

High-Skilled Migration and Global Innovation

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Abstract

Science and engineering (S&E) workers are the fundamental inputs into scientific innovation and technology adoption. In the United States, more than 20% of the S&E workers are immigrants from developing countries. In this paper, I evaluate the impact of such brain drain from non-OECD (i.e., developing) countries using a multi-country endogenous growth model. The proposed framework introduces and quantifies a “frontier growth effect” of skilled migration: migrants from developing countries create more frontier knowledge in the U.S., and the non-rivalrous knowledge diffuses to all countries. In particular, each source country is able to adopt technology invented by migrants from other countries, a previously ignored externality of skilled migration. I quantify the model by matching both micro and macro moments, and then consider counterfactuals wherein U.S. immigration policy changes. My results suggest that a policy – which doubles the number of immigrants from every non-OECD country – would boost U.S. productivity growth by 0.1 percentage point per year, and improve average welfare in the U.S. by 3.3%. Such a policy can also benefit the source countries because of the “frontier growth effect”. Taking India as an example source country, I find that the same policy would lead to faster long-run growth and a 0.9% increase in average welfare in India. This welfare gain in India is largely the result of additional non-Indian migrants, indicating the significance of the previously overlooked externality.

Keywords: High-Skilled Migration, Endogenous Growth, International Knowledge Diffusion, U.S. Immigration Policy, Consumption-Equivalent Welfare

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1 Introduction

High-skilled immigrants contribute significantly to innovation and entrepreneurship in the United States. They account for roughly a quarter of the U.S. workers in Science and Engineering (S&E) occupations and a similar fraction of patents (Kerr, 2008a) and business creation (Wadhwa et al., 2007). The quantity of high-skilled immigrants has been growing over the last three decades thanks to the establishment of visas permitting the entry of high-skilled workers.¹ The increase is mostly driven by immigrants from developing countries, who now make up three quarters of foreign-born S&E workers and 60% of immigrant inventors in the U.S. (see Figure 1 and 2).

A large literature attempts to estimate the effect of skilled immigrants on native workers in the U.S. and on remaining workers in developing countries. For the U.S., immigrants can have a significant adverse impact on the earnings of native-born workers in the short run.² At the same time, they enhance innovation and productivity growth in the U.S., which benefits all native workers in the long run.³ To evaluate the net impact of skilled immigrants on the U.S., it is necessary to combine the crowding-out effect with the long-run boost in productivity. Yet no formal study has incorporated both effects in a general equilibrium framework.

For developing source countries, the emigration of highly skilled individuals to the U.S. – often referred to as the “brain drain” – can have negative welfare consequences for those left behind.⁴ Recent literature, however, emphasizes that various channels of “beneficial brain drain” – such as remittances, facilitation of technology adoption, increased incentives to invest in human capital, and induced trade – may compensate the sending countries for their loss of talent.⁵ The net impact of the brain drain, however, remains to be quantified in a general

¹These include temporary work visas, such as the H-1B specialty occupation visas and the L-1 intra-company transferees visas for managers and specialty workers, and certain classes of employment-based green cards.

²See Borjas (2003), Borjas (2005), Aydemir and Borjas (2007), Borjas et al. (2011) and Doran et al. (2015).

³See Peri et al. (2013) for evidence on productivity growth; see Kerr and Lincoln (2010), Hunt and Gauthier-Loiselle (2010), Hunt (2011), Kerr (2013) and Moser et al. (2014) for evidence on patenting. One exception is Borjas and Doran (2012), wherein the authors found a strong crowding-out effect of Soviet mathematicians on American ones. The crowding-out effect was so strong that they found *no* evidence for a significant increase in the size of the “mathematics pie”.

⁴ see Bhagwati and Koichi (1974) and McCulloch and Yellen (1977).

⁵See Rapoport and Docquier (2005) and Bollard et al. (2011) on remittances; Kerr (2008b), Nanda and Khanna (2010) and Agrawal et al. (2011) on network externalities from a diaspora; Mountford (1997), Beine et al. (2001) and Beine et al. (2011) on increased incentives to invest in human capital; and Gould (1994), Rauch and Trindade (2002), Aleksynska and Peri (2012) and Ortega and Peri (2013) on induced trade and FDI. Docquier and Rapoport (2012) review the brain drain literature.

Figure 1: Composition of Immigrant S&E Workers

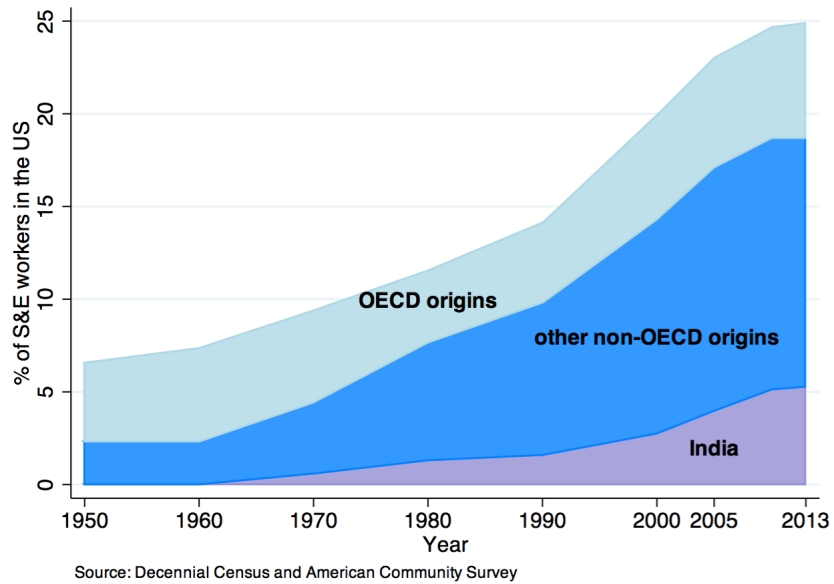
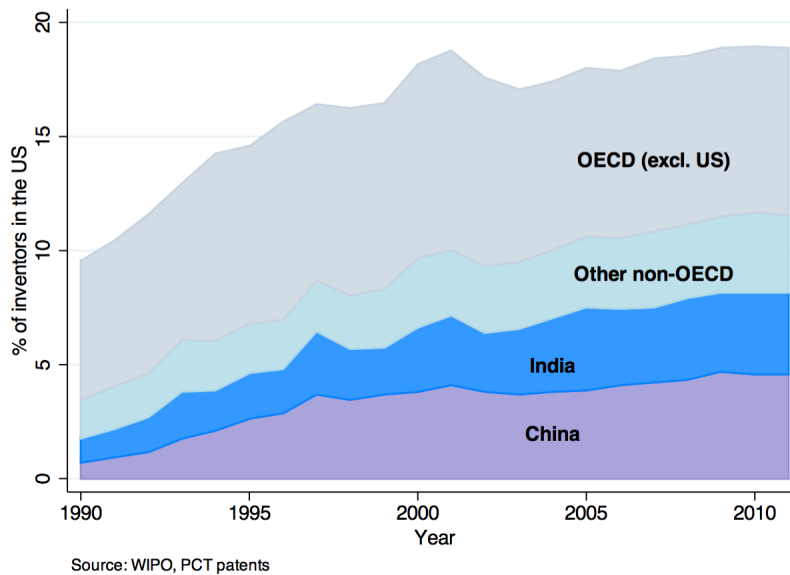


Figure 2: Composition of Immigrant Inventors in the U.S.



Note: The statistics on immigrant inventors are based on information included in patent applications filed under the Patent Cooperation Treaty (see Miguelez and Fink, 2013 for a description of the database). “Immigrant” in the inventor database refers to U.S. residents who are *foreign nationals*, which is a subset of *foreign-born* immigrant inventors.

equilibrium framework.⁶

The objective of this paper is to fill the gaps in the literature by proposing a general equilibrium (GE) framework to quantify the *net* impact of skilled migration on global innovation and on welfare. In particular, I emphasize the link between high-skilled migration and global innovation, and explore whether this channel alone can overcome the crowding-out effect on native workers in the U.S., and whether it can offset the negative effects of talent loss on remaining workers in the source country.

My GE framework has three building blocks. First, I use a standard multi-country endogenous growth model with international knowledge diffusion.⁷ In the model, the U.S. is the leading economy in technology and drives long-term growth through scientific research. Follower economies, namely non-OECD countries, learn from the leader and grow through technology adoption.

Second, I impose the assumption that the distribution of an individual's talent in doing scientific research follows a Pareto distribution. The dispersion of research talent is used to capture different skill levels in the labor force. Every individual, knowing his/her talent, chooses between two occupations: doing research or producing consumption goods. The wage rate in each occupation and agent's occupational choice are endogenous objects.

Third, I introduce high-skilled migration from follower economies to the United States.⁸ I do not consider immigration from other OECD countries based on the assumption that scientists in those countries are already working with the state-of-the-art facilities and institutions, and their migration to the U.S. would not significantly change the rate of innovation from the global standpoint. To model the migration process in a tractable way, I assume an individual from a developing country can migrate to the U.S. with positive probability, if and only if her research talent is above some threshold. Both the probability and the talent threshold of migration are country-specific.⁹

⁶Docquier and Rapoport (2009) is the only paper, to my knowledge, that brings together various costs and benefits of brain drain and tries to quantify its net effect. The static, partial equilibrium model they adopt is simple to implement, and suited for the purpose of combining a broader range of brain gain channels. However, it fails to consider general-equilibrium effects and dynamic responses of the source economy, which may bias the welfare analysis.

⁷See Nelson and Phelps (1966); Grossman and Helpman (1991); Aghion and Howitt (1992); Barro and Sala-i Martin (1997); Benhabib et al. (2014).

⁸For the purpose of this paper, I do not model low skilled migration.

⁹Note that the origin-specific threshold and migration probability are not endogenous objects in my model. Instead, I estimate them externally using the American Community Survey, and use the estimates as moments

The proposed model highlights and quantifies a new channel of benefit through frontier knowledge creation. Migrants from developing countries can innovate more efficiently in the U.S. than in their home countries.¹⁰ As a result, global innovation will be enhanced through skilled migration. Since knowledge is non-rivalrous, the frontier knowledge created by immigrants will diffuse to the source countries. I refer to this induced benefit of skilled migration as the “frontier growth effect”.

Although the idea of frontier growth effect is not new to the literature, there has been no serious attempt to quantify it.¹¹ Moreover, the size of the frontier growth effect depends on the *total* number of skilled immigrants in the U.S. Therefore, each source country is able to freely benefit from the brain drain of the other source countries. This free-rider effect has not been captured by previous work, which usually studies brain drain in a bilateral setting.

Another advantage of the proposed framework is the inclusion of transition dynamics in emerging economies. Previous work analyzing the effect of brain drain usually adopted a static approach or focused on the short-run impact. Ignoring the dynamic nature of agents’ choices or not accounting for the transition path can lead to significant biases in welfare calculation, especially for emerging economies. The incorporation of transition dynamics also overcomes the usual limitation of steady state analysis in endogenous growth models.

To quantify the proposed model under the baseline environment – i.e., the actual world with the observed level of migration, I discipline its parameters with both micro and macro moments. Specifically, I divide the labor force into S&E workers and non-S&E workers to match the occupational choice in the model.¹² Then I use national survey data to get key moments to match, including the share of S&E workers in the labor force, number of S&E workers from each developing country, and wage rates of S&E workers in the U.S. Other

to calibrate the model.

¹⁰Kahn and MacGarvie (Forthcoming) found that the U.S. is much more productive in conducting scientific research than countries with low income per capita, but not more productive than countries with high income per capita.

¹¹Grubel and Scott (1966) pointed out that “the pure research of scientists and engineers in the foreign countries” could be the “potentially largest benefit to the people remaining behind”. A more recent paper by Kuhn and MacAusland (2006) showed qualitatively that the remaining residents of a country can be better off if emigrants produce higher-quality knowledge abroad.

¹²S&E workers correspond to “researchers” in the model. In the data, they refer to full-time workers with college degrees and working in S&E occupations. Based on the classification provided by the National Science Foundation, S&E occupations include 1) Biological, agricultural, and environmental life scientists; 2) Computer and mathematical scientists; 3) Physical scientists; 4) Social scientists; 5) Engineers; 6) S&E postsecondary teachers.

moments, such as the growth rates of total factor productivity, are obtained from the latest Penn World Table (Feenstra et al., forthcoming).

After calibrating the baseline model, I gauge the net impact of skilled migration by analyzing counterfactual scenarios under different U.S. immigration policies. First, I consider a policy that doubles the probability of skilled migration for each source country. My quantitative analysis suggests that the productivity growth rate in the U.S. would increase from 1% to 1.1% under the counterfactual scenario.¹³ Faster growth would boost welfare in the U.S.: consumption-equivalent average welfare for native-born U.S. workers would be 3.25% higher compared to the baseline environment. Workers with different skill levels would be affected differentially: low-skilled workers would gain 3.43% in welfare, whereas high-skilled workers would suffer a 4.36% welfare loss. These results have important implications for immigration policy, especially under the current concern of growth slowdown in the U.S.

For the net effect of the brain drain, I choose India as an example source country, as it is the top origin for foreign-born S&E workers. In the model, the Indian economy has been going through transitions since 1993, because the productivity growth in India has been well above that in the U.S.¹⁴ Comparing the transition path under the counterfactual scenario to that in the baseline environment, productivity growth rates in India would be lower due to a loss of talent, but only in the short run. Over time, or more specifically after three decades, the negative effect of the policy would be reversed, as the frontier growth effect would accumulate exponentially and the cost of talent loss would be mitigated over time.¹⁵

The long-run growth boosts in India would lead to a 0.87% higher average welfare (including Indian expatriates in the U.S.). Welfare for *remaining* workers in India would rise by 0.81%. Remaining high-skilled workers would experience a bigger welfare increase than low-skilled workers. The new emigrants' welfare would more than double due to the wage gap

¹³The average growth rate of Hicks-neutral total factor productivity in the U.S. is roughly 1% since 1980, according to Penn World Table 8.1. Note that the 10% increase in growth rate is much smaller than the actual contribution of the additional skilled immigrants, because they would push down the wage for S&E workers and some native S&E workers would switch to non-S&E occupations.

¹⁴According to the PWT8.1, the Hick-neutral TFP growth in India averaged 1.67% per year from 1993 to 2009. The higher growth rates can be interpreted as a result of the economic liberalization in the early 1990s. In the context of the model, one can interpret the reforms as a parameter change in 1993 that led India on a transition path to a higher steady state.

