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Skilled Emigration and its Impact on Economic Development

by

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Abstract

This paper analyzes the impact of skilled emigration on the economic development of sending countries. Specifically, our study is concerned with how feedback effects of brain drain may mitigate some of the loss incurred from the outflow of talent. We construct an endogenous growth model incorporating skilled emigration to consider in detail how the inflow of remittances, network externalities of the diaspora and the incentive effect influence economic growth. Our model suggests that the overall impact on growth is co-determined by the level of development in the source economy. While intermediately advanced countries most likely experience beneficial effects on productivity growth, low-income and high-income economies may be hindered by binding budget constraints and an inoperative incentive effect, respectively. While some model implications hold up when tested empirically, others do not which might be related to shortcomings in our data and consequential inconsistencies in productivity estimates.

Keywords: Brain Drain, migration, growth, human capital, diaspora, remittances, incentive effect

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1 Introduction

In 1990, more than 42 million migrants over the age of 25 were living in the OECD. By the beginning of the new millennium this number had risen by almost 40% to a total of 59.3 million. At the same time the stock of college degree-holding immigrants increased by more than 65% and accounted for more than one third of all immigrants in 2000, thereby significantly exceeding the global average of around 11%. Interestingly, OECD destinations only account for around half of total international migration, whereas 75% of high-skilled emigrants decide to settle in one of the organization's member states.

This asymmetric agglomeration of talent in high-income economies is a symptom of positive self-selection of highly-educated emigrants, a phenomenon that is most conspicuous among developing countries. Among emigrants heading from the least developed and low-income regions to non-OECD countries, only 3.5% and 4.1% have post-secondary education, which stands in strong contrast to 34.6% and 38.0% of emigrants to OECD members, respectively (Artuç et al. 2015).

In addition, this development is driven by increasing international demand for skilled labor. When looking at immigration laws, one might come to think that cross-border mobility of talent has never been easier. Ever since the value of human capital for economic development gained international recognition, first identified by Nelson and Phelps (1966) and later by Lucas (1988) and Mankiw et al. (1992), the world has begun engaging in what seems to be a competition to attract the world's best and brightest, by implementing policies and programs that favor highly-skilled immigrants (Kuptsch and Pang 2006).

At the same time, countries experiencing an outflow of skilled labor are concerned about the economic and social consequences of this "Brain Drain" and implement policies that attempt to impede on their citizens' emigration intentions (Executive Council of the African Union 2006).

The overall impact of skilled emigration on the domestic economy, however, is to date highly uncertain. The absence of reliable data on migration by educational attainment has long limited researchers to theoretical analyses and therefore impinged on the quantification of the effect. In particular, international migration, and even more so for the highly skilled, is accompanied by a series of side effects that may mitigate some of the damage caused by the human capital loss, implying that the overall repercussions of brain drain are at the very least ambiguous.

While much research effort has been dedicated to the identification and quantification of single channels, there is, to our knowledge, no study that analyzes the combined impact of multiple feedback effects on economic growth.

Our study aims to fill this gap by building a comprehensive growth model integrating three indirect impacts of brain drain and analyzing, both theoretically and empirically, how they affect development in source countries. A first feedback effect relates to human capital formation. Specifically, the rationale is that the prospects of emigrating to a high-income economy may incentivize people to acquire a higher academic degree in order to maximize their employment chances on labor markets abroad. Thus, the mobility of talent may stimulate capital accumulation in source economies. Secondly, it is well known that many foreign workers send money back to their families at home. Added up, these enormous capital inflows often exceed those of foreign aid and FDI in less developed regions (Ratha et al. 2016). The remittances can be used for educational expenses or investments and hence have the potential to improve welfare in source economies. Finally, as highly-educated emigrants settle all over the developed world, both cultural and informational frictions between host and home country diminish. Thereby, emigrant diasporas contribute to the reduction of transaction costs which, in turn, can stimulate capital flows, trade, foreign direct investment and technology diffusion (Rapoport 2016).[1]

We conduct this investigation by setting up an endogenous growth model of skilled migration, following Vandenbussche et al. (2006) and Lodigiani (2008). The economy advances through a combination of innovation and imitation, the former being more efficient closer to, the latter further from the technological frontier. Additionally, network effects of the diaspora promote the effectiveness of the imitation sector. We then formalize the underlying mechanisms of the incentive effect by endogenizing human capital formation based on an augmented framework by Beine et al. (2011) that integrates remittances into the growth model. Thereby, we allow interdependencies between and heterogeneity within the effects.

Our findings suggest that the level of development of source countries strongly influences how brain drain affects the economy. In low-to-intermediately advanced economies, skilled migration can promote growth both through the incentive effect, by stimulating human capital formation, and the diaspora channel, provided that households' budget constraints do not restrict educational decisions. This implies that remittances are most effective at low levels of development. Finally, since migration prospects do not trigger the incentive effect in high-income economies, skilled emigration negatively affects growth by depleting human capital.

We test these implications empirically on a panel of 111 countries from 1980-2014. The results only partly confirm our theoretical implications, which is most likely caused by misspecification and data limitations, impinging on the construction of our dependent variable. Poor data quality in many developing countries remains a crucial inhibitor of sophisticated empirical investigations. Therefore,

[1] This list of concomitants is by no means complete. Our selection is guided on the one hand, by our judging of relative significance in the context of development and on the other hand, by data paucity limiting our choice of channels to measure.

research strongly lags behind in the design of policy implications targeted at minimizing the damage and promoting the benefits of the mobility of talent.

The remainder of this paper is organized as follows: Section 2 provides an overview over the literature on brain drain. In section 3 we construct our theoretical framework and derive the model's implications, which will be tested empirically in section 4. Section 5 concludes with some final remarks.

2 Literature Review

In comparison to the relatively recent surge in skilled migration, research into brain drain has a long history, during which efforts have exclusively been dedicated to the evaluation of the effects on the generally poorer source countries.[2]

Earliest contributions date back to the 1960s and ever since, researchers have widely agreed that the emigration of skilled entails a loss of welfare in the sending countries (Oteiza 1965; Perkins 1965). By reducing average human capital brain drain was found to lower long-run economic growth and exacerbate inequality by stimulating progress in wealthy countries at the cost of the developing world. These findings were reconfirmed under heterogeneous institutional contexts (Bhagwati and Hamada 1974; McCulloch and Yellen 1977) and in endogenous growth models (Miyagiwa 1991; Haque and Kim 1994; Wong and Yip 1999).

Just before the turn of the millennium, however, researchers began to question the assumed inevitability of human capital depletion and inequality amplification, which opened a new avenue of research around the movement of talent. A first major contribution from this shift in perspective was the incentive effect. In a wave of theoretical papers it was shown that under certain circumstances an increase in the skilled emigration rate incentivizes people to invest in education and therefore may lead to a rise in human capital – a Brain Gain (Mountford 1997; Stark et al. 1997; Vidal 1998; Docquier et al. 1999).

A major obstacle to the first four decades of research was the absence of adequate data, resulting in a total lack of evidence for the theoretical findings.[3] Empirical investigations only became possible after the construction of the first extensive dataset on emigration stocks and rates by educational attainment in 2006 (Docquier and Marfouk). The cross-section of 195 source countries in 1990 and 2000 constituted the fundament for a multitude of empirical studies and extensions: Beine et al. (2007) improve upon the quality of the estimates by controlling for the age of entry, thereby ruling out individuals that emigrate for a short period of time to study abroad. Docquier et al. (2009) update the database by adding

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[2] One exception is given by a small number of studies that focused on the aggregate effects on the world economy as opposed to individual country considerations. Based on neoclassical trade theory these models thus highlighted the benefits of free labor mobility (Grubel and Scott 1966; Berry and Soligo 1969; Johnson 1967).

[3] The first study to empirically investigate the incentive effect used gross migration as a proxy for the skilled migration rate (Beine et al. 2001). Although a positive and significant relationship between migration prospects and human capital formation is found in 37 developing countries, the results must be taken with caution given to the inaccuracy of the data.

information on the emigrants' gender. In order to gain a better understanding of the full extent of the international flow of skills, first Docquier and Rapoport (2012) and later Artuç et al. (2015) add non-OECD destinations to the existing databases. Finally, Defoort (2008) and more recently Brücker et al. (2013) enable the investigation of long-run trends and patterns in migration by constructing panel datasets on emigration stocks and rates by educational attainment.

The growing body of databases gave rise to an entirely new branch of research, triggering a wave of empirical studies aimed at re-examining the established theorems. For the sake of brevity, the following overview only considers research on the three feedback effects integrated in our model.[4]

In a cross-section of 127 developing countries Beine et al. (2008) find a broad, positive and significant relationship between anticipated migration chances and human capital accumulation, thus confirming the existence of the incentive effect. However, once they examine the post-migration impact of the brain drain, the outcome turns out highly heterogeneous. Countries with a relatively small initial share of well-educated citizens and low emigration rates exhibit a mildly positive impact on their human capital level. However, only few countries fulfill these characteristics. In contrast, in more than half of the observed economies, many of which sustain emigration rates above 50%, human capital is left depleted. The relative losses of the "losers" exceed the relative gains of the "winners" but since the latter consist of populous countries such as China, India and Brazil, the aggregate impact on the developing world is human capital enhancing.[5]

Surprisingly, no such evidence of drained net human capital levels is found by Easterly and Nyarko (2009) who apply a growth accounting framework on a set of African countries. They use former colonial links and distance to popular destination countries to instrument the brain drain rate and their estimations confirm that migration prospects trigger gross human capital formation.

To overcome the shortcomings of cross-sectional regressions Beine et al. (2011) conduct a panel analysis on the incentive effect for 147 countries over 25 years.[6] Moreover, they extend previous estimates of the incentive effect by conditioning on the level of development of the source countries. Their claim of an ambiguous link between the magnitude of the incentive and the level of income is confirmed by their estimation results. The expected positive and significant impact of migration prospects on human capital accumulation was found exclusively for low-income countries. This suggests that in middle- and high-income nations skilled emigration rates mirror a direct decline of human capital. A potential source of bias in their estimates lies in unobserved return migration. The rise

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[4] The interested reader should see Docquier and Rapoport (2012) for a more extensive overview.

[5] The authors reinvestigate their results in 2010 to test their robustness. They use adjusted brain drain measures controlling for the age of entry and alternative human capital indicators and test them on different functional forms. The results remain qualitatively similar (Beine et al. 2010).

[6] These shortcomings mostly refer to omitted variable bias in regressions as unobserved country heterogeneity cannot be captured by cross-sectional data, thus remaining in the error term (see Islam 1995 for a more extensive discussion).

in domestic human capital caused by the return of former skilled emigrants is subsumed in the incentive effect and thus leads to an overestimation of its impact. However, due to the absence of comprehensive data on return migration it is not yet possible to control for this issue.

Batista et al. (2012) work with micro-level data to quantify the incentive generated by brain drain. In addition to confirming previous research, they find evidence that emigration prospects are the primary motivation for skill creation in Cape Verde. Remaining at the micro-level but shifting regionally to the Pacific, in a study with survey data from Tonga, New Zealand and Papua New Guinea, Gibson and McKenzie (2009) show that emigration prospects induce high-performing students to attend supplementary classes and adjust their curriculum in favor of subjects that are easily transferrable to labor markets abroad.

