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Migration, Human Capital, and Climate Change

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Introduction

Human migration is one of the key components of the international integration process that has been shaping the world over past decades. The acceleration of global development has been accompanied by increasing individual human mobility at all spatial scales. First, the number of international migrants has been steadily growing in recent years. According to the United Nations Population Division, the stock of international migrants increased by more than 100 millions, from 153 millions in 1990 to 258 millions in 2017. This corresponds to an increase in the share of international migrants as a percentage of the global population from 2.9 percent in 1990 to 3.4 percent in 2017. Second, the United Nations Population Division estimates that the share of the global population residing in urban areas increased from 43.0 percent in 1990 to 55.3 percent in 2018. Part of this urbanization process is attributable to increasing numbers of individuals moving from rural to urban areas (United Nations, 2015). The mobility at the local level, rural-to-urban migration, or the individual movement from one country to another are facilitated by the process of globalization and advances in technological development.

The recent rise in human migration has sparked public debates and increased interest about this topic. Numerous analyses reveal that human mobility is multidimensional, interconnected with global development inequality and affected by diverse phenomena. One of the factors that are closely connected with migration streams is education. The literature demonstrates that in particular high-skilled educational attainment is affected by international migration. High-skilled individuals have been shown to be the most mobile group of individuals and are positively selected. Hence, an investigation of the education-migration nexus is of critical importance and a crucial part of this thesis analyzes the interdependence between human migration and high-skilled educational attainment. Furthermore, a second factor that is closely linked with human mobility is the phenomenon of climate change. The projected future slow-onset effects of climate change are expected to induce large migration streams. Given that climate change will likely have very heterogeneous impacts in distinct world regions, human migration will be affected at different scales. A second part of this thesis addresses the connection between climate change and individual human mobility. Finally, this thesis analyzes how these different factors and phenomena are interconnected. The aim of the thesis is to focus on the relationship between human capital accumulation, climate change and inequality, on the one hand, and local, regional and international mobility, on the other hand. In this way, the thesis intends to jointly discuss important elements connected with migration that are usually discussed separately.

The analysis starts with an assessment of the geographic distribution of skills. By addressing the education-migration nexus, the first chapter of this thesis provides a basis for the discussion in the subsequent parts. Chapter 1, coauthored with Michał Burzyński and Frédéric Docquier, analyzes the relationship between human capital and global development inequality. It discusses how the mobility of high-skilled individuals, defined as workers with completed tertiary education, shapes development disparities between regions and countries. To this end, a multi-country model with two sectors (rural and urban) and two classes of workers (high-skilled and low-skilled) is developed. The model endogenizes individual education and migration decisions, population growth, and income inequality between countries and between rural and urban regions. Calibrating the model for a set of 179 countries enables us to project income, population, education, and urbanization levels for the 21st century. The calibrated model matches data for the past decades and official projections of the global population, the share of high-skilled workers and urbanization patterns. We find that the geography of skills has a large impact on global inequality. In a final part of this chapter we analyze the effect of policies aiming at improving the access to education or to the urban sector. We conclude that such policies have potentially a large beneficial impact on future development inequality.

In the second chapter, coauthored with Michał Burzyński, Frédéric Docquier, and Jaime de Melo, we widen the focus of the analysis. We include the phenomenon of climate change in the discussion about the education-migration nexus by extending the theoretical framework developed in Chapter 1. In addition to the endogenous components of the model described above, the model in Chapter 2 further endogenizes the effect of temperature and sea level rise on productivity and individual mobility. The extended model allows us to investigate the effect of global warming on human mobility at the local, regional and international scale. We distinguish and assess the impact of several different future scenarios derived from official projections on temperature levels and rise in sea level. The analysis also includes extreme scenarios that address the impact of conflicts or direct utility losses triggered by increasing temperature levels. Moreover, Chapter 2 evaluates the effects of migration policies on extreme poverty in the context of global warming. We find that climate change induces about 120 million individuals to move over the 21st century. The majority of this movement is at a local level and less than a fifth of these additional migrants move to another country. This general conclusion holds also for the more extreme scenarios that account for the impact of potential climate-induced conflicts or direct utility losses and project higher levels of migration. The findings further indicate that current international migration policies are already fairly restrictive, particularly for the poorest groups. We conclude that international migration may only serve as an adaptation strategy to climate change of last resort.

While Chapter 1 and Chapter 2 analyze the development at the global level, the third chapter focuses on the more regional context in Africa. It directly addresses the link between climate change and high-skilled human capital accumulation in African economies. The particular aim of this chapter is to further develop the understanding of the mechanisms through which weather changes affect tertiary educational attainment. The analysis addresses the slow-onset effects of climate change and investigates specific links between education and climate change in a world region in which the impacts of climate change are expected to be particularly large. Building on the central finding of the previous chapter, which states that climate change predominantly induces local migration, a two-sector model is developed that endogenizes internal migration and education decisions. The model predicts that adverse climatic conditions, such as decreases in rainfall or increases in temperature levels, promote the process of urbanization. This in turn impacts on high-skilled educational attainment, because the access and returns to education are higher in urban areas. The third chapter also contains an empirical analysis with several different empirical specifications focusing on 37 African countries and 111 African provinces. The empirical findings validate the key predictions derived from the theoretical framework. The analysis leads to the conclusion that adverse weather changes in Africa may increase high-skilled educational attainment.

In Chapter 4, coauthored with Frédéric Docquier, the focus of the analysis returns to the global scale and to migration across country borders. This chapter addresses the connection between international migration, high-skilled human capital accumulation and inequality. It refines the conclusions drawn from the many studies on the brain drain phenomenon. In a first part, an update of the macro-econometrical findings on the relationship between migration and higher education is provided. In a second part, a dyadic micro-founded model is developed that analyzes high-skilled education and international migration decisions. This model is calibrated for a set of 174 countries and matches the migration patterns of the past two decades well. Contrary to the standard approach of the literature, our calibrated model allows us to investigate country-specific effects of international migration prospects on educational attainment. Our model predicts smaller average effects of international migration on human capital accumulation than the standard macroeconometric models. Furthermore, Chapter 4 analyzes how public education policies are affected by international migration. On average, we find small effects and conclude that the impact of international migration on the global distribution of human capital is rather limited.

Overall, the four chapters show that human mobility, high-skilled educational attainment, global economic inequality and climate change are interconnected phenomena. This thesis attempts to illuminate and address some of the mechanisms through which these phenomena are connected. In this way, the following chapters seek to contribute to the debate about the multidimensional effects of migration, in the context of increasing human mobility.

Chapter 1

The geography of skills and global inequality

Abstract[1]

This chapter analyzes the factors underlying the evolution of the worldwide distribution of skills and their implications for global inequality. We develop and parameterize a two-sector, two-class, world economy model that endogenizes education and mobility decisions, population growth, and income disparities across and within countries. First, our static experiments reveal that the geography of skills matters for global inequality. Low access to education and sectoral misallocation of skills substantially impact income in poor countries. Second, we produce unified projections of population and income for the 21st century. Assuming the continuation of recent education and migration policies, we predict stable disparities in the world distribution of skills, slow-growing urbanization in developing countries and a rebound in income inequality. These prospects are sensitive to future education costs and to internal mobility frictions, which suggests that policies targeting access to all levels of education and sustainable urban development are vital to reduce demographic pressures and global inequality in the long term.

Keywords: human capital, migration, urbanization, growth, inequality

JEL codes: E24, J24, O15

1.1 Introduction

It is commonly accepted that human capital acts as a proximate cause of development. Recent studies show that highly educated workers, namely, those who have completed a tertiary/college education, exhibit the highest productivity levels, generate labor market

[1] This chapter is coauthored with Michał Burzyński and Frédéric Docquier. The chapter benefited from helpful comments from two anonymous referees. We also thank the participants of the EDEEM Summer Meeting 2016 (Universidade Nova de Lisboa, July 2016), participants of the First NOVAFRICA Workshop on Migration and Development (Universidade Nova de Lisboa, July 2016), participants of the OLG Days (University of Luxembourg, December 2016), seminar participants at the University of Western Australia (February 2017), participants of the CSAE Conference 2017: Economic Development in Africa (University of Oxford, March 2017), participants of the International Conference on Migration and Welfare (Sapienza Università di Roma, May 2017), and seminar participants at the University of Paris 1 Panthéon-Sorbonne (May 2017) for their helpful comments.

complementarities with the less educated, and are instrumental in supporting democratization and in facilitating innovation and technology diffusion when knowledge becomes *economically useful*.[2] However, the factors governing the geography of skills, its long-term developments, and its interaction with the world distribution of income are quantitatively uncertain.

In this chapter, we *quantitatively analyze the root drivers underlying the long-term trend in the worldwide distribution of skills* (i.e., domestic access to education, sector allocation of workers, and international migration) and *highlight the implications of these root drivers for economic convergence and global inequality*. To do so, we develop a two-sector, two-class, world economy model that endogenizes education and labor mobility decisions, population growth, and income disparities across countries and across regions/sectors. In our framework, each country has two sectors/regions (urban and rural or equivalently, nonagriculture and agriculture), which are populated by two types of adult workers (those who have completed a college education and the less educated) and by their offspring. Production and income depend on the size and structure of the domestic labor force. We parameterize the model to match the current structure of the world economy and the ongoing socio-demographic trends. We then carry out a set of static and dynamic numerical experiments. By decomposing contemporaneous income inequality, we find that the allocation of educated workers explains a significant part of global disparities. In particular, we find that the divergence across countries is induced mainly by the heterogeneity with respect to the overall supply of tertiary educated workers rather than by the different patterns in across-sectors and cross-border mobility. With our dynamic simulations for the years 2010-2100, we give suggestive evidence that convergence and inequality prospects reveal significant sensitivity to education and mobility policies.

We first use the model to quantify the fraction of contemporaneous income inequality that is explained by the geographic allocation of skills. In particular, we shed light on the global inequality implications of disparities in education policies, for the allocation of labor across sectors and for international migration. We then use dynamic simulations to gain an understanding of the main drivers of the geography of skills and of its interaction with global inequality. Again, we study the sensitivity of future disparities in human capital and income to the convergence in education costs, to immigration policies and to internal mobility frictions. We also assess the robustness of our results to the technological and preference assumptions of the model.

Figure 1.1 illustrates the importance of the subject matter. In many countries and regions, college graduates form a minority. Although the worldwide average proportion of college graduates increased from only 2.4% in 1970 to 8.8% in 2010, this share is currently smaller than 1% in fifteen developing countries, such as Niger, Malawi, Zambia, Zimbabwe, and Tanzania (Barro and Lee, 2013). Using our human capital estimates (see Section 1.4 below), Figure 1.1a shows the evolution of human capital inequality in ten-year intervals from 1970 to 2010. We use the Theil index of inequality and investigate its between-country component (capturing differences in the country average proportion of college graduates) and the within-country component (capturing differences between rural and urban regions). Human capital disparities are predominantly explained by the

[2]This was the case during the Industrial Revolution (Mokyr, 2005; Squicciarini and Voigtländer, 2015) and it is still relevant in the modern world: see Castelló-Climent and Mukhopadhyay (2013), Jones (2014), Kerr et al. (2016) on productivity growth, or Castelló-Climent (2008), Bobba and Coviello (2007), Murtin and Wacziarg (2014) on democratization.

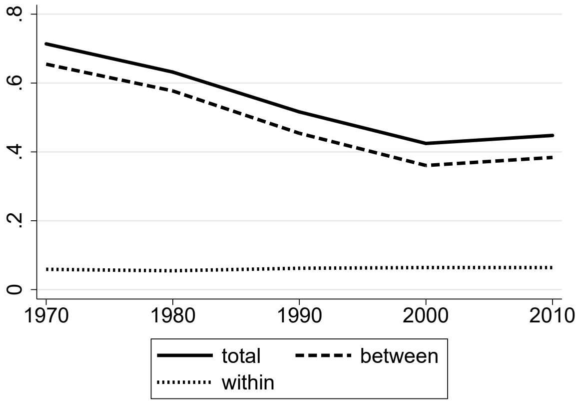
between-country component (as illustrated on Figure 1.1c). This means that between-country disparities are much greater than the within-country ones. Since 1970, the number of skilled workers has grown faster in poor countries. Hence, the Theil index has decreased, reflecting unconditional convergence in the share of college graduates (with a speed of approximately 0.7% per year). However, this process stalled after 2000, and large differences persist between the tails of the distribution. The latter is illustrated in Figure 1.1b, which depicts the density of the shares of college-educated workers in the year 2010 for a sample of 179 countries and 358 regions (i.e., rural and urban regions of the 179 countries). Figure 1.1d shows that the ratio of human capital between agriculture and nonagriculture reaches the lowest values for the developing countries. Hence, in poor countries, the share of college graduates is remarkably low in the rural areas (often smaller than 4%), in which a large fraction of the population lives.

We study the drivers and implications of these geographic disparities in the world distribution of skills. The accumulation of human capital is clearly endogenous: higher-education investments are costly; returns to schooling depend on production technologies and labor market characteristics; and workers are mobile across nations and regions. To study interdependencies between the accumulation of skills and global income inequality, our model endogenizes the formation of human capital and the mobility decisions of workers. Adults decide how much to consume, how many of their children will be provided with higher education, and where to live. Internal and international migration decisions depend on geographic disparities in income and on moving costs. Accounting for international labor mobility helps to identify the effect of skill-biased migration flows on human capital and income disparities. Distinguishing between urban and rural regions allows us to model the differential in the access to education across regions (as in Lucas, 2009) and helps us to quantify the role of internal mobility frictions (as in Rodrik, 2013). The model is stylized and omits several features of the real world.[3] However, it does account for long-run interactions between human capital accumulation, migration and economic growth. Our quantitative theory is helpful for investigating how the geography of skills affects economic development and for identifying the key factors governing future demographic pressures and global inequality.

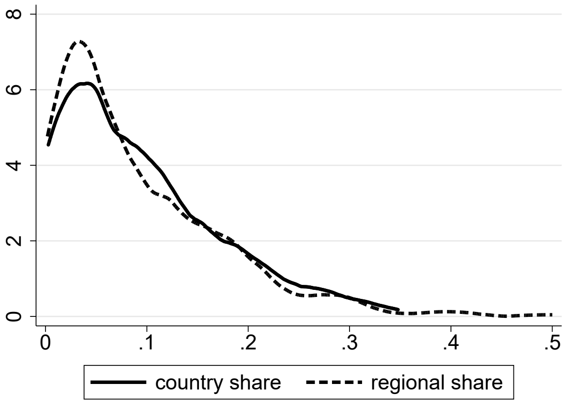
We first run static numerical experiments and use the technological block of the model to quantify the fraction of contemporaneous inequality that is explained by disparities in the share of college-educated workers. We show that the geography of skills matters for development, regardless of the size of technological externalities. In the absence of technological externality, transposing the US full educational structure (i.e., the US national share of college graduates and its allocation by sector/region) increases income per workers by a factor of 2.5 in the poorest countries (i.e., the bottom quartile of the income distribution). This is very much in line with Jones (2014); we obtain greater effects because in our two-sector model, transposing the US educational structure implies increasing the share of the labor force employed in the urban sector, in which productivity is greater. Our baseline scenario is even more optimistic; it assumes that half the correlation between productivity (aggregate or skill bias) and the share of college-educated workers is due to technological externalities. In this context, the growth factor increases from 2.5 to 5 in the poorest countries.[4] Interestingly, we show that keeping the share of

[3]The model does not account for all demographic variables (such as mortality or aging) and economic variables (such as trade, unemployment, or redistribution).

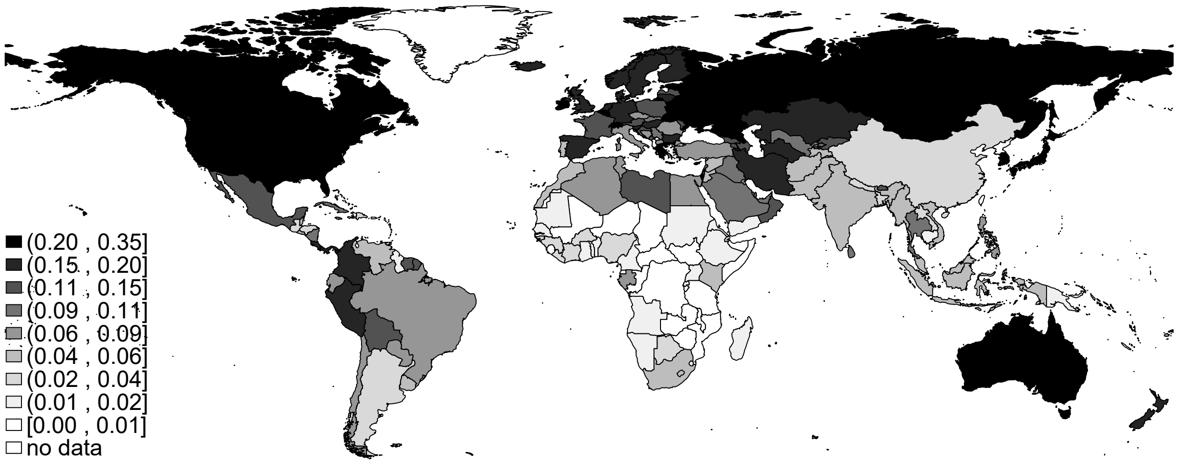
[4]In a maximalist scenario in which the sizes of externality are proxied by the correlations, human capital almost becomes the single determining factor for global inequality.



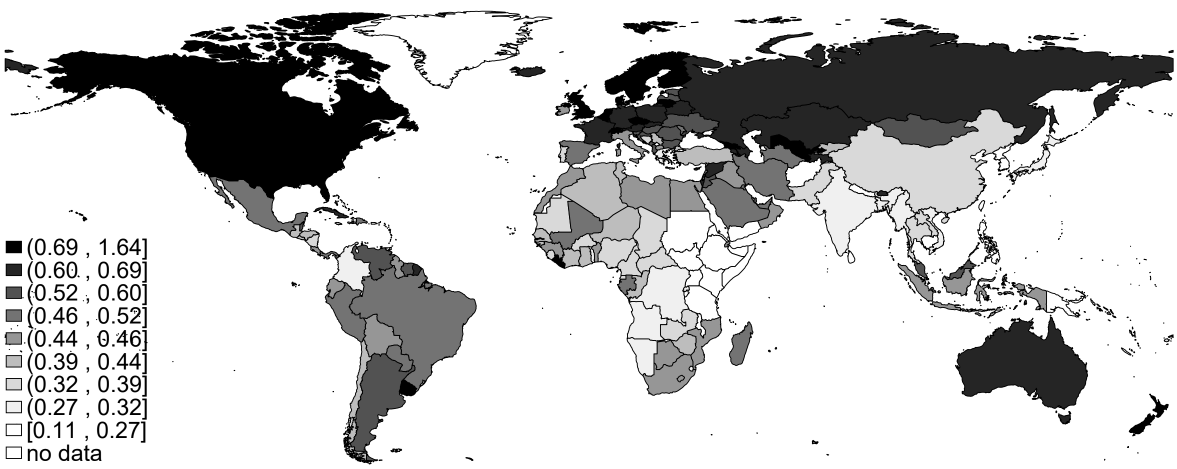
(a) Theil index of inequality in the share of college graduates 1970-2010



(b) Kernel density of the share of college graduates in 2010



(c) Share of college graduates by country in 2010



(d) Agriculture-to-nonagriculture ratio in the share of college graduates by country in 2010

Figure 1.1: Worldwide distribution of skills

college-educated workers constant but transposing the US sector allocation explains one third of the total effect above. This suggests that internal mobility frictions (such as liquidity constraints, imperfect information, or congestion effects) generate a misallocation of workers in poor countries and shows the relevance of a two-sector approach (see Hsieh and Klenow, 2009; Bryan et al., 2014). In contrast, with the exception of small island developing states, the effect of international migration on economic development is small.

Second, we use the model to predict the future geography of skills (i.e., the evolution of human capital and urbanization), population and income during the 21st century. Accounting for interdependencies among demographic, economic and educational variables has rarely been done in projection exercises.[5] In contrast, our micro-founded structure enables us to produce consistent projections and to identify the key factors that will govern the future geography of skills and income. Our baseline scenario assumes a continuation of the ongoing convergence trends in the access to education (possibly initiated by the Millennium Development Goals). In terms of education and urbanization, our baseline prospects are less optimistic than official projections. In line with the evolution of the last decade (see Figure 1.1a), the baseline predicts fairly stable disparities in the world distribution of skills. We also envisage slower urbanization in developing countries, due to persistent mobility frictions. When extrapolating ongoing trends, the dynamics of the geography of skills *per se* does not translate into drastic changes in global income inequality. These socio-demographic and inequality prospects are highly robust to the size of technological externalities, to the preference structure, and to future international migration policies.