¹⁵The frontier growth effect accumulates exponentially because the growth rate is permanently higher in the U.S. in the counterfactual. The cost of losing talent would get smaller over time because the relative wage of researchers in each period would adjust up in the counterfactual. Higher wages would attract new researchers and hence reduce the negative impact on India's imitation ability.

between the two countries.

Note that the increase in welfare of Indian workers, with the collective brain drain, may be driven by increase in non-Indian immigrants in the US. To estimate the net effect of an Indian brain drain, I consider a second policy change wherein the probability of migration was *only* doubled in India. I find that the frontier growth effect of Indian migrants alone can almost offset the cost of talent loss.

The rest of the paper proceeds as follows. In **Section 2**, I lay out the model. In **Section 3**, I parameterize the model with moments obtained from micro and macro data. In **Section 4**, I conduct counterfactual analysis to quantify the growth and welfare impact of immigrants on the U.S. and on India. In **Section 5**, I gauge robustness of the main findings to alternative assumptions and parameter values. **Section 6** concludes.

2 A General-Equilibrium Model of Skilled Migration

2.1 The Basic Model without Migration

Consider a world economy with one technological leading economy and M follower economies. Given that the objective of this paper is to study skilled migration from developing countries to the U.S., the leading economy would be the U.S. and the follower economies correspond to non-OECD countries. The U.S. has access to the technology frontier and innovates, whereas the follower economies learn from the frontier and try to catch up.¹⁶ To keep the model tractable, all economies are closed, except for international knowledge diffusion and migration of skilled workers.

The innovation process in the U.S. follows the standard quality ladder model (Aghion and Howitt 1992). The learning process in follower economies is similar to the innovation process except for an additional technology diffusion term. In addition, the follower economies have weak intellectual property protection. To enforce their patents and prevent imitators, producers of intermediate goods need to pay a flow cost to the government. This specific research wedge is introduced to explain the low research intensity in developing countries.

¹⁶This assumption can be easily relaxed. In a more general setup where every country can innovate or learn from the frontier, imitation would arise as an equilibrium choice of follower economies as long as their innovation technology is worse than their imitation technology.

The detailed construction of the general equilibrium framework without migration is presented below. To simplify notation, I omit country subscripts whenever possible.

2.1.1 Demand and supply of final goods

An economy is populated by a mass L of infinitely-lived individuals (no population growth as in standard growth models). Each individual has an innate talent of doing research ϵ , which is randomly drawn from a Pareto distribution whose cumulative density function is $1 - \epsilon^{-\theta}$.¹⁷ $\theta > 1$ is the shape parameter of the Pareto distribution: a larger θ means less talent dispersion. The innate talent distribution is assumed to be the same across countries. In addition to the research talent, each individual is born with the same productivity in making final goods. Agents choose between doing research and making final goods, given their talent and the market wage rates.

Each individual maximizes his/her present discounted utility:

$$U(\epsilon, t) = \int_t^\infty e^{-\rho(\tau-t)} \frac{c(\epsilon, \tau)^{1-\gamma} - 1}{1-\gamma} d\tau$$

subject to the budget constraint

$$\dot{a}(\epsilon, t) + c(\epsilon, t) = a(\epsilon, t)r(t) + w(\epsilon, t) \tag{1}$$

where $c(\epsilon, \tau)$ is consumption of an agent with talent ϵ at time t . Inasmuch as talent ϵ varies across individuals, so does income and consumption. The consumption good serves as numeraire and its price at every moment is normalized to one. It follows from the individual's intertemporal optimization problem that

$$\frac{\dot{c}(\epsilon, t)}{c(\epsilon, t)} = \frac{1}{\gamma} (r(t) - \rho) \tag{2}$$

where $r(t)$ is the interest rate at time t in terms of consumption goods.

There is a unique final good that is produced using labor and a continuum of intermediate

¹⁷The assumption that agents' talent follows a Pareto distribution is standard in the literature (see Jaimovich and Rebelo, 2012 and Jones, 2015). The scale parameter is normalized to 1 without loss of generality.

products under perfect competition. The specific production function is given by

$$Y(t) = \int_0^1 A(i, t)x(i, t)^\alpha di \cdot L_Y(t)^{1-\alpha} \quad (3)$$

where $A(i, t)$ is the quality and $x(i, t)$ is the quantity of intermediate good i ; and $L_Y(t)$ is the amount of labor used in final goods production. One can think of intermediate goods as machines that depreciate fully each period. The parameter α captures substitutability between different varieties of machines.

Final goods producers take the price of intermediate goods $p(i, t)$ and the wage of workers $w_Y(t)$ as given. The equilibrium demand of intermediate goods can be obtained by equating the price with the marginal product:

$$x(i, t) = (\alpha A(i, t)/p(i, t))^{1-\alpha} \quad (4)$$

Similarly, demand of labor in final goods production satisfies the following condition:

$$w_Y(t) = (1 - \alpha) \int_0^1 A(i, t)x(i, t)^\alpha di \cdot L_Y(t)^{-\alpha} \quad (5)$$

2.1.2 Supply, pricing, and profits of intermediate goods

The measure of intermediate varieties used in final goods production is normalized to 1. Each variety climbs up a quality ladder with step size $\lambda > 1$. In equilibrium, each variety is only produced by the firm who can make the highest quality of that machine. The state-of-the-art quality of variety i at time t is $A(i, t)$. The marginal cost of producing an intermediate good is proportional to its quality. Under monopolistic competition, incumbent can charge a markup above marginal cost until it is replaced by an entrant who improves the quality from $A(i, t)$ to $\lambda A(i, t)$.

Under non-drastic innovation, i.e., when $\lambda < \alpha^{-\frac{\alpha}{1-\alpha}}$, intermediate producers cannot charge the unconstrained monopoly price.¹⁸ Instead, their quality-adjusted price cannot be bigger

¹⁸Note that the effective step size of each quality improvement is $\lambda^{\frac{1}{\alpha}}$ because intermediate goods have decreasing returns to scale in final goods production. Drastic innovation would imply a monopoly markup of $1/\alpha$. If we match a labor share of $2/3$ in final goods production, α would be $1/3$ and the price markup would be 200% over the marginal cost, which is unrealistically high. Therefore, the innovation needs to be non-drastic to fit a reasonable level of markup.

than the marginal cost of the second best machine. The limit pricing condition of the monopolist making variety i is given by

$$p(i, t) = \frac{\psi A(i, t)}{\lambda} \cdot \lambda^{\frac{1}{\alpha}} \quad (6)$$

where $\frac{\psi A(i, t)}{\lambda}$ is the marginal cost of the second best machine, and $\lambda^{\frac{1}{\alpha}}$ is the quality premium over the second-best machine. The markup of each variety is then

$$\frac{p(i, t)}{\psi A(i, t)} = \lambda^{\frac{1}{\alpha}-1}$$

From (4), we can derive the demand of each intermediate good as:

$$x(i, t) = \left(\frac{\alpha}{\psi}\right)^{\frac{1}{1-\alpha}} \lambda^{-\frac{1}{\alpha}} L_Y(t) \quad (7)$$

Note that the demand is constant across intermediate goods. The symmetry has a convenient implication: the average technology level in the economy can be calculated as a simple average quality across varieties $A(t) \equiv \int_0^1 \dot{A}(i, t) di$. Later when characterizing the equilibrium, I only need to derive the evolution of average quality $A(t)$.

Each period, the monopolist producing machine i makes the flow profit:

$$\begin{aligned} \pi(i, t) &= p(i, t)x(i, t) - \psi A(i, t)x(i, t) \\ &= \alpha^{\frac{1}{1-\alpha}} \psi^{-\frac{\alpha}{1-\alpha}} A(i, t) \left(\lambda^{-1} - \lambda^{-\frac{1}{\alpha}}\right) L_Y(t) \end{aligned} \quad (8)$$

The total cost of making intermediate goods in the economy is $X(t) = \psi \int_0^1 A(i, t)x(i, t) di$. This will enter the economy-wide resource constraint: $Y(t) = X(t) + C(t)$.

2.1.3 The R&D Processes

Endogenous growth comes from quality improvement of intermediate goods, and quality improvement results from R&D activities performed by either incumbents or entrants. Because of the replacement effect, the incumbent monopolists have weaker incentives to improve exist-

ing machines than entrants.¹⁹ As a result, only potential entrants try to improve the existing machines and they do so by hiring researchers to conduct R&D. The R&D process varies across countries and I will discuss it separately in the U.S. and in the follower economies.

In the U.S., researchers conduct innovative research and they improve upon the existing machines in the U.S. The innovation efficiency parameter is η_{us} , which means 1 unit of research talent can generate a flow rate η_{us} of success for inventing a new machine of quality $\lambda A_{us}(i, t)$ in some i . Since research is undirected and there is measure 1 of varieties, the Poisson arrival rate of innovation in each variety is given by:

$$z_{us}(t) = \eta_{us} H_{us,R}(t) \quad (9)$$

where η_{us} is the per unit arrival rate, and $H_{us,R}(t)$ is the total amount of research talent devoted to R&D. Given the creative destruction nature of the growth process, the arrival rate of innovation $z_{us}(t)$ is also the rate at which existing varieties are replaced.

In a follower economy $m \in \{1, 2, \dots, M\}$, researchers conduct research to catchup with the technology frontier in the U.S. Similar to the innovation process in the U.S., researchers in economy m improve upon the existing machines domestically. Their learning efficiency is the product of a country specific parameter ζ_m and a knowledge diffusion term $\left(\frac{A_{us}(t) - A_m(t)}{A_m(t)}\right)$. The specific interpretation is that 1 unit of research talent in country m generates a flow rate $\zeta_m \left(\frac{A_{us}(t) - A_m(t)}{A_m(t)}\right)$ of success for inventing a machine of quality $\lambda A_m(i, t)$ in some variety i . Note that the diffusion function takes the confined exponential form as in Nelson and Phelps (1966), and the speed of diffusion only depends on the average technology level in the U.S. and in country m . Summing up talent involved in research, the Poisson arrival rate of quality improvement is

$$z_m(t) = \zeta_m \left(\frac{A_{us}(t) - A_m(t)}{A_m(t)}\right) H_{m,R}(t) \quad (10)$$

in country m .

¹⁹By improving the current machine, the incumbent would be replacing its own profit-making technology, whereas the entrant would be replacing the incumbent and making the full monopolistic profit.

2.1.4 Free entry condition

As mentioned before, potential entrants hire researchers to come up with new machines. Once a new machine is invented, the entrant becomes the monopolistic incumbent and makes the flow profit specified in (8) until it is replaced by a new entrant making a better machine. This would be true if we assume patents are fully-enforced.

In reality, patent enforcement is far from perfect in developing countries. The incumbent would lose its monopolistic profit if their patent is not enforced. To capture the imperfect law enforcement in developing countries, I introduce a “patent-enforcement fee” paid by the incumbents to the government to keep out imitators, and the fee is proportional to the flow profit. Consequently, the net flow profit of producing variety i becomes $\pi(i, t)(1 - \kappa)$, where κ is the proportional cost to enforce patent each period.

Now consider a potential entrant who is deciding whether to hire researchers to invent new machines. The potential benefit of hiring one unit of research talent would be the arrival rate of new machines per unit of talent (i.e., η_{us} or $\zeta_m(A_{us}(t) - A_m(t))/A_m(t)$) times the expected value of a new machine. Since research is undirected, the expected value of a new machine is given by

$$\lambda \int_0^1 V(i, t) di = \lambda \int_0^1 \frac{\pi(i, t)(1 - \kappa)}{z_{ss} + r_{ss}} di \quad (11)$$

where z_{ss} is the replacement rate and r_{ss} is the real interest rate.²⁰

On the other hand, the cost of hiring one unit of research talent is given by the market wage for researchers. As long as the benefit exceeds the cost of hiring researchers, there would be more entrants hiring researchers. The increase in R&D investment would lead to a higher replacement rate z and a lower expected value of new machines V , which in turn discourages entry. In equilibrium, the benefit of hiring an additional unit of research talent equals to its cost. This is the free-entry condition of intermediate firms and it would pin down the

²⁰This simple expression of $V(\nu, t)$ is only true at steady state. The expression will be more complicated if the economy is going through transition, which will be discussed in detail later.

equilibrium wage rate for researchers:

$$\begin{aligned} w_{R,us}(t) &= \lambda\eta_{us} \int_0^1 (V_{us}(i, t)) di \\ w_{R,m}(t) &= \lambda\zeta_m \left(\frac{A_{us}(t) - A_m(t)}{A_m(t)} \right) \cdot \int_0^1 V_m(i, t) di \end{aligned} \quad (12)$$

Note that $w_R(t)$ is the payoff for each *unit* of research talent. For a researcher with talent ϵ , her wage income at t would be given by $\epsilon w_R(t)$.

Entrants need to pay wages to researchers upfront before they can collect monopolistic profits later. Where do entrants get the funding to hire researchers? Following the standard setup in the growth literature, I assume the household owns all intermediate firms, and each individual owns a diversified portfolio. As a result, the household would pay for the cost of entry and receive dividend each period from the flow profit of successful entrants. Since the portfolio is diversified, it pools the risk involved in the R&D process and the dividend flow is risk-less. The total asset holding in the economy would be the total value of intermediate firms, i.e.,

$$a(t) = \int_0^1 (V(i, t)) di$$

2.1.5 Government budget balance in economy m

In each period, the government in follower economies receive the fee paid by monopolistic incumbents to enforce their patents. To have a balanced budget, the government would distribute its income back to the agents in its economy. For simplicity, assume government uses the fee to refund workers. The condition for a balanced budget is given by:

$$s_m w_{mY}(t) L_{m,Y}(t) = \kappa_m \int_0^1 \pi_m(i, t) di \quad (13)$$

where s_m is the proportional refund to workers.

2.1.6 Occupational choice

Given the innate research talent and the market wage rates, each individual choose between being a worker and being a researcher each period. An individual with ϵ units of research

talent would choose to do research if her salary of being a researcher $\epsilon w_R(t)$ is greater than the flat wage of being a worker $w_Y(t)$. It is evident that more talented individuals would be researchers, and the talent cutoff $\epsilon^*(t)$ can be derived from the marginal agent who is indifferent between the two occupations:

$$w_Y(t) = \epsilon^*(t)w_R(t) \quad (14)$$

The wage rates have been pinned down previously from the first order condition of final goods producers and the free entry condition of intermediate firms. Specifically, $w_Y(t)$ can be expressed as a function of $A(t)$ by substituting (7) into (5), and $w_R(t)$ is a function of $A(t)$ and $L_Y(t)$ as in (12).