Apart from the incentive effect, one of the most prominent feedbacks of migration are remittances sent home by workers abroad. Two strands of literature have developed attempting to determine the impacts of remittances on the source country.

At a micro-level, one branch aims at uncovering how remittances affect household consumption and expenditures, yet, findings diverge. On the one hand, migrants' savings have the potential to enhance disposable income at home in a way to allow productive investments. In the long-run, this could lead to favorable effects for the economy through increases in human capital levels and productivity. On the other hand, a major concern is that the remitted funds are mainly spent on immediate consumption. A number of studies find evidence for the latter (Lipton 1980, Massey et al. 1990 and Brown and Ahlburg 1999). More recent research confirms the former hypothesis (e.g. Cox-Edwards and Ureta 2003; Taylor et al. 2003). In a quasi-experimental setting using exchange rate shocks to the Philippine Peso, Yang (2008) finds that remittances raise investment- rather than consumption-related expenditures. These include households' investments in education, entrepreneurship and self-employment, and are mirrored by, among other things, a reduction of child labor.

In a more global context, the other branch seeks to establish macroeconomic links from remittances to poverty and economic growth. Given the immensity of these foreign capital flows relative to total output in some developing countries expectations with respect to their impact are similarly high. However, research outcomes are rather mixed. Some find no significant relationship at all (Rao and Hassan 2011), whereas others even relate declines in the growth rate to remittances. It is argued that the high degree of fluctuations in the remittance flows generates output shocks that disrupt development (Ramey and Ramey 1994). In another study, this volatility is considered to only indent an overall favorable impact of remittances on growth and poverty reduction (Imai et al. 2014).

Akobeng (2016) uses a new approach to the examination of remittances' performance by suggesting poverty reduction instead of growth as the core variable of interest. He finds evidence that remittances not only reduce poverty but decrease inequality as well. A high level of financial development is found to reinforce this effect. In contrast, Giuliano and Ruiz-Arranz (2009) argue that remittances are most effective in countries with underdeveloped financial systems. By alleviating households' budget constraints and enabling investments, remittances provide a workaround for the given financial infrastructure and thereby promote growth.

Naturally the magnitude of the impact depends on the distributional character and the amounts received by each individual. In the context of brain drain, a growing body of literature is dealing with the question whether skilled emigrants remit more or less than unskilled. Yet, evidence to date is so inconclusive that robust deductions remain absent. [7]

A most recent contribution to the set of indirect effects of brain drain is the creation of scientific networks through the skilled diaspora. Researchers have found emigrant networks to constitute a direct connection from their home countries to the technology frontier which facilitates knowledge circulation, technology adoption and capital transfers.

For example, Kugler and Rapoport (2007), and later Javorcik et al. (2011), examine the link between skilled migration and bilateral FDI flows. They find that skilled migrants promote FDI contract formation in the destination country by stimulating information exchange. This, in turn, is shown to benefit the service and manufacturing sectors in their home countries. Interestingly, the opposite effect is observed for low-skilled migrants.

More recently, Kugler et al. (2018) use a gravity model to analyze capital flows from migrants' host to their home country. Their results confirm the findings of the aforementioned authors. Furthermore, the effect is shown to increase with cultural distance between the countries, sensitivity of the financial transaction and with the skill level of the migrant.

Smart and Hsu (2004) analyze the correlation between FDI and emigration patterns in China and find that foreign investment is to a large extent linked to the Chinese diaspora. Furthermore, they argue that the scientific network between high-tech sector in Taiwan and the Taiwanese diaspora in Silicon Valley fosters technology transfers which stimulates local productivity.

The relevance of the Chinese diaspora for technology diffusion is confirmed by Kerr (2008). In his study on network effects of U.S.-based skilled migrant communities, he uses international patent citations to proxy for the intangible flow of knowledge. His results show that higher involvement of immigrant scientists in American research publications causes increased manufacturing activities in the researcher's home country, strongly so in the case of Chinese diasporas and high-tech sectors.

From the perspective of the sending country, Agrawal et al. (2011) analyzes how access to scientific diaspora networks affects innovation in India. Again, patent citations are used to measure research output. He finds that the knowledge exchange with the foreign community leads to innovations of higher

[7] See Faini (2007) and Niimi et al. (2010) for studies in favor, and Bollard et al. (2011) for a study opposing the claim that skilled migrants remit less.

international recognition and thus of greater economic value.

Hence, while the loss of skilled labor may be harmful, highly-educated diasporas create growth and development opportunities for source countries which may eventually mitigate the adverse effects of brain drain.

Paradoxically, despite the widespread public concern about the long-run aggregate effects of brain drain, only few studies have investigated the combined influence of skilled migration and its side effects in the context of economic growth. Moreover, we are not aware of any research that integrates more than one feedback effect in a theoretical context. Docquier and Rapoport (2012) investigate a number of brain drain related topics and analyze these channels both theoretically, using a growth accounting framework, and empirically. As they consider each effect separately their study does not allow predictions on the overall effect.

Di Maria and Stryszowski (2009) set up a human capital-augmented growth model of an economy with skilled migration, in which firms' demand for educated labor increases with the level of development. Their study examines how the incentive effect changes the composition of the labor force and how this, in turn, affects the economy's growth rate. They find that the human capital enhancing effect distorts the labor supply by increasing the share of skilled, thus decelerating growth. The effect is shown to be most harmful to the least developed economies. However, the model does not account for the transfer of remittances or the diaspora's network effect.

Lodigiani (2008) investigates the diaspora's impact on technology adoption within an endogenous growth model. She extends previous contributions by relating the productivity of the network effect to the level of development in the source country. Her study shows that the more advanced an economy, the more does its growth depend on innovation relative to adoption. But her model abstracts from feedback effects on human capital and remittances. Nonetheless, we rely on her study in the design of our theoretical model and empirical specification.

Finally, in an empirical investigation Harnoss (2011) uses counterfactual simulations to analyze the net economic costs of skilled emigration in Malaysia. He finds an only moderate harmful effect on gross national income and shows that the outflow of talent is reduced as economic growth accelerates. Interestingly, his study suggests that the integration of highly qualified immigrants into the domestic labor supply may be a more efficient measure for compensating the outflow of talent than attempts to incentivize the return of the Malaysian diaspora. Yet, his study lacks a theoretical fundament to formally explain the underlying processes of the aggregate effect.

In summary, a careful consideration of the integrated effect based on a detailed and comprehensive approach seems key to shed light on the conflicting evidence thus far obtained in the brain drain literature and may help to deliver a more comprehensive picture of the global impact of skilled migration.

3 Theoretical Model

Consider a world with two types of countries. One economy is rich, leading the world at the technological frontier, the other is less advanced and follows. Each country is populated by skilled and unskilled individuals and firms. There is no population growth. High-skilled labor is mobile between the countries and there is no trade. Each economy consists of a perfectly competitive final good sector and a monopolistic intermediate goods sector with a continuum of products indexed i, where $i \in [0,1]$. Time is discrete.

3.1 Human Capital Formation

The economy's labor supply is provided inelastically by individuals that live for two periods. Without loss of generality the size of each generation can be normalized to 1 such that total population in each country is given by $N = 2$. Agents are risk-neutral and maximize their lifetime expected utility according to

$$E(U_t) = \ln\left(y_{t,1} - \mu\right) + \ln(y_{t+1,2})$$

where y_t denotes expected income in period t and μ is a parameter reflecting the minimal cost of living. This subsistence level is crucial for mirroring liquidity constraints that may binding on schooling decisions in developing countries. Following Beine et al. (2011) there is no subsistence level in the second half of life and we abstract from saving and intertemporal time-discount for simplicity.

In the first period of life, individuals work and in the follower-type economy earn the low-skilled wage w_t. In addition, they receive remittances, denoted r_t, from emigrants abroad. Naturally, there are no remittances in case of a closed economy such that $r_t = 0$ if $m_t = 0$. To ensure the young generation's participation in the labor market we assume that r_t lies below the subsistence level.

In their youth, individuals are faced with the decision whether to invest a share of their income in an educational program. Agents are heterogeneous in their initial levels of human capital and their respective skill endowment affects their cost of schooling, labeled h. Simply put, the smarter the individual, the easier she learns and the lower are her education costs. Formally, the cost of skill acquisition is given by $\tau h w_t$ where τ is a policy parameter reflecting educational subsidies and school infrastructure[8]. For simplicity h is uniformly distributed on $[0,1]$.

As adults, agents supply all their time to the labor market. Acquiring human capital when they are young enables them to earn a wage premium as high-skilled workers, given by σw_t with $\sigma > 1$, otherwise they again earn w_t. At the beginning of the second period skilled individuals have the chance to emigrate to a leading-type economy with probability m_{t+1}, whereas unskilled labor is considered immobile. Recalling the aforementioned international competition for talent this assumption reflects the exceeding emigration rates to OECD economies among the well-educated compared to their fellow citizens. As a skilled worker in high-income countries an immigrant receives the net-of-migration-costs wage σw_t^* (with $w_t^* > w_t$).

3.1.1 Incentive Effect

Within this probabilistic migration scenario, young individuals anticipate the emigration probability m_{t+1} when they face the decision whether to forgo a share of their current income for a chance to earn higher wages in the future. For the following analysis the migration rate m_{t+1} is treated as exogenous and we abstract from expectational errors on the part of the young generation.

Formally, investing in education is therefore optimal if

$$\ln(w_t + r_t - \tau h w_t - \mu) + m_{t+1} \ln(w^* \sigma) + (1 - m_{t+1}) \ln(w_{t+1} \sigma) > \ln(w_t + r_t - \mu) + \ln(w_{t+1}) \quad (1)$$

Solving for h yields

$$h_m < \frac{w_t + r_t - \mu}{\tau w_t} \left[\frac{\sigma \left(\frac{w^*}{w_{t+1}} \right)^{m_{t+1}} - 1}{\sigma \left(\frac{w^*}{w_{t+1}} \right)^{m_{t+1}}} \right] \quad (2)$$

h_m now denotes the threshold cost below which education is optimal. In other words, h_m stands for the inverse of the level of talent an individual must at least be endowed with to find it best to acquire education. At the same time, due to its uniform distribution, h_m reflects the share of young people that decides to invest in human capital, or the *ex ante* share of skilled labor. The *ex post* share is given by the proportion remaining after emigration. The threshold increases with the current local wage rate, remittance inflows, the skill premium σ as well as school subsidies and education quality (mirrored by a decreasing τ). On the other hand, the share of young opting for education is negatively affected by the subsistence level, thus reflecting the impact of a binding budget constraint. Thereby, the model is suitable to explain the low levels of human capital often observed in developing countries where

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[8] This captures anything from the number of schools per capita to quality of teachers.

domestic wages are too low to afford schooling or returns to schooling are too insignificant to compensate for the earlier loss in income (Beine et al. 2011).