Within the context of the convergence literature,[6] this means that the current convergence in the access to education is too slow to drastically reduce income inequality. The recent decline in inequality is due to the success of some of the largest countries in the planet (for example, China, India and the rest of Asia), which offsets the divergent incomes of the poorest countries (for example, the African continent). Demographic imbalances are such that the weight of the poorest countries will continuously increase. Without drastic changes in the ongoing productivity and socio-demographic trends, our baseline shows that world income inequality should start rising again. In addition, the future geography of skills and income is sensitive to education policies and to internal mobility frictions. Attenuating or eliminating the convergence in education costs induces dramatic effects on population growth, urbanization and income inequality. In the same vein, obstructing internal mobility generates huge misallocation costs. In line with the

[5]For example, the demographic projections of the United Nations do not anticipate the economic forces and policy reforms that shape demography (see Mountford and Rapoport, 2016). The recent projections by International Institute for Applied Systems Analysis (IIASA) include the educational dimension (see Samir et al., 2010), predicting the population of 120 countries by level of educational attainment and accounting for differentials in fertility, mortality and migration by education. However, assumptions about future educational development (e.g., partial convergence in enrollment rates) are also deterministic and seemingly disconnected from changes in the economic environment. Given the high correlation between economic and socio-demographic variables, assuming cross-country convergence in demographic indicators implicitly suggests that economic variables should also converge in the long run. This is not what historical data reveal (see Bourguignon and Morrisson, 2002, or Sala-i-Martin, 2006).

[6]The convergence literature studies the evolution of inequality between people and between countries. Absolute divergence in income per capita is obtained when countries are not weighted by their size (Pritchett, 1997). When country size is accounted for, global inequality continuously increased between the Industrial Revolution and the 1970s (Bourguignon and Morrison, 2002) but has decreased since then (Sala-I-Martin, 2006).

Sustainable Development Agenda, our analysis clearly suggests that policies targeting access to all levels of education (what is needed to promote higher education), education quality and sustainable urban development are vital to limit demographic pressures and global inequality.

The rest of this chapter is organized as follows. Section 1.2 provides a summary of the related literature. Section 1.3 describes our model. In Section 1.4, we parameterize this model to match historical data over the period 1980-2010 and the socio-demographic prospects for 2040. Section 1.5 discusses our simulation results, distinguishing between the contemporaneous implications of human capital inequality, the projections for the 21st century, and a sensitivity analysis. Finally, Section 1.6 concludes.

1.2 Related literature

This chapter speaks to the literature on the links between human capital accumulation and productivity growth and the literature on the determinants of labor mobility and its effect on economic development. In this section, we review the body of literature that helps contextualizing our approach.

Although the role of human capital as a determinant of productivity growth has been debated, its importance as a proximate cause of development is much less disputed (Glaeser et al., 2004; Acemoglu et al., 2014; Jones, 2014). Our technological specification distinguishes between college and non-college educated workers. This is consistent with Goldin and Katz (2008), Card (2009) and Ottaviano and Peri (2012), who find high substitutability between workers with no schooling and those with a high school degree but small substitutability between those with no schooling and workers with a college education. In this context, increasing the share of college-educated workers not only affects their average skill level and cognitive ability but also generates positive labor market complementarities for the less educated. Jones (2014) builds a generalized development accounting framework that includes such complementarities; he shows that for a reasonable level of the elasticity of substitution (e.g., equal to 2), human capital explains approximately 50% of the ratio of income per worker between the richest and poorest countries. Although such a success rate is still limited, it is greater than what was found in earlier studies that assumed perfect substitution between all categories of workers.[7]

Furthermore, greater contributions of human capital to growth can be obtained by assuming technological externalities. These externalities have been the focus of many recent articles and have generated a certain level of debate. Using data from US cities (Moretti, 2004) or US states (Acemoglu and Angrist, 2000; Iranzo and Peri, 2009), some instrumental-variable approaches show substantial externalities (Moretti, 2004), while others do not (Acemoglu and Angrist, 2000). In the cross-country literature, there is evidence of a positive effect of schooling on innovation and technology diffusion (see Benhabib and Spiegel, 1994; Caselli and Coleman, 2006; Ciccone and Papaioannou, 2009). Other studies identify skill-biased technical changes: when the supply of human capital increases, firms invest in skill-intensive technologies (Acemoglu, 2002; Autor et al., 2003; Restuccia and Vandenbroucke, 2013). Finally, another set of contributions highlights the effect of human capital on the quality of institutions (Castelló-Climent, 2008; Bobba

[7] Assuming the income per worker equals $100,000 in the richest countries and $5,000 in the poorest countries, a success rate of 50% means that income per capita would reach $10,000 in poor countries after transferring the human capital level of the richest countries to the poorest countries (i.e., the income ratio would decrease from 20 to 10).

and Coviello, 2007; Murtin and Wacziarg, 2014). Comparative development studies suggest that focusing on highly skilled workers is more appropriate for accounting for such externalities.[8] Squicciarini and Voigtländer (2015) show that upper-tail human capital was instrumental in explaining the process of technology diffusion during the French Industrial Revolution. However, they assert that mass education (proxied by the average level of literacy) was positively associated with development at the onset of the Industrial Revolution but did not explain growth. Confirming Mokyr's findings for the British Revolution, they conclude that the effect of "the educated elite" on local development becomes stronger when the aggregate technology frontier expands more rapidly. It can be argued that this situation also characterizes the modern globalized world, in which most rich countries use advanced technologies, while poor countries struggle to adopt them. The contemporaneous contributions of human capital in poor countries are studied in Castelló-Climent and Mukhopadhyay (2013). They use data on Indian states over the period 1961-2001 and show that a one percent change in the proportion of tertiary-educated workers has the same effect on growth as a 13% decrease in illiteracy rates (equivalently, a one standard deviation in the share of college graduates has the same effect as three standard deviations in literacy). Aggregate and skill-biased externalities cannot be ignored when dealing with long-run growth and inequality. However, given the uncertainty about their levels, our analyses and projections cover several plausible scenarios.

As far as the source of human capital disparities is concerned, the geography of skills is clearly endogenous. Investments in higher education depend on access to education - which varies across income groups (e.g., Galor and Zeira, 1993; Mookherjee and Ray, 2003) and regions (e.g., Lucas, 2009) - as well as on the quality of education (e.g., Castelló-Climent and Hidalgo-Cabrillana, 2012). Human capital disparities are also affected by international and internal labor mobility. International migration affects knowledge accumulation, as well-educated people exhibit much greater propensity to emigrate than do the less educated and tend to agglomerate in countries/regions with high rewards to skill (Grogger and Hanson, 2011; Belot and Hatton, 2012; Docquier and Rapoport, 2012; Kerr et al., 2016). This predominating high-skilled bias in international migration is due to migrants' self-selection (high-skilled people being more responsive to economic opportunities and political conditions abroad, having more transferable skills, having greater ability to gather information or finance emigration costs, etc.) and to the skill-selective immigration policies conducted in the major destination countries (Docquier et al., 2009).

Internal mobility frictions can also be responsible for development inequality. Rodrik (2013) demonstrates that manufacturing industries exhibit unconditional convergence in productivity, while the whole-economy income per worker does not converge across countries. The reason is that a fraction of workers is stuck in the wrong sectors and that these sectoral and/or regional misallocations are likely to be important in poor countries. Such misallocations can be driven by the existence of liquidity constraints, imperfect information, or congestion effects (Hsieh and Klenow, 2009; Bryan et al., 2014). In the same vein, our analysis sheds light on the effect of international migration on global inequality, on the fraction of income disparities explained by internal mobility frictions, and on the implications of labor mobility for future development.

[8] Meisenzahl and Mokyr (2012) argue that the British Industrial Revolution is not so much due to the few dozens of "great inventors" (scientists, PhD holders) nor to the mass of literate factory workers. Instead, in terms of skills, they highlight the role of the top 3-5% of the labor force, including artisans, entrepreneurs and employees.

1.3 Model

Our model sheds light on the interactions between the geography of skills and the distribution of income. It endogenizes the accumulation of skills and its implications for economic development.[9] We depict a set of economies with two sectors/regions, $r = (a, n)$, denoting agriculture (a) and nonagriculture (n), and two types of workers, $s = (h, l)$, denoting college-educated workers (h) and the less educated workers (l). We assume that agents live for two periods (childhood and adulthood). The number of adults of type s living in region r at time t is denoted by $L_{r,s,t}$. Time is discrete, and one period is meant to represent the active life of one generation (30 years). The retirement period is ignored. In the benchmark version of the model, goods produced in the two sectors are assumed to be perfectly substitutable from the point of view of consumers; their price is normalized to unity. In the robustness checks, we consider an alternative specification with imperfectly substitutable goods entering into a non-homothetic preference structure, as in Boppart (2014). Adults are the only decision makers. They maximize their well-being and decide where to live, how much to consume, and how much to invest in their children's quantity and quality. The latter decisions are governed by a warm-glow motive; adults directly value investments in the quality and quantity of their children, but they do not anticipate the future income and utility of their children (as in Galor and Weil, 2000; Galor, 2011; de la Croix and Doepke, 2003 and 2004). The dynamic structure of the model is thus totally recursive. The model endogenizes the levels of productivity of both sectors/regions (and the resulting productivity gap), human capital accumulation, fertility decisions, and internal and international labor mobility. This section describes our assumptions and defines the intertemporal equilibrium.

1.3.1 Technology

Total output in period t is a sum of the production in agriculture and nonagriculture, $Y_t = Y_{a,t} + Y_{n,t}$. In each sector, production is proportional to labor in efficiency units. Such a model without physical capital features a globalized economy with a common international interest rate. This hypothesis is in line with Kennan (2013) or Klein and Ventura (2009), who assume that capital "chases" labor.[10] In line with Gollin et al. (2014b) or Vollrath (2009), each country is characterized by a pair of production functions with two types of labor, college-educated and low-skilled labor ($\ell_{r,s,t}$ $\forall r, s$). We generalize their work by assuming CES (constant elasticity of substitution) specifications with sector-specific elasticities of substitution.[11] The supply of labor, $\ell_{r,s,t}$, differs from the adult population size, $L_{r,s,t}$, because participation rates are smaller than one: as

[9] Our model is similar to Delogu et al. (2018) but relies on a different training technology, accounts for richer technological externalities, includes two sectors per country, and jointly endogenizes internal and international migration flows.

[10] Ortega and Peri (2014) find that capital adjustments are rapid in open economies: an inflow of immigrants increases one-for-one employment and capital stocks in the short term (i.e. within one year), leaving the capital/labor ratio unchanged. In the medium term, demographic change may affect the worldwide capital/labor ratio. Nevertheless, in a closed setting *a la* Ramsey (1928) or Solow (1956), the interest rate is totally determined by the inter-temporal discount rate of individuals (or by the savings rate) on the long-run balanced growth path. In this chapter, we abstract from potential variations in the international interest rate and its impact on within- and between-country inequality.

[11] This elasticity plays a key role in development accounting and is shown to vary across sectors (Jones, 2014; Caselli and Ciccone, 2014; Lucas, 2009).

explained below, raising children induces a time cost and decreases labor market participation. Output levels at time t are given by the following:

$$Y_{r,t} = A_{r,t} \left(\sum_s \varpi_{r,s,t} \ell_{r,s,t}^{\frac{\sigma_r - 1}{\sigma_r}} \right)^{\frac{\sigma_r}{\sigma_r - 1}} \qquad \forall r, t, \tag{1.1}$$

where $A_{r,t}$ denotes the productivity scale in sector r at time t, $\varpi_{r,s,t}$ is a sector-specific variable governing the relative productivity of workers of type s (such that $\varpi_{r,h,t} + \varpi_{r,l,t} = 1$) and $\sigma_r \in \mathbb{R}_+$ is the sector-specific elasticity of substitution between the two types of workers employed in sector r.

The CES specification is flexible enough to account for substitutability differences across sectors. In particular, we consider a greater elasticity of substitution in the agricultural sector ($\sigma_a > \sigma_n$). Wage rates are determined by the marginal productivity of labor and there is no unemployment. This yields:

$$w_{r,s,t} = A_{r,t} \left(\sum_s \varpi_{r,s,t} \ell_{r,s,t}^{\frac{\sigma_r - 1}{\sigma_r}} \right)^{\frac{1}{\sigma_r - 1}} \varpi_{r,s,t} \ell_{r,s,t}^{\frac{-1}{\sigma_r}} \qquad \forall r, s, t. \tag{1.2}$$

It follows that the wage ratio between high-skilled and low-skilled workers in region r is given by the following:

$$R^w_{r,t} \equiv \frac{w_{r,h,t}}{w_{r,l,t}} = R^{\varpi}_{r,t} \left(R^{\ell}_{r,t} \right)^{\frac{-1}{\sigma_r}} \qquad \forall r, t, \tag{1.3}$$

where $R^{\ell}_{r,t} \equiv \frac{\ell_{r,h,t}}{\ell_{r,l,t}}$ is the skill ratio in the labor force of region r at time t and $R^{\varpi}_{r,t} \equiv \frac{\varpi_{r,h,t}}{\varpi_{r,l,t}}$ measures the skill bias in relative productivity. Although human capital is used in agriculture, the literature has emphasized that the marginal product of human capital is greater in the nonagricultural sector (see Lucas, 2009; Vollrath, 2009; Gollin et al., 2014b).

Two types of technological externality are factored in. First, we consider a simple Lucas-type, aggregate externality (see Lucas, 1988) and assume that the scale of the total productivity factor (TFP) in each sector is a concave function of the skill ratio in the resident labor force. This specification captures the fact that college-educated workers facilitate democratization, innovation and the adoption of advanced technologies. We assume that the region-specific TFP equals to the following:

$$A_{r,t} = \gamma^t \overline{A}_{r,t} \left(R^{\ell}_{r,t} \right)^{\epsilon_r} \qquad \forall r, t, \tag{1.4}$$

where γ^t is a time trend in productivity that is common to all countries ($\gamma > 1$), $\overline{A}_{r,t}$ is the exogenous component of TFP in region r (reflecting exogenous factors such as the proportion of arable land, climatic factors, soil fertility, ruggedness, etc.), and $\epsilon_r \in (0, 1)$ is a pair of elasticities of TFP to the skill-ratio in the sector. The TFP gap between the two sectors is thus given by the following:

$$\Gamma_t \equiv \frac{A_{n,t}}{A_{a,t}} = \frac{\overline{A}_{n,t} \left(R^{\ell}_{n,t} \right)^{\epsilon_n}}{\overline{A}_{a,t} \left(R^{\ell}_{a,t} \right)^{\epsilon_a}}. \tag{1.5}$$

In Gollin et al. (2014b), the "nonagriculture/agriculture" ratio of value added per worker decreases with development; it amounts to 5.6 in poor countries (bottom 25%) and 2.0 in rich countries (top 25%). After adjusting for hours worked and human capital, the ratio falls to 3.0 in poor countries and 1.7 in rich countries. In our model, on the one hand, the findings of Gollin et al. (2014b) can then be driven by the correlation between economic development. On the other hand, they can be triggered by (i) the exogenous productivity gap between sectors, $\overline{A}_{n,t} \neq \overline{A}_{a,t}$, (ii) the differences in the elasticity of TFP to human capital, $\epsilon_n \neq \epsilon_a$, or (iii) the disparities in human capital across sectors, $R^{\ell}_{n,t} \neq R^{\ell}_{a,t}$. The latter operate through the ratio of TFP (as shown in Equation (1.5)) and through labor market complementarities (captured by the CES transformation function in Equation (1.1)).

Second, we assume a skill-biased technical change. As the technology improves, the relative productivity of college-educated workers increases, and this is particularly the case in the nonagricultural sector (Acemoglu, 2002; Restuccia and Vandenbroucke, 2013). For example, Autor et al. (2003) show that computerization is associated with a declining relative industry demand for routine manual and non-cognitive tasks and an increased relative demand for non-routine cognitive tasks. The observed relative demand shift favors college versus non-college labor. We write:

$$R^{\varpi}_{r,t} = \overline{R}^{\varpi}_{r} \left(R^{\ell}_{r,t}\right)^{\kappa_r} \qquad \forall r, t, \tag{1.6}$$

where $\overline{R}^{\varpi}_{r}$ is an exogenous term, and $\kappa_r \in (0, 1)$ is a pair of elasticities of the skill-bias to the skill-ratio in the sector.

1.3.2 Preferences

We now model the process of skill accumulation as the outcome of education and mobility decisions. First, individual decisions to emigrate result from the comparison of discrete alternatives: staying in the region of birth, emigrating to the other region, or emigrating to a foreign country. To model these decisions, we use a logarithmic *outer utility function* with a deterministic and a random component. The utility of an adult of type s, who is born in region r^* and is moving to region/country r, is given by:

$$U_{r^*r,s,t} = \ln v_{r,s,t} + \ln(1 - x_{r^*r,s,t}) + \xi_{r^*r,s,t} \qquad \forall r^*, r, s, t, \tag{1.7}$$

where $v_{r,s,t} \in \mathbb{R}$ is the deterministic level of utility that can be reached in the location r at period t (governed by the inner utility function described below) and $x_{r^*r,s,t} \leq 1$ captures the effort required to migrate from region r^* to location r (such that $x_{r^*r^*,s,t} = 0$). Migration costs are exogenous; they vary across location pairs, across education levels, and over time. The individual-specific random taste shock for moving from country r^* to r is denoted by $\xi_{r^*r,s,t} \in \mathbb{R}$ and follows an *iid* Type-I Extreme Value distribution:

$$F(\xi) = \exp\left[-\exp\left(-\frac{\xi}{\mu} - \vartheta\right)\right],$$

where $\mu > 0$ is a common scale parameter governing the responsiveness of migration decisions to changes in $v_{r,s,t}$ and $x_{r^*r,s,t}$ and $\vartheta \approx 0.577$ is the Euler's constant. Although $\xi_{r^*r,s,t}$ is individual-specific, we omit individual subscripts for notational convenience.

Second, we model education decisions as in Galor and Weil (2000), Galor (2011), de la Croix and Doepke (2003, 2004), Delogu et al. (2018). We assume that the *inner utility* $\ln v_{r,s,t}$ is a function of consumption ($c_{r,s,t}$), fertility ($n_{r,s,t}$) and the probability that each child becomes highly skilled ($p_{r,s,t}$):

$$\ln v_{r,s,t} = \ln c_{r,s,t} + \theta \ln \left(n_{r,s,t} p_{r,s,t}\right) \quad \forall r, s, \tag{1.8}$$

where $\theta \in (0,1)$ is a preference parameter for the quantity and quality of children.

The probability that a child becomes high skilled increases with the share of time that is spent in education ($q_{r,s,t}$):

$$p_{r,s,t} = \left(\pi_r + q_{r,s,t}\right)^{\lambda} \quad \forall r, s, \tag{1.9}$$

where π_r is an exogenous parameter that is region-specific and λ governs the elasticity of knowledge acquisition to the education investment.

A type-s adult in region r receives a wage rate $w_{r,s,t}$ per unit of time worked. Raising a child requires a time cost ϕ (thereby reducing the labor market participation rate), and each unit of time spent by a child in education incurs a cost equal to $E_{r,t}$. The budget constraint is written as follows:

$$c_{r,s,t} = w_{r,s,t}(1 - \phi n_{r,s,t}) - n_{r,s,t} q_{r,s,t} E_{r,t}. \tag{1.10}$$

It follows that the labor supply of type-s adults in region r at time t is given by the following:

$$\ell_{r,s,t} = L_{r,s,t}(1 - \phi n_{r,s,t}). \tag{1.11}$$

In the following sub-sections, we solve the optimization problem backwards. We first determine the optimal fertility rate and investment in education in a given location r, which characterizes the optimal level of utility, $v_{r,s,t}$, that can be reached in any location. We then characterize the choice of the optimal location.

Education and fertility

Each adult in region r maximizes her utility (1.8) subject to the constraints (1.9) and (1.10). The first-order conditions for an interior solution are as follows:

$$\begin{aligned}
\frac{\phi w_{r,s,t} + q_{r,s,t} E_{r,t}}{w_{r,s,t}(1 - \phi n_{r,s,t}) - n_{r,s,t} q_{r,s,t} E_{r,t}} &= \frac{\theta}{n_{r,s,t}}, \\
\frac{n_{r,s,t} E_{r,t}}{w_{r,s,t}(1 - \phi n_{r,s,t}) - n_{r,s,t} q_{r,s,t} E_{r,t}} &= \frac{\theta \lambda}{\pi_r + q_{r,s,t}}.
\end{aligned}$$

Solving this system gives the following:

$$\left\{ \begin{array}{l} q_{r,s,t} = \frac{\lambda \phi w_{r,s,t} - \pi_r E_{r,t}}{(1-\lambda) E_{r,t}} \\ n_{r,s,t} = \frac{\theta(1-\lambda)}{1+\theta} \cdot \frac{w_{r,s,t}}{\phi w_{r,s,t} - \pi_r E_{r,t}} \end{array} \right. \quad \forall r, s.$$

The cost of education is assumed to be proportional to the wage of high-skilled workers in the region, multiplied by a fixed, region-specific factor $\psi_{r,t}$ (capturing education policy/quality, population density, average distance to schools, etc.):

$$E_{r,t} = \psi_{r,t} w_{r,h,t} \quad \forall r, s. \tag{1.12}$$

Factoring (1.12) into the first-order conditions gives the following:

$$\left\{ \begin{array}{l} q_{r,h,t} = \frac{\lambda \phi}{(1-\lambda)\psi_{r,t}} - \frac{\pi_r}{1-\lambda} \\ q_{r,l,t} = \frac{\lambda \phi}{(1-\lambda)\psi_r R^w_{r,t}} - \frac{\pi_r}{1-\lambda} \end{array} \right. \quad \text{and} \quad \left\{ \begin{array}{l} n_{r,h,t} = \frac{\theta(1-\lambda)}{1+\theta} \frac{1}{\phi - \pi_r \psi_r} \\ n_{r,l,t} = \frac{\theta(1-\lambda)}{1+\theta} \frac{1}{\phi - \pi_r \psi_r R^w_{r,t}} \end{array} \right. \tag{1.13}$$

Note that $R^w_{r,t} > 1$ implies that college-educated workers have fewer and more educated children in all regions ($q_{r,h,t} > q_{r,l,t}$ and $n_{r,h,t} < n_{r,l,t}$). The model also predicts that investments in education vary across regions, and are likely to be greater in the nonagricultural region. Under the plausible condition $\psi_{a,t}/\psi_{n,t} > 1$, college-educated workers living in urban areas have fewer and more educated children ($q_{n,h,t} > q_{a,h,t}$ and $n_{n,h,t} < n_{a,h,t}$). Finally, when $(\psi_{a,t}R^w_{a,t})/(\psi_{n,t}R^w_{n,t}) > 1$, this is also the case for the low skilled ($q_{n,l,t} > q_{a,l,t}$ and $n_{n,l,t} < n_{a,l,t}$). These results are in line with Lucas (2009), who assumes that human capital accumulation increases with the fraction of people living in cities (seen as *centers of intellectual interchange and recipients of technological inflows*).