2.1.7 Aggregate growth rate

After defining the talent cutoff of researchers, we can express the amount of research talent devoted to R&D as the following integral:

$$H_R(t) = \int_{\epsilon^*(t)}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L$$

Endogenous growth results from quality improvement of machines. Even though the arrival of new machines in each variety is uncertain, the aggregate technology – defined as the average quality of machines – grows according to the following law of motion:

$$\dot{A}(t) = z(t)(\lambda - 1)A(t) \quad (15)$$

where $z(t)$ is the arrival rate of quality improvement defined in (9) and (10). Rearranging the terms, we get the following aggregate technology growth rate

$$g_A(t) = z(t)(\lambda - 1)$$

2.1.8 Decentralized Equilibrium

A decentralized equilibrium *in each economy* consists of time paths of individual choices $\{c(\epsilon, t), a(\epsilon, t)\}_{t=0}^{\infty}$, average technology $\{A(t)\}_{t=0}^{\infty}$, efficiency wage of each occupation $\{w_Y(t), w_R(t)\}_{t=0}^{\infty}$,

labor demand in final goods sector $\{L_Y(t)\}_{t=0}^{\infty}$ aggregate quantities $\{Y(t), X(t), C(t)\}_{t=0}^{\infty}$, interest rate $\{r(t)\}_{t=0}^{\infty}$ and talent cutoff of researchers $\{\epsilon^*(t)\}_{t=0}^{\infty}$ such that

1. The standard Euler equation (2) holds for all individuals;
2. In the final goods sector, the demand of labor satisfies (5) and the demand of intermediate goods is given by (4);
3. Each monopolist of intermediate goods charges the limit price specified in (6);
4. There is free entry of intermediate firms, requiring $w_R(t)$ to satisfy (12);
5. An individual chooses to be a researcher if her research talent ϵ is greater than the talent cutoff $\epsilon^*(t)$, where $\epsilon^*(t)$ satisfies (14) taking wage rates $\{w_Y(t), w_R(t)\}$ as given;
6. Governments in follower economies run a balanced budget, i.e., (13);
7. The change in average technology $A(t)$ satisfies the law of motion (15);
8. The wage rates clear the labor market;
9. Goods market clears: $Y(t) - X(t) = C(t)$.

2.1.9 Balanced growth path

A balanced growth path (BGP) is an equilibrium path where $Y(t)$, $C(t)$, $A(t)$ and wage rates grow at a constant rate. Such an equilibrium can alternatively be referred to as a “steady state” because it is a steady state in detrended variables. I will be using the terms ‘steady state’ and ‘balanced growth path’ interchangeably throughout this paper.

Given my asymmetric setup where only the leading economy can innovate, the U.S. would always be on the balanced growth path, whereas the follower economies may go through transitions because of knowledge diffusion from the U.S. The formal statements on steady state properties are listed and proved below.

Proposition 1. *The leading economy, i.e., the U.S., is always at its steady state.*

Proof. Growth rate of technology is given by $g_A(t) = z(t)(\lambda - 1)$. In the U.S., the arrival rate of quality improvement $z_{us}(t)$ only depends on the instantaneous research input $H_{us,R}(t)$.

$H_{us,R}(t)$ is defined as an integral of talent among researchers, which is a function of the talent cutoff $\epsilon_{us}^*(t)$. Given that $\epsilon_{us}^*(t)$ is a jump variable, $H_{us,R}(t)$ can also move instantaneously without any path dependence. Therefore, the growth rate of technology does not depend on the level of technology, implying no transitional dynamics in the U.S. \square

Proposition 2. *All countries grow at the same rate at steady state.*

Proof. We can prove it by looking at the growth rate of technology in a follower economy m :

$$\begin{aligned} g_{m,A}(t) &= z_m(t)(\lambda - 1) \\ &= \zeta_m \left(\frac{A_{us}(t) - A_m(t)}{A_m(t)} \right) H_{m,R}(t)(\lambda - 1) \end{aligned}$$

At steady state, both $g_{m,A}$ and $H_{m,R}$ are constant, which implies that $\frac{A_{us}(t)}{A_m(t)}$ is a constant. Given that $A_{us}(t)$ is non-zero, $A_m(t)$ needs to grow at the same rate as $A_{us}(t)$. Therefore, all countries grow at the same rate at steady state, which is the growth rate in the U.S. \square

Now that we have the steady state growth rate in follower economies, a direct corollary follows:

Corollary 1. *Follower economies cannot fully catch up with the leading economy. Instead, it would converge to a certain technology level relative to the U.S. such that:*

$$\frac{A_m(t)}{A_{us}(t)} = \frac{(\lambda - 1)\zeta_m H_{m,R}}{(\lambda - 1)\zeta_m H_{m,R} + g_{A,us}} \quad (16)$$

Proof. From Proposition 2, we know that $g_{m,A,ss} = g_{us,A}$, $\forall m$. Rearranging the equation for technology growth rate, we can obtain the above expression for the relative technology level in economy m . \square

2.1.10 Steady State Comparative Statics

The steady state of this multi-country endogenous growth model can be solved analytically. The key variable to be determined in solving for the equilibrium is the talent cutoff $\epsilon^*(t)$ in each country. Therefore, I perform comparative statics of the steady state talent cutoff ϵ_{ss}^* with respect to parameters in the model. The results are stated as propositions below.

Proposition 3. *Talent cutoff in the U.S., ϵ_{us}^* , decreases with innovation efficiency η_{us} .*

Proof. I use the implicit function theorem to prove this result. Recall that the talent cutoff ϵ_{us}^* is the research talent of the marginal agent, and it satisfies (14). Substituting in the expressions for $w_{R,us}(t)$ and $w_{Y,us}(t)$ and canceling out common terms on both sides, we get:

$$0 = \epsilon_{us}^* \cdot \eta_{us} \frac{\lambda \left(1 - \lambda^{1-\frac{1}{\alpha}}\right)}{z_{us} + r_{us}} \alpha L_{us,Y} - (1 - \alpha) \equiv f(\epsilon_{us}^*, \eta_{us})$$

Note that z_{us} and r_{us} are functions of both η_{us} and ϵ_{us}^* , and $L_{us,Y}$ is a function of ϵ_{us}^* . I apply the implicit function theorem to obtain the following derivative:

$$\frac{d\epsilon_{us}^*}{d\eta_{us}} = -\frac{\partial f / \partial \eta_{us}}{\partial f / \partial \epsilon_{us}^*}$$

where the numerator $\partial f / \partial \eta_{us}$ has the same sign as $\partial \left(\frac{\eta_{us}}{z_{us} + r_{us}} \right) / \partial \eta_{us}$ and the denominator $\partial f / \partial \epsilon_{us}^*$ has the same sign as $\partial \left(\frac{\epsilon_{us}^*}{z_{us} + r_{us}} L_{us,Y} \right) / \partial \epsilon_{us}^*$. We can show that:

$$\partial \left(\frac{\eta_{us}}{z_{us} + r_{us}} \right) / \partial \eta_{us} = \frac{\rho}{(z_{us} + r_{us})^2} > 0$$

and

$$\partial \left(\frac{\epsilon_{us}^*}{z_{us} + r_{us}} L_{us,Y} \right) / \partial \epsilon_{us}^* = \frac{\partial \left(\frac{\epsilon_{us}^*}{z_{us} + r_{us}} \right)}{\partial \epsilon_{us}^*} + \frac{\epsilon_{us}^*}{z_{us} + r_{us}} \cdot \frac{\partial L_{us,Y}}{\partial \epsilon_{us}^*} > 0$$

Therefore,

$$\frac{d\epsilon_{us}^*}{d\eta_{us}} = -\frac{\partial f / \partial \eta_{us}}{\partial f / \partial \epsilon_{us}^*} < 0$$

□

A corollary of the above proposition is that growth rate g_{us} increases with η_{us} , because $g_{us} = \eta_{us}(\lambda - 1)H_{us,R}$, and $\partial H_{us,R} / \partial \eta_{us} = \frac{\partial H_{us,R}}{\partial \epsilon_{us}^*} \cdot \frac{\partial \epsilon_{us}^*}{\partial \eta_{us}} > 0$. In other words, frontier growth is faster if researchers in the U.S. are more efficient in innovation.

Proposition 4. *ϵ_{us}^* decreases with Pareto shape parameter θ .*

Proof. I apply implicit function theorem to the same equation:

$$0 = \epsilon_{us}^* \cdot \eta_{us} \frac{\lambda \left(1 - \lambda^{1-\frac{1}{\alpha}}\right)}{z_{us} + r_{us}} \alpha L_{us,Y} - (1 - \alpha) \equiv f(\epsilon_{us}^*, \eta_{us})$$

As I have proved in Proposition (3), $\partial f / \partial \epsilon_{us}^* > 0$. It is easy to see that $\partial f / \partial \theta$ has the same sign as $\partial \left(\frac{L_{us,Y}}{z_{us} + r_{us}} \right) / \partial \theta$, which can be simplified as:

$$\partial \left(\frac{L_{us,Y}}{z_{us} + r_{us}} \right) / \partial \theta = \frac{\frac{\partial L_{us,Y}}{\partial \theta} (z_{us} + r_{us}) - L_{us,Y} \left(\frac{\partial z_{us}}{\partial \theta} + \frac{\partial r_{us}}{\partial \theta} \right)}{(z_{us} + r_{us})^2} > 0$$

Therefore,

$$\frac{d\epsilon_{us}^*}{d\theta} = - \frac{\partial f / \partial \theta}{\partial f / \partial \epsilon_{us}^*} < 0$$

□

One should take caution when interpreting this result. The direct implication is that when there is more dispersion in talent (i.e., smaller θ), talent cutoff is higher and the number of researchers drops. However, it does not imply a decrease in growth rate. On the contrary, growth rate g_{us} would be higher when there is more dispersion in talent, which is proved below.

Proposition 5. *Growth rate in the U.S., i.e., g_{us} , decreases with Pareto shape parameter θ .*

Proof. First, I rewrite ϵ_{us}^* as a function of g_{us} , which is:

$$\epsilon_{us}^* = \left(\frac{g_{us}}{(\lambda - 1)\eta_{us} \frac{\theta}{\theta - 1}} \right)^{\frac{1}{1-\theta}}$$

Substitute that expression of ϵ_{us}^* into the same condition we used before:

$$0 = \epsilon_{us}^* \cdot \eta_{us} \frac{\lambda \left(1 - \lambda^{1-\frac{1}{\alpha}}\right)}{g_{us}/(\lambda - 1) + \gamma g_{us} + \rho} \alpha \left(1 - \epsilon_{us}^{*\theta}\right) - (1 - \alpha)$$

and define the right hand side as $h(g_{us}, \theta)$.

Second, apply implicit function theorem to the equation above. It is not hard to show that $\partial h / \partial \theta < 0$ and $\partial h / \partial g_{us} < 0$, which implies that $dg_{us} / d\theta > 0$. □

The comparative statics of ϵ_{us}^* with respect to the step size λ is not universally monotonic. Instead, it depends on the values of other parameters. Taking the standard values of the following parameters in the literature, i.e., labor share $1 - \alpha = 2/3$, discount rate $\rho = 0.02$, one can show (with some derivation) that

$$\frac{d\epsilon_{us}^*}{d\lambda} < 0$$

After analyzing the frontier economy, I will turn to the comparative statics in the follower economies. The two parameters in interest are research efficiency ζ_m and the proportional cost to enforce patents κ_m .

Proposition 6. *The steady state talent cutoff in economy m , i.e., $\epsilon_{m,ss}^*$, does not depend on the research efficiency ζ_m . Instead, it is pinned down by κ_m and is an increasing function of κ_m .*

Proof. First, I substitute the expressions for $w_{m,R}(t)$ and $w_{m,Y}(t)$ into (14) and simplify the equation to obtain:

$$(1 - \alpha)(1 + s_m) = \epsilon_m^* \cdot \zeta_m (a_m^{-1} - 1) \frac{\lambda(1 - \kappa_m)}{z_m + r} \left(1 - \lambda^{1 - \frac{1}{\alpha}}\right) \alpha L_{m,Y} \quad (17)$$

where $a_m \equiv \frac{A_m(t)}{A_{us}(t)}$, s_m is the equilibrium subsidy to workers. Note that there is no time subscript in the equation because we are analyzing the steady state. Recall (16) from Corollary (1), a_m can be written as a function of $H_{m,R}$ and g_{us} . Rearranging the terms, we get:

$$a_m^{-1} - 1 = \frac{g_{us}}{(\lambda - 1)\zeta_m H_{m,R}}$$

Plug this back into (17) and ζ_m would cancel out. In other words, ϵ_m^* does not depend on ζ_m .

Second, I use the implicit function theorem to show that ϵ_m^* increases with κ_m . Following the same procedure as before, it is easy to show that the implicit function derived from (17) decreases with κ_m and increases with ϵ_m^* . Therefore, $\partial\epsilon_m^*/\partial\kappa_m > 0$. It means that as the research wedge κ_m rises, the number of researchers decreases. \square

Even though ζ_m does not affect labor allocation, it would influence the relative technology level in economy m and hence the output and welfare of agents in economy m .

2.2 Introduce High-Skilled Migration

Here I add high-skilled migration from non-OECD countries to the basic model. Based on the latest PWT (Feenstra et al., forthcoming), production technology is more advanced in the U.S. than in non-OECD countries. As a result, wages in the U.S. are higher and everyone in developing countries would *want* to migrate to the U.S. in a frictionless world. In reality, migration to the U.S. is highly controlled and sometimes selected. For the purpose of this paper, I will restrict my attention to high-skilled migration.²¹

2.2.1 Assumptions

In the baseline model, I make four assumptions about the migration process. First, migration only happens once at $t = 0$. As a result, all my analysis will be about the stock of migrants instead of the flow. This is a natural assumption in a model with a constant number of infinitely-lived agents. If one were to match the flow of immigrants in the data, it would be necessary to adapt the current model to a overlapping generation setup, which is beyond the scope of this paper.

Second, I abstract away from any cost associated with migration and consider a simple probabilistic migration process: people with talent above a country-specific cutoff $\bar{\epsilon}_m$ can migrate to the U.S. with a country specific probability p_m .²² Values for $\bar{\epsilon}_m$ and p_m of each source country will be estimated with information on immigrants' income in Section 3.