The incentive effect is formally illustrated by the impact of a rise in expected emigration chances on the threshold level h. Taking the derivative of h_m with respect to m_{t+1} yields

$$\frac{\partial h_m}{\partial m_{t+1}} = \frac{w_t + r_t - \mu}{\tau w_t} \frac{\ln \frac{w^*}{w_{t+1}}}{\sigma \left(\frac{w^*}{w_{t+1}}\right)^{m_{t+1}}} \tag{3}$$

Which is > 0 as long as $\frac{w^*}{w_{t+1}} > 1$. Thus, human capital formation rises with migration probabilities as long as the wage differential between home and destination country is sufficiently large. This identifies a strong relationship between the level of development and the size of the incentive effect. However, this link is characterized by the competing forces that influence the incentive effect and whose magnitudes depend on the wealth of the country. On the one hand, the poorer the country the higher the income benefit to be obtained once emigrated. On the other hand, the more likely are liquidity constraints to prevent agents from responding to the incentive by acquiring education in the first place.

To formally show this, let wages depend on the local productivity level, denoted by A_{t-1}. The foreign wage then simply becomes a function of the technology frontier: $w^* = f(\bar{A}_{t-1})$. As the local productivity level increases, the distance to the frontier narrows, which is mirrored by a rise in local wages and a fall in the wage differential $\frac{w^*(\bar{A}_{t-1})}{w_t(A_{t-1})}$. To analyze the impact of this on the *ex ante* share of skilled, we consider the following derivative

$$\frac{\partial h_m}{\partial m_{t+1}} \frac{\partial}{\partial w} = \left(\frac{w_t + r_t - \mu}{\tau w_t} \frac{\ln \frac{w^*}{w_{t+1}}}{\sigma \left(\frac{w^*}{w_{t+1}}\right)^{m_{t+1}}} \right) \frac{\partial}{\partial w_t} \tag{4}$$

Which is ambiguous[9]. Once one considers the effects separately, it becomes clear that the income effect of growth naturally acts reinforcing towards human capital formation whereas the decrease in the wage differential depresses the incentive effect.

3.1.2 Implications

In the context of human capital formation, the primary outcome of interest is the share of educated that remains in the country after emigration. An increase in school enrollment following higher expected

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[9] Proof see Appendix A.

emigration chances is ultimately fruitless if it does not lead to an after-migration rise in the share of skilled labor. The net-of-migration, or *ex post*, share of skilled in the total labor force is given by

$$\bar{S}_{t+1} = \frac{(1 - m_{t+1})h_t}{2 - m_{t+1}h_t} \tag{5}$$

In the steady-state, an increase in the migration rate will affect the ex post share of skilled according to

$$\frac{\partial \bar{S}}{\partial m} = \frac{2(1 - m)\frac{\partial h}{\partial m} - h(2 - h)}{(2 - mh)^2} \tag{6}$$

The sign of the derivative is not uniquely identifiable. It depends strongly on the initial level of schooling and the current rate of emigration, as well as on the magnitude of the incentive effect[10]. Nonetheless, some implications can be drawn. Clearly, if liquidity constraints are binding higher incentives are met with the incapacity of people to act upon them, such that $\frac{\partial h_m}{\partial m_{t+1}} = 0$. Thus, $\frac{\partial \bar{S}_{t+1}}{\partial m_{t+1}}$ is always negative and no Brain Gain is realized. This implies that the poorest nations are likely to experience a diminishing impact on their human capital level when skilled workers emigrate. Moreover, equations (3) and (4) suggest that the *ex post* effect could be negative for upper-middle and high-income countries that are close to the technological frontier, as the generated incentives are too weak to induce additional investment in education. Finally, it should be within the intermediate range of a that the incentive effect fully operates and gains to human capital can be expected from an increase in the migration rate.

3.2 Firms

Turning to the production side, each period the final good sector produces total output y according to

$$y_t = l^{1-\alpha} \int_0^1 A_{i,t}^{1-\alpha} x_{i,t}^{\alpha} \, di \qquad \text{with } 0 < \alpha < 1$$

where $A_{i,t}$ denotes productivity in sector i at time t and $x_{i,t}$ is the input flow of intermediate good i used in t. l denotes total land used in production and is set equal to 1. The final good is either used for consumption or as input in the production of intermediate goods and, without loss of generality, its price can be normalized to 1. GDP is therefore simply final output minus inputs, formally $GDP_t = y_t - \int_0^1 x_{i,t} \, di$.

[10] Beine et al. (2008) find that low initial levels of schooling (<5%) and moderate emigration rates (<20%) are the prerequisites for a beneficial net brain drain.

Every period one local monopolist in the intermediate sector i has the chance to manufacture intermediate goods at the technology level $A_{i,t}$ using final goods one-to-one as input. The current level of A_i is determined endogenously through a labor allocation process which will be described below. The monopolist maximizes her profits

$$\pi_{i,t} = p_{i,t}x_{i,t} - x_{i,t}$$

by choosing the supply of x. Given the competitiveness of the final good sector, the price of the intermediate product is equal to its marginal product

$$p_{i,t} = \frac{\partial y_t}{\partial x_{i,t}} = \alpha A_{i,t}^{1-\alpha} x_{i,t}^{\alpha-1}$$

such that

$$FOC: \quad \frac{\partial \pi_{i,t}}{\partial x_{i,t}} = 0 \quad \Longleftrightarrow \quad x_{i,t} = \alpha^{\frac{2}{1-\alpha}} A_{i,t}$$

whereupon solving for equilibrium profits yields $\pi^* = (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} A_{i,t} = \delta A_{i,t}$

3.2.1 Technological Progress

Technological progress is achieved by a combination of imitation and innovation (based on Vandenbussche et al. 2006, who follow Benhabib and Spiegel 1994 and Acemoglu et al. 2006). Imitation refers to the process of adopting technology from the frontier, whereas innovation indicates the enhancement upon the local productivity level by means of developing new technology. Both processes require skilled as well as unskilled labor, although at different intensities. At the beginning of each period the entrepreneur in sector i decides upon the amount of skilled and unskilled labor allocated to each activity in order to maximize the productivity level A.

Following Lodigiani (2008), productivity dynamics are given by

$$A_{i,t} = A_{i,t-1} + \varphi(D_t) u_{m,i,t}^{\beta} s_{m,i,t}^{1-\beta} (\bar{A}_{t-1} - A_{t-1}) + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{1-\phi} A_{t-1} \tag{7}$$

Where $\bar{A}_{t-1}$ is the world technology frontier at $t-1$, A_{t-1} is the local productivity level at the end of the last period, $u_{n,i,t}$ ($s_{n,i,t}$) is the amount of unskilled (skilled) labor employed in innovation in sector i at time t, and $u_{m,i,t}$ ($s_{m,i,t}$) denotes the equivalent for the imitation sector. $\gamma > 0$ captures the relative efficiency of innovation relative to imitation. The effect of imitation on local technology is determined by two factors, where one influences the productivity of the process and the other the magnitude of the change induced by it. The first component concerns emigration: $\varphi(D_t)$ captures the impact of the skilled diaspora D_t on imitation (with $\varphi'(D_t) > 0$ and $\varphi''(D_t) < 0$). Emigrants abroad work with the most advanced technology available, at maximum productivity. As explained in section 2, these networks generate knowledge spillovers to the home country which, in turn, facilitate the adoption of these technologies there. Intuitively, as modeled here, this effect increases with the diaspora but depreciates once a certain size has been reached. The second factor relates to the country's distance to the frontier and mirrors the so-called "advantage of backwardness" (Gerschenkron 1962). The less developed the economy, i.e. the bigger $(\bar{A}_{t-1} - A_{t-1})$, the more substantial the forward leap in productivity caused by imitation of leading technology.

The parameters β and ϕ reflect the elasticity of unskilled workers in imitation and innovation respectively. Following Nelson and Phelps (1966) it is assumed that $\beta > \phi$, meaning skilled workers are relatively more productive in innovation than in imitation. The rationale behind this is quite straightforward: As explained above, imitation is a process of copying already developed technology. This follows an established and known technique that requires routine rather than comprehension. On the other hand, innovation is a more complex activity that calls for expertise in the underlying subject which can best be provided by workers with a higher level of human capital.

3.2.2 Productivity Maximization

As already mentioned in section 3.1 we let wages depend on the local productivity level such that income differentials mirror the development gap between the countries. Thus, wages are given by $w_u A_{t-1}$ and $w_s A_{t-1}$ for skilled and unskilled workers respectively[11]. Given the quasi-infinite number of equal firms in the intermediate sector, each individual firm does not internalize its impact on the aggregate productivity level and therefore on its labor cost. Thus, monopolists will allocate skilled and unskilled labor across imitation and innovation activities to maximize

$$\begin{aligned} \max_{u_{m,i}, u_{n,i}, s_{m,i}, s_{n,i}} \; & \delta \left[1 + \varphi(D_t) u_{m,i,t}^{\beta} s_{m,i,t}^{1-\beta} (1/a_{t-1} - 1) + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{1-\phi}\right] A_{t-1} \\ & - \left[w_u A_{t-1}\left(u_{m,i} + u_{n,i}\right) + w_s A_{t-1}\left(s_{m,i} + s_{n,i}\right)\right] \end{aligned} \tag{8}$$

Where $a_{t-1} = \frac{A_{t-1}}{\bar{A}_{t-1}}$ is the proximity to the technology frontier. Given that all firms are equal, they encounter the same maximization problem such that in equilibrium

$$u_{m,i,t} = u_{m,t}\, , u_{n,i,t} = u_{n,t}, s_{m,i,t} = s_{m,t}, s_{n,i,t} = s_{n,t}$$

[11] Redefining wages to be fully harmonized across firms and individuals, i.e. rewriting $\sigma w_t A_{t-1}$ instead of $w_s A_{t-1}$ does not affect our results and is therefore refrained from for convenience.

Consequently, the effect on productivity will be equal for all sectors i, such that

$$A_t = \int_0^1 A_{i,t} di = A_{i,t}$$

The full employment condition in the labor market dictates

$$U = u_{n,t} + u_{m,t} \quad ; \quad S = s_{n,t} + s_{m,t} \tag{9}$$

where U is the total stock of unskilled labor and S is the stock of skilled remaining in the country after emigration, determined according to the process described in section 3.1.

After some manipulation we obtain[12]

$$(\psi - 1)s_m = f(a, D)U - S \tag{10}$$

where $f(a, D) = \left(\frac{\varphi(D)\left(\frac{1}{a}-1\right)(1-\beta)\psi^{\beta}}{(1-\phi)\gamma}\right)^{\frac{1}{\beta-\phi}}$ and $\psi = \frac{\beta(1-\phi)}{\phi(1-\beta)} > 1$

Assuming interior solutions, i.e. when both imitation and innovation are carried out in equilibrium, the relative intensities of labor are given by

$$\frac{u_m}{s_m} = \frac{\psi}{f(a, D)} \tag{11}$$

$$\frac{u_n}{s_n} = \frac{1}{f(a, D)} \tag{12}$$

All derivations can be found in Appendix A. $f(a, D)$ is an increasing function of D and thereby m, and decreases with a. The implications of (11) and (12) are best summarized in the following Lemma:

> "*When both imitation and innovation are performed in equilibrium, the optimal amount of skilled and unskilled labor employed in imitation is increasing (resp. decreasing) in the total number of unskilled (resp. skilled) units of labor U (resp. S), and decreasing in the distance to the frontier a."* (Vandenbussche et al. 2006, p. 105).