The deterministic indirect utility function can be obtained by substituting (1.13) into (1.8):

$$\begin{cases} \ln v_{r,h,t} = \chi + \ln(w_{r,h,t}) + \theta\lambda \ln\left(\frac{1}{\psi_{r,t}}\right) - \theta(1-\lambda)\ln(\phi - \pi_r\psi_{r,t}) \\ \ln v_{r,l,t} = \chi + \ln(w_{r,l,t}) + \theta\lambda \ln\left(\frac{1}{\psi_{r,t}}\right) - \theta(1-\lambda)\ln\left(\phi - \pi_r\psi_{r,t}R^w_{r,t}\right) \\ \qquad + \ln\left(\frac{\phi\left(1+\theta\lambda\left(1-1/R^w_{r,t}\right)\right) - \pi_r\psi_{r,t}R_{r,t}\left(1+\theta\left(1-1/R^w_{r,t}\right)\right)}{\phi - \pi_r\psi_{r,t}R^w_{r,t}}\right) \end{cases} \tag{1.14}$$

where $\chi = \theta \ln\left(\frac{\theta}{1+\theta}(1-\lambda)^{1-\lambda}\lambda^\lambda\right) - \ln(1+\theta)$ is a constant.

Together with the number and structure of the resident population at time t ($L_{r,s,t}$ $\forall r, s$), fertility and education decisions ($n_{r,s,t}, q_{r,s,t}$ $\forall r, s$) determine the size and structure of the native population before migration ($N_{r,s,t+1}$ $\forall r, s$) at time $t+1$. We have the following:

$$\begin{cases} N_{r,h,t+1} = L_{r,h,t}n_{r,h,t}p_{r,h,t} + L_{r,l,t}n_{r,l,t}p_{r,l,t} \\ N_{r,l,t+1} = L_{r,h,t}n_{r,h,t}\left[1 - p_{r,h,t}\right] + L_{r,l,t}n_{r,l,t}\left[1 - p_{r,l,t}\right] \end{cases} \quad \forall r, t. \tag{1.15}$$

Migration and population dynamics

Given their taste characteristics (captured by ξ), individuals choose the location that maximizes her/his utility, defined in Equation (1.7). Under the Type I Extreme Value distribution for ξ, McFadden (1974) shows that the solution to a discrete choice problem (that is, in our context, a decision to migrate from region r to $r*$) is governed by a logit expression. The emigration rate is given by the following:

$$\frac{M_{r^*r,s,t}}{N_{r^*,s,t}} = \frac{\exp\left(\frac{\ln v_{r,s,t} + \ln(1-x_{r^*r,s,t})}{\mu}\right)}{\sum_k \exp\left(\frac{\ln v_{k,s,t} + \ln(1-x_{r^*k,s,t})}{\mu}\right)} = \frac{(v_{r,s,t})^{1/\mu}(1-x_{r^*r,s,t})^{1/\mu}}{\sum_k (v_{k,s,t})^{1/\mu}(1-x_{r^*k,s,t})^{1/\mu}}.$$

Skill-specific emigration rates are endogenous and restricted between 0 and 1. Staying rates ($M_{r^*r^*,s,t}/N_{r^*,s,t}$) are governed by the same logit model. It follows that the emigrant-to-stayer ratio ($m_{r^*r,s,t}$) is governed by the following expression:

$$m_{r^*r,s,t} \equiv \frac{M_{r^*r,s,t}}{M_{r^*r^*,s,t}} = \left(\frac{v_{r,s,t}}{v_{r^*,s,t}}\right)^{1/\mu}(1-x_{r^*r,s,t})^{1/\mu}. \tag{1.16}$$

Equation (1.16) is a gravity-like migration equation, which states that the ratio of emigrants from region r^* to location r to stayers in region r^* (i.e., individuals born in r^* who remain in r^*) is an increasing function of the utility achievable in the destination location r and a decreasing function of the utility attainable in r^*. The proportion of migrants from r^* to r also decreases with the bilateral migration cost $x_{r^*r,s,t}$. Heterogeneity in migration tastes implies that emigrants select all destinations for which $x_{r^*r,s,t} < 1$ (if $x_{r^*r,s,t} = 1$, the corridor is empty).

Individuals born in region n (respectively a) have the choice between staying in their region of origin n (respectively a), moving to the other region a (respectively n), or emigrating to a foreign country f. Contrary to Hansen and Prescott (2002) or Lucas (2009), labor is not perfectly mobile across sectors/regions; internal migration costs ($x_{an,s,t}$ and $x_{na,s,t}$) capture all private costs that migrants must incur to move between regions. In line with Young (2013), internal mobility is driven by self-selection, i.e., skill-specific disparities in utility across regions as well as heterogeneity in individual unobserved characteristics (ξ). Overall, if $v_{n,s,t} > v_{a,s,t}$, net migration is in favor of urban areas, but migration is limited by the existence of migration costs, whose sizes govern the sectoral misallocations of workers (Rodrik, 2013). Similarly, international migration costs ($x_{af,s,t}$ and $x_{nf,s,t}$) capture private costs and the legal/visa costs imposed by the destination countries. They are also assumed to be exogenous.

Using (1.16), we can characterize the equilibrium structure of the resident population at time t:

$$\begin{cases} L_{n,s,t} = \frac{N_{n,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{m_{an,s,t}N_{a,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + I_{n,s,t} \\ L_{a,s,t} = \frac{N_{a,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{m_{na,s,t}N_{n,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + I_{a,s,t} \end{cases} \quad \forall s, \tag{1.17}$$

where $I_{r,s,t}$ stands for the inflow of immigrants (which only applies to migration from developing to OECD member states). For simplicity, we assume that the distribution of immigrants by OECD destination is time-invariant and calibrated on the year 2010. Equation (1.16) also determines the outflow of international migrants by education level ($O_{s,t}$):

$$\begin{aligned} O_{s,t} &= M_{nf,s,t} + M_{af,s,t} \\ &= \frac{m_{nf,s,t}N_{n,s,t}}{1 + m_{na,s,t} + m_{nf,s,t}} + \frac{m_{af,s,t}N_{a,s,t}}{1 + m_{an,s,t} + m_{af,s,t}} \quad \forall s, \end{aligned} \tag{1.18}$$

where $N_{r,s,t}$ is a predetermined variable given by (1.15).

1.3.3 Intertemporal equilibrium

An intertemporal equilibrium for the world economy can be defined as following:

Definition 1.1 *For a set $\{\gamma, \theta, \lambda, \phi, \mu\}$ of common parameters, a set $\{\sigma_r, \epsilon_r, \kappa_r\}$ of sector-specific elasticities, a set $\left\{\overline{A}_{r,t}, \overline{R}^{\varpi}_{r,t}, \overline{x}_{r^*r,s,t}, \psi_r, \pi_r\right\}$ of country- and region-specific exogenous characteristics, and a set $\{N_{r,s,0}\}$ of predetermined variables, an intertemporal equilibrium is a reduced set $\{A_{r,t}, \varpi_{r,h,t}, w_{r,s,t}, n_{r,s,t}, q_{r,s,t}, v_{r,s,t}, E_{r,t}, m_{r^*r,s,t}, N_{r,s,t+1}, L_{r,s,t}\}$ of endogenous variables, which simultaneously satisfies technological constraints (1.4), (1.6) and (1.12), profit maximization conditions (1.2), utility maximization conditions (1.13), (1.14) and (1.16) in all countries and regions of the world, and such that the equilibrium structure and dynamics of population satisfy (1.15) and (1.17).*

The equilibrium level of the other variables described above (in particular, $\ell_{r,s,t}$, $R^{\ell}_{r,t}$, $R^{\varpi}_{r,t}$, $R^{w}_{r,t}$, Γ_t as well as urbanization rates and international migration outflows) can be computed as a by-product of the reduced set of endogenous variables. Note that equilibrium wage rates are obtained by substituting the labor force variables into the wage equation (1.2), thereby assuming full employment. By the Walras law, the market for goods is automatically balanced.

1.4 Data and parameterization

In this section, we describe our parameterization strategy for 145 developing countries and for the entire set of 34 OECD countries.[12] Our parameterization strategy consists in calibrating a few common elasticities and a large number of region-specific parameters in order to (perfectly) match socio-demographic and economic data for the years 1980 and 2010 (including internal and international migrations) and to be in line with official socio-demographic projections for the year 2040.[13] We use all the degrees of freedom of the data to identify the parameters needed. Consequently, our model is exactly identified and cannot produce a test of its assumptions. However, it is worth noticing that we use relatively consensual specifications for the production and migration technologies and that we test the robustness of our results in the Appendix. We start describing how we estimate the geographic distribution of skills. Then, the parameterization of the technological and preference parameters is outlined. More details about the calibration can be found in Section 1.A.1 in the Appendix. We finally explain the general hypotheses used to initialize our baseline projections for the 21st century.

Estimating the geography of skills. To construct labor force data by education level and by sector ($L_{r,s,t}$), we follow the four steps described below.

In the *first step*, we extract population data by age group from the United Nations Population Division and combine it with the database on educational attainment described in Barro and Lee (2013). For the years 1980 and 2010, we proxy the working age population with the number of residents aged 25 to 60. To proxy the number of high-skilled workers in each country, we multiply the working age population by Barro and Lee's estimates of the proportion of individuals aged 25 and over with tertiary education completed (denoted by H_t). The rest of the working age population is treated as a homogeneous group of less educated workers. Barro and Lee's data are available for 143 countries. For the other countries, we make use of estimated data from Artuç et al. (2015). Note that Barro and Lee (2013) also document the average years of schooling of the working age population ($\text{Yo}S_t$), a variable that we use in the third step of our estimation strategy. We are able to characterize the total number of workers ($\Sigma_{r,s} L_{r,s,t}$) and the total number of college-educated and less educated workers ($\Sigma_r L_{r,h,t}$ and $\Sigma_r L_{r,l,t}$) by country. The same strategy has been applied to all decades between 1970 and 2010 to compute the between-country index of inequality depicted in Figure 1.1.

In the *second step*, we split the total population data by region/sector. When it is possible, we use the share of employment in agriculture, which is available from the World Development Indicators. This variable is available for 134 countries in 2010 and for 61 in 1980. However, the same database also provides information on the share of people living in rural areas, which is highly correlated with the share of employment in agriculture (correlation of 0.71 in 2010 and 0.75 in 1980). When the share of employment in agriculture is not available, we predict it using estimates from year-specific regressions as a function of the share of people living in rural areas. This determines the total number of workers ($\Sigma_s L_{r,s,t}$) in both sectors.

The major problem is that, to the best of our knowledge, there is no database documenting the share of college graduates by region or by sector ($H_{r,t}$). We estimate these

[12] With the exceptions of Macao, North-Korea, Somalia and Taiwan, all countries that are not covered by our sample have less than 100,000 inhabitants.

[13] Our set of region-specific parameters includes TFP and skill-bias levels, education costs, internal and international migration costs.

shares and compare them with nationally representative data from the Gallup World Polls. More details on the Gallup World Polls are provided in Section 1.A.1 in the Appendix. To compute these shares, we collect or construct data on the years of schooling by sector (Yo$S_{r,t}$) and use them to predict the sector-specific shares of college graduates as a function of Yo$S_{r,t}$. Hence, our *third step* consists of gathering data on Yo$S_{r,t}$ and imputing the missing values. Gollin et al. (2014b) and Ulubasoglu and Cardak (2007) provide incomplete data on the countrywide average years of schooling and on the average years of schooling in agriculture and nonagricultural for different years.[14] We have data for 20 countries around the year 1980 and for 65 countries around the year 2010. We match these data to the closest year that marks the beginning of the 1980 and 2010 decades. For the missing countries, we take advantage of the high correlation between the gap in years of schooling, Yo$S_{n,t}/YoS_{a,t}$, and the average years of schooling in the country, YoS_t. We predict the schooling gap by using estimates from year-specific regressions of this gap on YoS_t.[15]

Finally, in the *fourth step*, we take advantage of the high correlation between the average years of schooling and the proportion of college graduates in the labor force at the national level. We estimate the relationship between these variables, $H_t = f(YoS_t)$, using Barro and Lee's data, and then use the estimated coefficients to predict the share of college graduates in the urban sector, $H_{r,t} = f(YoS_{r,t})$.[16] We then fit the average share of college graduates from Barro and Lee by adjusting the share of college graduates in the rural sector.

To validate our estimation strategy, we compute the correlation between the sector-specific estimated shares of college graduates and the shares obtained from household surveys. Using the Gallup World Poll data (available for approximately 145 countries), we can estimate the skill-ratio $R^{\ell}_{r,t}$ in the number of respondents by country and region (corrected by sample weights); on average, the correlation between the Gallup sample and our estimates is equal to 0.70 in the urban region and to 0.73 in the rural region. The same imputation strategy can be used to identify the sector-specific shares of college graduates in total employment for all decades between 1970 and 2010. We use it to compute the within-country index of inequality depicted in Figure 1.1. Additional stylized facts are provided in Section 1.A.1 in the Appendix.

Technology parameters. The output in each sector depends on the size and skill structure of employment. Below, we explain how fertility rates are calibrated for each skill group and for each region/sector. Combining labor force data ($L_{r,s,t}$) with fertility rates ($n_{r,s,t}$) allows us to quantify the employment levels ($\ell_{r,s,t}$) and the total employment in efficiency unit using (1.11).

To calibrate the set of technological parameters $\left\{\sigma_r, \epsilon_r, \kappa_r, \overline{R}^{\varpi}_r, \overline{A}_{r,t}\right\}$, we proceed in two steps. First, we calibrate the parameters affecting the private returns to higher education. For each sector, we combine our estimates for $\ell_{r,s,t}$ with cross-country data on the income gap between college graduates and the less educated. This enables us to parameterize the elasticities of substitution between workers (σ_r), the relative productivity of college graduates (R^{ϖ}_r), the magnitude of the skill-biased externalities (κ_r), and the

[14] In Gollin et al. (2014b) and Vollrath (2009), the nonagriculture/agriculture ratio of years of schooling varies between 2.0 or 1.5 in poor countries and is close to 1.0 in rich countries.

[15] Simple OLS regressions give $\log \frac{YoS_n}{YoS_a} = 1.944 - 0.744 \log YoS$ (R^2=0.809) in 2010, and $\log \frac{YoS_n}{YoS_a} = 1.464 - 0.550 \log YoS$ (R^2=0.905) in 1980.

[16] Simple OLS regressions give $\log H = -4.804 + 0.279 \log YoS$ ($R^2 = 0.496$) in 2010, and $\log H = -5.133 + 0.306 \log YoS$ ($R^2 = 0.575$) in 1980.

scale factors of the skill-bias technology ($\overline{R}_r^{\varpi}$). In the second step, we focus on the social returns to education. We use output data by sector and identify the level of total factor productivity that matches the GDP data by sector. We then investigate the relationship between TFP and the skill ratio, which enables us to estimate the size of the aggregate TFP externalities (ϵ_r) and the TFP scale factors ($\overline{A}_{r,t}$). Figure 1.A2 in the Appendix summarizes our main findings.

In the *first step*, we calibrate the elasticity of substitution between college graduates and less educated workers, relying on existing studies. For the nonagricultural sector, there is a large number of influential papers that propose specific estimates for industrialized countries (i.e., countries where the employment share of agriculture is small). Johnson (1970) and Murphy et al. (1998) obtain values for σ_n of approximately 1.3. Ciccone and Peri (2005) and Krusell et al. (2000) find values of approximately 1.6, and Ottaviano and Peri (2012) suggest setting σ_n close to 2.0. Angrist (1995) recommends a value above 2 to explain the trends in the college premium in the Palestinian labor market. For the agricultural sector, it is usually assumed that the elasticity of substitution is much larger. For example, Vollrath (2009) or Lucas (2009) consider that labor productivity is determined by the average level of human capital of workers (thus assuming perfect substitution between skill groups). In line with the existing literature, we assume $\sigma_n = 2$ and $\sigma_a = \infty$.

Once the elasticities are chosen, we use sector-specific data on returns to schooling to calibrate the relative productivity of college-educated workers. In the agricultural sector, we rule out the possibility of a skill-biased technical change in agriculture ($\kappa_a = 0$), and assume a linear technology with a constant R_a^{ϖ} for all countries and all periods (we use $\varpi_a = 0.57$). For the nonagricultural sector, we use data on the skill premium and calibrate R_n^{ϖ} as a residual of (1.3). Regressing R_n^{ϖ} on R_n^{ℓ} yields an estimate of 0.38. Given the bidirectional causation relationship between the skill bias and education decisions, we consider this estimate as an upper bound for the skill-bias externality. In our baseline projections, we assume that half the correlation is due to the skill-bias externality (i.e., $\kappa_n = 0.19$). We calibrate the scale factor $\overline{R}_n^{\varpi}$ as a residual from (1.6).

In the *second step*, we use data on the national gross domestic product (GDP) and on the agriculture share in value added. We obtain data on output by sector in the year 2010 and identify the TFP levels ($A_{r,t}$) by dividing the sector-specific output by the quantity of labor in efficiency unit using (1.1). There is a clear positive relationship between TFP and the share of college-educated workers in both sectors. Regressing the log of $A_{r,t}$ on the log of $R_{r,t}^{\ell}$ gives a coefficient of 0.57 in the nonagricultural sector and 0.66 in agriculture. Given the reverse causation relationship between productivity and the education decision, we consider these estimates as upper bounds for the aggregate TFP externality. In our baseline scenario, we assume that half the correlation between TFP and the share of college-educated workers is due to the schooling externality (i.e., $\epsilon_n = 0.28$ and $\epsilon_a = 0.33$). We calibrate the scale factor $\overline{A}_n$ as a residual from (1.4).

Figure 1.A2 in the Appendix shows that these assumptions are consistent with the macro and microdata. Nevertheless, alternative technological scenarios are considered in the robustness checks (see Section 1.A.4 in the Appendix).

Preference parameters. The literature indicates some common values of several preference parameters. We assign the following values to the parameters that are time-invariant and equal for all countries: $\theta = 0.25$, $\lambda = 0.5$ and $\phi = 0.14$.[17] From (1.14) and (1.16), the

[17] Given the expression in (1.10), this assumption reflects setting the bound of the maximal number of

scale parameter of the distribution of migration tastes (μ) is the inverse of the elasticity of bilateral migration to the wage rate. Bertoli and Fernández-Huertas Moraga (2013) find a value between 0.6 and 0.7 for this elasticity. Hence, we use $\mu = 1.4$.

Parameters π_r and $\psi_{r,t}$ are country- and sector-specific. They govern the fertility and education decisions. We calibrate them to match the population dynamics between the years 1980 and 2010, i.e., the transition from the resident population in 1980 and the native population in 2010. We begin by estimating the size of the *before-migration* population in 2010 by skill group ($\sum_r N_{r,s,2010}$). The average (national) fertility rate ($\overline{n}_{1980}$) is thus obtained by dividing the total native population of adults in 2010 ($\sum_{r,s} N_{r,s,2010}$) by the total resident population of adults in 1980 ($\sum_{r,s} L_{r,s,1980}$). We also observe the skill structure of the native population in 2010 ($N_{r,s,2010}$), which helps identifying education decisions in 1980 ($\overline{q}_{1980}$). We use the Gallup World Polls and extract the Gallup-based average number of children per household by region and by skill level for 2010 to proxy the fertility differentials. We calibrate π_r and $\psi_{r,t}$ to match $n_{r,s,1980}$ and $\overline{q}_{1980}$. From 2010 onwards, the number of children and education decisions are endogenous.

We then estimate the skill and regional distribution of workers in 1980 and 2010 and calibrate internal migration costs as a residual from Equation (1.16). For this, we assume there is only migration from rural to urban regions (i.e., $x_{an,s,t} < 1$ and $x_{na,s,t} = 1$). Similarly, we compute the average utility achievable in OECD destination countries and calibrate the international migration costs ($x_{af,s,t}$ and $x_{nf,s,t}$) as a unique solution from Equation (1.16) to match the DIOC migration data. Again, more details are provided in Section 1.A.1.

