the joint distribution over $z$ and $\epsilon$ 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 $j \in \{AA, AB, BB, BA\}$:

$$W_{AA}(z,\epsilon,t) = \max\{V_{AA}(z,\epsilon,t), m_t\left(V_{AB}(z,\epsilon,t) - \kappa\bar{A}_A(t)\right) + (1-m_t)V_{AA}(z,\epsilon,t)\}. \tag{19}$$

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

1. *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 article, I consider an application to two countries with asymmetric tax policies, $\tau_A < \tau_B$. In addition, countries have asymmetric migration policies, as previously outlined: country $A$ has a free immigration policy, whereas $B$ admits no more than $\bar{\mu}$ inventors per period. I

25. 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: $\tau_c(\mu_{Ac} + \mu_{Bc})^{\nu} \int p_{c,t}(q(z))dF_c(z) = T_cL_c$.

assume that the talent structure is identical across countries, as outlined in Assumption 1.[26]

ASSUMPTION 1. The exogenous occupational allocation and talent distribution 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.[27]

ASSUMPTION 2. Compared with 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 $B$, $\xi_{BA,BA} > \xi_{BB,BA}$, $\xi_{BA,AA} > \xi_{BB,AA}$, 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 $\epsilon$. This characterization of migration decisions is formalized in Proposition 6.

PROPOSITION 6. 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 $(z, \epsilon)$ of type:

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

26. This structure mimics the migration corridor between the EU (country $A$) and the United States (country $B$), which is analyzed in Section III and Section IV.A. A different application of this model could 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.

27. This structure is consistent with the observations on collaborations in the microdata, as discussed in Section III. These data are used to calibrate meeting frictions in Section IV.

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

*Proof.* See Online 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 $\kappa$, 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 features positive complementarity in talent; thus, more talented inventors gain more from an interaction network with a higher average talent. Thus, the assumptions that profits and learning opportunities are increasing in talent generate positive sorting of migrants from $B$ to $A$. In equilibrium, country $B$ has more numerous and talented inventors, resulting in higher innovation and aggregate productivity.

Why do migrant inventors ever return to their origin country? In this model, return decisions result from the evolution of the productivity shock, $\epsilon$. For a given value of $z$, locals move when their productivity abroad, $\epsilon$, is high enough. Once they are abroad, they decide to return if $\epsilon$ evolves to a sufficiently low value. This result is formalized in Proposition 7. Heterogeneity across $\epsilon$ also implies that not all individuals with the same talent $z$ make the same decisions. Those with high enough $\epsilon$ choose to move abroad, whereas the others stay.

PROPOSITION 7. 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 $(z, \epsilon)$ 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 Online Appendix A.

The equilibrium of the model is solved numerically in Section IV. A visualization of the migration thresholds and stationary talent distributions is provided in Online Appendix C.

## III. Data, Measurement, and Empirical Findings

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

### *III.A. 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 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 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) are 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.

An additional description and comparison of the patent data sets from the PCT and the EPO is provided in Online Appendix B.

1. *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 a person 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 classification also has some shortcomings. First, only people with at least two patents can be categorized into migrants and nonmigrants, because the procedure compares addresses in different patent applications. Second, those who migrate before ever filing a patent will not be categorized as migrants with this procedure. As a result, the migrants classification in the EPO data yields an undercount of the total number of migrants. To

address this limitation, I rely on the PCT data to provide an accurate measure of aggregate inventors' migration flows.

The result of the migrants' classification procedure in the EPO data is a new data set 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 complement the data set with an analysis of the ethnic origin of names using the commercial software Namsor.[28] The software takes as 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. I use this information to infer the most likely country of origin of the international migrants in my data set.[29]

The EPO data contain records of 4,009,660 unique inventors, of which 1,287,257 file more than one patent and can be classified into migrants and nonmigrants. I identify 12,713 unique migrants. For individuals who file at least three patents, I can also define "return migrants" as those who return to their first country after filing patents in another country for a certain period. I identify 2,489 return migrants in the data. The EU and the United States are the two most prominent geographical locations covered in the data set, accounting for 67% of total inventors and 79% of all migrants. For this reason, in the calibration of the model, I set the EU to be location $A$ and the United States to be country $B$ (see Section IV.A); thus, the empirical results focus on migration between the United States and the EU. Summary statistics on inventors and migrants in the EPO data are reported in Online Appendix Table B.1.

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

2. *Measuring Productivity and Interactions.* The empirical analysis sheds light on key channels of the model, particularly on

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

29. Online Appendix B provides further details on the sample construction and on different assumptions on the imputation of migrants' nationality and the migration year.

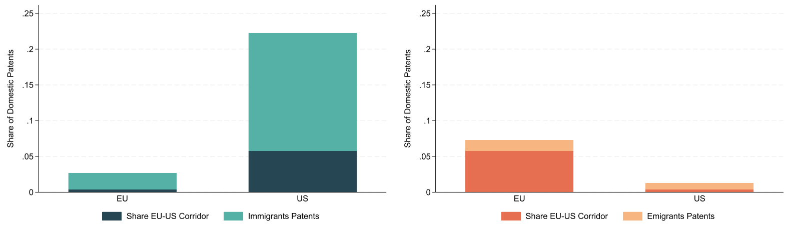
how migration is connected with changes in the productivity and interactions of inventors. In this section, I describe the measurement of individuals' productivity and interactions in the patent data, following the literature on innovation (most closely, Akcigit et al. 2018).

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) truncation-adjusted 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 $i$. The second measure accounts for the issue of truncation of citations, that is, the fact that older patents mechanically have more time to accumulate citations, as described in Hall et al. (2001).

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).[30] As a result, using citations to assess the productivity of a migrant across different locations can be misleading because citations could be collected differently in different locations. This issue is evident in Online Appendix Table B.1, Panel B, presenting the average value of a set of variables in the full sample, EU sample, and U.S. sample. All variables take similar values across the EU sample and U.S. sample except for citation measures, which are substantially lower in the U.S. sample. Because of 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

30. The literature on innovation and citations is mostly based on data from the U.S. 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.




(A) Patents by Immigrants (B) Patents by Emigrants

FIGURE II

Immigration and Emigration of Inventors in the U.S. and EU, 2000–2010

Panel A illustrates the patents filed by immigrants as a share of patents filed by nationals in the United States and EU. Panel B illustrates the patents filed by U.S. and EU emigrants in foreign countries as a share of patents filed by U.S. and EU nationals in the home country. The darker shaded areas also highlight the share of patents accounted for by the migrants in the EU–U.S. corridor for each group. *Source:* PCT data set.

define the co-inventors of individual $i$ in year $t$ as all inventors who are listed on patent applications submitted by $i$ in year $t$.

### *III.B. Empirical Findings*

Here I present the empirical results, which document four main findings:

(i) Migration flows between the EU and the United States are asymmetric: the United States 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, detailed in Section IV.A.

1. *Migration Flows between the EU and the United States.* Migration flows for the EU and the United States are shown in Figure II, based on PCT data. Panel A shows patents filed by immigrants as a share of all patents filed by U.S. locals. Over the period 2000–2010, patents filed by immigrants in the United States

accounted for about 22% of patents filed by locals in the United States under the PCT. EU immigrants accounted for about 27% of all patents filed by immigrants in the United States.[31] By contrast, in the EU, patents filed by immigrants accounted for only about 3% of patents filed by EU locals. U.S. 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 U.S. emigrants account for only about 1% of patents filed by locals in the United States; 40% of emigrant patents are accounted for by U.S. emigrants to the EU. On the other hand, patents filed by EU emigrants are about 7% of patents filed by local EU inventors and emigrants to the United States account for 62% of all emigrants' patents.

Migration flows are thus largely asymmetric. The United States 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 immigrants are arriving, resulting in a brain drain. This asymmetry is true both when considering the U.S.–EU migration corridor and 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 explore whether the aggregate migration flows are accompanied by indirect effects along two dimensions: whether migrants become more productive after moving and whether migrants generate positive spillovers on locals.