In other words, the reallocation effects are similar to the Rybczynski theorem of international trade. The rationale for these findings is the following. Given the higher productivity of unskilled labor in imitation relative to innovation ($\beta > \phi$) it is optimal for firms to reallocate unskilled workers to imitation when

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[12] Time indices are removed for convenience.

U increases. As a result, the marginal productivity of skilled labor rises in imitation, drawing trained workers away from the innovation sector. This reinforces the relative drop of productivity of unskilled labor in innovation which triggers a further reallocation of units into the imitation sector. In contrast, a relative increase in the endowment of skilled labor will have the opposite effect and ultimately lead to a rise in total employment in the innovation sector, independent of the type of labor.

The relationship to the proximity to the frontier a is explained by the relative efficiency of innovation and imitation activities at different levels of technological development. Distant to the frontier, when a is low and thereby $f(a, D)$ is large, it is more profitable for firms to employ labor in imitation since the catch-up effect is fairly large. As the economy develops and approaches the frontier, the advantage of backwardness fades and it becomes more attractive to stimulate the innovation sector.

Finally, an exogenous increase in the skilled emigration rate m has heterogeneous effects. First, for any given level of development there will emerge the tendency to push resources towards imitation. This is driven by the growth of the skilled diaspora which promotes the relative efficiency of imitation activities. Moreover, in the poorest countries this effect may be reinforced by the net decrease in skilled labor. This triggers a reallocation of labor into the imitation sector in order to exploit the productivity advantage of unskilled workers. As explained earlier, similar human capital outcomes are presumed in the high-income nations such that the economies experience the same shift towards imitation following a rise in the migration rate. Finally, for intermediate levels of a the net effect on human capital is ambiguous. Therefore, it is possible that no significant reallocation occurs, or that the increase of skilled labor even renders innovation more attractive.

3.3 Growth

In equilibrium the productivity growth rate is given by

$$g_{i,t} = \int_0^1 \frac{A_{i,t} - A_{t-1}}{A_{t-1}} di = \frac{A_t - A_{t-1}}{A_{t-1}} = g_t \tag{13}$$

Which can be rewritten to

$$g_t = \gamma\left[\phi f(a, D)^{1-\phi}(1 - \bar{S}) + (1 - \phi) f(a, D)^{-\phi} \bar{S}\right] \tag{14}$$

Where $\bar{S}$ is given by equation (5).

Following Lodigiani (2008) we use the total differential to divide the total impact of migration on growth into two channels:

$$\frac{1}{\gamma}\frac{dg}{dm} = \underbrace{\frac{\partial g}{\partial f(a,D)}\frac{\partial f}{\partial m}}_{\text{Diaspora effect}} + \underbrace{\frac{\partial g}{\partial \bar{S}}\frac{\partial \bar{S}}{\partial m}}_{\text{Human capital}}$$

The first refers to the skilled diaspora's effect on technology adoption, the other channel operates via the country's human capital endowment. For clarity, we will study these individually.

3.3.1 Diaspora Channel

$$\frac{\partial g}{\partial f(a,D)}\frac{\partial f}{\partial m} = \frac{\varphi'(D)}{\varphi(D)}\frac{\phi(1-\phi)}{\beta-\phi}\left[f(a,D)^{1-\phi}(1-\bar{S}) - f(a,D)^{-\phi}\bar{S}\right]$$

Given the assumptions made on $\varphi(D)$, β and ϕ the marginal effect will be positive if the term in the bracket is > 0. Formally this is the case when $f(a,D) > \frac{\bar{S}}{\bar{U}}$. More intuitively, the effect of migration on technology adoption, and thereby growth, will be beneficial as long as some labor is dedicated to imitation (Lodigiani 2008). Two factors determine the magnitude of this growth-promoting effect: the distance to the frontier a via $f(a,D)$ and the skilled labor share $\bar{S}$. Following the rationale from section 3.2, the size of the diaspora effect increases with the distance to the frontier as the importance of imitation grows at lower levels of development.

$$\left(\frac{\partial g}{\partial f(a,D)}\frac{\partial f}{\partial m}\right)\frac{\partial}{\partial a} = \frac{\varphi'(D)}{\varphi(D)}\frac{\beta(1-\phi)}{\beta-\phi}\left[(1-\phi)(1-\bar{S})f(a,D)^{-\phi} + \phi\bar{S}f(a,D)^{-(1+\phi)}\right]\frac{\partial f}{\partial a}$$

Which is always negative as $\frac{\partial f}{\partial a} < 0$. At the same time, a rise in the share of skilled labor will depress the impact. As relatively more trained units become available firms allocate more workers into the innovation sector at the expense of imitation.

$$\left(\frac{\partial g}{\partial f(a,D)}\frac{\partial f}{\partial m}\right)\frac{\partial}{\partial \bar{S}} = -\frac{\varphi'(D)}{\varphi(D)}\frac{\phi(1-\beta)}{\beta-\phi}\left[f(a,D)^{1-\phi} + f(a,D)^{-\phi}\right] < 0$$

3.3.2 Human Capital Channel

As mentioned above, the second channel through which the emigration of skilled affects productivity growth is human capital. In order to bring the impact of migration on skill formation and that of human capital on growth together it is useful to first clarify the roles different types of labor play in the growth process.

From section 3.2 we know that the efficiency of the two productivity enhancing activities depends on the distance to the frontier. Imitation is more effective at low levels of development whereas innovation becomes more important closer to the frontier. Furthermore, recall that both types of labor have different marginal productivities across the activities, with skilled labor working more efficiently in innovation and unskilled labor in imitation. This implies that skilled labor is more growth-enhancing the closer the economy is to the frontier and unskilled labor is the prime driver of growth at greater distances from it. Formally this is mirrored in the ambiguity of the derivative of growth with respect to the skilled labor share

$$\frac{\partial g}{\partial \bar{S}} = -\phi f(a,D)^{1-\phi} + (1-\phi) f(a,D)^{-\phi} \lesseqgtr 0$$

The condition for positivity is $\frac{1-\phi}{\phi} > f(a,D)$. It expresses that a reallocation of labor into innovation, following a rise in the skilled labor share $\bar{S}$, must productivity-wise compensate for the thereby induced production drop in imitation. Since the productivity of imitation increases through knowledge transfers from the diaspora, this becomes harder the larger the emigrant community is.

$$\frac{\partial g}{\partial \bar{S}} \frac{\partial}{\partial D} = \left[-\phi(1-\phi) f(a,D)^{-\phi} - \phi(1-\phi) f(a,D)^{-(1+\phi)}\right] \frac{\partial f}{\partial D} < 0$$

At the same time, a higher level of development facilitates this, since $\frac{\partial f}{\partial a} < 0$.

$$\frac{\partial g}{\partial \bar{S}} \frac{\partial}{\partial a} = \left[-\phi(1-\phi) f(a,D)^{-\phi} - \phi(1-\phi) f(a,D)^{-(1+\phi)}\right] \frac{\partial f}{\partial a} > 0$$

With these inferences we can next examine what the overall effect looks like. Formally it is given by

$$\frac{\partial g}{\partial \bar{S}} \frac{\partial \bar{S}}{\partial m} = \left[-\phi f(a,D)^{1-\phi} + (1-\phi) f(a,D)^{-\phi}\right] \frac{\partial \bar{S}}{\partial m}$$

Where $\frac{\partial \bar{S}}{\partial m} = \frac{2(1-m)\frac{\partial h}{\partial m} - h(2-h)}{(2-mh)^2}$

Clearly, this will be positive only when both terms have the same sign. This means that a depreciating effect of emigration on net human capital can only be positive for growth in a country with a low level of development or a sufficiently large diaspora, i.e. where imitation activities are the main driver of growth. On the other hand, a net Brain Gain enhances productivity growth only when the innovation sector sufficiently compensates for the loss in imitation.

More important, however, are the scenarios in which migration leads to negative growth. In these cases, migration causes such a distortion in the composition of the labor supply that firms must deviate from their optimal employment choices, which lowers the growth rate. According to the model, this kind of disruption can be observed in advanced economies. The attenuation of the incentive effect at close ranges to the frontier increases the likelihood for a diminished ex post share of skilled in the economy. At the same time, the importance of the innovation sector, and thereby educated workers, grows with the proximity to the frontier, as the catch-up effect from imitation depreciates.

3.3.3 Implications

Our main implications can be summarized as follows:

As in Lodigiani (2008), the beneficial impact of the skilled diaspora on growth is stronger in imitation-intensive economies and loses importance as the economy approaches the technological frontier. Thus, at low and intermediate levels of a, an increase in the migration rate promotes growth both through the incentive effect and by increasing the size of the diaspora.

However, in economies that are at the lowest level of development, the extreme poverty may lead to binding budget constraints on educational decisions, thereby inhibiting the human capital promoting effect of skilled migration and leading to a net loss of skilled labor. However, this need not be detrimental for growth, as at great distances to the frontier unskilled labor and technology imitation are believed to be the prime drivers of development. Nonetheless, this suggest that remittances are most useful for households in lower-income economies in promoting investments in education.

Instead, when the income premium of emigration is too low, an increase in expected migration does not incentivize individuals to invest in education. This case applies to economies operating close to the technological frontier. Since skilled workers in the innovation sector are the prime drivers of growth in these economies, an increase in the emigration rate is expected to have detrimental impacts on the growth rate.

4 Empirical Analysis

Having established the main testable predictions in chapter 3, the aim of this section is to analyze their empirically validity. Specifically, the heterogeneity of the explained relationships with respect to the levels of development are investigated. It should be noted that we estimate a linearized version of the productivity growth equation given by (14) and the incentive effect function (3), which does not reflect functional form. Thus, estimation attempts only to replicate the signs of the derivative of interest and to evaluate the economic significance of the respective coefficient.

4.1 Data Description

I collect data from six different sources to construct a panel consisting of 111 countries between 1980 and 2014 in five-year intervals[13]. We mostly follow the procedure by Lodigiani (2008, LOD) and Vandenbussche et al. (2006, VAM).

4.1.1 Migration Data

Data on skilled migration is taken from Brücker et al. (2013). Based on population registries and census data on the immigrant population aged 25 and over from 20 OECD member states, their panel provides data on emigration rates and stocks by country of origin, educational attainment and sex for 195 countries. The variables we obtain from this database are the skilled emigration rate and the total skilled diaspora.

The emigration rate of skill type e from country i at time t is measured according to

$$m_{e,t}^{i} = \frac{M_{OECD20,e,t}^{i}}{R_{e,t}^{i} + M_{OECD20,e,t}^{i}}$$

Where $M_{OECD20,e,t}^{i}$ is the total stock of emigrants of the same category from country i living in the 20 receiving states combined and $R_{e,t}^{i}$ is the resident population in i of the same education level[14]. By

[13] The last interval consists of only four years, i.e. 2010-2014.

[14] As the gender perspective is not subject of our work, we don't categorize according to sex and add stocks of both genders together.

weighing the emigrants with the total workforce of their country – emigrant and resident –, this variable is a direct indicator of the human capital loss suffered through emigration.