Baseline trajectory for the 21st century. Our parameter set is such that the model matches the geographic disparities in income, population and human capital in the year 2010, and their evolution between 1980 and 2010. Our baseline also includes technological externalities, assuming that half the correlation between TFP (and skill bias) and the share of college-educated workers is due to the schooling externality. Alternative technological and preference scenarios are considered in Section 1.A.4 in the Appendix.

The philosophy of our baseline projection exercise is to predict the future trends in income, population and human capital if all parameters, with the exception of the TFP scale factor (assumed to grow at a constant rate of 1.5% per year in all countries) and the parameters governing access to education, remain constant. More precisely, we constrain our baseline trajectory to be compatible with official socio-demographic projections for the year 2040 for each country. The rationale for matching medium-term projections is that the size and skill structure of the national population in 2040 are determined by fertility and education decisions in the contemporaneous period (i.e., the years 2010 to 2040). Hence, the reliability of medium-term projections is high, and their consistency with the economic environment is good. Nevertheless, we let the micro-founded model predict the sectoral allocation of labor and international migration rates in 2040 as well as the evolution of socio-demographic variables beyond 2040. The comparison between our simulations and official projections is discussed in Section 1.5.2.

To match the size and skill structure of the national population in 2040, we allow for country-specific proportional adjustments in $\psi_{r,t}$ ($r = a, n$) (i.e., the same relative change in both sectors, keeping $\psi_{a,t}/\psi_{n,t}$ constant) that minimizes the sum of squared differences in total population and in its skill structure between the baseline simulations and the

children equal to 7 (i.e., 14 children per couple). See Docquier et al. (2016) for a brief review of studies using similar parameter values.

UN projections for the year 2040. Remember $\psi_{r,t}$ determines the access to education in the region. Comparing the new levels of $\psi_{r,2010}$ with those obtained in 1980 (i.e., $\psi_{r,1980}$), we identify a conditional convergence process in the access to education. We see it as a likely consequence of the Millennium Development policy. More precisely, we estimate two quadratic, region-specific convergence equations, considering the US as the benchmark frontier:

$$\ln\left(\psi_{r,t+1}/\psi_{r,t}\right) = \alpha_r + \beta_r \ln\left(\psi_{r,t}^{USA}/\psi_{r,t}\right) + \gamma_r \left(\ln\left(\psi_{r,t}^{USA}/\psi_{r,t}\right)\right)^2. \tag{1.19}$$

We obtain $\gamma_a = 0.032$, $\gamma_n = 0.046$, $\beta_a = -0.195$ and $\beta_n = -0.223$, in which all parameters are highly significant. This quadratic convergence process implies that middle-income countries converge more rapidly than low-income countries do. For subsequent years, our baseline scenario assumes a continuation of this quadratic convergence process, in line with the new Sustainable Development Agenda. Alternative (i.e., more and less optimistic) convergence scenarios will also be considered in Section 1.5.3.

1.5 Results

Our model is used to investigate the interactions between the current/future distributions of skills and global inequality worldwide. First, in line with the development accounting methodology, we only use the (parameterized) technological block of the model and disregard the endogeneity of human capital accumulation. Section 1.5.1 describes a set of counterfactual experiments that allow identifying the causal impact of skills accumulation on inequality. More precisely, we quantify the fraction of contemporaneous development inequality that is explained by differences in the national proportion of highly educated workers, by their allocation across sectors, and by international migration. Second, our attention is turned to the determinants of the geography of skills. In Section 1.5.2, we provide integrated projections of worldwide population, urbanization, human capital and income per capita for the 21st century. Then, we assess the sensitivity of our projections to future educational policies (Section 1.5.3) and to future mobility frictions (Section 1.5.4).[18] Section 1.5.5 describes the underlying income inequality prospects and discusses their sensitivity.

1.5.1 How much does the current geography of skills matter for global inequality?

In line with the development accounting methodology (Jones, 2014), we consider the US as the base-case economy and proceed with three static counterfactual experiments to quantify the economic implications of skill accumulation in the year 2010. The advantage of our two-sector model is that we can separately quantify the development implications of skill accumulation, of the sectoral allocation of labor, and of international labor mobility. For each country, we first simulate the counterfactual level of national income per worker (y_{CF}) obtained after transposing the US shares of college-educated workers in each sector. We then compare it with the observed level (y_{obs}). The second counterfactual consists of keeping the country-specific share of college-educated residents constant but

[18] Section 1.A.4 in the Appendix shows that our socio-demographic projections are highly robust to the size of technological externalities as well as to the way preferences for agricultural and nonagricultural goods are modeled.

allocating high-skilled and low-skilled workers across sectors based on their allocation in the US economy. In the third counterfactual, we keep the country-specific share of college-educated natives constant but simulate a no-migration scenario (US international emigration rates are almost nil). The results are depicted in Figure 1.2.

Figures 1.2a and 1.2b give the counterfactual levels of income per capita and the smoothed growth factor ($y_{\mathrm{CF}}/y_{\mathrm{obs}}$) obtained under three technological scenarios after transposing the US shares of college-educated workers. Under these scenarios, all countries have the same national fraction of college graduates as the US has and the same regional shares by educational level. In Figure 1.2a, the bold line shows the observed income levels; countries are ranked by ascending order with respect to the observed level of income per worker. Most studies in development accounting disregard technological externalities (see Jones, 2015) or consider that externalities are small (Caselli and Ciccone, 2014). In contrast, our baseline scenario (solid line) assumes that externality sizes are equal to 50% of the correlations between human capital and technological characteristics (i.e., $\kappa_n = 0.19$, $\kappa_a = 0$, $\epsilon_n = 0.28$ and $\epsilon_a = 0.33$). The variants (dashed line) assume no externality, or externalities equal to 100% of the correlations (i.e., $\kappa_n = 0.38$, $\kappa_a = 0$, $\epsilon_n = 0.56$ and $\epsilon_a = 0.66$). Figure 1.2b gives the smoothed growth factor induced by the counterfactual under the same externality variants.

We show that the geography of skills matters for development, regardless of the size of technological externalities. In the absence of any externality, transposing the US educational structure increases income per worker by a factor of 2.5 for countries in the lowest quartile of the income distribution (i.e., from \$5,000 to \$12,500). The growth factor decreases with economic development, as the distance to the technology frontier gets smaller. This is in line with Jones (2014), who finds a growth factor of 2 for poor countries with the same elasticity of substitution. As in Jones, the effect is mainly driven by the fact that high-skilled workers are more productive and by the labor market complementarity with less educated workers. In addition, our model accounts for the sector allocation of labor. Transposing the US skill shares and the US sectoral allocation of workers not only increases the level of education but also increases the size of the urban (more productive) sector. This is equivalent to raising the average TFP level in a one-sector model and explains our greater success rate. In our baseline scenario with conservative externalities, transposing the US skill shares increases income per worker by a factor of 5 in the poorest countries (i.e., y increases from \$5,000 to \$25,000) after transposing the US educational structure. In the full-externality scenario, human capital almost becomes the single determining factor for economic development. Unsurprisingly, the size of technological externalities has a strong influence on the global inequality effect of the geography of skills.[19]

Figures 1.2c and 1.2d illustrate the role of the sector allocation of skills under the same externality scenarios. We simulate the effect of transposing the US skill-specific urban shares (keeping the country-wide share of college graduates at the observed levels). The baseline scenario is shown as the solid line, while the zero- and the full-externality scenarios are shown as dashed lines. Under the baseline, transposing the US urban shares

[19] In unreported simulations, we used the baseline externality scenario (50% of correlations) and included one externality at a time. The results are highly sensitive to the aggregate TFP externality (almost equivalent to the baseline with both externalities). However, the skill-biased externality affects within-country wage disparities but plays a negligible role in explaining income per capita differentials (almost equivalent to the no-externality scenario). Directed technical changes slightly exacerbate income disparities across countries (poorest countries are better off in the absence of skill-biased technical changes, unlike richest countries).

for each category of worker increases income per worker by a factor of 1.7 in the lowest quartile of the distribution (i.e., about one third of the total effect identified above). Transposing the US shares in employment means increasing the urban share from 20% to 95% in the poorest countries. This shock drastically increases the mean levels of productivity and income. Poor countries are unable to realize these gains because individuals have no incentives to move due to liquidity constraints, imperfect information, or congestion effects (Hsieh and Klenow, 2009; Bryan et al., 2014). In line with Rodrik (2013), our results suggest that internal mobility frictions are responsible for a large misallocation of workers in poor countries and shows the relevance of a two-sector approach.

Under the same externality scenarios, Figures 1.2e and 1.2f illustrate the role of international migration. We simulate the effect of returning all expatriates to their home country (no-migration scenario). The baseline scenario is shown as the solid line, while the zero- and the full-externality scenarios are shown as dashed lines. With the exception of Small Island Developing States (corresponding to the peaks on Figure 1.2e), the effect of international migration on global inequality is small. On average, returning all international migrants to origin countries in the bottom quartile of the distribution increases income per workers by a factor of 1.2 in the baseline case (and by a factor of 1.5 with full externalities). This is because average emigration rates to the OECD are small in developing countries (approximately 5% for college graduates and less than 1% for the low-skilled). Contrary to the previous experiments, the global inequality response to international migration is rather limited.[20]

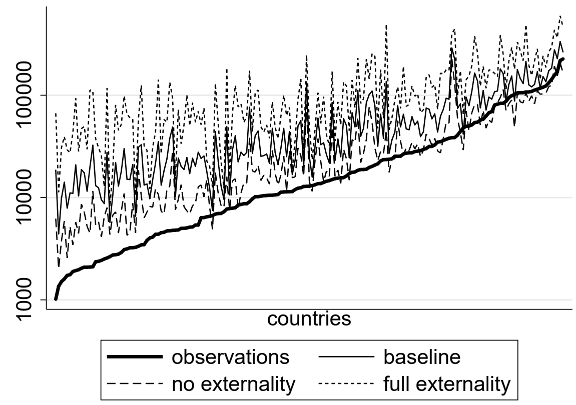
1.5.2 The changing geography of skills: baseline prospects

Disparities in the level and in the sector allocation of skills explain a significant fraction of economic inequality across countries. We now turn our attention to the factors governing the long-term trend in the geography of skills. This section compares our baseline socio-demographic prospects for the 21st century with the widely used projections of the United Nations Population Division (the UN medium variant).

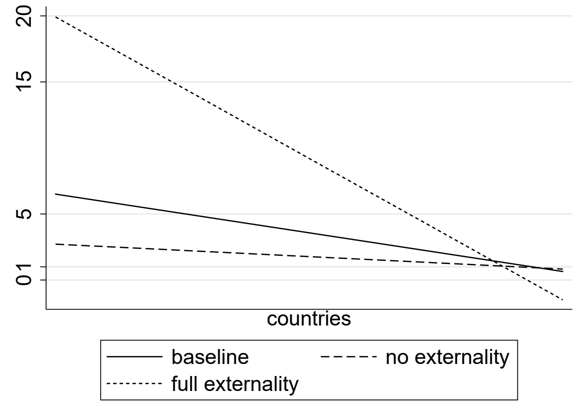
The UN projections assume a long-term convergence in fertility, mortality and education attainment, and constant immigration flows. Given the high correlation between socio-demographic and economic variables, the UN medium variant implicitly assumes income convergence between countries. In the medium term, the UN projections also predict higher demographic growth in developing countries. These facts are incompatible with the hypothesis of constant migration flows. In contrast, our micro-founded model provides consistent projections of fertility, education, migration and income inequality. As explained above, our baseline projections rely on a minimum of assumptions. Note that we assume a quadratic, region-specific convergence process in access to education (i.e., in $\psi_{r,t}$). This implies that regions at an intermediate level of development converge towards the US frontier more rapidly than do the poor ones. We keep all other parameters constant, including the medium level of technological externalities.

Prospective results are described in Figure 1.3. The simulated (dashed lines) and official (continuous lines) trajectories of population, share of college graduates, and share

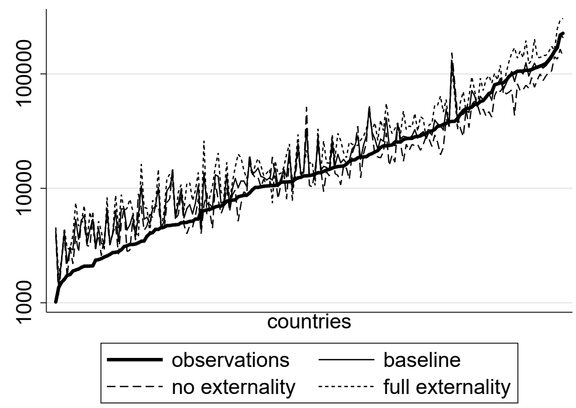
[20]Table 1.A1 and Table 1.A2 in the Appendix give a more detailed description of the effect of the different static counterfactual experiments for the US and for the 15^{th} (Cambodia), 25^{th} (Ghana), 50^{th} (Tunisia), 75^{th} (Mexico) and 85^{th} (Greece) percentiles of the income distribution. The presentation is organized as in Jones (2014). Table 1.A1 focuses on the average level of income per worker, while Table 1.A2 distinguishes between the two production sectors.



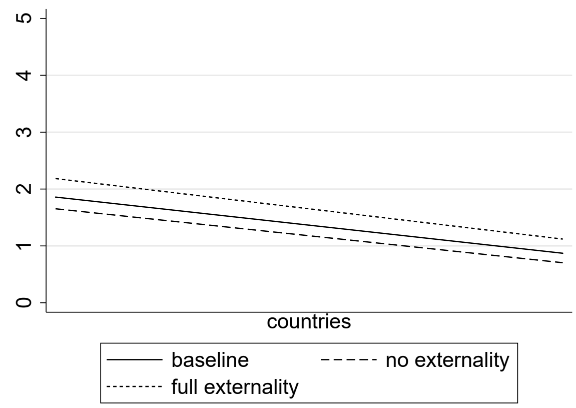
(a) Distribution of GDP per capita: Transposing US skill shares



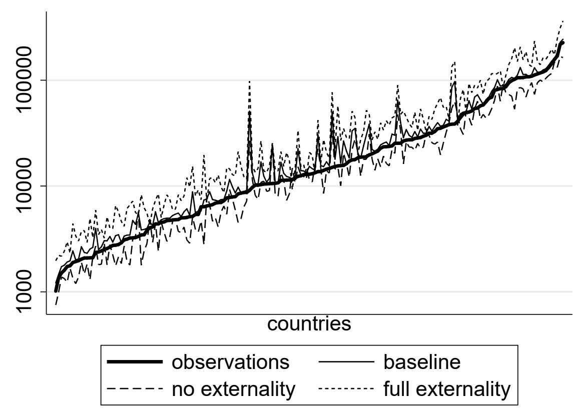
(b) Smoothed growth factor: Transposing US skill shares



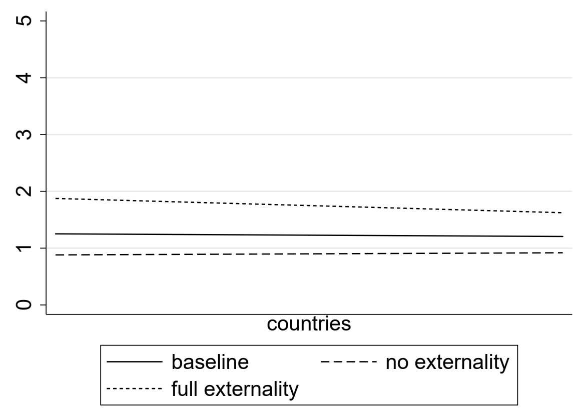
(c) Distribution of GDP per capita: Transposing US urban shares



(d) Smoothed growth factor: Transposing US urban shares



(e) Distribution of GDP per capita: No international migration



(f) Smoothed growth factor: No international migration

Figure 1.2: Geography of skills and income per worker: static counterfactuals

Notes: On the horizontal axis, countries are ranked by ascending order with respect to the observed level of GDP per capita and the respective scenario. Results are depicted for the baseline, zero- and full-externality scenarios.

of the urban population are depicted in Figures 1.3a, 1.3c and 1.3e, respectively. Separate curves are provided for OECD countries, for developing countries, and for the entire world.[21] The cross-country correlations between our simulations (Y-axis) and official projections (X-axis) for population, share of college graduates, and share of the urban population for the year 2100 are described in Figures 1.3b, 1.3d and 1.3f, respectively. Bubbles are proportional to country size (OECD countries in light gray and developing countries in dark gray). The 45-degree line allows visualizing whether our long-term simulations are greater or smaller than official projections.

Figures 1.3a and 1.3b show that our baseline trajectory is very much in line with official socio-demographic projections. Although we only initialize our simulations to be compatible with the 2040 national population levels, our long-term level of the adult population is almost equal to official projections. Furthermore, the cross-country correlation between simulated and UN population sizes in the year 2100 equals 0.98.[22]

Nevertheless, we obtain significant differences when focusing on the evolution of education and urbanization. As far as education is concerned, we are less optimistic than the United Nations. Figure 1.3c shows that the long-term, worldwide share of college graduates is smaller than that reflected in official projections. This share increases from 8.8% in 2010 to 17.3% in 2100 in our model, against 21.4% in the UN medium scenario. Similar differences are obtained for OECD and developing countries. As shown on Figure 1.3d, the cross-country correlation between simulated and UN shares of college graduates in the year 2100 is large (0.91).[23] However, most countries are below the 45 degree line, and for a large number of small OECD countries, compared with the UN projections, the simulated shares of college graduates is multiplied by a factor between 0.7 and 0.9. According to our baseline prospects for the 21st century, the share of college graduates increases from 20.5% to 48% in OECD countries and from 5.1% to 12.5% in the developing world. Assuming a continuation of the ongoing convergence in access to education, the ratio of skill shares between OECD and developing countries increases from 3.3 to 3.8.

Similarly, Figure 1.3e shows that our predicted share of the population living in urban areas is smaller than the UN projections. The worldwide urban share increases slightly from 53.0% in 2010 to 58.3% in 2100. These trends are the outcomes of two opposing forces: the rural/urban fertility differential and the net internal mobility towards cities (driven by the rising educational attainment). The former is important and imprecisely modeled in official projections. In Figure 1.3f, the cross-country correlation between simulated and UN urban shares in the year 2100 equals 0.83.[24] Again, most countries are below the 45-degree line, and for a large number of developing countries, our simulated urban share is multiplied by a factor between 0.5 and 0.8, compared with the UN one. Comparing OECD member states with developing countries, our baseline prospects predict fairly stable disparities in urbanization.

These comparisons give suggestive evidence that our stylized model does a good job in generating realistic and consistent, although less optimistic, projections of population, human capital, and urbanization for the coming decades. Despite a convergence in access

[21]The definition of the developing countries follows the official definition of the United Nations. The remaining 29 countries (not reported) are neither classified as an OECD nor as a developing country.

[22]The regression line of Figure 1.3b is given by: $baseline = -0.33 + 1.02 \cdot$ *official* ($R^2 = 0.97$).

[23]The regression line of Figure 1.3d is given by the following: $baseline = -0.03 + 0.92 \cdot$ *official* ($R^2 = 0.82$).

[24]The regression line of Figure 1.3f is given by: $baseline = -0.15 + 1.11 \cdot$ *official* ($R^2 = 0.69$).

to education, our baseline scenario neither predicts a fall in human capital inequality nor a strong convergence in the sector allocation of skills. Importantly, as it is micro-founded, the model also enables us to identify the key factors that will govern the future of the world population and global inequality. In particular, we can assess whether the evolution of population and global inequality is sensitive to future educational policies (i.e., convergence in the access to education) and geographic mobility costs. In Section 1.A.4 in the Appendix, we show that our socio-demographic prospects are highly robust to technological externalities and to the structure of preferences.

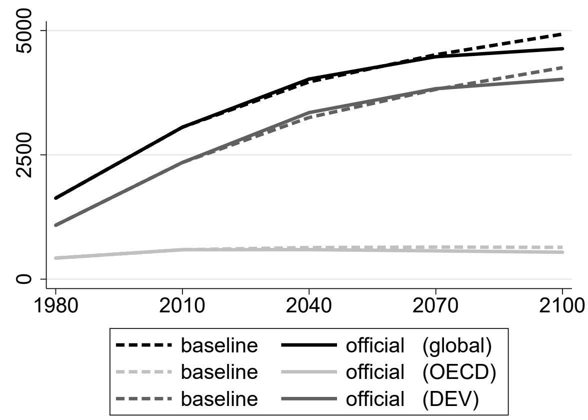
1.5.3 Sensitivity to education policies

We first assess whether our socio-demographic prospects are sensitive to policies affecting future access to education. In line with the recent *Sustainable Development Agenda*, the baseline scenario assumes a continuation of the quadratic convergence process in education costs observed between 1980 and 2010; this implies that middle-income countries catch up more rapidly than low-income countries do. Figure 1.4 compares the baseline trajectories of population, education and urbanization with those obtained with a smaller magnitude of the quadratic convergence (we divide the convergence speed by two compared to the baseline) or when there is an unconditional, linear convergence process.