2. *Evolution of the 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 motive 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

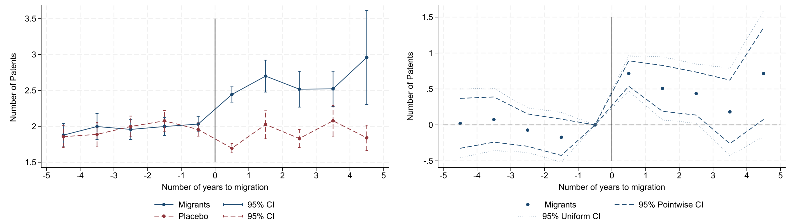
31. The EU is the largest origin of immigrant inventors to the United States, followed by China and India.

identify the causal effect of migration on innovative activity; 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, Petkova, and Bell (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.[32] In addition, I require individuals in the control group to file for a patent in the first year after the migration, consistent with the sample construction of actual migrants. Using this procedure, 855 out of 1,065 migrants from the EU to the United States find an exact match, and 490 out of 512 migrants from the United States to the EU find an exact match. Thus, the matching procedure results in a total of 2,690 individuals, which I use for the analysis. Online Appendix B presents the summary statistics and balance tables before and after matching for individuals of EU and U.S. origin, respectively.

Figure III, Panel A 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 patenting activity of migrants is on a similar trajectory as the placebo control group before the time of migration, but it increases afterwards. 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 the credibility of the empirical

32. 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 the technology field is possible, but it reduces the number of exact matches substantially.




(A) Raw Means (B) Coefficients $\beta_\tau^{Mig}$ for migrants

FIGURE III

Patenting Activity by Migrant Inventors Around the Time of Migration

The figure displays changes in migrants' productivity around migration time relative to the placebo control group. Panel A displays the raw means. Panel B displays the estimated coefficients from the regression specification in equation (20). Unbalanced panel. EU migrants: 4,731 observations. U.S. migrants: 2,598 observations. EU placebo: 4,673 observations. U.S. placebo: 2,463 observations. Standard errors are clustered at the inventor and year level.

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 $\tau$ 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 $\{\beta_\tau^{All}\}_{\tau=-5}^{5}$. I also include individual fixed effects ($\alpha_i$), year fixed effects ($\alpha_t$), and experience fixed effects ($\alpha_e$). The resulting OLS specification is the following:

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

$$+ \alpha_i + \alpha_t + \alpha_e + \epsilon_{it}. \tag{20}$$

The main outcome variable of interest, $x_{it}$, is the number of patent applications per year. The coefficients of interest are $\{\beta_\tau^{Mig}\}_{\tau=-5}^{5}$, which denote the differential productivity of migrants. The individual fixed effects control for permanent individual

TABLE I

PATENTING ACTIVITY OF MIGRANTS AROUND THE TIME OF MIGRATION

| | Number of patent applications per year | | |
|---|---|---|---|
| | All (1) | EU origin (2) | U.S. origin (3) |
| Post migration | 0.6915*** | 0.6053*** | 0.8670*** |
| | (0.0624) | (0.0759) | (0.1418) |
| Observations | 14,463 | 9,403 | 5,060 |
| $R^2$ | 0.351 | 0.408 | 0.318 |
| Inventor FE | X | X | X |
| Year FE | X | X | X |

*Notes.* The table displays the estimated change in migrants' productivity around migration time relative to the placebo control group from the regression specification in equation (21). Column (1) displays the benchmark regression results for all migrants along the U.S.–EU corridor. Column (2) includes only the sample of migrants of EU origin. Column (3) includes only the sample of migrants of U.S. origin. Standard errors in parentheses are clustered at inventor and year level. * $p < .10$; ** $p < .05$; *** $p < .01$.

characteristics, whereas the lags and leads common to all ($L_{it}^{All}$) control for joint dynamics around the time of migration.

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

$$x_{it} = \beta^{Mig} AfterMigration_{it}^{Mig} + \beta^{All} AfterMigration_{it}^{All} + \alpha_i + \alpha_t + \alpha_e + \epsilon_{it}. \tag{21}$$

Figure III, Panel B reports the estimates and the 95% pointwise and uniform confidence intervals for the coefficients $\beta_{\tau}^{Mig}$ from specification (20).[33] The figure indicates that migration is associated with an increase in patent applications per year for migrants, compared with the placebo control group. The increase in productivity accrues immediately on migration and 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 (21). The results are reported in Table I, column (1). The estimated coefficient for $\beta^{Mig}$ indicates that migrants apply for 0.69 more patents per year than the locals in the placebo control group after migration on average, with a standard error of 0.06. The coefficient is

33. The point estimate on the lag in the year before migration is normalized to one.

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 33% relative to the sample average (equal to about 2.1 patent applications per year for individuals in the event study sample).

I use the same specification to investigate the heterogeneity of this result. In Table I, columns (2) and (3), I explore whether the effect is different for the subsample of migrants of EU and U.S. origin, respectively. The point estimates indicate that the average increase in patents relative to the locals per year after migration is 0.61 for EU and 0.87 for U.S. inventors. These estimates correspond to an increase in patent applications per year after migration of about 29% for EU inventors and 40% relative to the sample average (which is 2.1 patent applications per year for EU and 2.15 for U.S. inventors).[34]

Online 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 (20). I show that results are similar when using alternative estimators. An additional concern is that many migrants remain employed by a foreign subsidiary of the same company after moving. The observed change in patenting could 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 who switch companies. Finally, I show robustness when using citation-based measures and different assumptions on the imputation of migrants' nationality and the migration year.

Overall, these findings suggest that migrants tend to become more productive after migration, consistent with the model. The larger productivity change for U.S. migrants than for EU migrants is consistent with the model, where U.S. inventors are willing to move to the EU only when they draw a large foreign productivity differential, which makes them more productive in the EU, to compensate them for giving up better returns and learning opportunities in the United States, which is the frontier economy with the higher return to innovation and higher human capital. These results help inform the calibration of the expected increase in productivity for a migrant relative to a local inventor.

34. Dynamic event studies for the EU and U.S. samples are reported in Online Appendix B.

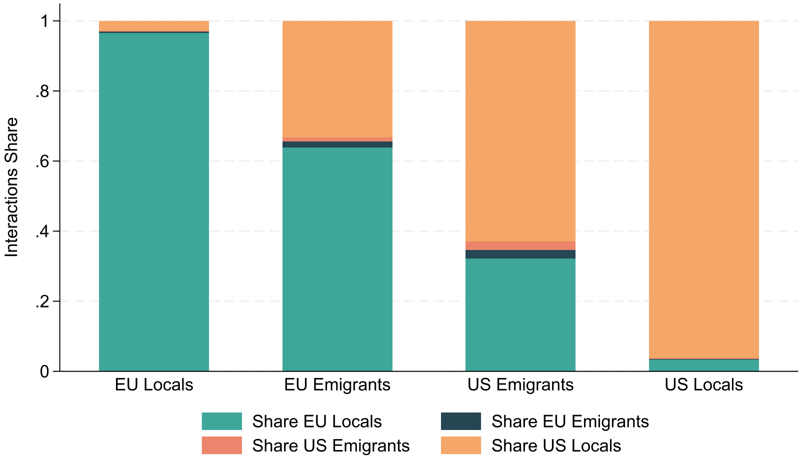



FIGURE IV

Interaction Networks

The figure is based on the inventor-coinventor pairs in the EPO data set. Inventors are grouped into four categories: EU locals, EU migrants, U.S. migrants, and U.S. locals. For each category, the co-inventors are also grouped into the same four categories. The figure displays the share of co-inventorship relationships belonging to each category.