The size of the diaspora of country i at time t is therefore simply given by

$$D_t^i = \sum_{k=1980}^{t} M_{OECD20,e,k}^i$$

4.1.2 Human Capital Data

As is standard in the literature, we combine two datasets to obtain data on educational attainment[15]: Barro and Lee (2013) for developing and emerging economies and de la Fuente and Doménech (2015) for 22 OECD states. Both give detailed information on the skill structure of the population, the average years of schooling and the share of adults (age 25+) belonging to each of six (D&D) or seven (B&L) categories of educational attainment[16]. When considering the share of skilled adults for our regression we follow the definition by Brücker et al. (2013) and unite the upper two sections of both datasets, thereby including anyone with post-secondary education, whether graduated or not. While this is a fairly broad classification, it is essential for developing countries where the proportion of degree- holding adults in the labor force isn't seldom lower than 1%.

4.1.3 Economic and Financial Data

Data on remittances is taken from the World Bank (2018). The information on capital inflows is based, among other sources, on data from IMF Balance of Payments Statistics and data releases from national central banks. The data, given in current nominal USD, is deflated to obtain values in constant 2011 USD and ensure compatibility with GDP data. Subsequently, it is divided by output to obtain remittances' share of GDP.

Finally, we take capital stock and GDP data from the Penn World Tables 9.0, constructed by Feenstra et al. (2015). The database contains yearly data on several economic indicators from 1950-2014 for a large number of countries. The latest version of the dataset provides a measure of the capital stock by country which had not been available for the studies by VAM or LOD who instead construct the variable using a perpetual inventory method. Despite our intentions of following their methodology, we rely on

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[15] see e.g. Docquier and Marfouk 2006; Artuç et al. 2015; Vandenbussche et al. 2006 and more.

[16] B&L: no schooling, some primary, complete primary, some secondary, complete secondary, some tertiary, complete tertiary. D&D: illiterate, primary, lower secondary, upper secondary, lower tertiary, upper tertiary.

the data by Feenstra et al. (2015) for our regressions. As the PWT measure is the result of careful estimation and data collection it should provide a more appropriate value of the capital stock, as the perpetual inventory method relies on a series of assumptions that may lead to inconsistent results.[17]

As a next step we construct the dependent variable, total factor productivity (TFP) which is given by the Solow residual according to

$$A_{i,t} = \ln\left(\frac{Y_{i,t}}{L_{i,t}}\right) - capsh * \ln\left(\frac{K_{i,t}}{L_{i,t}}\right)$$

Where Y is output, L is the working-age population, $capsh$ indicates the output elasticity of capital and K is the capital stock. To obtain output and capital per worker, data on the population between the ages of 15-64 is taken from the United Nations Population Division (2017)[18]. Data on capital shares is taken from the PWT. VAM and LO assume constant labor shares of .7, implying a capital elasticity of .3 across all countries and years. This is a common approach in development accounting (see e.g. Topel 1999, Bernanke and Gürkaynak 2001), but is hardly supported by empirically findings. The PWT9.0 provide a new country specific and time-variant estimate of the labor share of output. It accounts for the perpetual increase of capital shares in GDP that has been observed over time, and, with an average of 0.52, points to a systematic underestimation of capital elasticity in the literature (Feenstra et al. 2015). Given the high variety of economies in our sample, we deem the variable a more appropriate measure.

Using TFP, the distance to the technological frontier is defined as the ratio of a country's productivity level to that of the US. Although according to the calculations the USA is not in all years the most technological advanced economy, it is by far the prime destination for emigrants from all over the world, even more so for highly-educated migrants. Importantly, this is also true for scientists and academics from Western European countries, with an equally high standard of living, whose calculated TFP level exceeded that of the US in several years.[19]

The sample of countries is then obtained by the intersection of these 6 datasets. Table 1 provides descriptive statistics on the most important variables.

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[17] For example, the formula is based on the assumption that the rate of capital accumulation is equal to GDP growth. Furthermore, VAM and LOD assume constant depreciation rates of 6% and 3% respectively for all countries. These are unlikely to mirror the individual rates of the large variety of countries in our sample.

[18] Vandenbussche et al. (2006) use the World Development Indicators as the source for labor force data. However, in order to maintain consistency with our migration data, which is based on UN population data, we do not follow their lead.

[19] In these cases we use the US' TFP level as upper limit in order to maintain consistency with the proximity variable. Furthermore, we follow Brücker et al. (2013) and aggregate East and West Germany, North and South Sudan, and North and South Korea. Due to data limitations on educational attainment, we only consider West Germany before the reunification.

Table 1 Summary Statistics

	Number of observations	Mean	SD	Min	Max
Productivity Growth	648	0.01	0.16	-0.65	0.92
Distance to Technology Frontier	648	-1.26	0.71	-3.67	0.00
Skill Share	529	0.13	0.10	0.0002	0.60
Diaspora	529	1.5e+05	2.5e+05	100.0	1.9e+06
Emigration Rate	529	0.14	0.15	0.0009	0.83
Remittances/GDP	589	0.013	0.027	0.00	0.35

Note: The statistics presented in this table are based on the basline estimates depicted in Table 2.

4.2 Empirical Specification

Following LOD and VAM we set up the following empirical model

$$g_{i,t} = \beta_0 + \beta_1 a_{t-1} + \beta_2 h_{t-1} + \beta_3 D_{t-1} + \beta_4 m_{t-1} + \beta_5 rem_{t-1} + \beta_6 a_{t-1} * h_{t-1} + \beta_7 a_{t-1} * D_{t-1} + \beta_8 a_{t-1} * m_{t-1} + \beta_9 a_{t-1} * rem_{t-1} + \varepsilon_{i,t}$$

Where $g_{i,t}$ is the growth rate of TFP, given by $\ln A_{i,t} - \ln A_{i,t-1}$, and $A_{i,t}$ is total factor productivity in country i at time t. a_{t-1} gives a country's distance to the technological frontier in the previous period, calculated according to $\ln A_{t-1} - \ln \bar{A}_{t-1}$. Note that this variable is negative per construction. Thus, a negative coefficient would confirm a catching-up effect of less developed nations. The lagged share of tertiary educated adults in the labor force is given by h_{t-1}, the variable D_{t-1} represents the log of the skilled diaspora abroad in the previous period. Both are expected to enhance productivity growth, however differently so at diverging levels of development. m_{t-1} is the emigration rate of skilled in the previous period and rem_{t-1} represents the remittances inflow as a share of GDP. What follows are interaction terms of all variables with the proximity term. Finally, β_0 represents country dummies which are added to capture unobserved country-specific factors that may influence productivity. Moreover, when included in the regression, they eliminate serial correlation. In addition, all regressions are run with time dummies for each year to control for time-dependent shocks.

Furthermore, in order to test the effect of migration on human capital formation, we estimate

$$g_t^{exante} = \alpha_0 + \alpha_1 a_{t-1} + \alpha_2 rem_{t-1} + \alpha_3 m_{t-1} + \alpha_4 a_{t-1} * rem_{t-1} + \alpha_5 a_{t-1} * m_{t-1} + \omega_{i,t}$$

Where g_t^{exante} denotes the growth rate of the pre-emigration stock of skilled. The reason for using the growth rate, as opposed to for example the share of skilled, is to control for the global trend of increasing educational attainment. Thus, our regression tests if emigration prospects, via the incentive effect, enhance the human capital accumulation even further. α_0 are, as before, country dummies, which will be alternated with a Sub-Sahara Africa dummy $SSAD$. All other variables remain as in the first specification and again, time dummies are included in each regression.

Before conducting any estimations, we first address some econometric issues. A particular concern is the endogeneity of the distance variable, remittances' share of GDP and the emigration rate. The former two are per construction linked to the lagged values of the dependent variable. At the same time the emigration decision of skilled workers naturally depends on the economic situation in their home country. Push factors may include a limited availability of suitable employment, low income, or lack of funding for scientific research. Regarding the second specification, reverse causality between the human capital level and the emigration rate could be an issue. A higher initial share of educated among natives implies, ceteris paribus, a bigger proportion of teachers, which in turn increases the quality of education. A high standard of schooling facilitates the transfer of skills onto foreign labor markets and thus decreases international employment frictions in for potential emigrants. Immigration policies of developed countries, comparable to quota systems, potentially constitute another source of simultaneity. If the destination country only grants immigration to a certain number of skilled workers a higher share of educated among natives would lower the chances of emigration for each individual (Beine et al. 2011).

Therefore, we implement as instruments the log distance to the frontier lagged twice, the emigration rate and the remittances variable lagged two periods, the two previous period's share of skilled among the labor force and all interaction terms lagged twice.[20] Despite the ad hoc nature of using lagged endogenous variables as instruments, this method may be less problematic than alternative instruments, as these typically skew the sample towards high-income economies due to an uneven data coverage. Finally, we apply robust standard errors to control for heteroscedasticity. The estimation method we will use is Instrumental Variables on within-group variation, as we eliminate country-specific effects through dummies. This method of fixed effects is known to produce downward-biased results in short panels (Nickell 1981). However, as LOD suggest, it may be more appropriate than a first-difference estimator, as the latter would exhibit an even greater bias. Given the high persistence of the variables, the instruments are inadequate to predict first differences in human capital levels and distance to the frontier, thus distorting the results of the first-difference estimator.

[20] The reason for taking the second lag is to balance the elimination of endogeneity with the preservation of a sufficient number of observations, given the brevity of the time dimension (see LOD, VAM).

4.3 Estimation Results

4.3.1 TFP Growth Equation

Following LOD, we begin with pure level regressions and add the interaction terms with the proximity variable later. Moreover, the first regressions are run including only the diaspora variable as an effect of migration and add both the emigration rate and the remittances' share of GDP in a second specification. The result of the TFP growth specification are given in Table 2 below. The results of the first stage estimation can be found in Appendix B.

We will focus on the results of the specification excluding remittances and the emigration rate first (columns 1-4). The coefficient for the skilled labor share is positive and highly significant in all specifications, thus confirming the importance of educated workers for innovation. Regarding the variables individually, evidence for a backward advantage of less developed economies is found in the highly significant negative coefficient of the lagged distance to the frontier. In turn, the coefficient for the logarithm of the diaspora validates the productivity-enhancing impact of skilled emigrants abroad. The estimated effect of the interaction term of proximity to the frontier and the diaspora is as predicted by theory, once country characteristics are accounted for: the skilled diaspora, and thus imitation, is more relevant for productivity enhancement far from the frontier. However, no other variables remain significant once the interaction terms are included.

The same pattern is observed once the emigration rate and remittances' share of GDP are added. While remittances are found to be beneficial for growth individually, they become insignificant once we allow country dummies to capture unobserved determinants on TFP and remain so when interacted with the distance to the frontier. Similarly, an increase in the emigration rate is productivity-enhancing only when country-specific factors are controlled for and interaction terms are excluded. Remarkably, albeit only weakly significant, the diaspora effect turns negative when the other feedback effects of the brain drain, together with country dummies, are added.