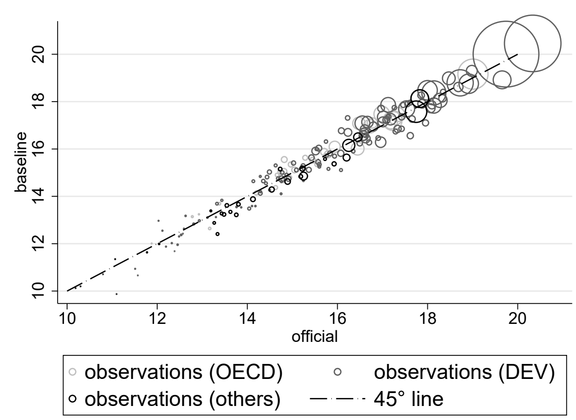
Under the linear convergence scenario, the poorest countries are the most prone to converge. We investigate this possibility by estimating a linear convergence equation for education cost (instead of a second-order polynomial in the baseline): $\ln\left(\psi_{r,t+1}/\psi_{r,t}\right) = \alpha_r + \beta_r \ln\left(\psi^{USA}_{r,t}/\psi_{r,t}\right)$. We obtain the following estimates: $\beta_a = 0.056$ for rural regions, and $\beta_n = 0.074$ for urban regions. Compared to the baseline, this scenario predicts faster human capital accumulation and urbanization in the poorest countries of the world, as shown on Figures 1.4b, 1.4d and 1.4f. Looking at worldwide aggregates, in the long run, this implies a significantly smaller population size, a greater share of college graduates and a greater urban share of the population. Nevertheless, Figures 1.4a, 1.4c and 1.4e show that these aggregate changes are relatively small due to the small demographic size of the low-income countries. With the exception of the poorest countries, our projections are almost identical when using a well-fitted linear or a quadratic convergence model. In other words, when extrapolating current trends in education costs, socio-demographic prospects are fairly robust to the specification of the estimated convergence process.

However, if we assume a slow-down of convergence (i.e., if we divide by two the convergence speed), it drastically affects the geography of skills and long-term population growth. In the developing world, the proportion of college graduates and the share of the urban population stagnate after 2040. The long-term level of the population is 20% to 25% greater than in the baseline. These changes are noticeable in all developing countries, including the largest ones (see Figures 1.4b, 1.4d and 1.4f). Hence, Figures 1.4a, 1.4c and 1.4e show that the changes in the size and skill structure of the world population are important. In line with the *Sustainable Development Agenda*, our results suggest that policies targeting access to all levels of education and education quality are vital to reduce the demographic pressures and to stimulate human capital accumulation.[25]

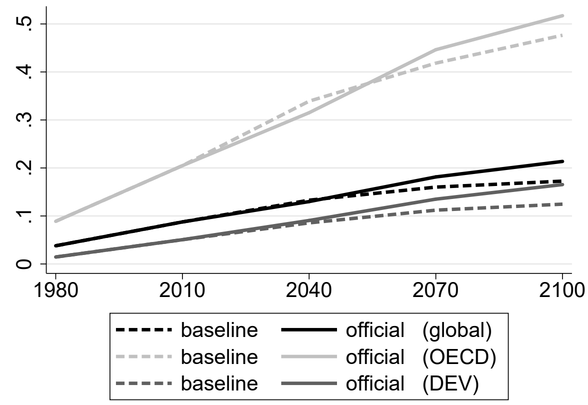
[25] Changing demographic shares have drastic implications in terms of immigration and emigration (see Table 1.A2 in Appendix 1.A.2). In the half-convergence scenario, the number of international migrants increases by 22% compared to the baseline, due to the larger population in developing countries.



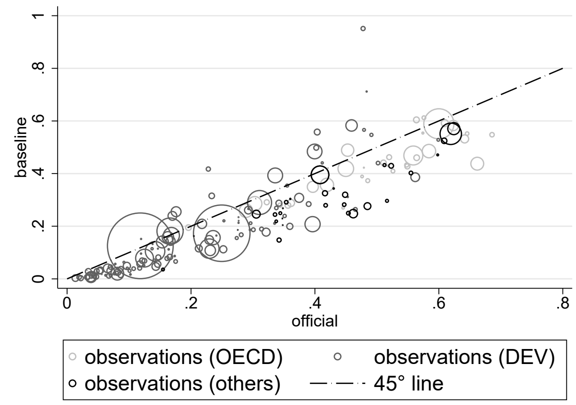
(a) Population (in million of people)



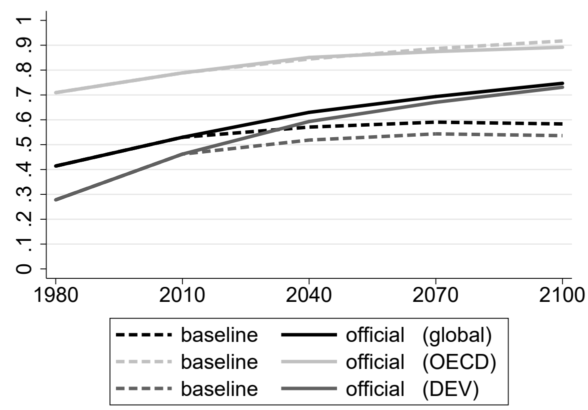
(b) Population in 2100 by countries



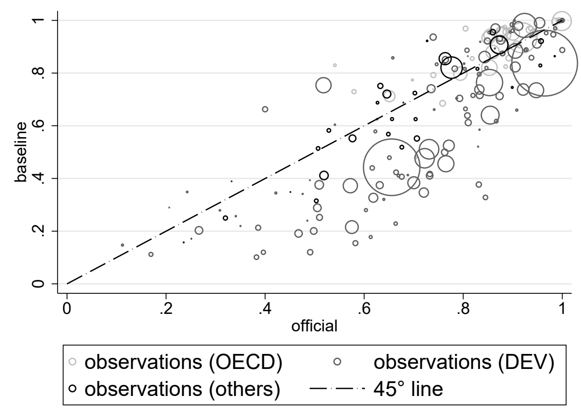
(c) Worldwide share of college-educated workers



(d) Share of college-educated in 2100 by countries



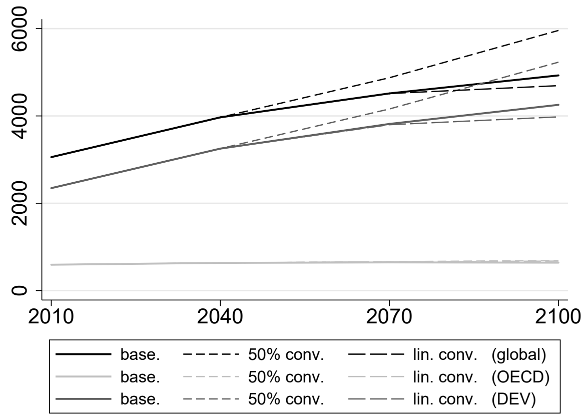
(e) Urban share



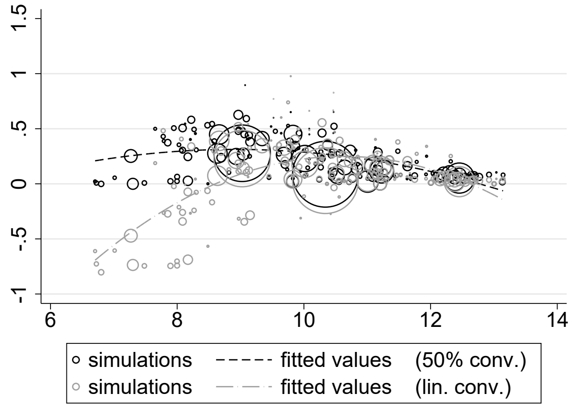
(f) Urban share in 2100 by countries

Figure 1.3: Comparison of the baseline trajectory with official projections by the UN

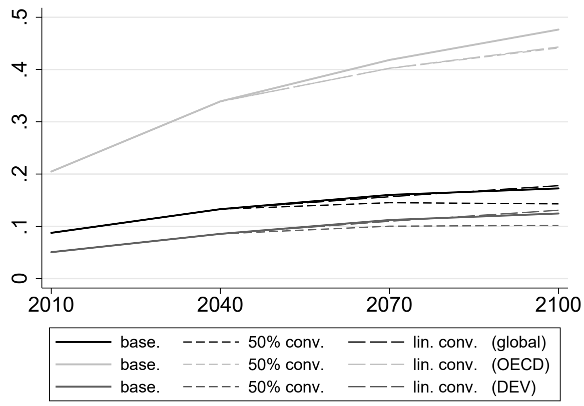
Notes: The left panel reports the projected population size, the share of college educated workers, and the share of urban population for the baseline and for offical projections (UN medium variant). Results are depicted for the worlwide averages, for countries in the OECD and for developing countries (DEV). The right panel compares the simulated levels in 2100 with official projections. Bubbles are proportional to country size.



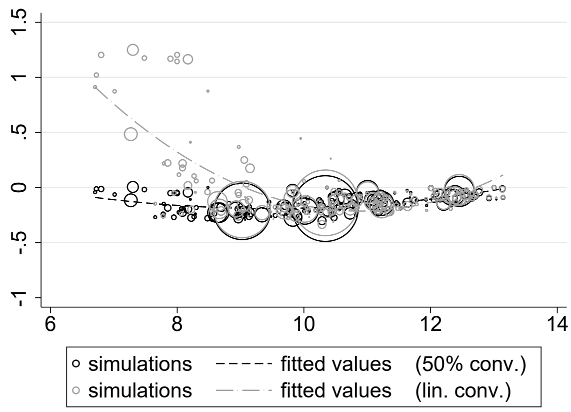
(a) Population (in million of people)



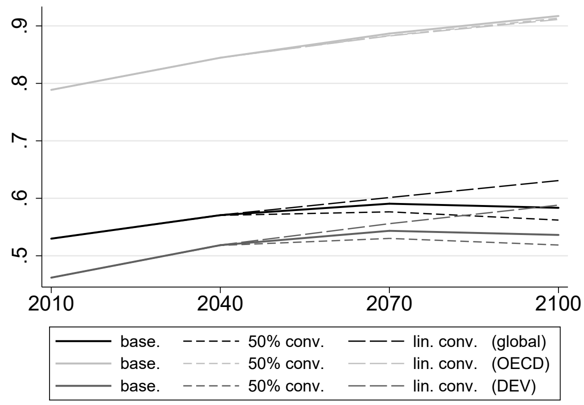
(b) Relative deviations from the baseline in 2100



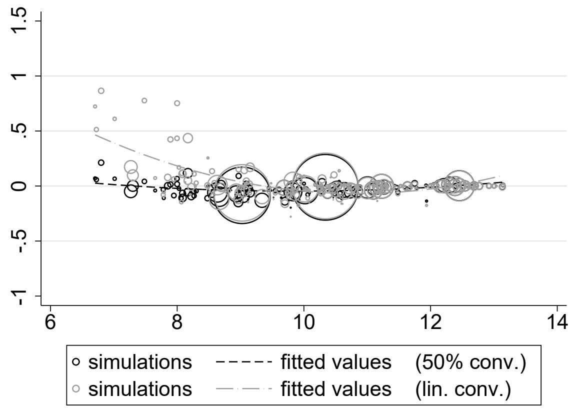
(c) Share of college educated workers



(d) Relative deviations from the baseline in 2100



(e) Share of urban population



(f) Relative deviations from the baseline in 2100

Figure 1.4: Sensitivity to educational policies

Notes: This figure reports the projected population size, the share of college educated workers, and the share of urban population for the baseline and the respective counterfactual scenario. The "lin. conv." scenario assumes a monotonic convergence in $\psi_{r,t}$. The "50% conv." scenario assumes a slower conditional convergence process.

1.5.4 Sensitivity to mobility constraints

We now investigate whether our socio-demographic prospects are sensitive to future mobility frictions. The baseline scenario assumes constant international and internal migration costs in the future. It predicts that the international migration pressures drastically intensify in the OECD countries (see Table 1.A1 in Appendix 1.A.2). We consider here an extreme no-international migration scenario for the future ($x_{rf,s,t} = 1$ after 2010). In the same vein, our static experiments suggest that internal mobility frictions drastically affect the (mis-)allocation of workers between sectors. We consider a no-internal migration scenario with maximal frictions ($x_{an,s,t} = 1$ after 2010). Figure 1.5 compares the baseline trajectories of population, education, and urbanization with those obtained without international or internal mobility.

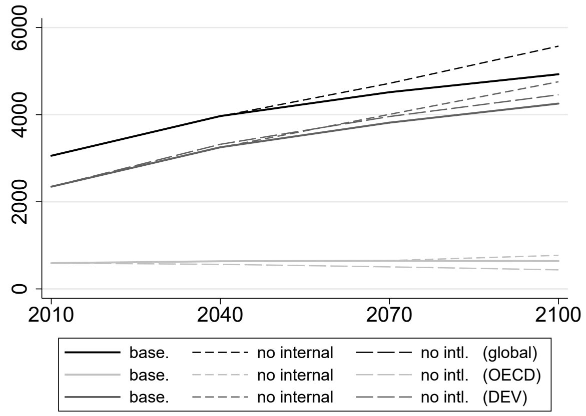
In line with the static development accounting exercise, we find that international migration has limited (and often negligible) effects on aggregated socio-demographic prospects (Figure 1.5a, 1.5c and 1.5e). In the no-migration scenario, Figure 1.5d shows that the share of college-educated workers increases in developing countries and that the effect is particularly strong in the poorest countries in which emigrants are highly positively selected. However, in general, the trend is mostly governed by small countries (and small developing islands in particular), exhibiting large emigration rates. The effect is small in large countries.[26] Comparing OECD member states with developing countries, the ratio of skill shares in the year 2100 reaches 3.4 (instead of 3.8 in the baseline), but this change is mostly due to the decrease in human capital in OECD countries. Figures 1.5e and 1.5f show that the urbanization responses are small, except in OECD countries. This is because immigrants to OECD countries usually reside in urban regions. As far as population is concerned, the no-migration scenario predicts a substantial decrease in the size of the population in Western economies, which is completely balanced out by an increase in developing countries.

The socio-demographic effects of internal mobility are greater. Preventing the movement of people from rural to urban areas has larger implications for human capital accumulation in large countries (access to education is better in cities), for the continuation of the urbanization process, and for population growth. Without internal mobility, the long-term level of the population increases by 16% in the developing world, the share of college graduates peaks at 10%, and the urban share declines by half compared to the baseline. This confirms that internal mobility frictions are important to reduce the demographic pressures and to boost human capital accumulation worldwide. Without internal mobility, the long-term ratio of skill shares between OECD member states and developing countries reaches 4.3 (instead of 3.8 in the baseline), and the sector allocation of skills drastically deteriorates in the developing world.

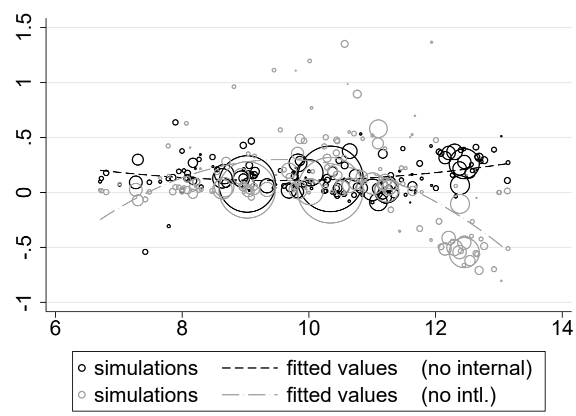
1.5.5 The geography of skills and geography of income

This last section connects the results of the static development accounting experiments with our socio-demographic prospects. Our static analysis shows that global inequality is influenced by the geography of skills. The prospective part shows that a continuation of ongoing trends should neither lead to a drastic fall in human capital inequality nor

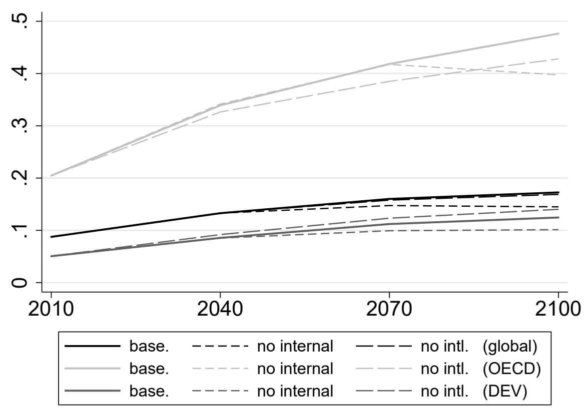
[26] Migration barriers can also affect an individual's incentives to acquire higher education. However, Docquier and Machado (2016) and Delogu et al. (2018) numerically demonstrate that the latter brain gain mechanism has little impact on the world distribution of skills.



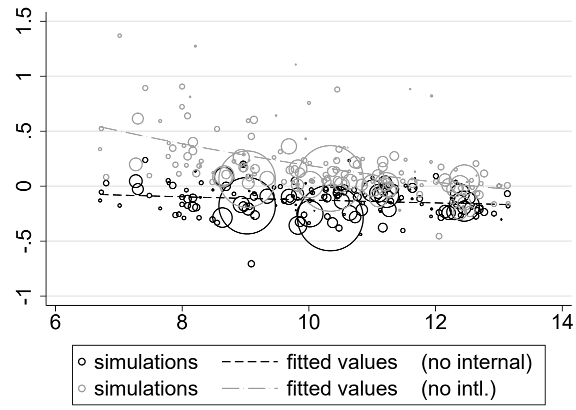
(a) Population (in million of people)



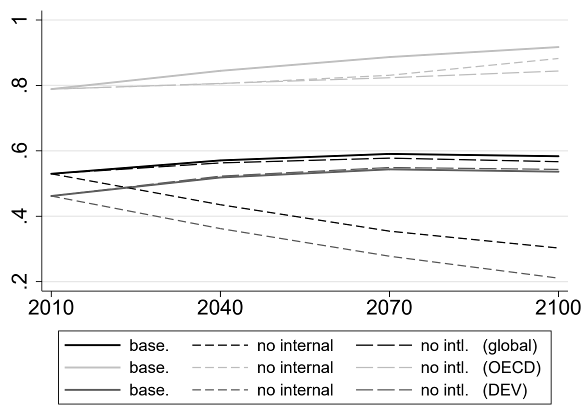
(b) Relative deviations from the baseline in 2100



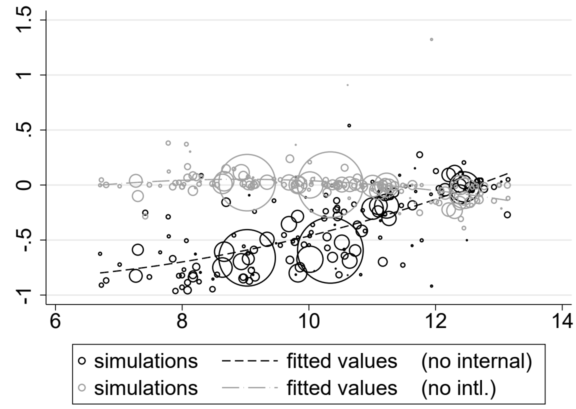
(c) Share of college educated workers



(d) Relative deviations from the baseline in 2100



(e) Share of urban population



(f) Relative deviations from the baseline in 2100

Figure 1.5: Sensitivity to mobility constraints

Notes: This figure reports the projected population size, the share of college educated workers, and the share of urban population for the baseline and the respective counterfactual scenario. The scenario "no intl." refers to the scenario with prohibitively high international migration costs ($x_{rf,s,t} = 1$) after 2010. The scenario "no internal" refers to the scenario with prohibitively high internal migration costs ($x_{an,s,t} = 1$) after 2010.

to strong improvement in the sector allocation of skills.[27] Nevertheless, the geography of skills can be affected by public policies affecting education and labor mobility. We now examine how these policies impact the world distribution of income. Our baseline prospects involve a variation of the Theil index of income inequality from 0.81 in 1980 to 1.14 in 2100 (see Figure 1.A3a in Appendix 1.A.3). Figure 1.6 illustrates this result and analyzes its sensitivity to education and mobility policies. The left panel depicts the trajectory of the average level of income per capita in the OECD member states, in developing countries and in the world. The right panel depicts the sensitivity of the Theil index of income inequality.