3. *Interaction Networks.* In the model, collaboration networks are different for locals and migrants. Nonetheless, migrants continue interacting with inventors in their origin country after migration. To discipline interactions in the data, I explore the network of co-inventors of locals and migrants.

I consider four groups of inventors in the data: EU locals, EU emigrants (i.e., migrants from the EU to the United States), U.S. locals, and U.S. emigrants (i.e., migrants from the United States to the EU). For each inventor, I collect the set of all their collaborations, that is, the list of all of their co-inventors.[35] 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 IV, which reveals that the interaction networks are very different for locals and migrants and depend on the country of origin.

35. 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.

The figure shows that locals co-invent mostly with other locals in the same location. In particular, for EU locals, the share of interactions with other EU locals is 96%, and the same number holds for the share of collaborations of U.S. locals with other U.S. locals. For EU locals, other interactions are accounted for by EU emigrants for 1%, U.S. locals for 3%, and U.S. emigrants for only 0.1%. For U.S. locals, collaborations with U.S. emigrants account for 0.2% of their interactions, EU locals for about 3.5%, and EU migrants for 0.3%. Migrants have more heterogeneous co-inventors. In particular, for EU emigrants, 64% of co-inventors are EU locals, 2% are other EU emigrants, 33% are U.S. locals, and 1% are U.S. emigrants. For U.S. emigrants, 63% of interactions are with U.S. locals, 2.5% with other U.S. emigrants, 32% with EU locals, and 2.5% with EU emigrants.

Figure IV provides evidence that migrants have a different interaction network than locals, but 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 (21) on the sample of migrant inventors and the placebo control group. The results are displayed in Table II. The outcomes of interest are the share of migrants' co-inventors who are locals in the place of origin (Panel A) and locals at destination (Panel B). Column (1) indicates that the migrants' share of local co-inventors at origin declines by about 0.13 on average after migration relative to the control group, while the share at destination increases by about 0.11. The estimates are statistically significant and sizable, given that they amount to an increase of about 15% and 89% relative to the sample average of the share of local co-inventors at origin and destination, respectively. The results are similar for migrants of EU origin, in column (2), and U.S. origin, in column (3).[36]

Overall, these results provide evidence that migrants access different interaction networks after migration, but importantly, they also keep collaborating with inventors at origin after moving.

36. Additional details and dynamic specifications are described in Online Appendix B.

TABLE II

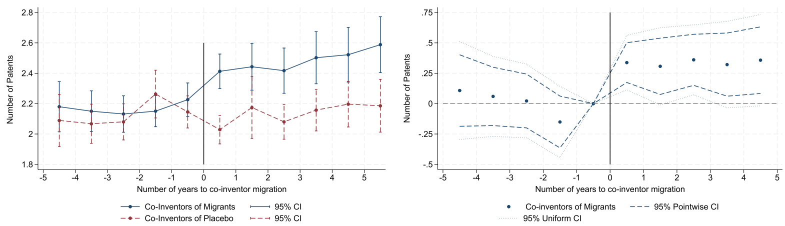
INTERACTIONS OF MIGRANTS AROUND THE TIME OF MIGRATION

| | All (1) | EU origin (2) | U.S. origin (3) |
|---|---|---|---|
| | *Panel A: Co-inventors at origin* | | |
| Post migration | −0.1274*** | −0.1347*** | −0.1145*** |
| | (0.0077) | (0.0097) | (0.0126) |
| Observations | 12,839 | 8,206 | 4,631 |
| $R^2$ | 0.735 | 0.712 | 0.765 |
| Inventor FE | X | X | X |
| Year FE | X | X | X |
| | *Panel B: Co-inventors at destination* | | |
| Post migration | 0.1064*** | 0.1201*** | 0.1088*** |
| | (0.0078) | (0.0101) | (0.0122) |
| Observations | 12,839 | 8,206 | 4,631 |
| $R^2$ | 0.715 | 0.689 | 0.747 |
| 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 inventors of EU origin. Column (3) displays the estimates for inventors of U.S. origin. Standard errors in parentheses are clustered at the inventor and year level. * $p < .10$; ** $p < .05$; *** $p < .01$.

4. *Local Inventors and Interactions with Emigrants.* The previous results documented that migrants become more productive after migration and keep collaborating with inventors in their origin country. 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 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 also 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 12,627 co-inventors of EU migrants, 4,733 co-inventors of U.S. migrants, 19,478 co-




(A) Raw means for local co-inventors of emigrants (B) Coefficients $\beta_{\tau}^{Mig}$ for co-inventors of emigrants

FIGURE V

Patenting Activity by Co-inventors of Migrants Around the Time of Migration

The figure displays the changes in the productivity of local co-inventors of migrants in the country of origin around migration time relative 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 (20). Unbalanced panel. EU co-inventors of migrants: 20,073 observations; U.S. co-inventors of migrants: 9,196 observations; EU co-inventors of placebo: 17,233 observations; U.S. co-inventors of placebo: 12,397 observations. Standard errors are clustered at the associated migrant inventor and year levels.

inventors of EU placebos, and 8,621 co-inventors of U.S. placebos. Online Appendix B presents the summary statistics and balance tables for co-inventors of migrants and placebo inventors of EU and U.S. origin.

I 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.

Figure V, Panel A 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 OLS specification as in equation (20) on the sample of co-inventors of migrants and placebos, who never migrate. The relative time in this event study, denoted by $\tau$, now indicates the number of years relative to the year of migration of the associated emigrant. Figure V, Panel B shows the estimated coefficients and 95% point-wise and uniform confidence intervals for $\beta_{\tau}^{Mig}$ from specification (20) run on the sample of co-inventors. The figure shows 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.[37]

To summarize the results, I implement specification (21) on the sample of co-inventors, where time is relative to the year of migration of the associated co-inventor. Table III reports the results. Column (1) indicates that co-inventors of migrants file about 0.35 more patents a year than co-inventors 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 a 16% increase in patenting relative to the sample mean.

Columns (2) and (3) show the results for the subsamples of inventors of EU and U.S. origin, respectively. The estimated coefficients are positive and statistically significant in both cases. The point estimates are 0.25 for EU inventors and 0.48 for U.S. inventors, corresponding to an average increase in patenting of about 11% and 22% per year, respectively, relative to the sample mean.[38]

Online Appendix B presents more results and robustness checks. I replicate the event studies with alternative estimators.

37. In this setup, there may be serial correlation in an inventor's outcomes over time and the outcomes of local co-inventors associated with 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 and year; see Jaravel, Petkova, and Bell (2018).

38. Dynamic event studies for the EU and U.S. samples are reported in Online Appendix B.

TABLE III
PATENTING ACTIVITY OF CO-INVENTORS OF MIGRANTS AROUND THE TIME OF MIGRATION

| | Number of patent applications per year | | |
|---|---|---|---|
| | All (1) | EU origin (2) | U.S. origin (3) |
| Post co-inventor migration | 0.3507*** | 0.2498** | 0.4831*** |
| | (0.0674) | (0.0934) | (0.1136) |
| Observations | 58,898 | 37,305 | 21,591 |
| $R^2$ | 0.440 | 0.455 | 0.416 |
| 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 relative to the co-inventors of the placebo control group from the regression specification in equation (21). 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 U.S. origin. Standard errors in parentheses are clustered at the associated migrant inventor and year level. * $p < .10$; ** $p < .05$; *** $p < .01$.

I document that the increase in productivity is more pronounced for local co-inventors who continue to co-invent with the migrant after she moves away.[39] I show that results are robust for co-inventors of migrants who switch firm upon migration and co-inventors of return migrants. I also show that results are robust when excluding patents that are co-invented with migrants. I implement an IV strategy to provide causal identification of the effect of exposure to migration on local inventors' productivity, using a shift-share instrument based on immigrant enclaves.

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.

## IV. QUANTITATIVE ANALYSIS

This section quantifies the effects of migration and knowledge transfers on innovation and productivity and studies the

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

effects of counterfactual taxation and immigration policy. To do this, I calibrate the model from Section II along a BGP to match the empirical results from Section III. I 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.