Third, immigrants will take up the same efficiency to innovate (i.e., η_{us}) as native researchers once they migrate to the U.S. This assumption can be partly justified by the fact that a large proportion of them received their highest degrees in the U.S. based on the National Survey of College Graduates in 2010.

Last, I assume immigrant researchers are perfect substitutes for native researchers. As I mentioned in Introduction, there is a large literature on the substitutability between immigrants and native-born workers. For the purpose of my analysis, I do not take a stand on that issue. To test if the baseline results are robust to the assumption of perfect substitution, I will resolve the model with imperfect substitution as a robustness check in Section 5. Note that

²¹Low-skilled migration is definitely an interesting and equally important topic, but it is beyond the scope of this paper.

²²The country-specific selection reflects the empirical fact that origins differ in their socio-economic status and U.S. immigration policy towards them.

the model would predict no return migration as wages are higher in the U.S.²³

2.2.2 New arrival rates of ideas

After introducing migration from non-OECD countries to the U.S., talent distribution will change in all countries, which affects the expression for arrival rates of ideas. In the U.S., skilled immigrants will lead to a discontinuous jump in the density of talent in the right tail. This change in talent distribution is analogous to a smaller θ in the comparative statics, and so the arrival rate of ideas will increase and the endogenous talent cutoff for researchers will rise. In a non-OECD country m , the loss of talent will reduce the idea arrival rate and lower the talent cutoff. Mathematically, the new arrival rate of ideas for the U.S. and country m can be rewritten as follows.

$$z_{us} = \eta_{us} \left(\int_{\epsilon_{us}^*}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L_{us} + \sum_m p_m \int_{\bar{\epsilon}_m}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L_m \right) \quad (18)$$

$$z_m(t) = \zeta_m \left(\frac{A_{us}(t)}{A_m(t)} - 1 \right) \left(\int_{\epsilon_m^*(t)}^{\infty} \epsilon f(\epsilon) d\epsilon - p_m \int_{\max\{\epsilon_m^*(t), \bar{\epsilon}_m\}}^{\infty} \epsilon f(\epsilon) d\epsilon \right) \cdot L_m \quad (19)$$

where ϵ_{us}^* and $\epsilon_m^*(t)$ are the new talent cutoffs after migration; $\bar{\epsilon}_m$ is the talent cutoff for migrants from country m ; p_m is the migration probability among the skilled labor force in country m ; and L_m is the labor force in country m .²⁴

The selection of immigrants, namely $\bar{\epsilon}_m$ and p_m in the model, may vary by origins due to different migration cost, visa and green card quotas, etc. To correctly quantify the effects of migration, we should estimate $\bar{\epsilon}_m$ and p_m for each country instead of using the average across all source countries.²⁵

²³Empirically, return rates among skilled professionals tend to increase with home country skill prices and growth prospects. Because of the high skill premium in the U.S. compared to sending countries, skilled immigrants from non-OECD countries rarely go back and the return migration flow is composed of the least skilled immigrants (Borjas and Bratsberg, 1996). The high stay rate is especially true for foreign doctorate recipients in the U.S. based on a study by Finn (2014). Among all doctorates, 65% of them remain in the U.S. 10 years after they graduated. The stay rates are highest (more than 80%) among doctorates from China and India.

²⁴Note that ϵ_{us}^* and z_{us} are not functions of time, because the U.S., as the leading economy, is always on the balanced growth path. On the other hand, $\epsilon_m^*(t)$ and $z_m(t)$ depend on where they are on the transition path.

²⁵Using the wage premium of immigrants from all non-OECD countries will under-estimate the total research talent of immigrants according to Jensen's inequality.

2.2.3 Effects of high-skilled migration

After adding high-skilled migration to the general equilibrium framework, the model captures key benefits and costs of high-skilled migration for the U.S. and source countries. Taken to the data, the calibrated model can be used to perform counterfactual analysis and provide quantitative estimates of the net effects.

A major benefit of skilled migration is the faster growth of frontier knowledge. This frontier growth effects have been ignored in the literature due to the absence of a general equilibrium framework. A key contribution of this paper is to introduce and quantify of this new channel of beneficial brain drain. Skilled migration leads to more innovation because migrants would not have been able to contribute to world technology frontier had they not migrated. As the technology frontier grows faster, non-OECD countries can benefit from it through knowledge diffusion. This frontier growth effect can be small if we only consider one source country in the model (Agrawal et al., 2011). However, once we include multiple source countries in the framework, immigrants from one origin can push up the frontier and benefit research in other source countries through knowledge diffusion. This positive externality summed over all source countries will make the frontier growth effect quantitatively important. The presence of externality also suggests that the socially optimal migration rate could be higher than the observed level, which has important implications on countries' migration policies.

Migration of skilled workers can also encourage research activities in both the U.S. and the source countries. In the U.S., immigrant researchers earn higher wages than native researchers, indicating that they are more talented on average.²⁶ Since immigrants and native-born researchers are assumed to be perfect substitutes, some marginal native researchers will be displaced by more talented immigrants. Both the quality and quantity of the researcher pool will improve in the U.S. For source countries like India, the observed low research intensity indicates a high cost to enforce patent or other frictions on R&D investment.²⁷ Those frictions make the allocation of research talent less efficient than in the competitive equilibrium.²⁸ Skilled migration may improve the talent allocation by encouraging talented agents, who would not have been researchers in their home countries due to frictions, to become researchers in

²⁶This is based on a simple analysis of earnings by S&E workers in the American Community Survey. The details are discussed in Section 3.

²⁷Examples for other frictions include high entry cost, fixed cost and financial constraint.

²⁸As I will show in one of the robustness checks, the competitive equilibrium is not socially optimal either.

the U.S. My quantitative results show that the talent cutoffs in the U.S. and in India converge with more skilled migration, suggesting an improvement in the allocation of research talent.

Despite the potential benefit mentioned above, skilled migration may have negative impact on the U.S. and the source countries. In the U.S., immigrants may reduce the wage of researchers and crowd out marginal native researchers. Source countries may suffer from lower technology adoption rates due to the direct brain drain effect. Whether the cost of migration outweighs the benefit is an important question to be answered with a quantified model and counterfactual analysis in Section 4.

2.3 Transition Paths

As discussed in research processes, the U.S. is always on the balanced growth path. However, that is not the case for non-OECD countries as follower economies. Because of knowledge diffusion from the U.S., they will go through transitions as long as they are growing at a different rate than the U.S. According to the latest Penn World Table (Feenstra et al., forthcoming), most non-OECD countries have been growing at a faster rate than the U.S. in the past two decades, suggesting that they are in a transition phase. To match this important observation, I solve for transition paths of source countries and incorporate them in the welfare analysis.

I follow the iterative procedure in Lee (2005) to calculate the rational expectations equilibrium during transition.²⁹ The idea is to start from a constant talent cutoff and update it until the talent cutoff sequence on the transition path converges. In the first iteration, we solve the talent cutoff at period t assuming that future talent cutoffs will be the same as current ones, from which we get a sequence of talent cutoffs $E^{(1)} = \{\epsilon_{m,t}^{(1)}\}_{t=1}^T$.³⁰ Notice that $E^{(1)}$ is an equilibrium but it is not a rational expectations equilibrium because $\epsilon_{m,t}^{(1)}$ is not constant over time as was assumed in solving for the cutoff at time t . The rational expectations equilibrium, $E^* = \{\epsilon_{m,t}^*\}_{t=1}^T$, is one that is consistent with people's expectations of future talent cutoffs. Therefore, finding $E^* = \{\epsilon_{m,t}^*\}_{t=1}^T$ is equivalent to finding the fixed point talent cutoff sequence in the model.

After obtaining the first iteration equilibrium, $E^{(1)}$, we go to the second iteration and

²⁹The model is discretized to calculate the transition paths.

³⁰Note that we don't know ex ante how long it takes for the source country to converge to its new steady state, and so we need to choose a T that's large enough.

assume the ratio of talent cutoff series is the one obtained from the first iteration:

$$\frac{\epsilon_{m,t+1}^{(2)}}{\epsilon_{m,t}^{(2)}} = \frac{\epsilon_{m,t+1}^{(1)}}{\epsilon_{m,t}^{(1)}}, \forall t \quad (20)$$

This assumed relationship yields a sequence of talent cutoffs that can be written solely in terms of $\epsilon_{m,1}^{(2)}$ and we can solve for the equilibrium level of $\epsilon_{m,1}^{(2)}$. Similarly $\epsilon_{m,2}^{(2)}$ can be calculated by writing all talent cutoffs from $t = 2$ on as a function of $\epsilon_{m,2}^{(2)}$ and we can solve for the equilibrium level of $\epsilon_{m,2}^{(2)}$. Repeat this procedure to the final period T and we get a sequence of talent cutoffs that clears the labor market in each period, denoted by $E^{(2)} = \left\{ \epsilon_{m,t}^{(2)} \right\}_{t=1}^T$. Compare $E^{(2)}$ with $E^{(1)}$, if the distance between the two iterations is not close enough, the assumption in (20) would be hold and we continue on to the third iteration. This process is continued to get iterations of the talent cutoff sequences until a sequence $E^{(n)}$ is close enough to $E^{(n-1)}$ under some criterion.³¹ The converged talent cutoff sequence $E^{(n)}$ would be the rational expectations equilibrium where people’s expectation about future replacement rate (as a function of talent cutoffs) is realized as the equilibrium replacement rate.

3 Empirically Quantifying the Baseline Model

3.1 Data

Due to multi-country nature of the model, I use data from multiple sources. For information about the U.S. labor market, I use data from the 2010-2012 American Community Survey (ACS).³² I make two restriction to the data. First, I only include individuals between the ages of 23 and 64. Those currently enrolled in schools are also dropped. This restriction focuses the analysis on individuals after they finish schooling and prior to retirement. Second, I exclude individuals who usually work less than thirty hours per week, and those who report being unemployed (not working but searching for work). Note that self-employed workers are included in the sample. I divide the restricted sample of employed workers into two groups: “S&E workers” and “non-S&E workers”. College graduates working in S&E occupations are

³¹The convergence criterion used here is: $|E^{(n)} - E^{(n-1)}| < 10^{-6}$

³²When using the 2010-2012 ACS data, I pool all three years together and treat them as one cross section. Henceforth, I refer to the pooled 2010-2012 sample as the 2012 sample.

classified as “S&E workers”, and the other workers are classified as “non-S&E workers”.³³ The ACS suits basic need of my quantitative analysis as the sample is large enough to allow a focus on S&E workers and distinctions by immigrant origin.³⁴

For the Indian labor market, I use micro-data from the 66th Round of the National Sample Survey (NSS) in 2009-2010.³⁵ The two sample restrictions to the ACS are applied to the Indian survey data. Workers are also classified as “S&E workers” or “non-S&E workers” based on the NSF classification.

In addition to the national survey data, I use three other data sources. First, I use the Penn World Table 8.1 (Feenstra et al., forthcoming) to get estimates of the Total Factor Productivity (TFP). Second, I extract information on research performance of individual researchers from the *InCites: Essential Science Indicators*.³⁶ My sample includes the publication of the top 200 researchers in each of the 21 fields defined by a unique grouping of Thomson-indexed journals.³⁷ The publication data are used to provide an alternative estimate of talent dispersion in the model. Lastly, I use the National Survey of College Graduates (NSCG) to get more detailed information on individual’s advanced degrees and occupations.³⁸ It is only used as a supplemental data source because the sample size is too small to study S&E workers by immigrant origin.

³³Based on the classification provided by the National Science Foundation, S&E occupations include 1) Biological, agricultural, and environmental life scientists; 2) Computer and mathematical scientists; 3) Physical scientists; 4) Social scientists; 5) Engineers; 6) S&E postsecondary teachers.

³⁴Note that I define immigrants as those born abroad, except those born in U.S. territories and born abroad as U.S. citizens.

³⁵The data are generously provided by Prof. Peter Klenow.

³⁶I thank Tian Qin, a student at University of Southern California, for her help in accessing The *InCites: Essential Science Indicators* through the USC library.

³⁷Researchers are ranked by their citation-weighted publication counts during the decade of 2003-2013. The 21 fields include Agricultural Sciences, Biology and Biochemistry, Chemistry, Clinical Medicine, Computer Science, Economics and Business, Engineering, Environment/Ecology, Geosciences, Immunology, Materials Science, Mathematics, Microbiology, Molecular Biology and Genetics, Neuroscience and Behavior, Pharmacology and Toxicology, Physics, Plant and Animal Science, Psychiatry/Psychology, General Social Sciences and Space Science.

³⁸The National Survey of College Graduates (<http://www.nsf.gov/statistics/srvygrads/>) is a longitudinal biennial survey conducted since the 1970s that provides data on the nation’s college graduates, with particular focus on those in the science and engineering workforce. The public-use micro data contains useful information on respondent’s education history, entry visa type and patenting activities that is unavailable elsewhere.

3.2 Micro-based Moments

There are four micro-based moments that would determine the impact of immigrants. First, the share of employed workers in S&E occupations in each country. Second, fraction of S&E workers in the U.S. who are immigrants. Third, how talented the immigrant researchers are. Fourth, how much talent dispersion there is in the population. Each of the four moments will be discussed in detail here.

3.2.1 Researchers in the labor force

In the model, individual chooses between two occupations: being a researcher or a worker. In reality, there are many more occupational choices. To bridge the model with the data, I classify S&E workers – who are responsible for most of the innovative activities in the economy – as researchers, and non-S&E workers as workers.

Based on the detailed information on occupation and education achievement in the ACS, the share of S&E workers among the employed is 4.13% in the U.S. in 2012. Similarly, the share of researchers among the employed in India is estimated to be 0.88% based on the NSS in 2009. The share of S&E workers in the U.S. will help pin down the research efficiency in the U.S. (i.e., η_{us}). That share in India is essential in determining the research wedge κ in India.