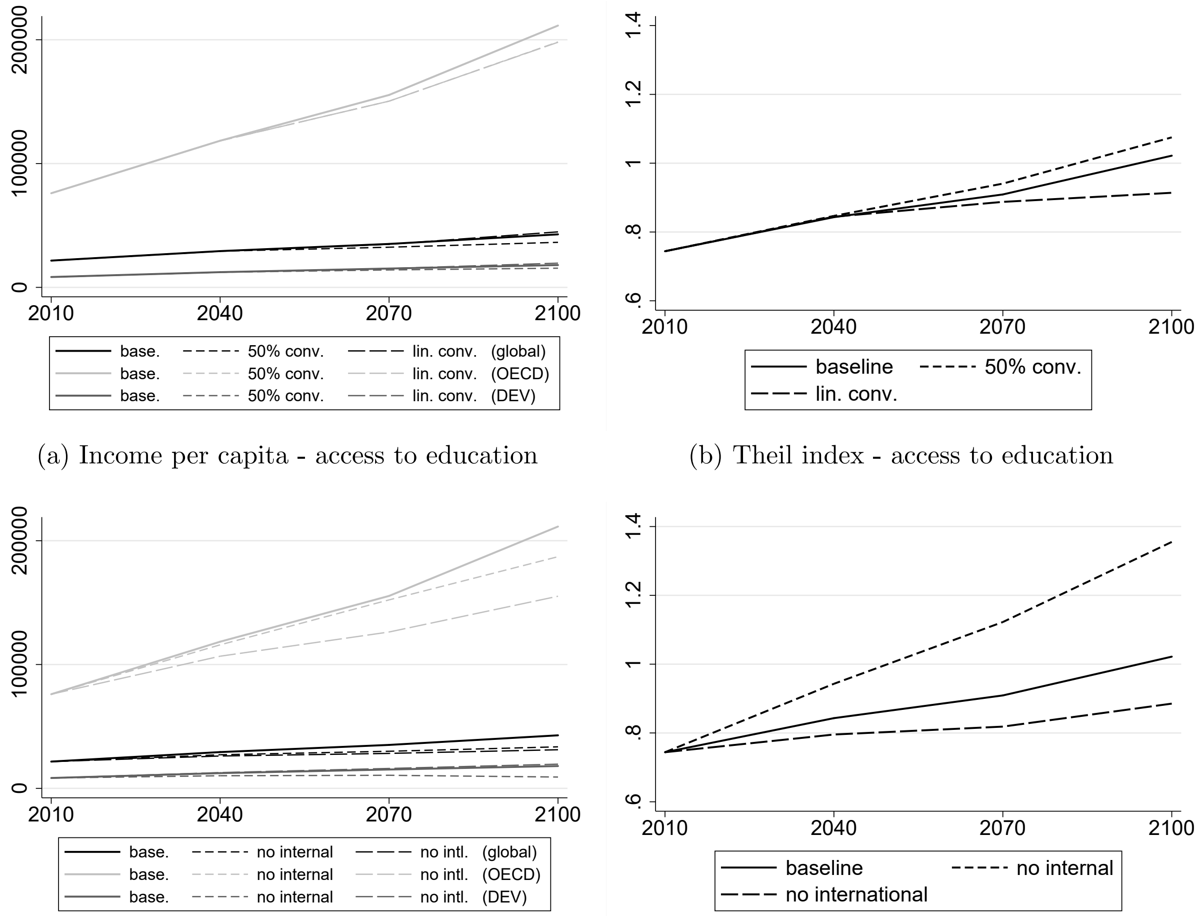
Figures 1.6a and 1.6b show the sensitivity of the world distribution of income to education policies. Compared to the baseline, the Theil index is unsurprisingly smaller when we assume linear convergence in the access to education and greater when we divide the coefficients of the quadratic convergence equation by two. However, as illustrated in Figure 1.6a, the trajectory of income per capita in all regions is not greatly affected by the convergence assumption. Variations in the Theil index are rather mechanical and linked to the construction of the index: the variations are mostly explained by the changing demographic shares of the developed and developing world (as illustrated in Figure 1.4a).

Figures 1.6c and 1.6d show the sensitivity of the world distribution of income to future mobility frictions. Preventing people from migrating internationally markedly reduces the world GDP (as it prevents individuals to move from low-productivity to high-productivity countries) and reduces global income inequality. However, Figure 1.6c shows that it has a negligible effect on income per capita in the developing world. In other words, development prospects are robust to future international migration barriers.[28] Again, the effect on global inequality is rather mechanical and linked to the construction of the Theil index: cutting migration decreases the demographic share of industrialized countries and increases the share of developing countries. In contrast, the level of income per capita in developing countries is more sensitive to internal migration policies. Preventing rural-to-urban migration reduces income and drastically increases the Theil index of income inequality. In line with our static numerical experiments, internal mobility frictions can induce a large misallocation of workers in poor countries (Rodrik, 2013). Policies targeting sustainable urban development are vital to reduce the demographic pressure and global inequality.

Section 1.A.4 in the Appendix demonstrates that these conclusions are highly robust to the modeling assumptions. If we change the size of technological externalities or if we consider that agricultural and nonagricultural goods are imperfect substitutes, as in Boppart (2014), we obtain similar trajectories for the Theil index of income inequality. The size of technological externalities affects the levels of income per capita in developing and developed countries but has negligible effect on inequality. The structure of preferences has little effect on the levels of income per capita and on its distribution.

[27] The results reported in Appendix 1.A.3 indicate that the Theil index of human capital inequality remains almost stable over the 21st century. It ranges from 0.63 in 1980 to 0.56 in 2100.

[28] We are aware that the real contribution of international migration to development might be underestimated here, as the model disregards diaspora externalities (Docquier and Rapoport, 2012) and the link between education decisions and migration prospects.



(a) Income per capita - access to education

(b) Theil index - access to education

(c) Income per capita - mobility variant

(d) Theil index - mobility variant

Figure 1.6: Implications for global income inequality

1.6 Conclusion

This chapter analyzes the root drivers of the geographic distribution of skills and its effect on current and future development disparities. We use a multi-country, two-sector, two-class, dynamic model of the world economy that endogenizes population growth, human capital formation and income in all countries and regions. We consider various sizes for technological externalities, alternative structures of preferences, as well as scenarios of access to education, internal and international mobility. Overall, we argue that the geography of skills explains a non-negligible fraction of development disparities between countries and regions. An important part of this effect is due to disparities in the (national) average level of schooling. Nevertheless, when considering the bottom quartile of the income distribution, one third of the total effect is due to disparities, which result from internal mobility frictions, in the sector allocations of workers. Compared to results from the standard, one-sector development accounting model, taking into account within-country disparities in human capital reinforces the role of the geographic allocation of skills. However, although migrants are positively selected in terms of their education level, international migration has little effect on the world distribution of skills and income.

Assuming a continuation of the ongoing convergence process in the access to schooling, we provide unified projections of socio-demographic and economic variables for the 21st century. Our baseline prospects show fairly stable disparities in the world's distribution of skills and slow urbanization in developing countries. This implies that the future geography of skills *per se* is unlikely to bring down global income inequality if access to education does not converge faster than it has over the last 30 years. On the contrary, increasing inequality occurs if the speed of convergence in education cost decreases or if internal mobility frictions increase. In line with the Sustainable Development Agenda, our analysis clearly suggests that policies targeting access to all levels of education, education quality and sustainable urban development are vital to reduce the demographic pressure and global inequality. These conclusions are highly robust to the technological and preference assumptions and to future international migration policies.

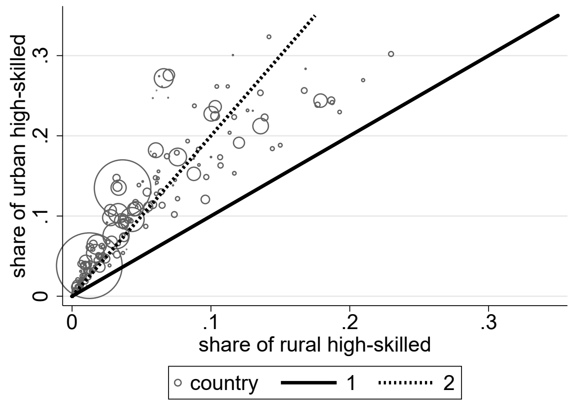
1.A Appendix

1.A.1 Calibration details

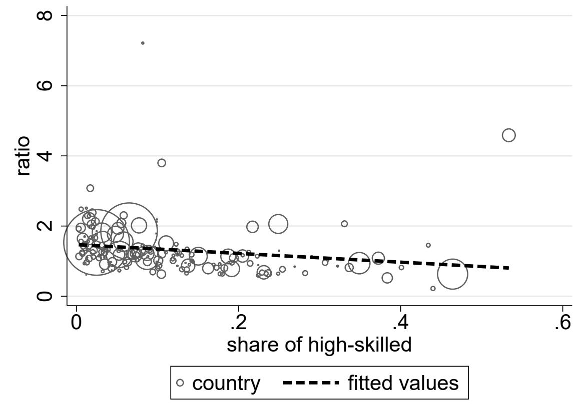
Data from the Gallup World Polls. – The data sources used to parameterize our model are described in Section 1.4. To identify the structure of income, fertility and migration intentions by region and by skill level, we use individual data from the Gallup World Poll (GWP) surveys. GWP covers about 150 countries between the years 2007 and 2016. For the majority of countries, the data are collected through face-to-face interviews. In some cases, interviews were conducted through phone calls. On average, the sample includes about 1,000 randomly selected respondents per year and per country. Data weighting is used to ensure a nationally representative sample for each country and is intended to be used for calculations within a country. To construct post-stratification weights, Gallup uses population statistics by gender, age, education or socioeconomic status, and region. The sampling frame is such that GWP data are representative of the entire population aged 15 and over (including populations from rural areas). However, in line with our model and with the macro databases used in the calibration, we only consider individuals aged 25 to 64. We aggregate the available 10 waves and assume they correspond to the year 2010 of our model. Hence, our income, fertility and migration intention proxies are drawn from about 10,000 responses per country.

Estimated geography of skills. – Figure 1.A1 characterizes the geography of skills in the year 2010, and describes the worldwide evolution of urbanization and human capital between 1970 and 2010. Figure 1.A1a shows that the urban share of college graduates is larger than the rural share in all countries. This is particularly true in poor countries. In line with Gollin et al. (2014b), Figure 1.A1b shows that the gap between regions decreases with the economy-wide proportion of college graduates. Figure 1.A1c shows that the college-educated minority is predominantly and increasingly employed in the nonagricultural sector. As far as less educated workers are concerned (i.e., the large majority of people in the world), the fraction of them employed in the nonagricultural sector increased from 37.8% in 1970 to 50.5% in 2010. Figure 1.A1d is the mirror image of Figure 1.A1c: it depicts the evolution of the share of the college graduates in the labor force of each sector. On average, the world average proportion of college graduates increased from 2.4% to 8.8% between 1970 and 2010. In relative terms, the rise is greater in agriculture (from 1.1% to 3.9%) than in nonagriculture (from 4.6% to 13.1%). In absolute terms, the magnitude of the change is reversed; the small share of college-educated professionals and technicians in agriculture limits the capacity for innovation in poor countries (as argued in World Bank, 2007).

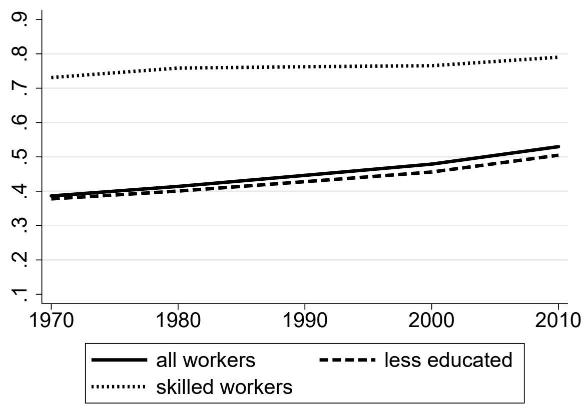
Technology parameters. – Figure 1.A2 provides stylized facts on technological differences across countries, and summarizes the main findings of our calibration strategy. In line with the existing literature, we assume $\sigma_n = 2$ and $\sigma_a = \infty$. Once the elasticities are chosen, we use sector-specific data on returns to schooling to calibrate the relative productivity of college-educated workers. In the agricultural sector, we use the Gallup World Polls and compute the average household income per adult member as a function of the education level of the household head. As a proxy for the wage ratio in rural regions ($R^w_{a,t}$), we divide the average income of households with a college-educated household head by the average income of households with a less educated household head. Combining (1.3) and (1.6), the elasticity of R^w_a to R^ℓ_a is equal to $\kappa_a - 1/\sigma_a$. Assuming $\sigma_a = \infty$, this elasticity boils down to κ_a. Figure 1.A2a shows that the correlation between R^ϖ_a and



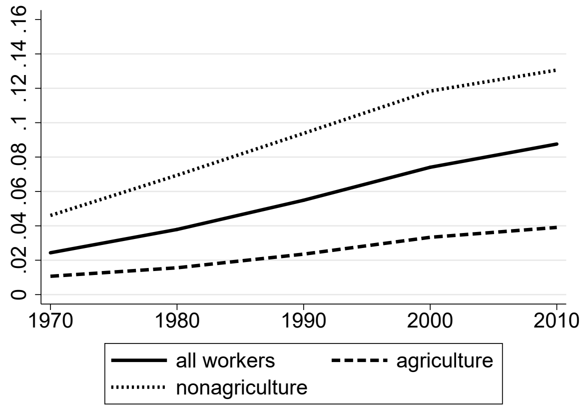
(a) Share of college graduates in agriculture ($H_{a,t}$) and nonagriculture ($H_{n,t}$) in 2010



(b) Regional ratio of skills ($H_{n,t}/H_{a,t}$) and national share of college graduates (H_t) in 2010



(c) World population share in nonagriculture by skill group



(d) World share of college graduates in population by sector

Figure 1.A1: Additional stylized facts on the geography of skills

Notes: In Figure 1.A1a and 1.A1b, bubble sizes are proportional to the population of the country.

R_a^ℓ is virtually nil. We thus rule out the possibility of skill-biased technical change in agriculture ($\kappa_a = 0$), and assume a linear technology with a constant R_a^ϖ for all countries and all periods. The value of R_a^ϖ is given by the population-weighted average of R_a^w, leading to $\varpi_a = 0.57$. We use this value for all countries and assume it is time-invariant.

As for the nonagricultural sector, we use data on the wage ratio from Biavaschi et al. (2016) for 143 countries.[29] We calibrate R_n^ϖ using (1.3). Regressing R_n^ϖ on R_n^ℓ yields a correlation of 0.38. Given the bidirectional causation relationship between the skill bias and education decisions, we consider this estimate as an upper bound for the skill-bias externality. In our baseline projections, we assume that half the correlation is due to the skill-bias externality (i.e., $\kappa_n = 0.19$). Alternative scenarios are also considered in the simulation section. We calibrate $\overline{R}_n^\varpi$ as a residual from (1.6). Again, from (1.3) and (1.6), the elasticity of the R_n^w to R_n^ℓ is equal to $\kappa_n - 1/\sigma_n$, which is equal to -0.37. Figure 1.A2b

[29]For the missing countries we predict the wage ratio using the estimated relationship between the log wage ratio on the log skill ratio.

shows that this elasticity is in line with the Gallup data on income per adult member.

In the *second step*, we use data on national Gross Domestic Product (GDP) for all countries from the Economic Research Service of the United States Department of Agriculture (USDA).[30] Data on the agriculture share in the value added are taken from the Food and Agriculture Organization of the UN (FAOSTAT).[31] We construct data on output by sector in the year 2010, and identify the TFP levels ($A_{r,t}$) by dividing the sector-specific output by the quantity of labor in efficiency unit using (1.1). There is a clear positive relationship between TFP and the share of college-educated workers in both sectors. Indeed, regressing the log of $A_{r,t}$ on the log of $R^{\ell}_{r,t}$ gives a coefficient of 0.57 in the nonagricultural sector, and 0.66 in agriculture, as shown in Figures 1.A2c and 1.A2d. Given the reverse causation relationship between productivity and education decision, we consider these estimates as upper bounds for the aggregate TFP externality. In our baseline scenario, we assume that half the correlation between TFP and the share of college-educated workers is due to the schooling externality (i.e., $\epsilon_n = 0.28$ and $\epsilon_a = 0.33$). Alternative scenarios are also considered in the simulation section. We calibrate $\overline{A}_n$ as a residual from (1.4).

Let us make two remarks on the calibration of the technology. First, Figure 1.A2e and 1.A2f show the distribution of A_r and $\overline{A}_r$ in the agricultural and nonagricultural sector and for the year 2010. These distributions are relatively similar, meaning that a large fraction of TFP differences is explained by exogenous determinants. Remember that we assume a TFP externality equal to half of the correlation between TFP and the skill ratio. Second, the methodology used to calibrate the TFP parameters can be also used for the year 1980. Comparing the calibrated scale factors ($\overline{A}_n$) in 1980 and 2010, we obtain a high correlation of 0.78 and no sign of convergence or divergence (i.e., log changes in $\overline{A}_n$ are not significantly correlated with their initial level). It follows that we can reasonably consider these scale factors as time-invariant in our numerical experiments.

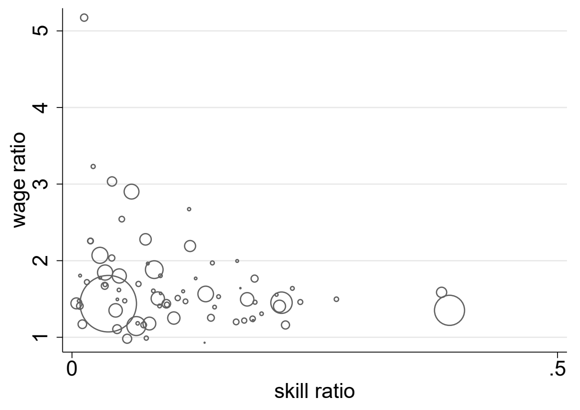
Preference parameters. – We assign the following values to the parameters that are time-invariant and equal for all countries: $\theta = 0.25$, $\lambda = 0.5$ and $\phi = 0.14$.[32] From (1.14) and (1.16), the scale parameter of the distribution of migration tastes (μ) is the inverse of the elasticity of bilateral migration to the wage rate. Bertoli and Fernández-Huertas Moraga (2013) find a value between 0.6 and 0.7 for this elasticity. Hence, we use $\mu = 1.4$.

Let us now explain how we calibrate the values of π_r and $\psi_{r,t}$. These two parameters are country- and sector-specific, and affect the fertility and education decisions. We calibrate them to match the population dynamics between the years 1980 and 2010, i.e., the transition from the resident population in 1980 and the native population in 2010. We begin by estimating the size of the *before-migration* population in 2010 by skill group ($\sum_r N_{r,s,2010}$). We do this by adding the number of international migrants by region and skill level to the respective number of high-skilled and low-skilled workers by region of our basic data set, the after-migration population ($L_{r,s,2010}$). For simplicity, we focus on international migration to OECD countries only. From the Database on Immigrants in

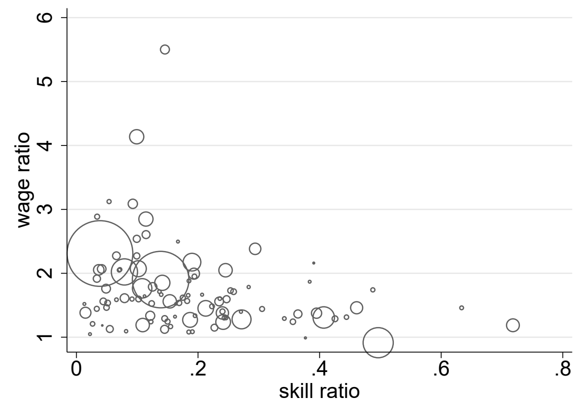
[30] For a few missing observations we impute values by making use of the Maddison database and data from the World Bank.

[31] For a few missing observations we impute values by making use of data from the World Bank. Since data is volatile for several countries, the average of five data points around the data point of interest is used.

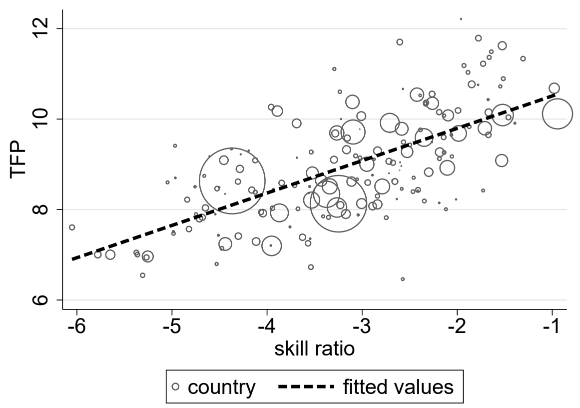
[32] Given the expression in (1.10), this assumption reflects setting the bound of the maximal number of children equal to 7 (i.e., 14 children per couple). See Docquier et al. (2016) for a brief review of studies using similar parameter values.