### *IV.A. Calibration*

I calibrate the model along a BGP equilibrium to match features of the EU–U.S. migration corridor, setting the EU to be country $A$ and the U.S. to be country $B$. The benchmark calibration aims to study 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 the share of inventors to be the same across locations; that is, $\theta_A = \theta_B$, and $I_A = I_B$. The total population is also the same in the two locations and normalized to a mass of one.[40]

Given this restriction, 23 parameters remain to be calibrated, described in Table IV.

These parameters are $\{\beta, r, \delta, \alpha, \nu, \tau_A, \tau_B, I_A, \bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega_A, \omega_B\}$ 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 nine parameters are jointly calibrated using the simulated method of moments (SMM) to match important features of the microdata ($\bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega_A, \omega_B$).

1. *External Calibration.* In the model, production and preferences are similar to the existing literature. The key inno-

40. The assumption that the two locations have the same total population is motivated by the application to the United States and the EU, which have roughly similar population sizes. In Online Appendix C.2.1, I present a robustness exercise where I allow the number of inventors to be different across the two locations. The relative scale of the two countries in terms of total population is relevant for the results of the model, because inventors' profits are increasing in the population size. If the United States were compared to another smaller country, or to any of the single EU countries taken alone instead of the EU altogether, it would be more difficult for a small country to attract U.S. migrant inventors because of the small market size.

TABLE IV
PARAMETER VALUES

| Parameter | Description | Value | Standard error |
|---|---|---|---|
| | *Panel A: External calibration* | | |
| $\beta$ | Discount rate | 0.97 | |
| $r$ | Interest rate | 0.03 | |
| $\delta$ | Survival rate | 0.95 | |
| $\alpha$ | Final-good production | 0.11 | |
| $\nu$ | Inventor-firm match rate | 1.00 | |
| $\tau_A$ | Tax rate EU | 0.40 | |
| $\tau_B$ | Tax rate United States | 0.30 | |
| $I_A$ | Share R&D workers | 0.01 | |
| | *Panel B: Direct match to data* | | |
| $\xi_{AB,AA}$ | Meeting frictions | 1.34 | |
| $\xi_{AB,BB}$ | Meeting frictions | 0.67 | |
| $\xi_{BB,AA}$ | Meeting frictions | 0.07 | |
| $\xi_{BA,AA}$ | Meeting frictions | 0.68 | |
| $\xi_{BA,AB}$ | Meeting frictions | 1.04 | |
| $\xi_{BA,BB}$ | Meeting frictions | 1.27 | |
| | *Panel C: SMM calibration* | | |
| $\bar{\mu}$ | Migration cap to United States (share of inventors) | 0.010 | 0.0003 |
| $\kappa$ | Cost of migration | 0.128 | 0.039 |
| $\lambda$ | Meeting intensity | 0.052 | 0.005 |
| $\eta$ | Learning technology | 0.531 | 0.008 |
| $\sigma$ | Technology absorption | 0.011 | 0.001 |
| $\theta$ | Talent cumulative distribution function | 14.533 | 2.074 |
| $\rho$ | Location shock persistence | 0.460 | 0.128 |
| $\omega_A$ | Location shock SD A | 0.530 | 0.040 |
| $\omega_B$ | Location shock SD B | 0.285 | 0.011 |

*Notes.* For the simulated method of moments (SMM) calibration (Panel C), all parameters are calibrated jointly; standard errors are computed with a bootstrap procedure.

vation 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, Pearce, and Prato forthcoming). The parameter $\nu$ governs the matches between firms and inventors. A value $\nu < 1$ means 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. 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 United States displaced U.S. scientists working in the same field. To account for contrasting evidence, in Online Appendix C, I explore robustness to different values of $\nu$. 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 United States (OECD 2021b).[41] The parameters are listed in Table IV, Panel A.

2. *Direct Match to Microdata.* The parameters for the meeting frictions are calibrated to directly match the microdata on co-inventors, presented in Figure IV. This figure displays, for any group of inventors, the share of co-inventors that are EU locals, U.S. locals, EU migrants, or U.S. 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 one; 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 Table IV, Panel B.

3. *Internal Calibration Using SMM.* For the remaining nine parameters $\{\bar{\mu}, \kappa, \lambda, \eta, \sigma, \theta_A, \rho, \omega_A, \omega_B\}$, I select nine informative moments from the data and empirical results in Section III. I 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 implement the SMM,

41. I consider taxes on labor income because most inventors in the EPO patent data are employees for private firms and for consistency with the literature (Akcigit, Baslandze, and Stantcheva 2016).

minimizing the squared percent distance between the model-simulated moments, $M(\Theta)$, and their empirical counterparts, $M^E$, by searching over the parameter space $\Theta$, 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, I provide a heuristic discussion of the most relevant moment for each parameter.

*i. Share of Migrants EU–U.S.* The share of inventors with nationality from one of the 28 EU countries who patented from a U.S. address was, on average, 5.7% of local Europeans in the years 2000–2010 in the PCT data (Figure II). This moment primarily informs the mass of inventors allowed to enter country $B$ in every period, $\bar{\mu}$. [42]

*ii. Share Migrants U.S.–EU.* The share of inventors with U.S. nationality who patented from a EU address was, on average, 0.4% of local Americans in the years 2000–2010 in the PCT data (Figure II). This moment primarily informs the cost of migration, $\kappa$.

*iii. Share of Return Migrants.* The share of inventors who return to their original country in any given year, as a fraction of active migrants, is 0.135, on average, in the EPO data. This moment primarily informs the persistence of productivity shocks, $\rho$, because in the model, inventors choose to return to their country of origin when they are affected by a negative enough productivity shock abroad.

*iv. $\Delta$ Productivity Migrants from the EU to the United States.* I target the average change in productivity after migration for migrant inventors from the EU to the United States. I replicate an event study equivalent to Figure III using data generated from the model. Specifically, I simulate the steady state of the model and collect a sample of migrants, with the same number of individuals as the data sample.[43] I match every migrant with a local

42. The migration restriction to country $B$ is modeled to represent features of the H1B visa program for high-skilled immigrants into the United States.

43. In the data, individuals need to file for a patent before and after moving to different countries to be classified as migrants. For consistency, I drop from the model-simulated sample those inventors who move before their first innovation or exit the economy after moving but before producing an innovation at destination.

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." 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 take the average value of coefficients $\beta_\tau^{Mig}$ for five periods after migration. I transform it into a percentage change 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 0.231. In the model, the productivity of migrants, after they move, is boosted by the productivity shock $\epsilon$. Thus, this moment primarily informs the standard deviation of the productivity shock for EU-born inventors, $\omega_A$.

*v. Δ Productivity of Migrants from the United States to the EU.* The construction of the target moment in the model and in the data is analogous to the case for migrants from the EU to the United States. In this case, I target the average percentage change in productivity after migration for migrant inventors from the United States to the EU, with a target value of 0.333. This moment primarily informs the standard deviation of the productivity shock for U.S.-born inventors, $\omega_B$.

*vi. Δ Productivity of Co-inventors of Migrants in the EU.* I target the average change in productivity for locals in the EU after they interact with a EU emigrant in the United States, as reported in Table III, column (2). 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 run an event study on the group of locals who interact with migrants versus locals who interact with "placebo." Time 0 in the event study corresponds to the first interaction of the local with a migrant (or placebo). I match the coefficient from the model-simulated event study to the coefficient in the empirical event study. I transform it into a 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 0.118. In the model, locals can boost their productivity as they learn from interactions. Thus, this moment, along with the equivalent coefficient for U.S. locals, primarily informs the parameters that govern the learning process, $\eta$ and $\lambda$.