Table 2 : TFP Growth Specification

	excluding emigration rate and remittances				including emigration rate and remittances			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Proximity	-0.0467***	-0.913***	0.00606	0.292	-0.0434***	-0.262***	-0.116	-0.151
	(0.0141)	(0.146)	(0.0704)	(0.304)	(0.0131)	(0.0961)	(0.0861)	(0.334)
Skill share	0.00191***	0.00622**	0.00205*	0.0153***	0.00184**	0.000908	0.00114	0.000961
	(0.000718)	(0.00307)	(0.00120)	(0.00554)	(0.000749)	(0.00253)	(0.00115)	(0.00520)
Diaspora	0.0100**	0.0775*	0.000449	-0.0526	0.00557	-0.0319*	0.0159	-0.0528*
	(0.00410)	(0.0456)	(0.0118)	(0.0544)	(0.00463)	(0.0165)	(0.0120)	(0.0290)
Emigration rate					0.000221	0.00878***	-3.78e-05	0.00103
					(0.000526)	(0.00310)	(0.00151)	(0.00519)
Remittances/GDP					0.00285*	0.00866	0.00642	0.0791
					(0.00170)	(0.00666)	(0.0142)	(0.0688)
Proximity * Skill share			1.23e-05	0.00269			-0.000727	-0.00197
			(0.00116)	(0.00443)			(0.00131)	(0.00466)
Proximity * Diaspora			-0.00558	-0.114***			0.00769	-0.0258
			(0.00748)	(0.0289)			(0.00840)	(0.0349)
Proximity * Emigr. Rate							-0.000224	-0.00390
							(0.000945)	(0.00275)
Proximity * Rem/GDP							0.00220	0.0542
							(0.00790)	(0.0489)
Observations	648	648	558	558	539	539	539	539
R-squared	0.040	0.178	0.046	0.253	0.037	0.189	0.037	0.292
Country FE	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include year fixed-effects.

4.3.2 Incentive Effect Equation

We observe the same pattern in our second specification. Our pure level regressions (columns 1, 2 and 3), show a strong negative effect of emigration on the growth of the *ex ante* stock of educated labor, both in the baseline specification and when the Sub-Sahara Africa dummy is included. At the same time proximity to the frontier promotes the growth rate. In turn, remittances are only found to benefit human capital formation once country-specific factors are controlled for. Thereafter, once the proximity interaction terms are added, the whole regression loses explanatory power.

Table 3: Incentive Effect Equation

	dependent variable: growth rate of exante skill stock					
	Baseline (1)	*SSAD* (2)	*Country FE* (3)	*Interaction* (4)	*SSAD* (5)	*Country FE* (6)
Emigration Rate	-0.0439***	-0.0451***	-0.0638	-0.0184	-0.0187	-0.0118
	(0.0107)	(0.00916)	(0.0636)	(0.0186)	(0.0185)	(0.183)
Proximity	1.308***	0.562**	0.0381	0.0256	0.0145	-7.072
	(0.221)	(0.262)	(1.051)	(0.138)	(0.156)	(15.01)
Remittances/GDP	-0.0537	-0.0186	0.600***	0.109	0.107	0.433
	(0.0867)	(0.0859)	(0.137)	(0.128)	(0.129)	(1.238)
Proximity * migr. Rate				-0.0113	-0.0115	0.0257
				(0.0101)	(0.00995)	(0.217)
Proximity * Rem/GDP				0.0574	0.0562	0.341
				(0.0711)	(0.0723)	(0.939)
SSAD		-2.377***			-0.0464	
		(0.390)			(0.238)	
Constant	2.707***	2.256***	0.796	0.324	0.319	-7.540
	(0.445)	(0.440)	(1.338)	(0.256)	(0.258)	(14.33)
Observations	343	343	343	438	438	438
R-squared	0.183	0.268	0.570	0.004	0.004	
Country FE	NO	NO	YES	NO	NO	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include year fixed effects.

Since the loss in significance seems to be directly related to the proximity variable, we estimate a variant of the specification replacing a_{t-1} with a category variable for income level. We thereby aim to avoid any remaining endogeneity issues and misspecification related to the proximity term. The variable *CLASS* categorizes four different income levels: 1 represents lower middle income, 2 upper middle income and 3 high income economies. The base category 0 represents low income countries[21]. The results of the estimation are given in table 4 below.

[21] We follow the methodology by Beine et al. (2011), using income classifications from the World Bank based on GNI/capita data.

Table 4: World Bank Income Group Classification

	growth rate of exante skill stock		
	Baseline	*SSAD*	*Country FE*
	(1)	*(2)*	*(3)*
CLASS			
Lower-middle income	2.012***	1.213**	1.919**
	(0.524)	(0.481)	(0.770)
Upper-middle income	2.225***	1.322**	1544
	(0.604)	(0.578)	(0.985)
High income	2.781***	1.523**	1499
	(0.634)	(0.646)	-1349
Emigration			
Low income * m	-0.00345	0.00175	0.0204
	(0.0174)	(0.0149)	(0.0175)
Low-mid income * m	-0.0237	-0.0224	-0.0184
	(0.0171)	(0.0143)	(0.0200)
Up-mid income *m	-0.0324**	-0.0353**	-0.0108
	(0.0148)	(0.0155)	(0.0187)
High income * m	-0.0581***	-0.0605***	-0.0286
	(0.0119)	(0.0121)	(0.0203)
Remittances			
Low income * rem	0.0524***	0.0526***	0.0932***
	(0.0167)	(0.0122)	(0.0325)
Low-mid income * rem	-0.167*	-0.140**	-0.109
	(0.0855)	(0.0643)	(0.0969)
Up-mid income *rem	-0.146	-0.178	-0.140
	(0.184)	(0.200)	(0.164)
High income * rem	0.402**	0.400**	0.287*
	(0.169)	(0.178)	(0.168)
SSAD	-	-2.470***	-
		(0.421)	
Constant	-1.171**	0.109	-2.139***
	(0.518)	(0.509)	(0.435)
Observations	480	480	480
Number of ID	131	131	131
Country FE	NO	NO	YES
Year FE	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include year fixed effects.

The estimates confirm our main implications on the heterogeneity of the incentive effect with respect to the level of development. Highly significant negative coefficients of emigration rates interacted with upper-middle and high-income economies reflect the failure of migration prospects to generate an incentive for additional schooling and thus imply a direct loss of human capital from emigration suffered in wealthier nations. Additionally, we find an alleviating effect of remittances on budget constraints that bind on schooling decisions, and thereby add to the evidence that households do spend remittances on education. We consider this as an indicator for poverty as a crucial inhibitor of human capital formation in the least developed regions. However, these implications should be taken with some caution as the same positive effect of remittances is found in high income economies. Finally, our results clearly show a general human capital advantage of more wealthy nations, which can most likely be attributed to their longer history of public investments in schooling.

4.3.3 Analysis

Despite the more encouraging findings with respect to the incentive effect, the results of the productivity growth estimation clearly contradict the predictions of the theoretical model. Specifically, the heterogeneity of the effects with respect to the level of development, one of the main implications of our theoretical model cannot be reproduced empirically. As can be seen in section 3, endogenizing human capital formation and adding remittances to the model leads to changes in the final outcome that are too marginal to cause such a distortion in the empirical results. Therefore, it is unlikely that our extension of the theoretical model is the culprit in this respect. Instead, the difference is most likely rooted in the empirical model. Specifically, we suggest that some of the findings of the previous study by LOD may be driven by empirical misspecification and data selection.

The first shortcoming is linked to the choice of migration data. LOD considers exclusively U.S. immigration data as a proxy for the skilled diaspora. This disregards emigration to other destinations, which particularly affects the African region where colonial ties and common language are crucial determinants for emigration to European economies. We avoid this potential bias by relying on a dataset on migration which is based on immigration census from 20 destination countries. Secondly, by considering only the emigrant stock as opposed to the emigration rate, LOD's estimation does not account for the real loss of human capital suffered through emigration. Clearly, populous countries may have large diasporas while maintaining low emigration rates, thereby experiencing relatively small human capital losses at the same time as significant gains through network effects. Indeed, both China and India are among the Top 10 countries by size of the skilled diaspora during the last 25 years of our sample, however, neither country has ever borne emigration rates of more than 5% (Brücker et al. 2013).

Finally, the construction of the capital stock variable using a perpetual inventory method is based on several assumptions that are unlikely to apply for the entire panel. A prime concern is that the steady-state approach, followed by LOD, is based on the neoclassical initial condition that the country is in equilibrium, implying that capital accumulates at the same rate as GDP grows. Hence, estimates of the initial capital stock are easily biased by short-term shocks on output or investment, which then carry on throughout the series (Berlemann and Wesselhöft 2014)[22]. Moreover, given the brevity of the time dimension, the error generated by the initial condition is directly transferred to the productivity estimate[23]. Assuming a constant depreciation rate of 3% reinforces this problem. In fact, Feenstra et al. (2015) provide yearly, country-specific estimates of the depreciation rate that range from 1.3% to 10.4% and have an average of 4.6%. These diverging parameters suggest that such general assumptions may be inadequate for such wide varieties of economies.

These factors certainly introduce a bias to the estimation of the brain drain's impact on productivity growth by LOD and could therefore be a main driver of the obtained estimates. Nonetheless, having controlled for these shortcomings in our study we obtain contradicting results to our theoretical hypotheses. This suggests that there are several additional flaws in our specification to be addressed in further research.

As explained in section 2, the direct effect of remittances on growth is ambivalent and often difficult to estimate. As Clemens and McKenzie (2018) point out, using remittances' share of GDP as a proxy for the macroeconomic relevance of the capital flows may be one of the reasons for this. They argue that while GDP is not constructed to directly include remittance receipts, through its formula the variable implicitly assumes that the capital inflows have no contemporaneous impact on output, but only enhance growth in later periods.

We identify the main weakness of our empirical model, however, to be linked to the total factor productivity related variables. This inference finds support in the improvement of our estimation's explanatory power once these terms are replaced in section 4.3.2. While estimating productivity using a standard Solow residual method is a convenient way to obtain a TFP measure, it features a series of weaknesses besides the already mentioned absorption of measurement errors by the residual.

Per construction, the residual captures any determinants of economic growth that are unaccounted for by labor and capital. Subsuming all these unobserved factors under the term productivity is a massive simplification and can easily lead to overestimations. This is best illustrated using the example of natural resources: following the methodology of LOD, the capital stock construction based the assumptions on

[22] For example, following the methodology by LOD we find that due to negative GDP growth in Cambodia during the 1970s and 80s the initial capital stock turns out negative, thus causing a permanent underestimation of capital in Cambodia. Clearly, estimation bias leading to negative capital stocks is easily detected and dealt with, however, this is not the case for overestimations.

[23] The only way to alleviate this problem is by calculating the initial capital stock far in the past of the actual estimations. LOD estimate the capital stock for their panel between 1980-2000 in 1980, most likely due to lack of data.

depreciation rate and capital shares, we find a rigorous overestimation of productivity that is almost exclusive to the oil-abundant Gulf States[24]. Moreover, due to the growth accounting model's simple form, one cannot consider labor and capital uncorrelated with the residual, which implies biased estimates. Instead, factor accumulation is driven by unobserved technological progress. Thus, the information we obtain from the coefficients is not the share of economic progress that can be attributed to capital or labor excluding technological progress, but the impact of capital or labor on growth including spillovers from productivity advances (see Barro 1998 and Aghion and Howitt 2008 for a more extensive discussion).