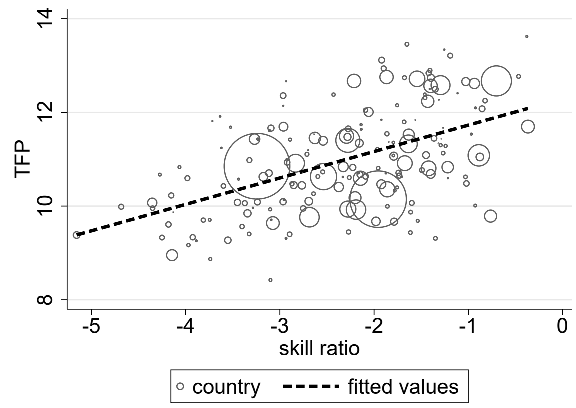
(a) Correlation between skill ratio (R_a^ℓ) and wage ratio (R_a^w) in agriculture



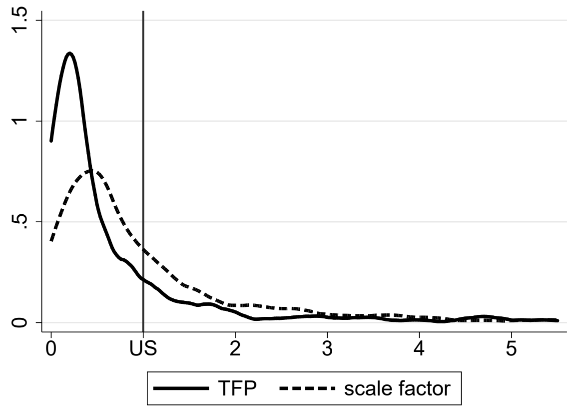
(b) Correlation between skill ratio (R_n^ℓ) and wage ratio (R_n^w) in nonagriculture



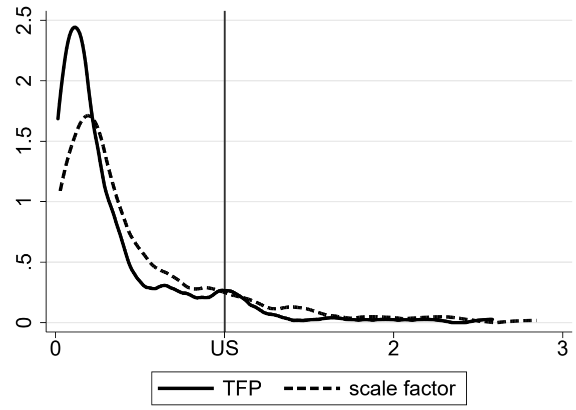
(c) Correlation between skill ratio ($log(R_a^\ell)$) and TFP ($log(A_a)$)



(d) Correlation between skill ratio ($log(R_n^\ell)$) and TFP ($log(A_n)$)



(e) Kernel density of TFP (A_a) and its scale factor ($\overline{A}_a$) in agriculture



(f) Kernel density of TFP (A_n) and its scale factor ($\overline{A}_n$) in nonagriculture

Figure 1.A2: Calibration of the technological parameters in 2010

Notes: In Figure 1.A2a-1.A2d, bubble sizes are proportional to the population of the country. Figures 1.A2e and 1.A2f assume that the elasticity of TFP or skill bias to the skill ratio is equal to 50% of the correlation between these variables.

OECD and non-OECD countries (DIOC), we extract the number of emigrants by education level to OECD countries for all countries in our sample and for the year 2010. The DIOC does not identify the region of origin of migrants (urban versus rural). However, for the majority of countries in our sample, skill- and region-specific information on the desire to emigrate can be extracted from the Gallup World Polls. Assuming the structure of migration aspirations is reflected in actual emigration stocks, we split the number of emigrants to OECD countries by region of origin and by education level.[33] The average fertility rate ($\overline{n}_{1980}$) is thus obtained by dividing the total native population of adults in 2010 ($\sum_{r,s} N_{r,s,2010}$) by the total resident population of adults in 1980 ($\sum_{r,s} L_{r,s,1980}$).[34] Moreover, our calibration requires data on the skill- and region-specific fertility for each country. By construction, we have $\overline{n}_t \equiv \sum_{r,s} L_{r,s,t} n_{r,s,t} / \sum_{r,s} L_{r,s,t}$. We use the Gallup World Polls and extract the Gallup-based average number of children per household by region and skill level for 2010.[35] We compute the fertility of the college educated workers by fitting the sector-specific low/high-skilled fertility differentials from the Gallup database. In this way, we obtain the fertility rates for each country for the year 1980. From 2010 onwards, the number of children is endogenous.

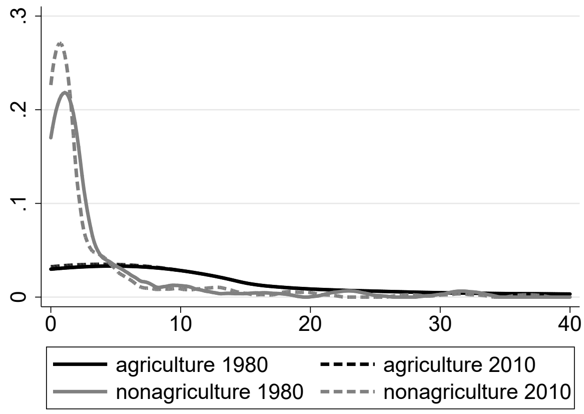
The last moment to fit in the procedure is the number of internal migrants between the years 1980 and 2010. Two factors may determine the difference in the evolution of skills in both sectors. First, this evolution may be brought about by the differences in educational prospects (given the already computed fertility differential). Second, it might be caused by the selectivity of rural-to-urban migrants. We decided to pin down the first of the two factors. This draws on the different probabilities to become high-skilled in urban and rural areas. These probabilities are calibrated by assuming a log-normal distribution of years of schooling in both sectors. The location parameters simply match the mean years of schooling in rural/urban areas, while the dispersion parameter is identical across sectors and is set to fit the country-specific share of high-skilled individuals (defined as the percentage of population with more than 17 years of schooling). Finally, the quested ratio of probabilities is the quotient of two respective probabilities of obtaining more than 17 years of schooling, derived from region-specific distributions. We set the ratio of the probabilities so that net internal migration is computed as a residual in the model. We arbitrary impose that the process of urbanization is the dominant one (which is the case in almost all countries). The matched number represents the net migration from rural to urban region. The net internal migration is then the difference between the "before-migration" population ($N_{r,s,2010}$) in 2010 and the sum of the resident population and the international migrants ($\sum_{r,s}(L_{r,s,2010} + M_{rf,s,2010})$) in 2010. In this way, the model perfectly matches the skill and regional distribution of workers in 1980 and 2010.

From Equation (1.13), the fertility rate in the model depends on the product of $\pi_r \psi_{r,t}$. Once fertility rates are matched we are able to identify the product $\pi_r \psi_{r,t}$. We then calibrate π_r and $\psi_{r,t}$ in order to match the educational structure of the native population in 2010, imposing the given value to the ratio of probabilities of becoming high-skilled across regions. Figures 1.A3a and 1.A3b show the distributions of π_r, $\psi_{r,t}$ for the two regions. Figure 1.A3a depicts the distributions for two periods (1980 and 2010). The

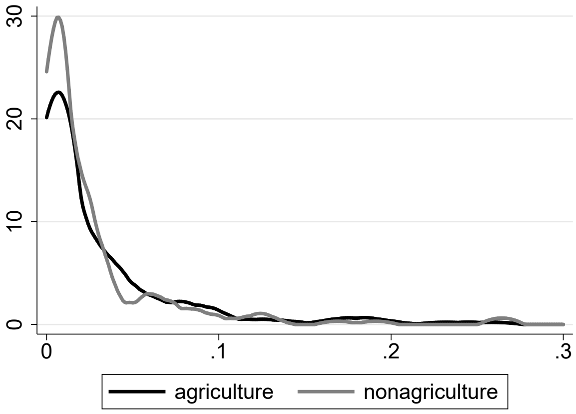
[33]Bertoli and Ruyssen (2016) show that aspirations to emigrate are correlated with emigration flows within five years.

[34]There is no mortality in the model. The average fertility rate at time t, $\overline{n}_t$, should be seen as a net population growth rate. Note that the average fertility rate is not affected by internal migration, so that we need to only account for international migration at this stage.

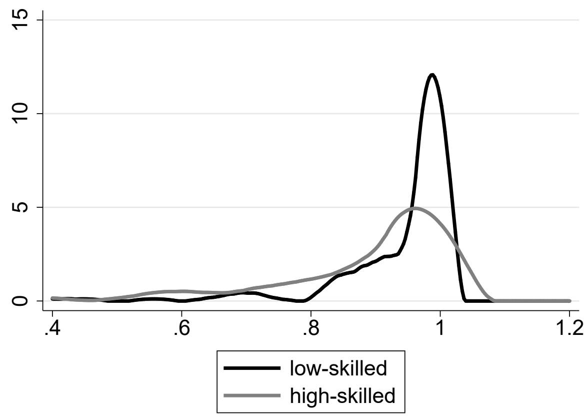
[35]We only include countries with at least ten respondents. When data are missing, crude birth rates from the World Health Organization are used.



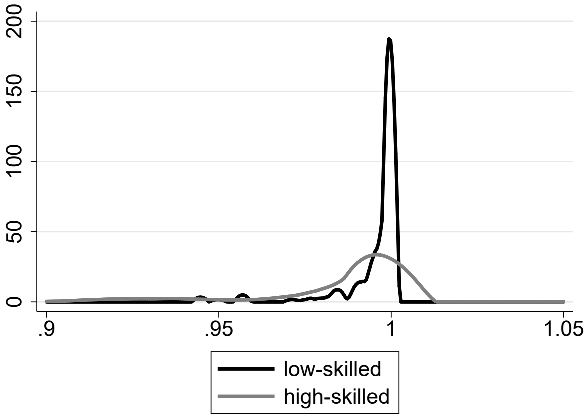
(a) Kernel density of $\psi_{r,t}$



(b) Kernel density of π_r



(c) Kernel density of $x_{an,s}$



(d) Kernel density of $x_{af,s}$

Figure 1.A3: Calibration of the preference parameters in 1980 and 2010

distribution of π_r is stable over time. As far as $\psi_{r,t}$ is concerned, the mean levels decreased between 1980 and 2010, reflecting expansive education policies that can be related to the Millennium Development Goals. As for internal migration costs, we assume there is only migration from rural to urban regions (i.e., $x_{an,s,t} < 1$ and $x_{na,s,t} = 1$). We obtain internal migration costs for rural-urban migration from Equation (1.16). Figure 1.A3c shows that moving costs are usually smaller for highly educated workers than for the less educated.

In order to determine the international migration costs ($x_{af,s,t}$ and $x_{nf,s,t}$), we begin by retrieving the utilities achievable abroad. We set these utilities equal to the skill-specific weighted average utilities of the OECD countries. The weights consist in the respective population sizes of the OECD countries. We then obtain the international migration costs from Equation (1.16). In line with Figure 1.A3c, Figure 1.A3d shows that international migration costs are smaller for college-educated workers.

1.A.2 The geography of skills and current income inequality - static experiments

In Section 1.5.1, we consider the US as the base-case economy and proceed with three static counterfactual experiments to quantify the role of skills accumulation in the year 2010. Figure 1.2 in the main text describes the changes in income per capita induced by an increase in the average skill level, or by a better geographical allocation of national skills. Results are presented in a different manner in the development accounting literature. For example, Jones (2014) uses the concept of success rate (SR), defined as the share of the income ratio explained by the counterfactual. In other words, SR equals one minus the counterfactual-to-observed ratio of income with the US (i.e., \$100,000 per year). Equivalently, the success rate measures the national income loss due to the lower level of human capital and/or to the sectoral allocation of workers when compared to the US:

$$SR = 1 - \frac{y_{US}/y_{CF}}{y_{US}/y_{obs}} = \frac{y_{CF} - y_{obs}}{y_{CF}}.$$

In development accounting studies, the success rate is usually provided for selected countries located at various percentiles of the income distribution. Table 1.A1 describes our static simulation results likewise. This table also reports the Theil index for each of the counterfactual experiments. For the baseline, the Theil index takes a value of 0.744. In case the US shares are transposed, the value falls to 0.354. If the US urban shares are transposed, the index takes a value of 0.607. With the repatriation of emigrant workers the Theil index is very similar to the baseline with a value of 0.735. Finally, Table 1.A2 decomposes the aggregate results by sector.

Table 1.A1: Geography of skills and income per worker in 2010

	15^{th} (Cambodia)	25^{th} (Ghana)	50^{th} (Tunisia)	75^{th} (Mexico)	85^{th} (Greece)	Theil Index
I. Observed levels and ratios of income per worker						
Income pw	2,018	3,651	9,032	20,761	55,262	0.744
US/ctry ratio	50.7	28.0	11.3	4.9	1.9	-
II. Counterfactual: Transposing the US skill shares in each sector						
Income pw	16,010	13,709	19,968	34,968	63,328	0.354
US/ctry ratio	6.4	7.5	5.2	2.9	1.6	-
Success	0.873	0.732	0.544	0.402	0.121	0.525
III. Counterfactual II with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Income pw	5,300	5,932	9,186	21,936	42,087	0.488
US/ctry ratio	16.9	15.1	9.7	4.1	2.1	-
Success	0.668	0.463	0.141	0.174	-0.146	0,345
IV. Counterfactual II with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Income pw	58,737	37,430	50,151	61,843	103,421	0.267
US/ctry ratio	2.1	3.3	2.5	2.0	1.2	-
Success	0.958	0.881	0.781	0.592	0.350	0.642
V. Counterfactual: Transposing the US urbanization share						
Income pw	4,681	4,028	10,007	20,785	54,482	0.607
US/ctry ratio	22.0	25.6	10.3	5.0	1.9	-
Success	0.566	0.087	0.091	-0.006	-0.021	0.184
VI. Counterfactual V with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Income pw	3,469	3,490	6,377	16,259	37,709	0.594
US/ctry ratio	25.2	25.1	13.7	5.4	2.3	-
Success	0.503	0.106	-0.211	-0.092	-0.253	0.202
VII. Counterfactual V with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Income pw	6,351	4,710	15,740	26,678	79,050	0.626
US/ctry ratio	19.1	25.8	7.7	4.6	1.5	-
Success	0.623	0.080	0.319	0.076	0.170	0.159
VIII. Counterfactual: Repatriation of emigrant workers						
Income pw	2,481	4,164	9,789	22,911	57,745	0.735
US/ctry ratio	41.8	24.9	10.6	4.5	1.8	-
Success	0.176	0.112	0.065	0.082	0.031	0.012
IX. Counterfactual VIII with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Income pw	1,290	2,988	5,815	17,750	38,584	0.772
US/ctry ratio	68.1	29.4	15.1	5.0	2.3	-
Success	-0.343	-0.049	-0.334	-0.004	-0.230	-0.038
X. Counterfactual VIII with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Income pw	4,775	5,855	16,495	29,606	86,428	0.707
US/ctry ratio	25.6	20.9	7.4	4.1	1.4	-
Success	0.495	0.254	0.345	0.162	0.236	0.049

Table 1.A2: Productivity by sector - development accounting

	15^{th} (Cambodia)	25^{th} (Ghana)	50^{th} (Tunisia)	75^{th} (Mexico)	85^{th} (Greece)	99^{th} (US)
I. Observed levels and ratios of income per worker						
Income pw (n)	7,169	5,020	12,904	25,726	68,259	125,133
Income pw (a)	807	1,987	1,707	4,310	15,026	10,214
US/ctry ratio (n)	17.5	24.9	9.7	4.9	1.8	1.0
US/ctry ratio (a)	12.7	5.1	6.0	2.4	0.7	1.0
College grads in n	0.036	0.030	0.105	0.148	0.297	0.326
II. Counterfactual: Transposing US skill shares in each sector						
Success (n)	0.624	0.671	0.458	0.378	0.060	-
Success (a)	0.743	0.726	0.548	0.468	0.385	-
III. Counterfactual II with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Success (n)	0.032	0.371	-0.011	0.151	-0.206	-
Success (a)	-0.136	0.139	-0.103	0.060	0.091	-
IV. Counterfactual II with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Success (n)	0.873	0.845	0.737	0.569	0.293	-
Success (a)	0.942	0.913	0.815	0.699	0.585	-
V. Counterfactual: Transposing the US urbanization share						
Success (n)	-0.286	-0.132	-0.085	-0.051	-0.096	-
Success (a)	0.121	0.143	0.175	0.178	0.305	-
VI. Counterfactual V with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Success (n)	-0.458	-0.074	-0.436	-0.129	-0.325	-
Success (a)	-0.267	-0.010	-0.207	0.021	0.074	-
VII. Counterfactual V with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Success (n)	-0.133	-0.193	0.181	0.022	0.094	-
Success (a)	0.390	0.273	0.436	0.337	0.478	-
VIII. Counterfactual: Repatriation of emigrant workers						
Success (n)	0.090	0.116	0.019	-0.027	-0.006	-
Success (a)	0.136	0.151	0.110	0.035	0.103	-
IX. Counterfactual VIII with exogenous TFP (A_r) and exogenous skill bias (R_r^ω)						
Success (n)	-0.461	0.009	-0.394	-0.118	-0.283	-
Success (a)	-0.267	-0.010	-0.214	-0.041	0.046	-
X. Counterfactual VIII with full TFP externality (A_r) and full skill bias externality (R_r^ω)						
Success (n)	0.434	0.211	0.309	0.056	0.211	-
Success (a)	0.411	0.286	0.348	0.105	0.157	

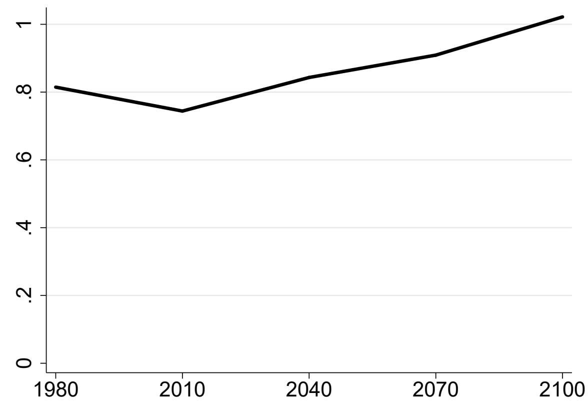
Notes: Tables 1.A1 and 1.A2 give the level of income per worker of Cambodia, Ghana, Tunisia, Mexico, and Greece for the baseline and the respective counterfactual scenario. Part I reports the observed level of income per worker and the US-to-country ratio. Part II reports the income levels and ratios obtained if the US shares were observed in each sector. Part V reports the income levels and ratios obtained if the US urbanization share was transposed. Part VIII reports the income levels and ratios obtained if emigration rates were nil. The remaining parts are variants of the respective scenario with different assumptions on the technological externalities. For each simulation, the success rate is the share of the wage ratio explained by the counterfactual, i.e., one minus the counterfactual-to-observed ratio of income differential with the US (in columns (2)-(6)), and one minus the counterfactual-to-observed ratio of Theil index (in column (7)).

1.A.3 Baseline prospects: geopolitical implications

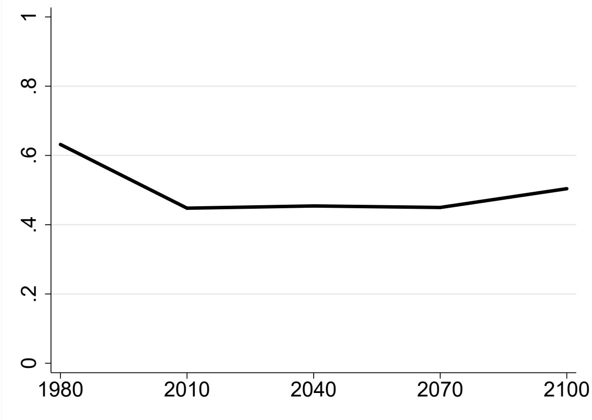
We examine the main geopolitical implications of the baseline projections described in Section 1.5.2. The model does not predict convergence in income per worker and in the share of college graduates across countries. The Theil index of human capital inequality remains almost stable over the 21st century. It ranges from 0.63 in 1980 to 0.5 in 2100 as illustrated in Figure 1.A4b. Similarly, income per capita does not converge. On the contrary, the Theil index of income inequality varies from 0.81 in 1980 to 1.02 in 2100 as depicted in Figure 1.A4a.

Figure 1.A4c depicts the evolution of the region/continent shares in the worldwide working-age population. The share of sub-Saharan Africa increases from 7.2% in 1980 to 34.0% in 2100. The share of OECD countries decreases from 25.8% to 13.0% over the same period of time. In addition, the OECD share in the college-educated population shrinks markedly, as illustrated in Figure 1.A4d. This is caused by the progress in higher education in the other regions, in particular in Asia, and by the rise of the demographic share of the developing world. Figure 1.A4e shows that the speed of urbanization is faster in Africa than in the other regions. Finally, Figure 1.A4f depicts the evolution of income shares. The OECD income share decreases by more than 13 percentage points (from 77.4% in 1980 to 64.1% in 2100) whereas the Asian share increases from 9.1% to 17.0% over the same period.

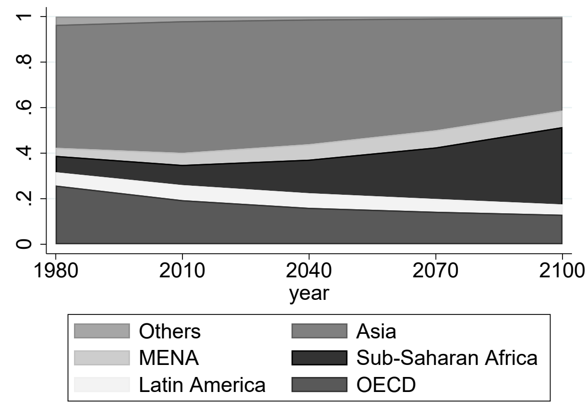
Table 1.A3 describes the international migration implications of our baseline projections. Assuming constant migration policies, we predict slight decreases in future emigration rates from the OECD member states. On the contrary, emigration rates from Latin America, from the Middle East and North Africa, from sub-Saharan Africa and from Asia increase. This is due to the rising share of college-educated workers (the most mobile individuals) in the population. Given its rising share in the world population, sub-Saharan Africa is responsible for drastic changes in worldwide migration pressures. As a result, the proportion of foreigners increases in European countries. In particular, the average immigration rate to the EU15 is expected to rise from 13.6% in 2010 to 21.2% in 2100. This is explained by four factors: (i) Europe is the main destination for African emigrants; (ii) the demographic ratio between Africa and Europe increases sharply; (iii) college-educated workers are more mobile than the less educated and the rise in African human capital has limited effects on income disparities between Africa and Europe; (iv) urbanization increases and international migration costs are lower for urban citizens than for villagers. Reinforcement of immigration restrictions are likely to be observed in European countries to curb the migration pressure; their implications are investigated in Section 1.5.4. Note that the share of immigrants increases less drastically in the US (from 16.0% to 19.2%), Australia (from 24.9% to 25.9%) and Canada (from 18.7% to 25.0%).