*vii. $\Delta$ Productivity of Co-inventors of Migrants in the United States.* I target the average change in productivity for locals in the United States after they interact with an American emigrant in the EU, as reported in Table III, column (3). The description of the moment is analogous to the one for EU locals. The target percentage change in productivity is 0.230.

*viii. 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, $\theta_A$.

*ix. TFP Gap.* In the model, the parameter $\sigma$ governs the average productivity gap between the two locations (see equation (17)). To obtain a similar counterpart in the data, I rely on the indicator of GDP per hour worked built by the Organisation for Economic Co-operation and Development (OECD 2021a) and compare the average productivity gap between the United States and the EU in the years 2000–2010.

## *IV.B. Quantitative Results*

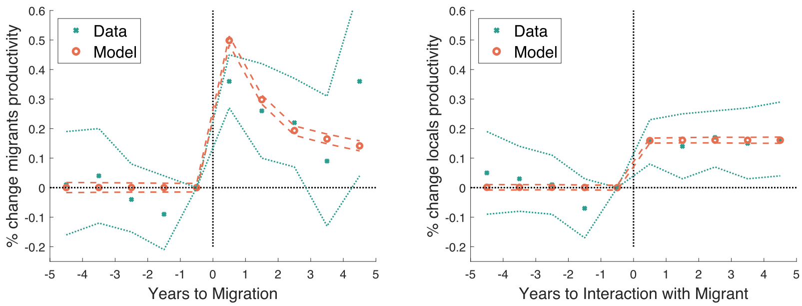
1. *Calibrated Parameters and Targeted Moments.* Table IV, Panel C displays the value of parameters calibrated with the SMM and the standard errors computed with a bootstrap procedure. The calibrated value of $\bar{\mu} = 0.01$ indicates that the flow of immigrant inventors allowed into the United States amounts to 1% of local U.S. inventors. The calibrated meeting intensity indicates that in the model, inventors have about a 5% probability of meeting other inventors in every period. The parameter $\eta = 0.531$ indicates that inventors can learn substantially from interactions. Finally, the calibrated cost of migration of $\kappa = 0.128$ indicates that the cost of moving is approximately equal to 0.3% of the discounted lifetime value of an inventor born in the EU.

Table V 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, it replicates the asymmetric migration flows of inventors between the United States and the EU. In addi-

TABLE V
MOMENTS

| Moment | Data | Model |
|---|---|---|
| Share migrants EU–U.S. (% domestic inventors) | 0.057 | 0.050 |
| Share migrants U.S.–EU (% domestic inventors) | 0.004 | 0.004 |
| Share return migrants (% migrants) | 0.135 | 0.239 |
| Δ productivity migrants from EU to U.S. (%) | 0.231 | 0.229 |
| Δ productivity migrants from U.S. to EU (%) | 0.333 | 0.334 |
| Δ productivity co-inventors of migrants EU (%) | 0.118 | 0.136 |
| Δ productivity co-inventors of migrants U.S. (%) | 0.230 | 0.228 |
| Growth rate (%) | 1.50 | 1.25 |
| TFP gap | 0.90 | 0.90 |

*Notes.* The table presents the value of moments in the data and in the calibrated model.




(A) Migrants around Time of Migration

(B) Locals around Interaction with Migrant

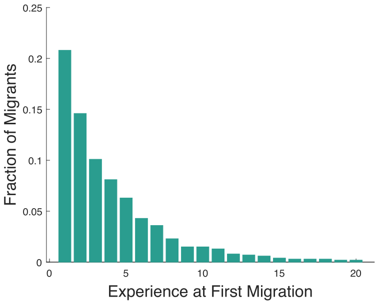
FIGURE VI

Event Studies on Productivity of Migrants and Locals: Data Versus Model

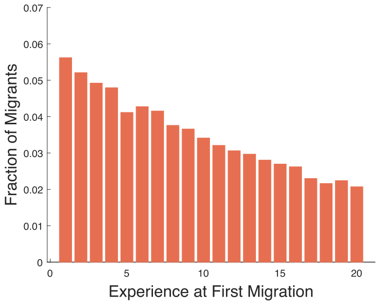
The figure describes event studies for changes in the productivity of migrants (Panel A) and local co-inventors of migrants in the country of origin (Panel B) around migration time. The circles indicate estimates from a model-simulated sample. The crosses indicate estimates from the data, corresponding to Figures III and V. The dotted and dashed lines indicate the 95% confidence intervals for the data and the model, respectively.

tion, the model generates an increase in productivity for migrants after migration. Importantly, the model also replicates the increase in productivity for local inventors due to interactions between migrants and locals.

2. *Non-targeted Moments.* Figure VI 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 III and V. The circles represent the event



(A) Data



(B) Model

FIGURE VII

Experience at First Migration: Data Versus Model

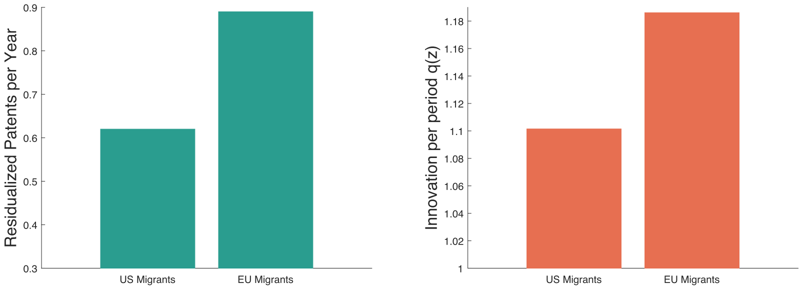
The figure displays histograms of the number of years of experience for migrants at migration time, in the data (Panel A) and the model (Panel B). Experience indicates the number of years since the first patent application.

studies generated from model-simulated data. The figure reports also the 95% confidence intervals for the model (dashed line) and the data (dotted line). Even if only the average effect after the event is targeted, 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 ($\epsilon$), 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 $\epsilon$.

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 sizable due to the foreign productivity differential $\epsilon$.

The model also replicates important qualitative features of the data. Figure VII, Panel A displays a histogram of the num-




(A) Average Patents per Year (Data) (B) Averge Innovation per Year, $q(z)$ (Model)

FIGURE VIII

Average Productivity of Migrants Before Migration: Data Versus Model

Panel A depicts the average residualized patent applications per year for U.S. 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 U.S. and EU migrants before migration.

ber 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 VIII. 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 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 United States tend to be more talented, before migration, than migrants from the United States to the EU. This finding is also true in the data, as confirmed by Figure VIII, Panel A: U.S. migrants to the EU file, on average, 0.62 patents per year before migration, versus 0.89 for EU migrants to the U.S., 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 U.S. migrants to the EU before migration is 1.10 on average, versus 1.19 for EU migrants to the United States.

*IV.C. 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 for studying counterfactual exercises. First, I quantify the importance of interactions and knowledge transfers for innovation and growth. Second, I assess the effect of counterfactual policy exercises that resemble real-world policies 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 United States, I study changes in the immigration cap. The goal of these exercises is to illustrate the multiple channels through which inventors' migration affects productivity growth. Among these channels, I emphasize the quantification of the forces central to this framework: talent reallocation through brain drain or brain gain and knowledge transfers through inventors' interactions.[44]

1. *Quantifying the Importance of Knowledge Transfers.* How important are interactions for developing human capital and innovation? To answer this question, I run two counterfactual exercises. First, I set the migration cost to infinity ($\kappa = \infty$), to generate an autarky scenario with no migration in equilibrium. Second, I shut down interactions across inventors ($\eta = 0$). In each exercise, I keep all other parameters fixed at their calibrated value, and I solve for the BGP equilibrium.

Table VI provides a decomposition of the growth rate for the EU and the United States comparing the baseline BGP to the cases of autarky and no interactions. The growth rate can be decomposed into the following components. First, for each country, total innovation is given by the weighted sum of the productiv-

44. The baseline economy is inefficient because inventors do not internalize the effect of their migration decisions on innovation, knowledge spillovers to other inventors, and crowding in the market for ideas. The full solution of the efficient allocation or planning problem is outside of the scope of this article and is left for future research.