Hence, the construction of two variables that are central to our specification using a relatively inaccurate measure may well be responsible for some of the unexpected estimates obtained.

[24] These are Bahrain, Brunei, Iraq, Kuwai, Lebanon, Oman, Qatar, Saudi Arabia, United Arab Emirates. Other outliers are states known as 'tax havens': Aruba, The Bahamas, Macao (China), Ireland, Trinidad and Tobago.

5 Conclusion

The impact of skilled emigration on development can no longer be considered unambiguously negative as a series of favorable concomitants mitigates some of the adverse impacts of the outflow of talent. Therefore, this study is concerned with how remittances, network externalities of diasporas and educational incentives driven by emigration influence economic growth in sending countries. Following previous work by Vandenbussche et al. (2006), Lodigiani (2008) and Beine et al. (2011), we extend an endogenous growth model incorporating skilled migration to account for the aforementioned byproducts of brain drain. In addition, we pay specific attention to the heterogeneity of the effects with respect to the level of development in the sending country, a factor that has often been overlooked in the literature. Subsequently, we assess the derived implications empirically using a panel dataset consisting of 111 countries between 1980-2014.

In doing so, our study is one of the first in the brain drain literature to approach the matter in a comprehensive and integrated way, both theoretically and empirically. Thereby our work adds to a more global understanding of the aggregate impact of brain drain on economic growth.

Our model implies that the level of development considerably influences the overall effect of skilled emigration. While highly skilled workers are needed in any type of economy, they are most crucial for technological progress in advanced countries. Instead a large emigrant diaspora enhances growth all the more, the wider a country's gap to the technology frontier. Similar correlations are found with respect to remittances: when a larger share of individuals is restricted from acquiring higher education due to low income, which is more likely to happen in low-income economies, remittances promote human capital formation more strongly by raising budget constraints. Even though the beneficial effect of these factors fades for higher levels of development, this does not become harmful for growth. The opposite is true for the ceasing of the incentive effect. In economies operating close to the frontier the prospect of emigrating to a marginally more advanced country does not induce individuals to increase their investments in schooling. Skilled emigration thus directly decreases the skilled labor force.

We find evidence for this lack of incentive in our empirical investigation. However, our estimates of the growth specification are highly inconclusive and thus do not allow any inference of policy implications. While our study has improved upon previous work with respect to data selection, we identify a central shortcoming in the construction of the productivity measure.

The estimation of a more precise measure of productivity thus remains for future research. Yet, data paucity is expected to remain a crucial inhibitor of research into brain drain in the medium term. This is particularly problematic, as research to date already lags considerably behind in understanding the synergy of the feedback effects and their long-run consequences. Moreover, as the degree of international integration and labor mobility increases, brain drain is likely to gain political, social and economic relevance. Thereby, we believe the primary issue that needs to be addressed lies in the frequency and quality of data acquisition, in particular in developing countries, but also regarding migration in general. Only then can research assist in the design of policies that reinforce the gains of skilled migration while attenuating decelerating impacts on development.

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Appendix A

Derivative of $\frac{\partial h_m}{\partial m_{t+1}}$ with respect to w

For clarity, consider the income effect and the incentive effect separately.

As the income effect is independent of the wage ratio, it is easiest illustrated in an example of a closed economy, in which no migration is possible. Young individuals will then decide to invest in education if

$$\ln(w_t - \tau h w_t - \mu) + \ln(\sigma w_{t+1}) > \ln(w_t - \mu) + \ln(w_{t+1})$$

Which solves for the critical level of ability (with the subscript c for closed)

$$h_{c,t} = \frac{w_t - \mu}{\tau w_t}\frac{\sigma - 1}{\sigma}$$

A technological enhancement, and the resulting rise in local wages, leads to an increase in the share of young agents opting for education, which can be seen from the following derivative

$$\frac{\partial h_{c,t}}{\partial w_t} = \frac{\tau w_t - (w_t - \mu)\tau}{(\tau w_t)^2}\frac{\sigma - 1}{\sigma} = \frac{\mu}{\tau w_t^2}\frac{\sigma - 1}{\sigma} > 0$$

Note that the second derivative with respect to w is negative, implying that the magnitude of the income effect fades as countries become wealthier.
Returning to the derivative of $\frac{\partial h_m}{\partial m_{t+1}}$ with respect to w, we can now easily separate the income effect from the equation:

$$\frac{\partial h_m}{\partial m_{t+1}}\frac{\partial}{\partial w} = \left(\underbrace{\frac{w_t + r - \mu}{\tau w_t}}_{\text{Income Effect}} \underbrace{\frac{\ln \frac{w^*}{w_{t+1}}}{\sigma \left(\frac{w^*}{w_{t+1}}\right)^{m_{t+1}}}}_{\text{Incentive Effect}} \right)\frac{\partial}{\partial w}$$

Therefore, in steady-state,

$$\left(\frac{\ln \frac{w^*}{w}}{\sigma \left(\frac{w^*}{w}\right)^{m}} \right)\frac{\partial}{\partial w} = \frac{1}{\sigma {w^*}^m} w^{m-1}\left[\ln\left(\left(\frac{w^*}{w}\right)^m\right) - 1\right] = \frac{1}{\sigma {w^*}^m} w^{m-1}\left[m \ln\left(\frac{w^*}{w}\right) - 1\right]$$

Which is negative for most of the reasonable combinations of m and $\left(\frac{w*}{w}\right)$, since $0 < m < 1$ (e.g. a 40% emigration rate together with foreign wages being 10 times as high as local income will still lead to a weakening of the incentive effect when domestic wages increase).

Productivity Dynamics

$$\max_{u_{m,i},u_{n,i},s_{m,i},s_{n,i}} \delta(1 + \varphi(D_t)u_{m,i,t}^{\beta}s_{m,i,t}^{1-\beta}\left(\frac{1}{a_{t-1}}-1\right)+\gamma u_{n,i,t}^{\phi}s_{n,i,t}^{1-\phi})A_{t-1}$$
$$-\left[w_u A_{t-1}(u_{m,i}+u_{n,i})+w_s A_{t-1}(s_{m,i}+s_{n,i})\right] =$$

First order conditions:

I. $\frac{\partial}{\partial u_m} = 0 = \left[\varphi(D_t)\beta u_m^{\beta-1}s_m^{1-\beta}\left(\frac{1}{a_{t-1}}-1\right)-w_u\right]A_{t-1}$

II. $\frac{\partial}{\partial u_n} = 0 = \left(\gamma\phi u_n^{\phi-1}s_n^{1-\phi}-w_u\right)A_{t-1}$

III. $\frac{\partial}{\partial s_m} = 0 = \left[\varphi(D_t)u_m^{\beta}(1-\beta)s_m^{-\beta}\left(\frac{1}{a_{t-1}}-1\right)-w_s\right]A_{t-1}$

IV. $\frac{\partial}{\partial s_n} = 0 = \left(\gamma u_n^{\phi-1}(1-\phi)s_n^{-\phi}-w_s\right)A_{t-1}$

Set I = II

V. $\varphi(D_t)\beta u_m^{\beta-1}s_m^{1-\beta}\left(\frac{1}{a_{t-1}}-1\right) = \gamma\phi u_n^{\phi-1}s_n^{1-\phi}$

Set III = IV

VI. $\varphi(D_t)u_m^{\beta}(1-\beta)s_m^{-\beta}\left(\frac{1}{a_{t-1}}-1\right) = \gamma u_n^{\phi-1}(1-\phi)s_n^{-\phi}$

Dividing V by VI and substituting U and S using the full employment condition (9) yields

VII. $\beta(1-\phi)s_m(U-u_m) = \phi(1-\beta)u_m(S-s_m)$

Which can be rewritten to

VIII. $\frac{\beta(1-\phi)}{\phi(1-\beta)}\frac{u_n}{s_n} = \frac{u_m}{s_m} = \psi\frac{u_n}{s_n} = \frac{u_m}{s_m}$ where $\psi > 1$

Solving VII for u_m yields

$$\beta(1-\phi)s_m U = \beta(1-\phi)s_m u_m + \phi(1-\beta)u_m(S-s_m)$$

$$u_m = \frac{\beta(1-\phi)s_m U}{\beta(1-\phi)s_m+\phi(1-\beta)(S-s_m)} = \frac{\frac{\beta(1-\phi)}{\phi(1-\beta)}s_m U}{S-s_m+\frac{\beta(1-\phi)}{\phi(1-\beta)}s_m}$$

IX. $u_m = \frac{\psi s_m U}{S+(\psi-1)s_m}$

Insert IX into V to obtain

$$\varphi(D_t)\beta(\psi s_m U)^{\beta-1}(S+(\psi-1)s_m)^{1-\beta}s_m^{1-\beta}\left(\frac{1}{a}-1\right)=\gamma\phi\left(U-\frac{\psi s_m U}{S+(\psi-1)s_m}\right)^{\phi-1}(S-s_m)^{1-\phi}$$

Then, raise to the power of $\frac{1}{\phi-1}$

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-1}\right)}\psi^{\left(\frac{\beta-1}{\varphi-1}\right)}U^{\left(\frac{\beta-1}{\varphi-1}\right)}[S+(\psi-1)s_m]^{\left(\frac{1-\beta}{\phi-1}\right)}$$
$$=(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}(S-s_m)^{-1}U-(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}(S-s_m)^{-1}U\psi s_m[S+(\psi-1)s_m]^{-1}$$

Multiply by $(S-s_m)$

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-1}\right)}\psi^{\left(\frac{\beta-1}{\varphi-1}\right)}U^{\left(\frac{\beta-1}{\varphi-1}\right)}[S+(\psi-1)s_m]^{\left(\frac{1-\beta}{\phi-1}\right)}(S-s_m)$$
$$=(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}U-(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}U\psi s_m[S+(\psi-1)s_m]^{-1}$$

Multiply by $[S+(\psi-1)s_m]$

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-1}\right)}\psi^{\left(\frac{\beta-1}{\phi-1}\right)}U^{\left(\frac{\beta-1}{\phi-1}\right)}[S+(\psi-1)s_m]^{\left(\frac{\phi-\beta}{\phi-1}\right)}(S-s_m)=(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}U(S-s_m)$$

Divide by $(S-s_m)$ and by U

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-1}\right)}\psi^{\left(\frac{\beta-1}{\phi-1}\right)}U^{\left(\frac{\beta-\phi}{\phi-1}\right)}[S+(\psi-1)s_m]^{\left(\frac{\phi-\beta}{\phi-1}\right)}=(\gamma\phi)^{\left(\frac{1}{\phi-1}\right)}$$

Raise to the power of $\frac{\phi-1}{\phi-\beta}$ and simplify

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-\beta}\right)}\psi^{\left(\frac{\beta-1}{\phi-\beta}\right)}U^{\left(\frac{\beta-\phi}{\phi-\beta}\right)}[S+(\psi-1)s_m]^{1}=(\gamma\phi)^{\left(\frac{1}{\phi-\beta}\right)}$$