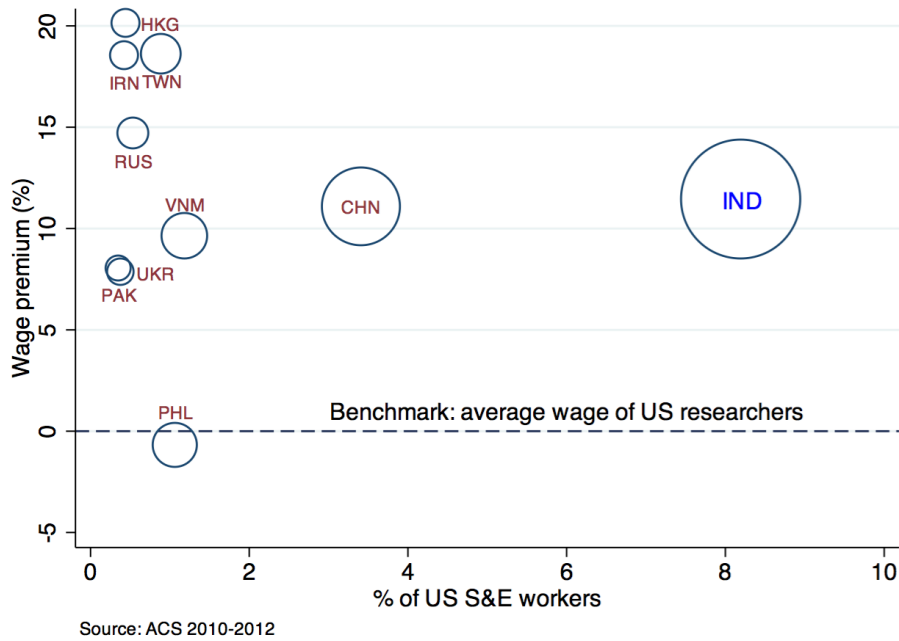
3.2.2 Quantity of skilled immigrants

The ACS contains information on country of origin, which can be used to estimate the share of researchers who are immigrants. Based on my estimation, 22.8% of the S&E workers in the U.S. in 2012 are immigrants from non-OECD countries. To estimate the probability of migration p_m in (18), I calculate the share of S&E workers in the U.S. from each country of origin. India and China are the top two origins: 8.2% of S&E workers are born from India and 3.4% from China.

3.2.3 Human capital of immigrants

I have shown that immigrants from developing countries are important quantity-wise. How much they contribute to innovation also depends on their human capital compared to native

Figure 3: Wage Differentials of Top 10 Origins



researchers. By assuming that researchers’ human capital can be proxied their hourly wages, I estimate the “wage differentials” of immigrants relative to native-born U.S. researchers using the following simple regression:³⁹

$$\log w_{it} = \beta_0 + \beta_1 D_i + \beta_2 \gamma_t + u_{it}$$

where w_{it} represents the hourly wage of worker i in year t ; D_i are dummy variables for countries of origin; and γ_t captures the time fixed effect.

The estimated vector of coefficients $\hat{\beta}_1$ can be interpreted as wage differentials of immigrants from each of the M source countries.⁴⁰ I plot the wage differentials of the top 10 origins in Figure 3. Size of the circle represents the population of skilled immigrants from each origin. The figure shows that immigrants from nine out of the 10 countries earn significantly higher wages than native-born U.S. researchers on average. Immigrants are not only impor-

³⁹I define hourly wage as total annual earnings divided by total hours worked in the previous year. Earnings are measured as the sum of labor, business, and farm income in the previous year. For earnings I restrict the sample to individuals who worked at least 48 weeks during the prior year, with more than 1000 dollars of earnings (in 2010 dollars) in the previous year, and who worked on average more than 30 hours per week.

⁴⁰For countries whose $\hat{\beta}_m$ is not significant or is based on a sample smaller than 10, wage differentials would be assigned to be zero.

tant in boosting the number of researchers in the U.S., but also improve the overall quality of researchers.

3.2.4 Talent dispersion

As mentioned before, I use hourly wage to proxy individual’s research talent. Talent dispersion can thus be measured by wage dispersion among S&E workers. In the model, talent dispersion of native population is assumed to be the same across countries.⁴¹ Therefore, the talent dispersion estimated using the U.S. data are also used for India.

To estimate the wage dispersion, I make two restrictions to the data. First, I only include *native* S&E workers. Talent dispersion in the model refers to the dispersion among native population. Given my positive estimates of wage differentials, including immigrants would lead to a upward bias on the talent dispersion.

Second, I restrict the sample to individuals whose wage is at least 45 dollars an hour. In other words, I use the right tail of the wage distribution to estimate the overall Pareto shape parameter.⁴² The cutoff of 45 dollars is chosen to obtain a wage distribution that is close enough to a Pareto distribution. The overall distribution of log hourly wage and the fit of exponential distribution to high wage individuals are shown in Figure 4.

Using the sample of native S&E workers whose wage is higher than 45 dollar per hour, I compute the maximum likelihood estimator for the Pareto shape parameter θ :

$$\hat{\theta}^{ACS} = \frac{\sum_i wt_i}{\sum_i wt_i (\ln x_i - \ln \hat{x}_m)} \quad (21)$$

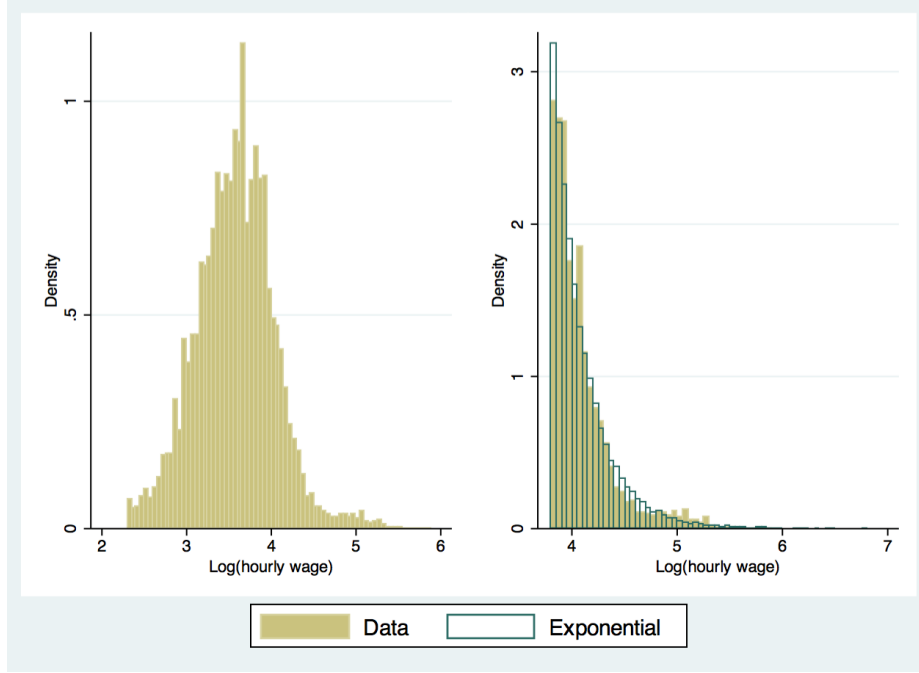
where wt_i is the sampling weight for each observation; x_i is the hourly wage of individual i ; $\hat{x}_m = \min_i x_i = 45$. The maximum likelihood estimator for $\hat{\theta}$ is 3.48, which is close to the talent dispersion estimated in Hsieh et al. (2013). Compared to the dispersion measure obtained from the top shares of wages (Piketty and Saez, 2003), my estimate of dispersion is much smaller.

Wage income may be a noisy measure of research talent, hence I use publication data

⁴¹Talent dispersion is captured by the Pareto shape parameter θ in the model. Any difference in average human capital across countries can be absorbed by the research efficiency parameters η_{us} and ζ_{ind} . In the model, labor allocation in India only depends on the dispersion of talent.

⁴²One attractive property of a Pareto distribution is that the right tail of a Pareto distribution is still Pareto with the same shape parameter.

Figure 4: Distribution of log hourly wage



from *InCites: Essential Science Indicators* (ESI) to obtain an alternative measure of talent dispersion. Specifically, I use citation-weighted publications by top 200 scientists in each of the 21 fields in my sample. Assuming publications are distributed Pareto with the same shape parameter across fields, we can construct a pooled maximum likelihood estimator for θ as follows:

$$\hat{\theta}^{ESI} = \frac{\sum_{f=1}^{21} N^f}{\sum_{f=1}^{21} \left[\sum_i \left(\ln x_i^f - \ln \hat{x}_m^f \right) \right]} \quad (22)$$

where $N^f = 200$ for each field; x_i^f is the number of citation-weighted publications by researcher i in field f ; $\hat{x}_m^f = \min_i x_i^f$ estimates the field-specific scale parameter.

The pooled maximum likelihood estimator for $\hat{\theta}^{ESI}$ is 2.48, much lower than the $\hat{\theta}$ estimated from wage income. There are two caveats to $\hat{\theta}^{ESI}$. First, dispersion in publication counts displays excess fat-tail property compared to other measures of talent, such as wage. Using top academics in each field may also bias the dispersion upward as using top income share would. Second, the database does not contain information on country of origin of the scientists. Pooling scientists from all countries may bias the estimate of θ , because the scale parameter

of talent distribution may vary across origins. Considering the potential concerns with the estimate based on publication data, I will only use it as one robustness check.

3.3 Other Moments

In addition to the four moments discussed above, I use national survey data to estimate the size of employment in the U.S. and in India. The number of employed full-time workers in India is roughly twice of that in the U.S.⁴³ This moment is important in the current version of the model, where strong scale effect is present.

TFP levels and growth rates are important macro moments to be matched. The latest Penn World Table 8.1 provides estimates for TFP levels for each country, from which I can calculate TFP growth rates. In the U.S., the long-run growth rate of TFP is roughly 1% from 1980 to 2011. Following the endogenous growth literature, I treat that growth rate as the steady state growth rate of productivity in the U.S. In India, TFP growth averaged 1.67% per year since 1993. I choose the starting year of 1993 for three reasons: it is a benchmark year for the Indian national accounts, it avoids the 1991 economic crisis, and the period can be identified with India post-reform. For the purpose of this paper, I do not try to explain why the TFP growth rate is higher in the post-liberalization period. Instead, I assume parameters in the model – such as research efficiency ζ_{ind} or research wedge κ – changed in 1993. As a result, the old steady state was disrupted and India went on a transition path to the new steady state. The average growth rate and India’s TFP relative to the U.S. in 2009 are key macro moments that will be matched in calibration.

3.4 Moment Matching

In this section, I show how parameters are disciplined by the micro-based and macro-based moments discussed above. I put the parameters into three groups: ones that are calibrated externally with common values used in the macroeconomics literature (Table 1), ones that are determined by one moment each (Table 2), and those that are calibrated jointly (Table 3).

⁴³In comparison, the size of labor force in India is more than three times of that in the U.S., because the share of unpaid family workers is high in India. The choice of becoming an unpaid family worker is not considered in the model and so I exclude them in the data.

Table 1: Parameters Set Externally

Parameter	Explanation	Source, Value
α	1- labor share	NIPA, 1/3
ρ	Discount rate	Annual interest rate $\approx 4\%$, 0.02
γ	CRRA	Hall (2009), 2.0
L_{us}	U.S. employment	Normalization, 1

Table 2: Parameters Set Independently

Parameter	Explanation	Source, Value
θ	Pareto shape	ACS, 3.5
$\{\bar{\epsilon}_m\}_{m \in \{1,2,\dots,M\}}$	Immigrant selection	ACS
$\{p_m \int_{\bar{\epsilon}_m}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L_m\}_{m \in \{1,2,\dots,M\}}$	Immigrants from origin m	ACS
L_{ind}	Employment in India	NSS, 2
p_{ind}	Implied migration prob.	ACS, 0.078

Table 3: Jointly Set Parameters

Parameter	Targeted Moments, Value	Source
$\eta_{us} = 0.735$	% of S&E workers in the U.S., 4.13%	ACS
$\lambda = 1.086$	U.S. TFP growth rate (Hicks-neutral), 1%	PWT 8.1
$\zeta_{ind} = 1.555$	% of S&E workers in India, 0.88%	NSS (2009)
$\kappa_{ind} = 0.835$	India's TFP growth rate since 1993, 1.67%	PWT 8.1
$a_{ind} = 0.457$	India's relative TFP level in 2009	PWT 8.1

4 Effects of Doubling Skilled Migration

I evaluate the net effects of migration on both the U.S. and India by considering two changes in U.S. immigration policy. First, suppose the the quota of H1-B visas was lifted permanently such that the probability of skilled migration doubled in each non-OECD country (i.e., $p_m^{\text{double}} = 2 \cdot p_m$). This policy experiment is considered not only for its direct policy inferences, but also because its effect can approximate the contribution of existing migrants to the U.S. and to their home countries.⁴⁴ Based on my calculation, doubling the probability of skilled migration can benefit both the U.S. and India, with a bigger welfare boost for the U.S.

The positive effect of the first policy experiment may be driven by the positive externality of immigrants from other countries. To exclude the positive externality effect, I perform the second counterfactual analysis wherein I double the probability of migration from India only. This would be a relevant policy exercise for source countries as they cannot affect migration policy of other countries. The resulting welfare and growth changes provide an estimate of the bilateral brain drain effect between the U.S. and India. In addition, the size of the positive externality effect can be implied by comparing the impact of the second policy experiment with that of the first one. The detailed results of both counterfactual analysis are presented and discussed below.

4.1 Technological Progress in the U.S.

Under each counterfactual scenario, I solve for the new equilibrium allocations in the U.S. As the technological leader, the U.S. is always on the balanced growth path. The steady state allocation and growth rate under each scenario is presented in Table 4.

In Counterfactual 1, with doubled migration probability in each origin, the stock of skilled immigrants in the U.S. would roughly double.⁴⁵ A back-of-the-envelope calculation would suggest the share of researchers in the labor force becomes $4.13\% + (4.13\% - 3.2\%) \approx 5\%$, and

⁴⁴The effect of doubling the current migration probability would be similar to that of increasing the probability from zero to the observed level, if the effect is approximately linear in the probability. To check that, I performed a counterfactual experiment wherein I send all immigrants back to their home countries. The qualitative and quantitative results are indeed very similar to those with doubled migration probability. The details are included in Appendix A.

⁴⁵The migration probability among skilled workers is below 0.5 in most source countries. There might be a few exceptions – such as Jamaica – where probability of migrating to the U.S. is already above 0.5. But they are usually small origins and the bias would not affect the results much.