TABLE VI
GROWTH DECOMPOSITION

| | Local inventors | | Immigrant inventors | | Total innovation | Technology diffusion | Growth |
|---|---|---|---|---|---|---|---|
| | Mass | Average productivity | Mass | Average productivity | | | |
| EU baseline | 0.950 | 1.19 | 0.004 | 2.04 | 1.14 | 0.11 | 1.25 |
| EU autarky | 1 | 1.18 | 0 | — | 1.18 | 0 | 1.18 |
| EU no interactions | 0.950 | 1.07 | 0.006 | 1.97 | 1.03 | 0.10 | 1.13 |
| U.S. baseline | 0.996 | 1.18 | 0.050 | 1.54 | 1.25 | 0 | 1.25 |
| U.S. autarky | 1 | 1.18 | 0 | — | 1.18 | 0 | 1.18 |
| U.S. no interactions | 0.994 | 1.07 | 0.050 | 1.43 | 1.13 | 0 | 1.13 |

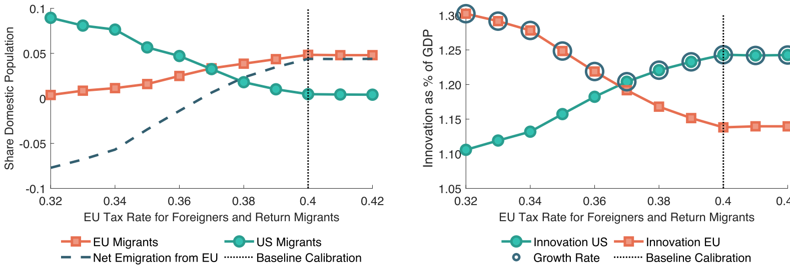
*Notes.* The table compares the outcome of three BGP equilibria: the baseline calibration; an autarky scenario, where $\kappa = \infty$; and a no interactions scenario, where $\eta = 0$. The table shows a decomposition of the sources of growth for the EU and the United States from local inventors, immigrant inventors, total innovation, and technology diffusion.

ity of local inventors and immigrant inventors, each weighted by their mass. Second, total innovation is summed to the technology diffusion from the frontier to the laggard country to obtain the growth rate. The results on innovation can thus be interpreted as the combination of quantity effects and quality effects on the allocation of talent.

In the autarky case, the prohibitive migration costs result in no migration in equilibrium, so that both the EU and United States rely only on their own local inventors. In particular, this talent reallocation eliminates the brain drain from the EU to the United States. The average productivity of EU locals decreases only slightly, due to two opposing forces. On the one hand, locals' productivity declines because they do not have the opportunity to interact with highly productive migrants. On the other hand, individuals who would migrate in the baseline, who are more talented than locals on average, become locals in the autarky scenario, increasing the overall average productivity of locals. Because of the talent reallocation, innovation increases in the EU, but it decreases in the United States, which loses the contribution of migrants. The decline in innovation at the frontier (the United States) also results in lower technology diffusion to the EU. Inventors are less productive on average because they do not take advantage of their idiosyncratic country-specific productivity shocks with migration and because their interaction opportunities decline. Overall, the growth rate declines by 6%.

In the case with no interactions, the equilibrium level of migration and brain drain from the EU to the United States are similar to the baseline. Despite the absence of interactions, individuals have an incentive to move because of the idiosyncratic productivity shocks and the different tax rates. However, the average productivity of EU and U.S. locals declines, as they cannot learn from interactions, resulting in lower innovation in both locations and lower growth compared with the baseline. In particular, in this scenario, the EU faces a similar level of brain drain as in the baseline, but EU innovation declines by 10% due to the lack of interactions.

The overarching message from these exercises is that interactions and knowledge transfers are quantitatively important and they partly offset the negative effect of brain drain on innovation by enabling local inventors to learn and become more productive.




(A) Stock of Migrants (B) Innovation and Growth

FIGURE IX

Tax Cut for Foreigners and Return Migrants in the EU: BGP Comparison

The figures compare counterfactual BGP equilibria for different values of the tax cut for foreigners and return migrants in the EU with a moving average to smooth simulation noise. Panel A shows equilibrium migration of EU inventors (squares) and U.S. inventors (circles) and net emigration from the EU (dashed line). Panel B shows equilibrium aggregate innovation in the EU (squares) and in the U.S. (circles) and the aggregate growth rate (open circles).

2. *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 for foreign inventors and return migrants, which I define as $\tilde{\tau}_A$. This exercise replicates the scope of policies to "reverse the brain drain," implemented in several EU countries, including the Netherlands, Denmark, Italy, France, Spain, and Ireland.

First, in Figure IX, I document the effect of the policy change on the BGP for different values of the EU tax rate for foreign inventors and return migrants, reported on the horizontal axis. Panel A describes the effect on the stock of EU migrants (squares), U.S. migrants (circles), and the net emigration rate, or brain drain, from the EU (dashed line). A lower tax rate encourages U.S. inventors to move to the EU, increasing the stock of U.S. migrants. At the same, a lower tax rate on return migrants has two effects on the stock of EU migrants. First, it increases the value of migration for EU inventors, who anticipate lower taxes if they migrate and then return to the EU. Thus, a larger mass of EU inventors would like to move, but they are constrained by the immigration cap in the United States, so that the flow of migrants from the EU to the United States remains unchanged. Second, the return intensity for EU migrants increases because of the lower tax rate upon return. As a result, the lower tax for return migrants is associated with a lower stock of EU migrants.

The reallocation of inventors toward the EU at lower values of $\tilde{\tau}_A$ is associated with two opposing forces. First, an increase in inventors is an expansion of the innovative talent pool with a positive effect on EU innovation, as additional inventors produce more ideas, by an amount that depends on their talent and productivity. Second, additional inventors also produce a crowding-out effect, reducing the matching probability between inventors and intermediate firms in the EU by an amount regulated by the parameter $\nu$, with a negative effect on EU innovation. In the baseline calibration, the former effect dominates given that $\nu = 1$, as explained in Section IV.A. In Online Appendix C.2, I show that the results are robust to lower values of $\nu$, associated with stronger crowding out.

Figure IX, Panel B illustrates the effect of talent reallocation on innovation. At lower EU tax rates for foreigners and return migrants, inventors reallocate toward the EU, and as a result, EU innovation increases (circles) and U.S. innovation declines (squares). Recall that the growth rate is equal to the highest level of innovation across the two locations, displayed by the open circles in Figure IX. The figure shows that in a region with the EU tax rate between about 0.37 and 0.42, the United States is the frontier country with the highest innovation, which is lower, together with aggregate growth, when the EU tax rate is lower. In the region for $\tilde{\tau}_A$ between 0.32 and 0.37, instead, the EU is the frontier country with the highest innovation, which is higher, together with the growth rate, at lower tax rates. Thus, for small tax cuts, EU innovation increases, U.S. innovation declines, but the aggregate growth rate also declines. For larger tax cuts, the EU has the potential to become the technology frontier by attracting foreign talent, given that it has the same economic fundamentals as the United States (population size, talent distribution, innovation capacity).[45]

45. Note that the model abstracts from details of the U.S. tax code, such as the taxation of foreign income for citizens, which would affect the migration rate for U.S. inventors. The growth rate reaches a higher value when the EU is the frontier because the EU does not have an immigration cap in place in the model.