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-\beta}\right)}\psi^{\left(\frac{\beta-1}{\phi-\beta}\right)}U^{-1}S+\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-\beta}\right)}\psi^{\left(\frac{\beta-1}{\phi-\beta}\right)}U^{-1}(\psi-1)s_m=(\gamma\phi)^{\left(\frac{1}{\phi-\beta}\right)}$$

$$\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-\beta}\right)}\psi^{\left(\frac{\beta-1}{\phi-\beta}\right)}U^{-1}(\psi-1)s_m=(\gamma\phi)^{\left(\frac{1}{\phi-\beta}\right)}-U^{-1}S$$

$$(\psi - 1)s_m = \frac{(\gamma\phi)^{\left(\frac{1}{\phi-\beta}\right)}}{\left[\varphi(D_t)\beta\left(\frac{1}{a}-1\right)\right]^{\left(\frac{1}{\phi-\beta}\right)}\psi^{\left(\frac{\beta-1}{\phi-\beta}\right)}}U - S$$

$$(\psi - 1)s_m = \left(\frac{\varphi(D_t)\left(\frac{1}{a}-1\right)(1-\beta)\psi^{\beta}}{(1-\phi)\gamma}\right)^{\left(\frac{1}{\beta-\phi}\right)} U - S$$

Equilibrium Growth Rate

Insert equation (7) into equation (13) to obtain

$$g_{i,t} = \frac{A_{t-1} + \ \varphi(D_t) u_{m,i,t}^{\beta} s_{m,i,t}^{1-\beta} (\bar{A}_{t-1} - A_{t-1}) + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{1-\phi} A_{t-1} - A_{t-1}}{A_{t-1}} =$$

$$= \ \varphi(D_t) u_{m,i,t}^{\beta} s_{m,i,t}^{1-\beta} \left(\frac{1}{a} - 1\right) + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{1-\phi}$$

Use equations (11) and (12) to replace u_m and u_n

$$g_t = \ \varphi(D_t) \left(\frac{\psi s_m}{f(a,D)}\right)^{\beta} s_m^{1-\beta} \left(\frac{1-a}{a}\right) + \ \gamma \left(\frac{s_n}{f(a,D)}\right)^{\phi} s_n^{(1-\phi)}$$

$$= \ \varphi(D_t) \left(\frac{\psi}{f(a,D)}\right)^{\beta} s_m \left(\frac{1-a}{a}\right) + \ \gamma \left(\frac{1}{f(a,D)}\right)^{\phi} s_n$$

Substitute $s_n = S - s_m$

$$g_t = \ \varphi(D_t) \left(\frac{\psi}{f(a,D)}\right)^{\beta} s_m \left(\frac{1-a}{a}\right) + \ \gamma \left(\frac{1}{f(a,D)}\right)^{\phi} (S - s_m)$$

Use equation (9) to replace s_m and simplify

$$g_t = \ \varphi(D_t) \left(\frac{\psi}{f}\right)^{\beta} \frac{1}{\psi - 1} (fU - S) \left(\frac{1-a}{a}\right) + \ \gamma \left(\frac{1}{f}\right)^{\phi} \left(S - \frac{1}{\psi - 1}(fU - S)\right) =$$

$$= \left[\varphi(D_t) \left(\frac{\psi}{f}\right)^{\beta} \left(\frac{1-a}{a}\right) - \gamma \left(\frac{1}{f}\right)^{\phi}\right] \frac{1}{\psi - 1} (fU - S) + \gamma \left(\frac{1}{f}\right)^{\phi} S$$

Insert the expression for $\frac{\psi^{\beta}}{f}$ obtained in Supplement A

$$g_t = \ \left[\varphi(D_t) \left[\frac{1}{\varphi(D)} \frac{(1-\phi)\gamma a}{(1-\beta)(1-a)}\right] f^{-\phi} \left(\frac{1-a}{a}\right) - \gamma \left(\frac{1}{f}\right)^{\phi}\right] \frac{1}{\psi - 1} (fU - S) + \gamma \left(\frac{1}{f}\right)^{\phi} S =$$

$$= \left[\left[\frac{(1-\phi)\gamma}{(1-\beta)}\right] f^{-\phi} - \gamma \left(\frac{1}{f}\right)^{\phi}\right] \frac{1}{\psi - 1} (fU - S) + \gamma \left(\frac{1}{f}\right)^{\phi} S =$$

$$= \ \left[\frac{(1-\phi)}{(1-\beta)} - 1\right] \gamma f^{-\phi} \frac{1}{\psi - 1} (fU - S) + \gamma \left(\frac{1}{f}\right)^{\phi} S =$$

$$= \left[\frac{(1-\phi)-(1-\beta)}{(1-\beta)}\right]\gamma f^{-\phi}\frac{1}{\psi-1}(fU-S)+\gamma\left(\frac{1}{f}\right)^{\phi}S =$$

$$= \left[\frac{\beta-\phi}{1-\beta}\right]\gamma f^{-\phi}\frac{1}{\psi-1}(fU-S)+\gamma\left(\frac{1}{f}\right)^{\phi}S$$

Finally, insert the expression for $\frac{1}{\psi-1}$ obtained in Supplement B

$$\left[\frac{\beta-\phi}{1-\beta}\right]\gamma f^{-\phi}\frac{\phi(1-\beta)}{\beta-\phi}(fU-S)+\gamma\left(\frac{1}{f}\right)^{\phi}S =$$

$$= \gamma f^{-\phi}\phi(fU-S)+\gamma f^{-\phi}S = \gamma\left[\phi f^{1-\phi}U-\phi S+f^{-\phi}S\right] =$$

$$g_t = \gamma\left[\phi f(a,D)^{(1-\phi)}U+(1-\phi)f(a,D)^{-\phi}S\right]$$

Supplement A

Solve $f(a,D)$ for ψ

$$f(a,D) = \left(\frac{\varphi(D)\left(\frac{1}{a}-1\right)(1-\beta)\psi^{\beta}}{(1-\phi)\gamma}\right)^{\frac{1}{\beta-\phi}}$$

$$f^{\beta-\phi} = \frac{\varphi(D)\left(\frac{1}{a}-1\right)(1-\beta)\psi^{\beta}}{(1-\phi)\gamma}$$

$$\psi^{\beta} = f^{\beta-\phi}\gamma(1-\phi)\,a\,\varphi(D)^{-1}(1-a)^{-1}(1-\beta)^{-1}$$

$$\psi = f^{\frac{\beta-\phi}{\beta}}\left[\frac{\gamma(1-\phi)a}{\varphi(D)(1-\beta)(1-a)}\right]^{\frac{1}{\beta}}$$

Insert into the expression $\frac{\psi^{\beta}}{f}$

$$\frac{\psi^{\beta}}{f} = \left\{\frac{f^{\frac{\beta-\phi}{\beta}}\left[\frac{\gamma(1-\phi)a}{\varphi(D)(1-\beta)(1-a)}\right]^{\frac{1}{\beta}}}{f}\right\}^{\beta} = \left[\frac{(1-\phi)\gamma a}{\varphi(D)(1-\beta)(1-a)}\right]f^{-\phi}$$

Supplement B

Use $\psi = \frac{\beta(1-\phi)}{\phi(1-\beta)}$

$$\frac{1}{\psi - 1} = \frac{1}{\frac{\beta(1-\phi) - \phi(1-\beta)}{\phi(1-\beta)}} = \frac{\phi(1-\beta)}{\beta - \phi}$$

Appendix B

Table 5: First Stage Regression

	lag proximity	*lag emigration rate*	*lag rem/GDP*	*lag prox * lag diaspora*	*lag prox * lag skillshare*	*lag prox * lag emigration*	*lag prox * lag rem/GDP*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
lag(2) proximity	0.482***	2.547	1.895	0.500***	0.609***	0.541***	0.507***
	(0.159)	(2.504)	(1.160)	(0.0386)	(0.134)	(0.131)	(0.164)
lag(2) emigration rate	-0.00280	0.555***	-0.0327	-0.00117*	-0.00655***	-0.0102***	-0.000968
	(0.00280)	(0.0443)	(0.0199)	(0.000682)	(0.00239)	(0.00277)	(0.00282)
lag(2) rem/GDP	0.000350	0.361	0.822***	-0.00542	-0.00243	-0.00200	-0.0220
	(0.0165)	(0.260)	(0.116)	(0.00401)	(0.0139)	(0.0136)	(0.0179)
lag skill share	-0.00602	-0.376***	0.0212	0.000419	0.0379***	-0.00334	-0.00615
	(0.00388)	(0.0613)	(0.0278)	(0.000947)	(0.00469)	(0.00334)	(0.00391)
lag(2) skill share	0.00799	0.420***	-0.0344	-0.00460***	-0.0367***	0.00197	0.00749
	(0.00603)	(0.0951)	(0.0429)	(0.00147)	(0.00613)	(0.00510)	(0.00601)
lag diaspora	-0.0547	9.387***	0.728***	0.110***	-0.0286	-0.109***	-0.0558
	(0.0374)	(0.591)	(0.271)	(0.00932)	(0.0317)	(0.0393)	(0.0384)
lag(2) diaspora	0.0516	-6.311***	-0.144	-0.0419***	0.0576*	0.0633*	0.0237
	(0.0406)	(0.641)	(0.291)	(0.00993)	(0.0343)	(0.0371)	(0.0410)
lag(2) prox*lag(2) m	0.000737	0.00280	-0.0134	-0.000151	-0.000596	-0.00585***	0.00106
	(0.00137)	(0.0216)	(0.00966)	(0.000334)	(0.00116)	(0.00122)	(0.00136)
lag(2) prox * lag(2) rem/GDP	-0.00269	0.265	0.235***	-0.00563**	-0.00566	-0.00448	-0.0119
	(0.0109)	(0.172)	(0.0769)	(0.00265)	(0.00923)	(0.00901)	(0.0111)
lag(2) prox * lag(2)skill share	0.00316	0.0919*	-0.0216	-0.000956	-0.0219***	0.000744	0.00227
	(0.00326)	(0.0515)	(0.0233)	(0.000794)	(0.00335)	(0.00270)	(0.00328)
lag(2) prox * lag(2) diaspora	-0.0118	-0.321	-0.0998	-0.0472***	-0.0159	-0.0118	-0.0164
	(0.0170)	(0.269)	(0.124)	(0.00416)	(0.0144)	(0.0140)	(0.0174)
Intercept	-1.200***	-29.13***	-4.089	-0.774***	-1.297***	-0.605*	-0.936**
	(0.378)	(5.969)	(2.826)	(0.0921)	(0.320)	(0.323)	(0.398)
Observations	553	553	539	553	553	553	539
R-squared	0.970	0.985	0.919	0.998	0.978	0.979	0.970
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include country fixed effects and year fixed effects.

Appendix C

Countries in our sample:

Argentina, Armenia, Australia, Austria, Bahrain, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Hong Kong (SAR), Macao (SAR), Colombia, Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Finland, France, Gabon, Germany, Greece, Guatemala, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Kyrgyzstan, Laos, Latvia, Lesotho, Lithuania, Luxembourg, Malaysia, Malta, Mauritania, Mauritiues, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Nicaragua, Niger, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Swaziland, Sweden, Switzerland, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, USA, Ukraine, United Kingdom, Uruguay, Venezuela, Zimbabwe.