Table 4: Growth and Labor Allocation in the U.S.

	g^{ss} (%)	$s_{us,R}$ (%)	$s_{us,R}^{dom}$ (%)	$\mathbb{E}(\epsilon \epsilon > \epsilon_{us}^*)$
1: double p for every origin	1.11	4.26	2.4	4.0
2: double p for India only	1.04	4.15	2.9	3.9
Baseline: actual	1.00	4.13	3.2	3.8

Note: g refers to the Hicks-neutral growth rate of total factor productivity, $s_{us,R}$ refers to the share of researchers among U.S. workers and $s_{us,R}^{dom}$ is the share of native-born researchers among U.S. workers. The last column indicates the average research talent among researchers.

new growth rate would be $1\% \times (1 + 22.8\%) = 1.23\%$. That simple calculation is incorrect, because it does not consider the displacement of native researchers due to a change in equilibrium wages. Specifically, additional skilled immigrants in the U.S. would lead to a faster replacement of incumbents (i.e. z_{us}) and a higher interest rate, both of which would reduce the value of a new idea. Since the wage for researchers depends on the value of ideas they generate, wage of researchers relative to that of workers would decrease, discouraging marginal agents to be researchers in the U.S.

Once we incorporate the general equilibrium effect, productivity growth rate would increase from 1% in the baseline environment to 1.10% in Counterfactual 1. The boost in growth rate comes from higher quantity and quality of researchers in the counterfactual scenario. In term of quantity, immigrants would raise the share of researchers in the labor force by 0.13 percentage point to 4.26%. The increase of immigrant researchers and that of total researchers is not one-to-one, because more than 20% of the native researchers are displaced. In terms of quality of the researcher pool, average talent would increase, because immigrant researchers from most origins are more talented than their native counterparts.

In Counterfactual 2, I only double the number of skilled immigrants from India by doubling the migration probability p_{ind} . The effect is similar to that of Counterfactual 1, but with smaller magnitude. As mentioned in the previous section, Indian immigrants account for a little more than 1/3 (8.1% / 22.8%) of the immigrant researchers in the U.S. . Therefore, doubling them would lead to a similar fraction of the growth boost in Counterfactual 1.

My model is able to capture both the crowding-out effect and the productivity-enhancing

Table 5: Welfare Impact on Native-born U.S. Workers

% change	W	R	R→W	Average
1: double p for every origin	3.43	-4.36	[-4.36, 3.43]	3.25

Note: “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration. “R→W” refers to those switching from being researchers to being workers.

effect of skilled immigrants.⁴⁶ My results suggest that immigrants can still make significant contribution to productivity growth in the U.S. even in the presence of strong crowding-out effect on natives. How does that growth boost translate into welfare of different types of agents in the U.S.? I will answer that question next by computing changes in welfare.

4.2 Welfare Impact on the U.S.

I use the concept of consumption-equivalent welfare proposed in Lucas (1987) to evaluate the effect of both policy experiments. Use ω to denote welfare changes. The welfare gains (or losses) can be solved from the following equations.

$$\int_0^\infty e^{-\rho t} \cdot \frac{[(1 + \omega_{us}(\epsilon)) \cdot c_{us,t}^{\text{old}}(\epsilon)]^{1-\gamma}}{1-\gamma} dt = \int_0^\infty e^{-\rho t} \cdot \frac{c_{us,t}^{\text{new}}(\epsilon)^{1-\gamma}}{1-\gamma} dt \quad (23)$$

$$\int_0^\infty e^{-\rho t} \cdot \int_1^\infty \frac{[(1 + \omega_{us}) \cdot c_{us,t}^{\text{old}}(\epsilon)]^{1-\gamma}}{1-\gamma} f(\epsilon) d\epsilon \cdot dt = \int_0^\infty e^{-\rho t} \cdot \int_1^\infty \frac{c_{us,t}^{\text{new}}(\epsilon)^{1-\gamma}}{1-\gamma} f(\epsilon) d\epsilon \cdot dt \quad (24)$$

where $\omega_{us}(\epsilon)$ denotes the *individual* welfare changes and ω_{us} denotes the *average* welfare changes in the U.S. The resulting welfare changes are summarized in Table 5.

Compared to the baseline environment, doubling the number of immigrants would improve average welfare in the U.S. by 3.25%. Agents would be affected differently, with *less* talented agents benefiting *more* from the policy. In particular, workers’ welfare would be 3.43% higher in Counterfactual 1, whereas researchers’ welfare would be of 4.36% lower. As discussed before, the marginal native researchers would be displaced and their welfare changes would range from -4.36% to 3.43% and be negatively correlated with their research talent.⁴⁷

⁴⁶See Borjas (2005); Borjas et al. (2011); Doran et al. (2015) for estimates of the crowding-out effect on native skilled workers; see Kerr and Lincoln (2010); Peri et al. (2013) for evidence of productivity-enhancing effect of immigrants.

⁴⁷Note that the positive welfare impact on workers dominates the negative impact on researchers, because workers make up more than 90% of the employed in the U.S.

The negative correlation between welfare changes and agents’ talent level indicates that the crowding-out effect dominates the growth boost for native-born U.S. researchers. This might be a result of the assumption that immigrants and native researchers are perfect substitutes. To gauge robustness of the results to that assumption, I assign a large but finite number to the elasticity of substitution between immigrants and native researchers. The qualitative results stay the same, and the crowding-out effect becomes weaker.⁴⁸

The estimated increase of 3.25% in average welfare is quantitatively significant. In comparison, the welfare gains from the elimination of business cycles are around 0.1-1.8%, and the static gains from trade according to recent work is approximately 2.0-2.5%.⁴⁹

4.3 Technological Progress in India

In the baseline environment, India is on a transition path because its growth rate is well above the U.S. With the migration probability being doubled, the U.S. would grow faster and India would lose some of its top talent. Both of the changes will lead to a new transition path and a new steady state for India. I use the parameter values calibrated in Section 3 and compute the new transition path for India. Its comparison with the baseline transition is presented in Figure 5.

The plot on the left shows the the ratio of technology level in India under the two counterfactuals and the baseline during the transition. In the short run, technology level is lower with doubled migration probability. This is because the negative effects of losing talent dominates the positive frontier growth effect. Over time, the frontier growth effect accumulates exponentially as growth rate in the U.S. is higher permanently. Meanwhile, the cost of talent loss is mitigated through endogenous adjustment of labor allocation, indicated by the plot on the right. Compared to the baseline, talent cutoff for researchers in India is lower in the counterfactual scenarios throughout the transition process.⁵⁰ Combining the two forces together, technology level in India would be higher in the counterfactual scenario in the long run – i.e., 32 years after the first policy change or 58 years after the policy change.

⁴⁸Details of that robustness check are included in Section 5.

⁴⁹See Krusell et al. (2009) for the welfare consequences of business cycles, and Costinot and Rodriguez-Clare (2015) for the welfare gains from trade.

⁵⁰The lower talent threshold for researchers comes from lower replacement rates of incumbents during the transition.

Figure 5: Baseline vs. Counterfactuals

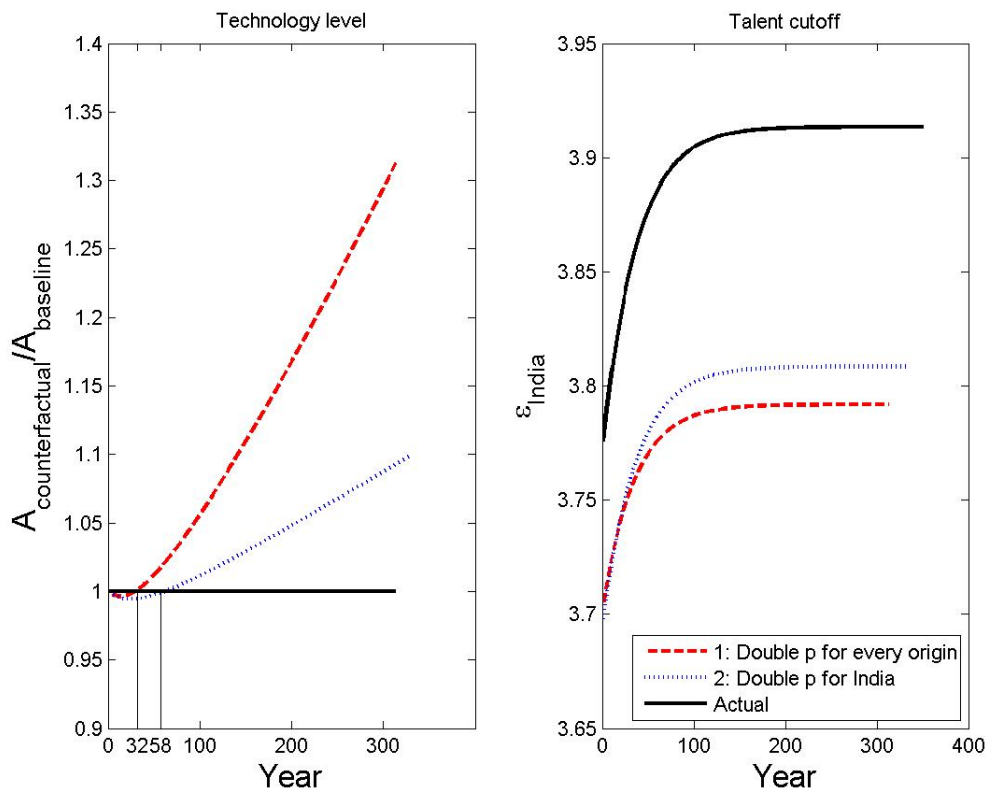
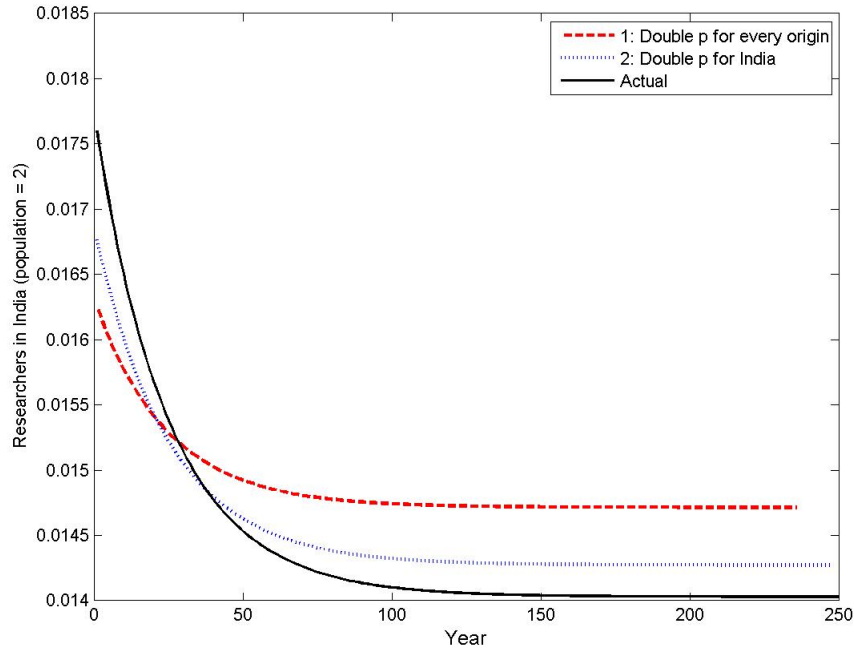


Figure 6: Equilibrium Number of Researchers in India



Note that the lower talent cutoff in Figure 5 does not necessarily mean more researchers because the talent distribution of talent changes after emigration doubles. In fact, the equilibrium number of researchers in India is smaller in the short run as illustrated in Figure 6.

In addition to transition dynamics, we can get additional insights from analyzing steady state labor allocation in India. As summarized in Table 6, , the average quality of remaining talent in India (i.e., $\mathbb{E}(\epsilon|\epsilon > \epsilon_{ind}^*)$) is lower under the counterfactual case, but the quantity of researchers (i.e., $l_{ind,R}^{ss}$) is higher because the technology frontier grows faster. The technology gap between the U.S. and India widens suggested by the decrease in a_{ind}^{ss} , even though the absolute technology level in India is much higher under the counterfactual case as illustrated in Figure 5.

4.4 Welfare Impact on India

As discussed above, technological level in India would be adversely affected in the short run but will benefit in the long run. To evaluate the average welfare impact of migration on India,

Table 6: Growth and Labor Allocation in India (steady state)

	g^{ss} (%)	$s_{ind,R}^{ss}$ (%)	a_{ind}^{ss}	$\mathbb{E}(\epsilon \epsilon > \epsilon_{ind}^{ss})$
1: double p for every origin	1.10	0.80	0.51	5.31
2: double p for India only	1.04	0.79	0.52	5.33
Baseline: actual	1.00	0.78	0.53	5.48

Note: I consider two changes to the U.S. immigration policy. Policy 1 doubles the probability of skilled migration for all source countries, whereas Policy 2 only doubles the probability of skilled migration for India. All values presented in this table are steady state levels. In the steady state, productivity in India would grow at the same rate as that in the U.S., which equals to g^{ss} ; $s_{ind,R}^{ss}$ refers to share of researchers in India; a_{ind}^{ss} refers to the technology level in India relative to the U.S.; the last column indicates the average research talent among researchers.

I compute the changes in consumption-equivalent welfare using similar formula as before.

$$\sum_{t=0}^{\infty} \beta^t \cdot \frac{\left((1 + \omega_{ind}(\epsilon)) \cdot c_{ind,t}^{old}(\epsilon) \right)^{1-\gamma}}{1-\gamma} = \sum_{t=0}^{\infty} \beta^t \cdot \frac{c_{ind,t}^{new}(\epsilon)^{1-\gamma}}{1-\gamma} \quad (25)$$

$$\sum_{t=0}^{\infty} \beta^t \cdot \int_1^{\infty} \left[\frac{(1 + \omega_{ind}) \cdot c_{ind,t}^{old}(\epsilon)}{1-\gamma} \right]^{1-\gamma} f(\epsilon) d\epsilon = \sum_{t=0}^{\infty} \beta^t \cdot \int_1^{\infty} \frac{c_{ind,t}^{new}(\epsilon)^{1-\gamma}}{1-\gamma} f(\epsilon) d\epsilon \quad (26)$$

The differential welfare impact on agents is summarized in Table 7.

The average welfare in Counterfactual 1 would be 0.9% higher than in the baseline environment, or 0.8% if we exclude welfare of emigrants. All types of agents would benefit from the policy, suggesting a large frontier growth effect dominating the cost of talent loss. The extent to which agents would benefit from the policy differs by their research talent. In general, more talented agents would benefit more from doubled migration. Specifically, remaining researchers would benefit 3.3% in consumption-equivalent welfare, which is higher than the 0.8% welfare increase among remaining workers. For the marginal agents who switched from working to doing research, their welfare changes would lie in the range of 0.8% to 3.3%, with more talented agents benefit more. This is the opposite to the case in the U.S., because the loss of talent would lead to a lower replacement rate and hence higher value of new ideas. The new emigrants to the U.S. would gain the most, as their welfare would more than double due to the U.S. wage premium.