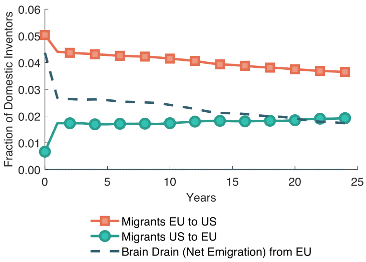
Note that the growth rate is higher when inventors are more geographically concentrated in either location. This is due to multiple forces. First, recall that migrants from the laggard to the frontier are positively selected on talent. Thus, concentrating migrants at the frontier improves the pool of highly productive interactions, generating learning opportunities that increase aggregate human capital and frontier innovation. Second, because of the exogenous technology diffusion, technologies produced at the frontier will eventually be available to the laggard for production and consumption (at a speed governed by the parameter $\sigma$). So the laggard benefits from higher innovation at the frontier through a higher growth rate on the BGP.

After describing the BGP effects, I study the transitional dynamics from an initial BGP with a tax rate of 0.4 for all inventors in the EU to a new BGP with a EU tax rate of 0.365 for foreign inventors and return migrants, which would eliminate the brain drain in the long run. This exercise mimics the preferential tax schemes for foreigners implemented in several EU countries.[46] For a tax cut of this size, the economies will transition toward a new BGP with lower net migration, higher innovation in the EU, lower innovation in the United States, and lower aggregate growth, as illustrated in Figure IX.

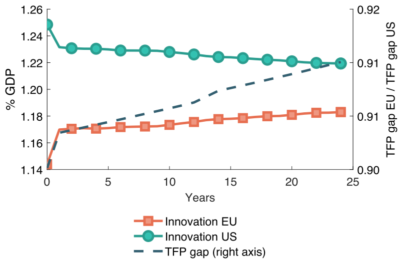
Figure X, Panel A plots the evolution of the mass of EU migrants (squares) and U.S. migrants (circles) along the transition. The tax cut immediately attracts U.S. immigrants to the EU, whose stock jumps significantly on the implementation of the policy, accounting for over 1% of local U.S. inventors. In addition, the stock of EU migrants (squares) to the US decreases over time, from about 5% to 3.5% of domestic EU inventors over 25 years. Thus, brain drain from the EU (or net emigration, depicted by

The immigration cap reduces innovation at the frontier, as discussed in the next section.

46. 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 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).




(A) Migrant Inventors by Nationality




(B) Innovation and TFP gap

FIGURE X

Transitional Dynamics After a Tax Cut for Foreigners and Return Migrants in the EU

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 0.365 with a moving average to smooth simulation noise. Panel A shows the equilibrium stock of EU emigrants (squares), U.S. emigrants (circles), and net emigration from the EU (dashed line). Panel B shows aggregate innovation in the EU (squares) and in the United States (circles), as well as the productivity gap (dashed line).

the dashed line) declines toward zero. 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.[47]

Panel B displays the effect of talent reallocation across countries on the evolution of EU innovation (squares), U.S. innovation (circles), and the productivity gap (dashed line). Twenty-five years after the policy implementation, innovation increases by about 3% in the EU and declines by 3% in the United States, due to the reallocation of inventors across countries. As a result of these two effects, aggregate productivity in the EU, relative to the United States, increases by about 1.5% in the span of 25 years, as predicted by equation (17).

What are the effects of the tax cut on aggregate productivity and output growth? The growth rate in the EU increases in the initial decades since policy implementation, but then it declines

47. The elasticity of the number of domestic inventors to the tax rate in this exercise is in the range 0.07–0.3 over the years 1–25 since the policy implementation. In comparison, Akcigit, Baslandze, and Stantcheva (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 VII
TAX CUT FOR FOREIGNERS AND RETURN MIGRANTS IN THE EU: EFFECTS ON THE EU'S GROWTH RATE

| Channel | Change in EU growth (percentage points) | |
|---|---|---|
| | After 25 years | New BGP |
| Direct reallocation (brain drain/gain) | + 0.065 | + 0.091 |
| Change in migrants' productivity | −0.006 | −0.010 |
| Migrants' selection | + 0.014 | + 0.018 |
| Change in technology diffusion from U.S. | −0.018 | −0.119 |
| Knowledge transfers | −0.020 | −0.021 |
| Net effect on the growth rate | + 0.036 | −0.040 |

*Notes.* The table illustrates the change in the EU growth rate after 25 years and in the new BGP after a cut in the tax rate for foreigners and return migrants in the EU from 0.4 to 0.365. The table documents the separate impact of different channels and their net effect.

due to the interaction of different forces, which are described in Table VII.

Table VII provides a decomposition of the changes in the EU growth rate due to different channels at different time horizons: after 25 years (first column) and in the new long-run BGP (second column). The first row of Table VII illustrates the direct reallocation effect, which captures the change in the number of local and migrant inventors, if they maintained the same level of productivity as in the old BGP. Twenty-five years after the tax cut, the reallocation of inventors to the EU increases the EU growth rate by 0.065 percentage points. However, those EU inventors who are migrants in the baseline BGP but are locals in the new equilibrium are on average less productive in the EU, because they miss the productivity differential $\epsilon$. This channel from a change in productivity reduces the direct effect by 0.006 percentage points. On the other hand, selection forces imply that returning EU migrants and U.S. immigrants have higher talent than the average local inventor, increasing growth by 0.014 percentage points. In addition, lower innovation in the United States reduces the exogenous diffusion of technologies to the EU, reducing growth by 0.018 percentage points. Finally, local EU inventors are less productive in the new equilibrium due to smaller knowledge transfers, since the mass of EU emigrants is smaller. The change in spillovers additionally reduces output by 0.02 percentage points. The net effect of these different forces leads to an increase in the EU growth rate by 0.036 percentage points after 25 years.

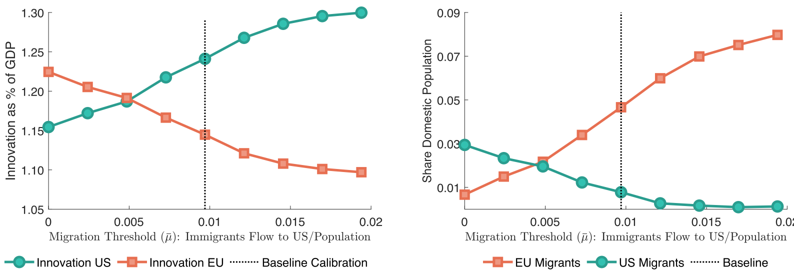
The second column of Table VII illustrates that while growth in the EU initially increases, the negative effects get larger over time, eventually reducing growth in the new long-run BGP relative to the old BGP. In particular, while the direct effect and change diffusion are the dominant forces, the decline in knowledge transfers also has a sizable effect on output in the long run, accounting for a −0.021 percentage point reduction in GDP. In the new long-run equilibrium, the EU and the United States grow at the same rate of 1.21%, which is about 0.04 percentage points lower than the old BGP.

Table VII thus shows that the effect of the policy change on growth is the result of multiple forces with opposite effects through which migration affects talent allocation and knowledge transfers. In terms of quantification, the main results show the direct effect of reducing the brain drain and the magnitude of knowledge transfers operating via inventors' interactions and learning, calibrated with the direct evidence presented in Section III. The direct effect of reducing the brain drain accounts for an increase in the long-run EU growth rate of 0.091 percentage points. This gain is more than offset by multiple negative forces, including the reduction in knowledge transfers, which has a sizable effect and accounts for about 50% of the decline in the long-run growth rate.