Table 7: Welfare Impact on Indian Workers

% change	W	R	W→R	New emig.	Average	
					Excl. emig.	All
1: double p for every origin	0.81	3.3	[0.81, 3.3]	[108, 169]	0.82	0.87
2: double p for India only	-0.15	2.2	[-0.15, 2.2]	[115, 177]	-0.14	-0.10
2b: no frontier growth effect	-0.69	1.6	[-0.70, 1.6]	[112, 174]	-0.68	-0.63

Note: “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration. “R→W” refers to those switching from being researchers to being workers. “New emig” are the additional migrants to the U.S. in the counterfactual scenarios. There are two measures of average welfare changes, one of which only considers remaining individuals in India, and the other includes welfare of all individuals of Indian origin.

Welfare changes in Counterfactual 2 indicates that the Pareto improvement in welfare in Counterfactual 1 is largely driven by the positive externality of immigrants from other countries. In Counterfactual 2, average welfare would be slightly lower than that in the baseline environment. The negative effect is due to welfare loss of workers. Researchers would still be better off but to a smaller extent. New emigrants would benefit more than they would in Counterfactual 1.⁵¹

The the frontier growth effect is the key source of benefit emphasized in this paper. To evaluate how much that channel matters for the bilateral brain drain effect, I consider an alternative scenario for India wherein everything is the same as in Counterfactual 2 except I ignore the frontier growth effect. In other words, frontier growth rate is assumed to be 1% instead of 1.04% throughout the process. The transition path is solved under scenario 2b and consumption equivalent-welfare changes are computed. A comparison between 2 and 2b suggests that the frontier growth effect is quantitatively important, in that it mitigates the average welfare loss of brain drain by almost 80%, from -0.63% to -0.10%. Even for remaining workers in India – the group who would be most negatively affected – their welfare loss would be reduced by more than three quarters if we consider the frontier growth effect.

My welfare analysis on India has two key implications. First, the positive externality effect is an order of magnitude more important than the bilateral brain drain effect, even

⁵¹In the model, existing Indian immigrants in the U.S. will be negatively affected by new immigrants due to wage decrease. This result is consistent with empirical findings that new immigrants have a substantial negative effect on wages of previous immigrants in the long run (Ottaviano and Peri, 2012).

for the largest sending country of skilled migrants. This comes from the observation that the welfare gain in Counterfactual 1 is more than ten times larger than the welfare loss in Counterfactual 2. However, most existing studies, empirical or theoretical, have overlooked the positive externality. My analysis could serve as a theoretical motivation for future empirical work to consider and rigorously estimate the magnitude of the positive externality effect.

Second, the frontier growth effect of skilled migration is quantitatively important with or without the positive externality channel. In particular, the benefit of a faster growing frontier can offset most of the negative effects of brain drain. The benefit can be further magnified when we include the network effects between expatriates and remaining workers facilitating technology diffusion.⁵² I incorporate the network effect in one of the robustness checks and the frontier growth effect is strong enough to result in a positive net effect in Counterfactual 2.

5 Robustness

Here I gauge the robustness to alternative assumptions, such as the elasticity of substitution between immigrants and native researchers. In each robustness check, I recalibrate the model and perform the same counterfactual analysis as in Section 4. Table 8 and 9 show that the growth and welfare impact of migration I find is quite robust. For the U.S., the magnitude of the growth and welfare changes varies somewhat across different assumptions, but the signs stay the same. For India, the net impact on welfare can become positive under some assumptions, but the magnitudes are not very different.

The main specification gives the most conservative case, in that it provides the least favorable estimates of immigrants' welfare impact. This is not accidental, but is a careful choice to ensure that the importance of the frontier growth effect is not overstated. The details of each alternative assumption are presented and discussed below.

5.1 More Talent Dispersion

Recall that the talent dispersion in the main specification is based on the wage income of researchers in the U.S. Alternatively, we can use a higher dispersion estimate (i.e., $\hat{\theta}^{ESI} = 2.5$)

⁵²See Agrawal et al. (2011) and Kerr (2008b).

Table 8: Robustness — U.S.

		$g^{ss}(\%)$	% Δ		
			W	R	Average
Benchmark	1: double p for every origin	1.10	3.4	-4.4	3.25
	2: double p for India only	1.05	1.4	-1.0	1.36
$\theta = 2.5$	1: double p for every origin	1.15	4.7	-3.6	4.5
	2: double p for India only	1.06	1.7	-1.4	1.6
$\rho = 0.01$	1: double p for every origin	1.11	5.6	-1.9	5.4
	2: double p for India only	1.04	2.0	-0.7	2.0
CES ($\sigma = 20$)	1: double p for every origin	1.14	4.3	-1.6	4.1
	2: double p for India only	1.05	1.6	-0.5	1.6
10% Subsidy	1: double p for every origin	1.13	4.0	-2.6	3.81
	2: double p for India only	1.05	1.4	-1.0	1.37

Note: g^{ss} is the steady state growth rate in the U.S. “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration.

Table 9: Robustness — India

		W	R	New emig.	Average	
					Excl. emig.	All
Benchmark	1: double p for every origin	0.91	3.3	[115, 182]	0.90	0.99
	2: double p for India only	-0.19	2.0	[118, 187]	-0.18	-0.08
$\theta = 2.5$	1: double p for every origin	1.2	3.9	[108, 215]	1.2	1.3
	2: double p for India only	-0.15	2.5	[113, 223]	-0.14	-0.04
$\rho = 0.01$	1: double p for every origin	1.8	3.9	[112, 181]	1.8	1.9
	2: double p for India only	0.06	2.3	[115, 184]	0.07	0.17
CES ($\sigma = 20$)	1: double p for every origin	1.2	3.0	[104, 186]	1.2	1.3
	2: double p for India only	0.02	1.7	[106, 188]	0.03	0.12
10% subsidy	1: double p for every origin	0.9	3.1	[114, 182]	0.92	1.01
	2: double p for India only	-0.19	2.0	[117, 186]	-0.17	-0.08
TFP gap	1: double p for every origin	1.7	4.2	[49, 96]	1.7	1.8
	2: double p for India only	0.25	2.5	[51, 99]	0.26	0.33
Diaspora network	1: double p for every origin	1.02	3.4	[114, 181]	1.03	1.12
	2: double p for India only	-0.06	2.2	[117, 186]	-0.05	0.05

Note: “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration. “New emig” are the additional migrants to the U.S. in the counterfactual scenarios. There are two measures of average welfare changes, one of which only considers remaining individuals in India, and the other includes welfare of all individuals of Indian origin.

based on the publication data from *InCites: Essential Science Indicators* (ESI). All the other parameters are recalibrated to match the moments specified in Section 3. Then, I perform the same counterfactual analysis as in Section 4.

In the U.S., the effect of migration on growth and welfare would be bigger with more talent dispersion. Specifically, growth rate would increase from 1% to 1.15% (instead of 1.13%) in Counterfactual 1, and to 1.06% (instead of 1.05%) in Counterfactual 2. The magnitude of welfare changes – with more talent dispersion – is larger for both workers and researchers, as shown in Table 8.

In India, more talent dispersion would generate a more positive effect of migration on welfare of people left behind (Table 9). As the benefit on each type of agent is higher, average welfare increase in Counterfactual 1 would become 1.3%, higher than 0.99% in the main specification. Similarly, the average welfare loss in Counterfactual 2 is also reduced from 0.08% to 0.04%. The larger benefit of migration partly comes from the higher growth rate in the U.S. Intuitively, the benefit of talent reallocation increases when the dispersion of talent rises. If all agents are homogeneous, moving people from India to the U.S. would have no additional effect on growth apart from the scale effect.

5.2 Lower Discount Rate

As argues in Caplin and Leahy (2004) and Farhi and Werning (2007), the social discount rate may be lower than the private discount rate. Therefore, I consider a discount rate of $\rho = 0.01$ – as opposed to $\rho = 0.02$ in the main specification – as a robustness check.

Under the new discount rate, the increase in growth rate with doubled migration probability is smaller. Welfare gain for U.S. works is bigger and the welfare loss for U.S. researchers is smaller, leading to a 40% increase in average welfare gain. In India, welfare gain is higher in Counterfactual 1, and the bilateral brain drain effect becomes positive for all agents in Counterfactual 2. The reason why migration becomes more beneficial to India is that the growth effect accumulates over time, but the brain drain effects are more severely in the short run. If the agents discount the future less, the benefit of the growth effects will be magnified and the short-run cost of brain drain will be weighed less.

5.3 Imperfect Substitution

Recall that in the main specification, I assumed perfect substitution between native and immigrant researchers. This assumption is supported by Borjas et al. (2011), but is challenged by Peri and Sparber (2010) and Ottaviano and Peri (2012). As a robustness check, I consider an alternative assumption that natives and immigrants are imperfect substitutes. The motivation is to explore whether the crowding-out effects of immigrants on native-born U.S. researchers can be weakened, and if so by how much.

Following the standard specification in the literature, I introduce the CES function to the idea generation process as follows:

$$z_{us} = \eta_{us} \left[\left(\int_{\epsilon_{us}^*}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L_{us} \right)^{\frac{\sigma-1}{\sigma}} + \left(\sum_m p_m \int_{\bar{\epsilon}_m}^{\infty} \epsilon f(\epsilon) d\epsilon \cdot L_m \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (27)$$

where z_{us} is the arrival rate of ideas in the U.S. and σ is the elasticity of substitution between native and immigrant researchers. I use an estimate of 20 for the elasticity of substitution obtained by Ottaviano and Peri (2012) and recalibrate the baseline model.

Under imperfect substitution, the growth boost and welfare benefit from migration are both higher in the U.S. In particular, welfare loss among researchers becomes 40% lower than that in the main specification. There are two implications. First, immigrants contribute more to the U.S. economy when their skills and expertise are not perfect substitutes to those of the native workers. Second, the magnitude of the crowding-out effect increases with the elasticity of substitution. Native workers would be affected less or even gain from migration if the immigrants' skills are somewhat complementary.

In India, the bilateral brain drain effect in Counterfactual 2 becomes positive under the new calibration. Compared to the net negative effect in the main specification, the new results may be due to a faster frontier growth in the U.S.

5.4 10% Research Subsidy

The current model has both monopolistic competition and business stealing effects. Therefore, the decentralized equilibrium may feature too much or too little research done (Acemoglu, 2009). Under the current specification, not enough research is done compared to the socially

optimal level, consistent with empirical findings in Bloom et al. (2013). In practice, the U.S. government encourages R&D activities through tax incentives and other policies. To test robustness of the current findings to R&D incentives, I introduce a generous research subsidy in the U.S. Specifically, the government would refund 10% of the R&D expenditure and the subsidy is funded by taxing labor income.

After recalibrating the model with the research subsidy, I perform the same counterfactual analysis. The results suggest that a 10% research subsidy hardly changes the effects of migration on growth or welfare. This is because the 10% research subsidy is present both in the baseline environment and in the counterfactuals.

5.5 Misallocation and Productivity Gap

In the main specification, I assume the TFP gap between India and the U.S. is solely due to India’s inferior production technology. However, as shown in Hsieh and Klenow (2009), resource misallocation can also lower aggregate TFP. By assuming away other causes for the TFP gap, my calibration would under-estimate India’s research capacity. As a robustness check, I attribute 50% of the TFP gap to misallocation in India.⁵³ Since misallocation is outside the scope of the model, I quantify India’s relative TFP to be $0.456 \times \sqrt{1/0.456} = 0.675$, wherein the raw relative TFP is 0.456.

A different calibration of India’s relative TFP only affects the welfare impact on India. In both counterfactuals, all types of agents in India are better off. The welfare boost is the largest among all alternative assumptions considered. Average welfare increase becomes 1.8% in the first counterfactual and 0.33% in the second counterfactual.

5.6 Diaspora Network Effect

Kerr (2008b), Agrawal et al. (2011) and Saxenian et al. (2002) found a significant diaspora network effect in facilitating knowledge diffusion. As one robustness check, I allow the speed of knowledge diffusion from the U.S. to India to depend on the size of Indian diaspora in the U.S. Specifically, the arrival rate of ideas in India would become $\zeta_{ind} (a_{ind}(t)^{-1} - 1) \left(1 + h_{f,R}^{diaspora}\right)^\phi$, where $\left(1 + h_{f,R}^{diaspora}\right)^\phi$ is the diaspora network effect. In the main specification, ϕ is assumed

⁵³The estimate is adopted from Hsieh and Klenow (2009).

to be zero. Here, I assign $\phi = 0.3$ and see how much that affects the welfare impact on India.⁵⁴

Intuitively, the diaspora network effect will enhance the speed of knowledge diffusion, and thus make the two policies more favorable for India. The quantitative results confirm that argument: average welfare *increases* slightly in Counterfactual 2 and the welfare loss among remaining workers is smaller. The magnitude of the changes, however, are very similar to that in the main specification.

6 Conclusion

How does high-skilled immigrants from developing countries affect long-run growth rates in the U.S. and in source countries? And what are the consequences of increasing migration for welfare? I develop a general-equilibrium framework to tackle these questions. This framework has three key features. First, immigrants can innovate more efficiently in the U.S. than in their home countries. Increasing skilled migration can, therefore, enhance global innovation. Second, immigrants' contribution to innovation in the U.S. can indirectly benefit the source countries through knowledge diffusion, which I call the "frontier growth effect". I use India as an example source country, and showed that the "frontier growth effect" – which has been overlooked in the literature – is quantitatively significant. Third, transition dynamics of source countries are computed and accounted for in the welfare analysis.

I quantify the proposed model and consider two changes in U.S. immigration policy to assess the impact of skilled migration. In the first policy, the probability of skilled migration is doubled for each source country. Total factor productivity growth rate would be boosted from 1% to 1.1%. The growth boost leads to welfare gains: the U.S. would gain by 3.3% and India would gain by 0.9%. My results suggest that the U.S. would benefit a lot from more skilled immigrants. Amidst concerns of declining U.S. growth, allowing more immigrant talent is a policy that should be on the table.