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 $\beta$ multiplied by the survival probability $\delta$.[48] The weighted average of welfare for EU individuals (including inventors and workers) increases by 0.7%. This result is driven by the initial increase in productivity and 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 U.S. individuals decreases by 0.9%, due to declining innovation and 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 policy maker. In the short run, this policy attracts foreign inventors and return migrants to the EU and boosts EU innovation, aggregate productivity, and wages. In the long run,

48. Online Appendix A describes the measure and computation of welfare.




**(A)** Innovation and TFP gap

**(B)** Stock of Migrants

FIGURE XI

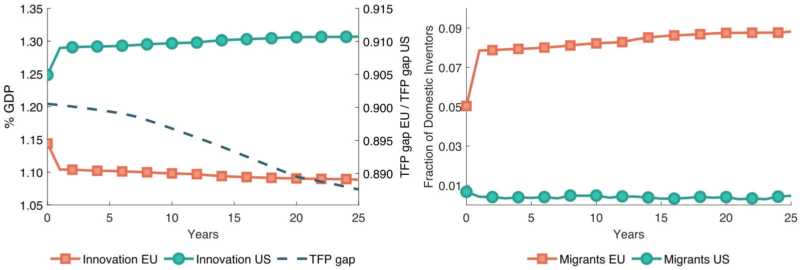
Counterfactual Change to U.S. Immigration Threshold ($\bar{\mu}$): BGP Comparison

The figures compare counterfactual BGP equilibria for different values of the immigration threshold to the United States with a moving average to smooth simulation noise. Panel A shows equilibrium aggregate innovation in the EU (squares) and in the United States (circles). Panel B shows the equilibrium migration of EU inventors (squares) and U.S. inventors (circles).

the growth rate of the global economy could either increase or decrease, depending on the overall effect of the policy on the allocation of inventors across locations and their ability to generate knowledge spillovers and technology diffusion.

3. *Policy Exercise: Changing the Migration Limit in the United States.* What are the implications of changing the number of immigrants allowed to flow into the United States ($\bar{\mu}$)? This exercise mimics changes to the H1B visa program, which regulates the immigration of high-skill workers in the United States.

Figure XI describes the BGP equilibrium of the model for different values of the migration threshold $\bar{\mu}$, plotted on the horizontal axis. Panel B describes the effects on innovation: as the threshold $\bar{\mu}$ increases (i.e., more inventors are allowed to enter the United States in every period), innovation increases in the United States (circles) and declines in the EU (squares). 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 (squares) and a decline in the mass of U.S. migrants (circls). The mass of EU migrants increases with the threshold be-




(A) Innovation and TFP Gap

(B) Stock of Migrants by Nationality

FIGURE XII

Counterfactual Increase of the U.S. Migration Threshold: Transitional Dynamics

The figures display transitional dynamics upon the implementation of a counterfactual increase of the migration threshold in the United States that doubles the inflow of immigrant inventors per year, with a moving average to smooth simulation noise. Panel A shows aggregate innovation in the EU (squares) and in the United States (circles) and the productivity gap (dashed line). Panel B shows the equilibrium migration of EU inventors (squares) and U.S. inventors (circles).

cause the migration threshold is binding in the initial BGP.[49] The mass of U.S. migrants declines with the threshold because higher innovation in the United States implies higher aggregate productivity and profits for domestic inventors, increasing the opportunity cost of moving to the EU. Changes in both EU and U.S. migration flows increase the number of inventors active in the United States in equilibrium, resulting in higher U.S. innovation.[50]

After comparing the BGP at different thresholds, I analyze the dynamic evolution of the economies on a doubling of the immigration threshold in the United States, displayed in Figure XII. This exercise mimics an increase in the issuance of H1B visas for skilled immigrants to the United States.

Figure XII, Panel A displays the evolution of innovation in the two economies and the productivity gap. Innovation increases in the United States, up by about 5% after 25 years. At the same time, innovation decreases by about 5% in the EU. These

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

50. 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 IV.A. In Online Appendix C.2, I analyze the results for lower values of $\nu$, associated with stronger crowding out.

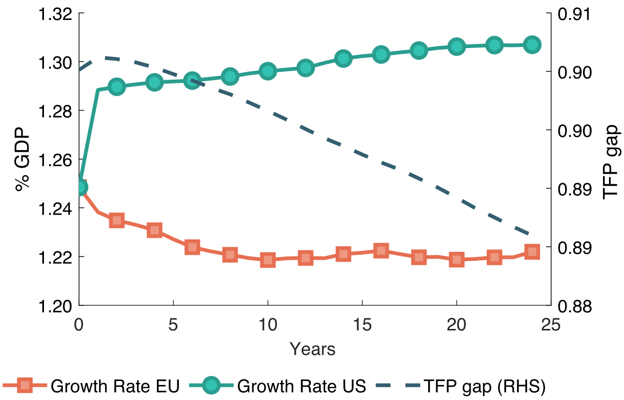



FIGURE XIII

Counterfactual Increase of the U.S. Migration Threshold: Growth Transitional Dynamics

The figure displays the transitional dynamics of the implementation of a counterfactual increase of the migration threshold in the United States that doubles the inflow of immigrant inventors per year. The figure shows the growth rate in the EU (squares) and in the United States (circles), as well as the productivity gap (dashed line).

effects increase the productivity gap between the United States and the EU by about 2%. Panel B plots the evolution of the mass of migrants of each nationality. The increase in the migration threshold leads to an increase in the stock of immigrants as a fraction of domestic inventors in the United States by about 80% after 25 years. The mass of U.S. migrants declines slightly; thus, the net brain drain from the EU increases.

The change in migration policy affects output and productivity growth. Figure XIII displays the evolution of the growth rate for the EU (squares) and the United States (circles) since the introduction of the policy. Due to the increase in U.S. innovation, the U.S. growth rate increases toward the new BGP, where the growth rate is 4% (or about 0.05 percentage points) higher compared with the initial equilibrium. On the other hand, the growth rate in the EU initially declines, because the policy lowers EU innovation. Twenty-five years after the policy change, the EU's growth rate is still about 2% (or 0.03 percentage points) lower compared to the old BGP. As a result, the TFP level in the EU relative to the United States (dashed line) falls by about 2% after 25 years. However, after the initial decline, the EU's growth rate starts increasing due to higher knowledge spillovers and technology diffusion from the United States, eventually converging toward the U.S.'s growth rate at the new BGP, where the growth rate is 4% higher compared with the initial equilibrium.

Overall this policy increases welfare in the United States by 0.3%, but it decreases welfare in the EU by 1.2%. The sorting of inventors to the United States increases innovation in the United States, which is the frontier economy, benefiting both the U.S. and EU economies. In the latter, the short-term decline in productivity from lower EU innovation generates a welfare loss that exceeds the benefit from long-term productivity gains from more significant knowledge spillovers and technology diffusion from the United States.

## V. 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 article builds an innovation-based endogenous model that microfounds migration decisions, interactions, and knowledge spillovers. One of the key contributions is to bring a general equilibrium macroeconomic model to a largely empirical literature.

This framework is apt for studying the global effects of migration. I link the model to a novel data set of migrants, which I build from patent data. The empirical results show that migrants move to 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 eliminating the brain drain. The effectiveness of this policy depends on the time horizon of the policy maker: in the short run, this policy can attract foreign inventors and return migrants to the EU and boost EU innovation, aggregate productivity, and wages. In the long run, it could either increase or reduce the growth rate of the global economy, depending on the overall effect on talent allocation, knowledge spillovers, and technology diffusion. On the migration policy side, increasing the size of the U.S. H1B visa program increases productivity in the United States 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 article paves the way for a new research agenda on the macroeconomic effects of migration for long-run growth. I discuss some 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 to study how migration interacts with the sorting of individuals between production and research. Second, the results 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. Third, the results rely on the assumption that knowledge produced in one country can freely flow and is relevant to other countries. However, in some contexts, such as industries with high security concerns, there are barriers in place that could considerably limit or prevent the diffusion of knowledge to other countries. Frontier technologies might not be relevant or appropriate for developing countries further from the frontier. Exploring the role of knowledge spillovers in these contexts is an interesting avenue for further research. Fourth, this study highlights the importance of inventors' interactions as a source of knowledge diffusion. It would be interesting to investigate further inventors' incentives to endogenously shape their connections to gain useful information and resources in a richer model of dynamic and strategic network formation.

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## Supplementary Material

An Online Appendix for this article can be found at the *The Quarterly Journal of Economics* online.

## DATA AVAILABILITY

The data underlying this article are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/IX6AW9 (Prato 2024).

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