Most of the gains for India come from the indirect externality of the additional non-Indian immigrants. To isolate the bilateral brain drain effect between India and the U.S., I consider the second policy where the migration probability is only doubled for India. I find that the

⁵⁴Kerr (2008b) estimated that manufacturing output in foreign countries increases with an elasticity of 0.1–0.3 to stronger scientific integration with the U.S. frontier. Although not the same elasticity as in my model, I use $\phi = 0.3$ here just to illustrate how much the ethnic network effect matters.

frontier growth effect on India is large enough to almost offset the negative effect of talent loss. The results from these two counterfactual scenarios suggest that the frontier growth effect is quantitatively significant, with or without the positive externality.

It is worth noting that the net effects of the two policies may vary across origins. My estimates for India would not apply to other source countries, whose population and emigration rates differ from India's. For instance. If I were to repeat the analysis for a small source country with high emigration rate among high-skilled workers (such as Jamaica according to Brucker et al.), the brain drain effect would be likely to overwhelm the frontier growth effect. The main message of the paper is not on the magnitude or the sign of the net brain drain effect, but rather on the quantitative significance of the collective benefit of allowing more skilled immigrants in the U.S. My results also provide motivation for future studies to carefully estimate the frontier growth effect using empirical data.

References

- Acemoglu, Daron, *Introduction to Modern Economic Growth*, Princeton University Press, 2009.
- Aghion, Philippe and Peter Howitt, “A Model of Growth Through Creative Destruction,” *Econometrica*, 1992, *60*(2), 323–351.
- Agrawal, Ajay, Devesh Kapur, John McHale, and Alexander Oettl, “Brain drain or brain bank? The impact of skilled emigration on poor-country innovation,” *Journal of Urban Economics*, 2011, *69*, 43–55.
- Aleksynska, Mariya and Giovanni Peri, “Isolating the Network Effect of Immigrants on Trade,” *IZA DP No. 6941*, 2012.
- Aydemir, Abdurrahman and George J. Borjas, “A Comparative Analysis of the Labor Market Impact of International Migration: Canada, Mexico and the United States,” *Journal of the European Economic Association*, 2007, *5*, 663–708.
- Barro, Robert J. and Xavier Sala i Martin, “Technological Diffusion, Convergence and Growth,” *Journal of Economic Growth*, 1997, *2*(1), 1–26.
- Beine, Michel, Frederic Docquier, and Cecily Oden-Defoort, “A Panel Data Analysis of the Brain Gain,” *World Development*, 2011, *39*(4), 523–532.
- , —, and Hillel Rapoport, “Brain Drain and Economic Growth: Theory and Evidence,” *Journal of Development Economics*, 2001, *64*, 275–289.
- Benhabib, Jess, Jesse Perla, and Christopher Tonetti, “Catch-up and fall-back through innovation and imitation,” *Journal of Economic Growth*, 2014, *19*, 1–35.
- Bhagwati, Jagdish N. and Koichi, “The Brain Drain, International Integration of Markets for Professionals and Unemployment,” *Journal of Development Economics*, 1974, *1*, 19–42.
- Bloom, Nicholas, Mark Schankerman, and John Van Reenen, “Identifying Technology Spillovers and Product Market Rivalry,” *Econometrica*, 2013, *81*(4), 1347–1393.

- Bollard, Albert, David McKenzie, Melanie Morten, and Hillel Rapoport, “Remittances and the Brain Drain Revisited: The Microdata Show that More Educated Migrants Remit More,” *The World Bank Economic Review*, 2011, *25(1)*, 132–156.
- Borjas, George J., “The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market,” *Quarterly Journal of Economics*, 2003, *118(4)*, 1335–1374.
- , “The Labor-Market Impact of High-Skilled Immigration,” *American Economic Review*, 2005, *95(2)*, 56–60.
- and Bernt Bratsberg, “Who Leaves? The Outmigration of the Foreign-Born,” *The Review of Economics and Statistics*, 1996.
- and Kirk Doran, “The Collapse of the Soviet Union and the Productivity of American Mathematicians,” *Quarterly Journal of Economics*, 2012, *127(3)*, 1143–1203.
- , Jeffrey Grogger, and Gordon H. Hanson, “Substitution between Immigrants, Natives and Skill Groups,” *NBER Working Paper*, 2011, *17461*.
- Brucker, Herbert, Stella Capuano, and Abdeslam Marfouk, “Education, gender and international migration: insights from a panel-dataset 1980-2010.” mimeo.
- Caplin, Andrew and John Leahy, “The Social Discount Rate,” *Journal of Political Economy*, 2004, *112(6)*, 1257–1268.
- Costinot, Arnaud and Andres Rodriguez-Clare, “Chapter 4. Trade Theory with Numbers: Quantifying the Consequences of Globalization,” *Handbook of International Economics*, 2015.
- Docquier, Frederic and Hillel Rapoport, “Quantifying the Impact of Highly-Skilled Emigration on Developing Countries,” *CEPR project*, 2009.
- and —, “Globalization, Brain Drain and Development,” *Journal of Economic Literature*, 2012, *50(3)*, 681–730.
- Doran, Kirk, Alexander Gelber, and Adam Isen, “The Effects of High-Skilled Immigration on Firms: Evidence from H-1B visa Lotteries,” *NBER Working Paper*, 2015.

- Farhi, Emmanuel and Ivan Werning, “Inequality and Social Discounting,” *Journal of Political Economy*, 2007, *115(3)*, 365–402.
- Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer, “The Next Generation of the Penn World Table,” *American Economic Review*, forthcoming.
- Finn, Michael G., “Stay Rates of Foreign Doctorate Recipients from U.S. Universities, 2011,” *Oak Ridge Institute for Science and Education*, 2014.
- Gould, David M., “Immigrant Links to the Home Country: Empirical Implications for U.S. Bilateral Trade Flows,” *The Review of Economics and Statistics*, 1994, *76(2)*, 302–316.
- Grossman, Gene M. and Elhanan Helpman, “Endogenous Product Cycles,” *The Economic Journal*, 1991, *101*, 1214–1229.
- Grubel, Herbert B. and Anthony D. Scott, “The International Flow of Human Capital,” *The American Economic Review*, 1966, *56*, 268–274.
- Hall, Robert E., “Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor,” *Journal of Political Economy*, 2009, *117(2)*, 281–323.
- Hsieh, Chang-Tai and Peter J. Klenow, “Misallocation and Manufacturing TFP in China and India,” *The Quarterly Journal of Economics*, 2009, *124*, 1403–1448.
- , Erik Hurst, Charles I. Jones, and Peter J. Klenow, “The Allocation of Talent and U.S. Economic Growth,” *Working Paper*, 2013.
- Hunt, Jennifer, “Which immigrants are most innovative and entrepreneurial? Distinctions by entry visa,” *Journal of Labor Economics*, 2011, *29(3)*, 417–457.
- and Gauthier-Loiselle, “How Much Does Immigration Boost Innovation?,” *American Economic Journal: Macroeconomics*, 2010, *2*, 31–56.
- Jaimovich, Nir and Sergio Rebelo, “Non-linear Effects of Taxation on Growth,” *NBER working paper*, 2012.
- Jones, Charles I., “Pareto and Piketty: The Macroeconomics of Top Income and Wealth Inequality,” *Journal of Economic Perspectives*, 2015, *29(1)*, 29–46.

- Kahn, Shulamit and Megan J. MacGarvie, “How Important is U.S. Location for Research in Science?,” *Review of Economics and Statistics*, Forthcoming.
- Kerr, William R., “The Ethnic Composition of US Inventors,” *HBS working paper*, 2008.
- , “Ethnic Scientific Communities and International Technology Diffusion,” *The Review of Economics and Statistics*, 2008, *90(3)*, 518–537.
- , “U.S. High-skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence,” *NBER working paper*, 2013.
- and William F. Lincoln, “The Supply Side of Innovation: H-1B Visa Reforms and US Ethnic Invention,” *Journal of Labor Economics*, 2010, *28(3)*, 473–508.
- Krusell, Per, Toshihiko Mukoyama, Aysegul Sahin, and Anthony A. Smith Jr., “Revisiting the welfare effects of eliminating business cycles,” *Review of Economic Dynamics*, 2009.
- Kuhn, Peter J. and Carol MacAusland, “The International Migration of Knowledge Workers: When is Brain Drain Beneficial?,” *NBER Working Paper*, 2006.
- Lee, Donghoon, “An Estimable Dynamic General Equilibrium Model of Work, Schooling, and Occupational Choice,” *International Economic Review*, 2005, *46(1)*, 1–34.
- Lucas, Robert E., *Models of Business Cycles*, New York: Basil Blackwell, 1987.
- McCulloch, Rachel and Janet L. Yellen, “Factor Mobility, Regional Development, and the Distribution of Income,” *Journal of Political Economy*, 1977, *85(1)*, 79–96.
- Miguelez, Ernest and Carsten Fink, “Measuring the International Mobility of Inventors: A New Database,” *WIPO Working Paper No.8*, 2013.
- Moser, Petra, Alessandra Voena, and Fabian Waldinger, “German Jewish Emigres and US Invention,” *American Economic Review*, 2014, *104(10)*, 3222–3255.
- Mountford, Andrew, “Can a brain drain be good for growth in the source economy?,” *Journal of Development Economics*, 1997, *53*, 287–303.

- Nanda, Ramana and Taun Khanna, “Diasporas and Domestic Entrepreneurs: Evidence from the Indian Software Industry,” *Journal of Economics and Management Strategy*, 2010, 19(4), 991–1012.
- Nelson, Richard and Edmund Phelps, “Investment in Humans, Technological Diffusion and Economic Growth,” *American Economic Review*, 1966, 56, 69–75.
- Ortega, Francesc and Giovanni Peri, “Migration, Trade and Income,” *IZA DP No. 7325*, 2013.
- Ottaviano, Gianmarco and Giovanni Peri, “Rethinking the Effect of Immigration on Wages,” *Journal of the European Economic Association*, 2012, 10(1), 152–197.
- Peri, Giovanni and Chad Sparber, “Highly-Educated Immigrants and Native Occupational Choice,” *Working paper*, 2010.
- , Kevin Shih, and Chad Sparber, “STEM Workers, H1B Visas and Productivity in US Cities,” *Working Paper*, 2013.
- Piketty, Thomas and Emmanuel Saez, “Income Inequality in the United States, 1913-1998,” *The Quarterly Journal of Economics*, 2003, 118(1), 1–39.
- Rapoport, Hillel and Frederic Docquier, “The Economics of Migrants’ Remittances,” *IZA discussion paper series*, 2005.
- Rauch, James E. and Vitor Trindade, “Ethnic Chinese Networks in International Trade,” *The Review of Economics and Statistics*, 2002, 84(1), 116–130.
- Saxenian, AnnaLee, Yasuyuki Motoyama, and Xiaohong Quan, “Local and Global Networks of Immigrant Professionals in Silicon Valley,” *Public Policy Institute of California*, 2002.
- Wadhwa, Vivek, AnnaLee Saxenian, Ben A. Rissing, and Gary Gereffi, “America’s New Immigrant Entrepreneurs: Part I,” *Duke Science, Technology & Innovation Paper*, 2007, 23.

Table A1: Growth and Labor Allocation in the U.S.

	g^{ss} (%)	$s_{us,R}$ (%)	$s_{us,R}^{dom}$ (%)	$\mathbb{E}(\epsilon \epsilon > \epsilon_{us}^*)$
A1: Send all imm back	0.89	4.0	4.0	3.5
A2: Send Indian imm back	0.96	4.1	3.5	3.7
Baseline: actual	1.00	4.3	3.2	3.8

Note: g refers to the Hicks-neutral growth rate of total factor productivity, $s_{us,R}$ refers to the share of researchers among U.S. workers and $s_{us,R}^{dom}$ is the share of native-born researchers among U.S. workers. The last column indicates the average research talent among researchers.

Table A2: Growth and Labor Allocation in India (steady state)

	g^{ss} (%)	$s_{ind,R}^{ss}$ (%)	$a_{ind,R}^{ss}$	$\mathbb{E}(\epsilon \epsilon > \epsilon_{ind}^{ss})$
Send all imm back	0.89	0.67	0.53	5.86
Send Indian imm back	0.96	0.69	0.52	5.80
Baseline: actual	1.00	0.70	0.51	5.64

Note: g refers to the Hicks-neutral growth rate of total factor productivity, $s_{us,R}$ refers to the share of researchers in the U.S. and $s_{us,R}^{dom}$ is the share of native-born researchers. The last column indicates the average research talent among researchers.

A Effects of Sending Immigrants Back

Here I consider the counterfactual scenarios of sending the immigrants back to their home countries. Comparing the baseline environment to those counterfactuals, I can evaluate existing immigrants' contribution to U.S. growth and welfare, as well as their impact on India.

Table A1 and A2 suggest that sending immigrants back has the opposite effects to doubling the stock of immigrants on both countries. In terms of magnitude, sending immigrants back has a slightly smaller impact, indicating some degree of non-linearity.

As illustrated in Section 4, faster growth would lead to higher average welfare. Following the same logic, sending immigrants back would slow growth down and thus hurt average welfare. For exposition purpose, I compute the welfare changes from the counterfactual scenarios to the baseline environment instead of the other way around. The percentage changes in welfare in Table A3 and A4 can be interpreted as the welfare contribution of existing immigrants.⁵⁵

⁵⁵If I were to compare the counterfactual scenarios to the baseline environment as I did in Section 4, the

Table A3: Welfare Impact on Native-born U.S. Workers:
actual compared to counterfactual

$\% \Delta$	W	R	R→W	Average
A1: Send all imm back	1.38	-0.98	[-0.98, 1.38]	1.32
A2: Send Indian imm back	3.66	-2.57	[-2.57, 3.66]	3.48

Note: “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration. “R→W” refers to those switching from being researchers to being workers.

Table A4: Welfare Impact on Indian Workers:
actual compared to counterfactual

$\% \Delta$	W	R	W→R	New emig	Average	
					Excl. emig	All
Send Indian imm back	-0.14	1.85	[-0.14, 1.85]	[119, 194]	-0.13	-0.04
Send all imm back	0.82	2.94	[0.82, 2.94]	[121, 197]	0.84	0.93

Note: “W” refers to those who are workers before and after introducing immigrants. “R” refers to those who remain researchers after introducing migration. “R→W” refers to those switching from being researchers to being workers.

I find a more modest effect on welfare from sending immigrants back.

sign of welfare changes would be flipped. That would make it hard to compare the results here to the main results in Section 4.