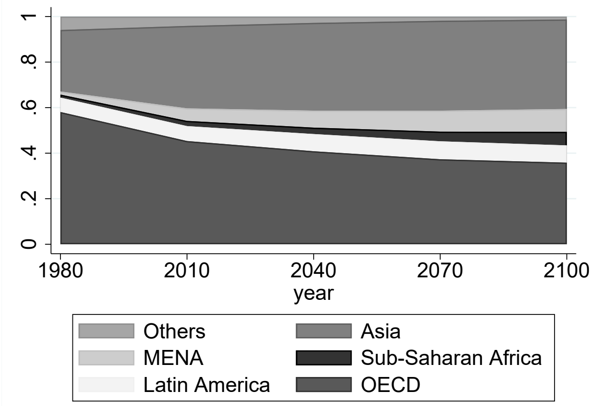
(a) Theil index of income inequality



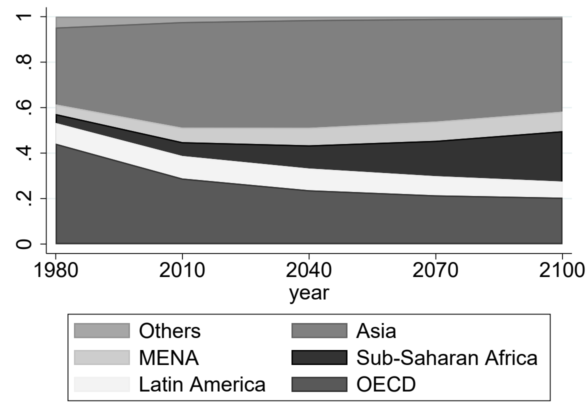
(b) Theil index of inequality in skills



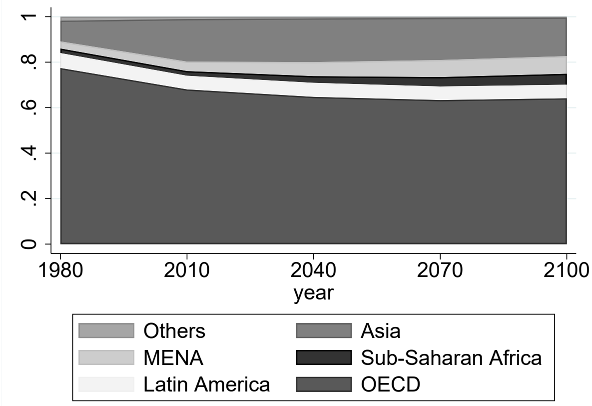
(c) Share of working age population



(d) Share of college-educated workers



(e) Share of urban population



(f) Share of GDP

Figure 1.A4: Global inequality and regional shares (1980-2100)

Notes: This figure reports the Theil index of income inequality, the Theil index of inequality in the share of skilled workers, the regional shares of global labor force, high-skilled workers, urban workers and GDP. In Figures 1.A4c-1.A4f countries are exclusively and completely assigned to one of six groups: OECD, Latin America, sub-Saharan Africa, Middle East and North Africa (MENA), Asia and Others

Table 1.A3: Projections of immigration and emigration rates

	Baseline scenario				Half	Linear	No internal
	2010	2040	2070	2100	2100	2100	2100
Emigration rates (as percent of native population)							
OECD	4.3	4.4	4.2	3.7	3.9	4.0	3.7
LAC	3.9	4.5	4.9	5.2	5.4	5.1	6.1
SSA	1.4	1.5	1.7	1.7	1.7	2.2	7.2
MENA	2.9	3.6	3.8	3.9	3.8	4.0	4.9
Asia	1.1	1.4	1.8	2.1	1.9	2.0	1.6
Others	13.9	15.1	16.0	16.3	16.6	16.8	17.1
Immigration rates (as percent of resident population)							
EU	12.1	16.1	18.7	20.1	21.8	20.5	29.4
EU 15	13.6	17.7	20.1	21.2	22.9	21.6	30.4
GER	*15.0*	*19.0*	*21.2*	*22.0*	*24.0*	*22.6*	*32.4*
FRA	*12.2*	*15.9*	*18.4*	*19.7*	*21.3*	*20.1*	*28.9*
GBR	*14.6*	*20.0*	*23.2*	*24.4*	*25.4*	*24.4*	*30.0*
ITA	*10.9*	*14.5*	*16.9*	*18.3*	*20.4*	*19.0*	*29.5*
ESP	*14.0*	*17.3*	*19.1*	*19.8*	*21.7*	*20.4*	*29.2*
USA	16.0	18.6	19.5	19.2	21.0	19.8	27.3
CAN	18.7	23.0	24.9	25.0	25.8	24.9	29.2
AUS	24.9	27.0	26.9	25.9	27.3	26.2	32.9

Notes: The upper part of the table gives the share of emigrants in the total native population for the OECD, Latin America and the Caribbean (LAC), sub-Saharan Africa (SSA), Middle East and North Africa (MENA), Asia, and Others. The bottom part of the table gives the share of immigrants in the working-age population for the European Union (EU), the 15 countries of the European Union (EU 15), Germany (GER), France (FRA), Great Britain (GBR), Italy (ITA), Spain (ESP), the United States (USA), Canada (CAN), and Australia (AUS). The first to fourth columns give the respective values for the baseline scenario for the years 2010-2100. Column "Half" gives the respective values for the counterfactual scenario where the coefficients of the (baseline) quadratic convergence equation are divided by two for the year 2100. Column "Linear" gives the respective values for the counterfactual scenario with the linear convergence in education costs for the year 2100. Column "No internal" gives the respective values for the counterfactual scenario with no internal mobility for the year 2100.

1.A.4 Sensitivity to technological externalities and to the preference structure

We assess the sensitivity of our socio-demographic projections to modeling assumptions. Firstly, we assess the extent to which technological externalities influence our socio-demographic and income projections. The static counterfactual experiments conducted in Section 1.5.1 show that the effect of human capital on global inequality quantitatively depends on the size of technological externalities.

Figure 1.A5 compares the baseline trajectories of population, education and urbanization with those obtained without or with full externalities. The evolution of socio-demographic variables is highly robust to the technological environment. The only exception is the share of college graduates in OECD countries, which depends on the intensity directed technical change. With full externalities, the skill premium and the cost of ed-

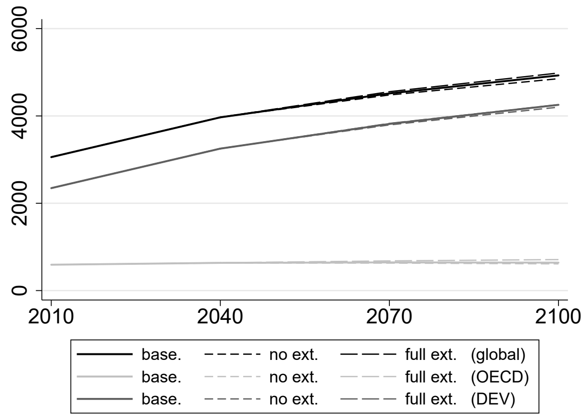
ucation increase. This makes access to education more difficult for poor households. At the world level, technological externalities have a negligible effects on future demographic pressures, urbanization and human capital accumulation.

Secondly, we challenge the assumption of homogenous consumption goods produced across sectors and of the homothetic preference structure. It is well documented in the macroeconomic literature on structural change that relative prices (Ngai and Pissarides, 2007) and income effects (Foellmi and Zweimüller, 2008) can influence consumption choices and welfare. In our framework, urbanization and human capital accumulation affect the quantity of goods produced in the agricultural and nonagricultural sectors, with potential implications on relative prices. In particular, if the relative price of agricultural goods increases, this may attenuate the process of urbanization and increasing access to education.

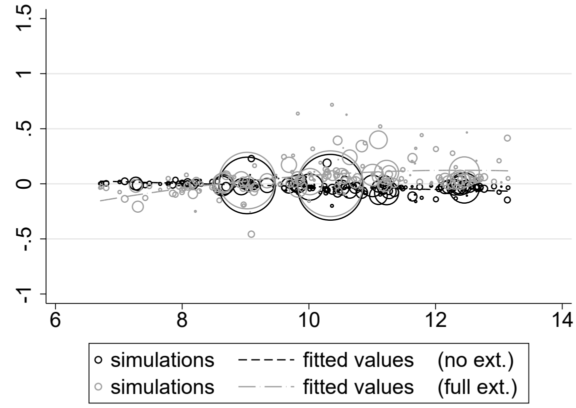
To investigate this mechanism, we extend our model and rely on the preference structure described in Boppart (2014). In each region, we assume that the utility of total consumption is a nonlinear transformation of the quantity of agricultural ($c^a_{r,s,t}$) and nonagricultural ($c^n_{r,s,t}$) goods produced in the country: $c_{r,s,t} = (c^a_{r,s,t})^\alpha + c^n_{r,s,t}$. We thus disregard trade, which would attenuate the average relative price variations. More precisely, consumption of agriculture goods is subject to diminishing marginal utility, as long as $\alpha \in (0, 1)$. Knowing that each good is characterized by a separate price level (with p^a serving as a numeraire in each country), and the total consumption expenditure is labeled by $c_{r,s,t}$ (as in Equation (1.10)), one can solve for the share of each good in the consumption basket, e.g. for the agricultural good: $c^a_{r,s,t}/c_{r,s,t} = \alpha^{\frac{1}{1-\alpha}}(p^n_{r,t})^{\frac{1}{1-\alpha}}c^{-1}_{r,s,t}$. The latter resembles Equation (20) in Boppart (2014), which is then structurally estimated to retrieve the value of α. According to his regressions, $\alpha \approx 0.67$, which we take as the reference value of the non-homotheticity parameter in individuals' utility. We also consider a scenario with a smaller substitutability between goods (i.e., $\alpha = 0.50$).

Figure 1.A6 compares the baseline trajectories of population, education and urbanization with those obtained with imperfectly substitutable goods and non homothetic preferences (using $\alpha = 0.67$ and $\alpha = 0.50$). Again, the evolution of socio-demographic variables is highly robust to preferences. At the world level, accounting for imperfect substitution as in Boppart (2014) has negligible effects on future demographic pressures, urbanization and human capital accumulation.

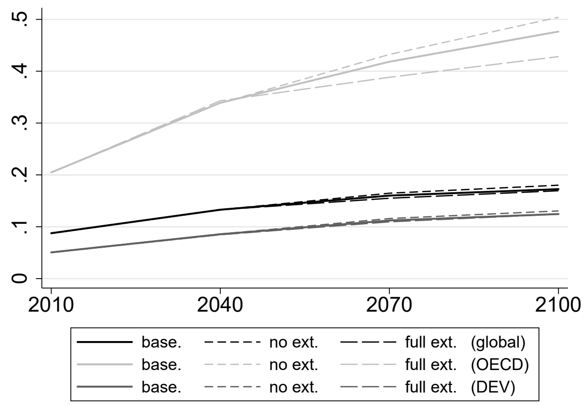
On Figure 1.A7, we illustrate the effect of our modeling assumption on income inequality. Figures 1.A7a and 1.A7b assess the sensitivity of the income distribution to the size of technological externalities. We find that the size of technological externalities affects the trajectory of income per capita in developing and developed countries, but has negligible effect on income inequality. Figures 1.A7c and 1.A7d assess the sensitivity of global inequality to the structure of preferences. Assuming imperfectly substitutable goods and non-homothetic preferences has little effect on the levels of income per capita and on the Theil index.



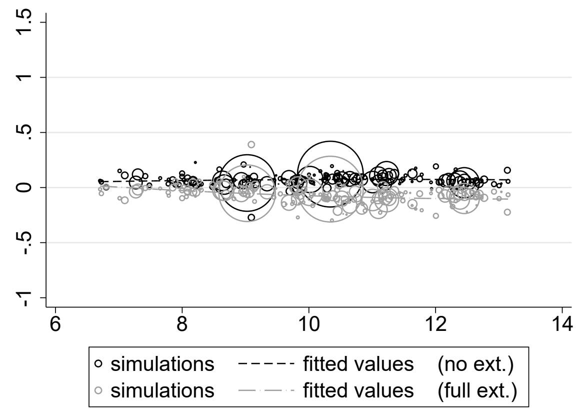
(a) Population (in million of people)



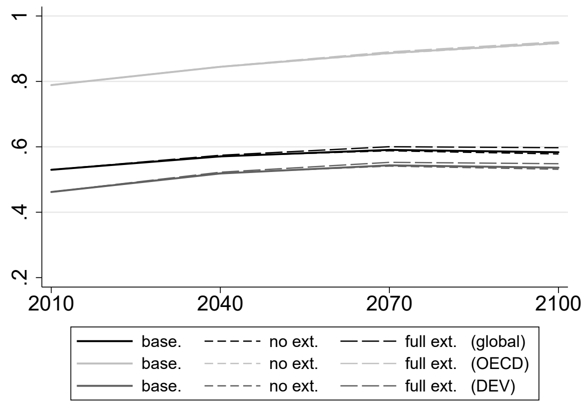
(b) Relative deviations from the baseline in 2100



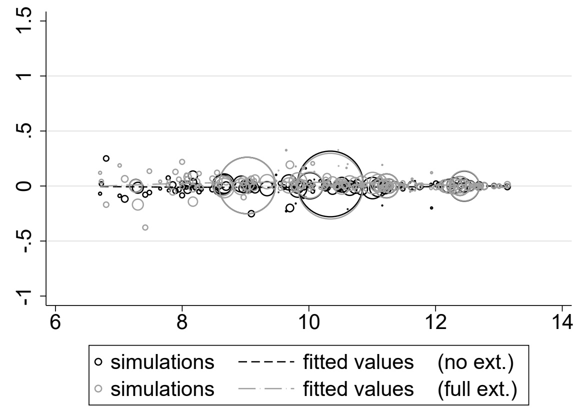
(c) Share of college educated workers



(d) Relative deviations from the baseline in 2100



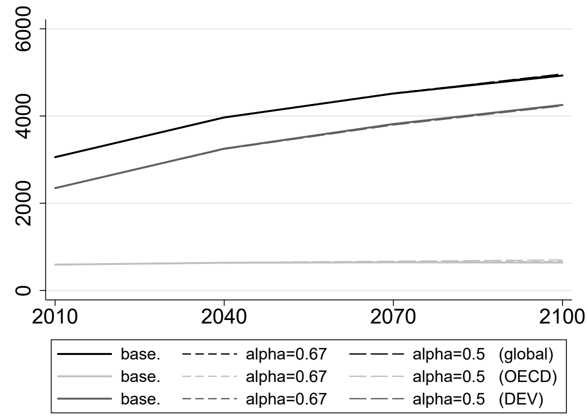
(e) Share of urban population



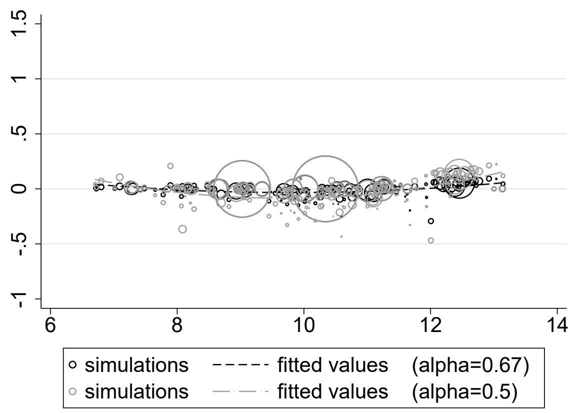
(f) Relative deviations from the baseline in 2100

Figure 1.A5: Sensitivity to technological scenarios

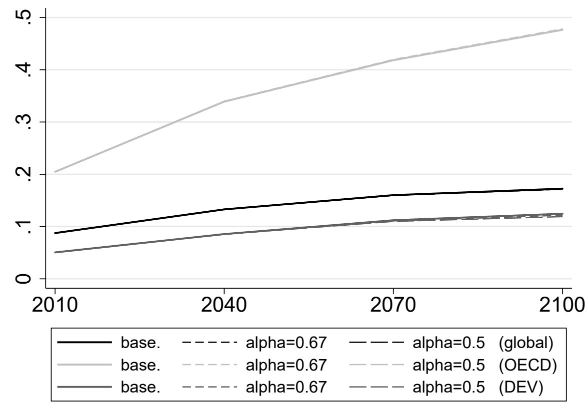
Notes: This figure reports the projected population size, the share of college educated workers, and the share of urban population for the baseline and the respective counterfactual scenario. The scenario "no ext." refers to the scenario with no technological externalities. The scenario "full ext." refers to the scenario with full technological externalities.



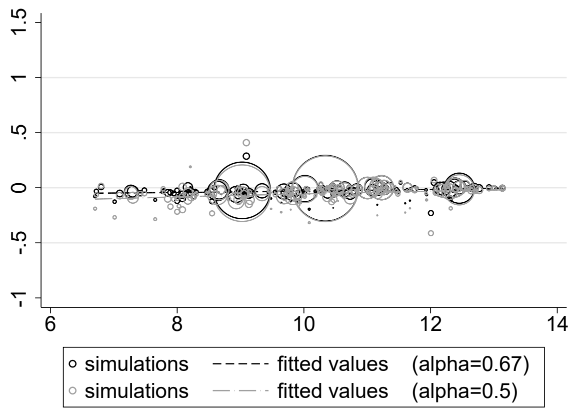
(a) Population (in million of people)



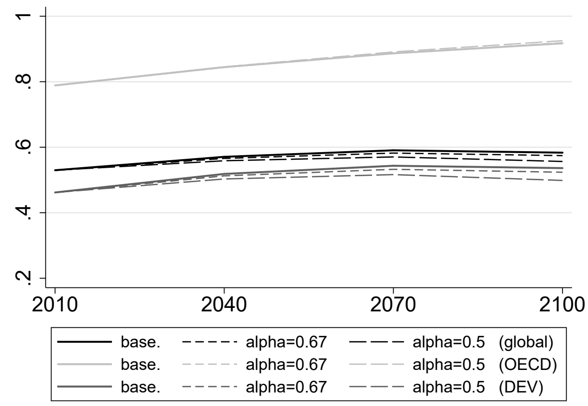
(b) Relative deviations from the baseline in 2100



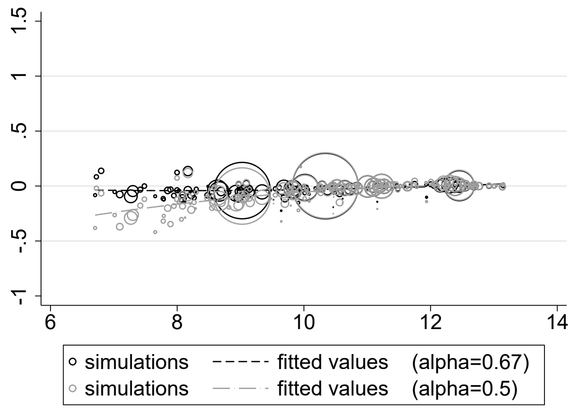
(c) Share of college educated workers



(d) Relative deviations from the baseline in 2100



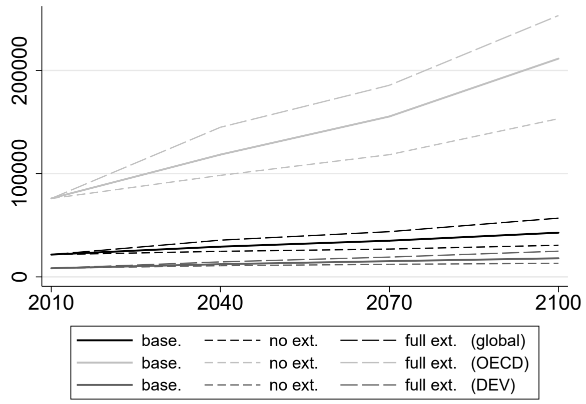
(e) Share of urban population



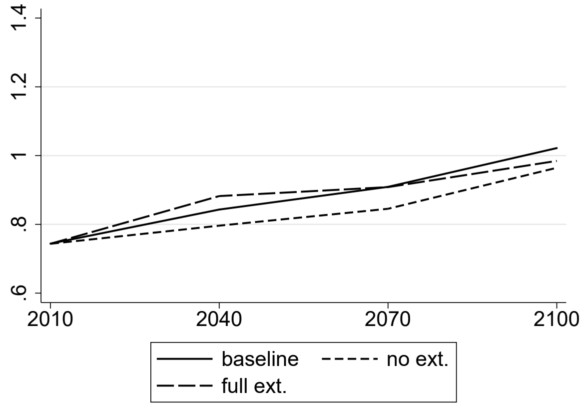
(f) Relative deviations from the baseline in 2100

Figure 1.A6: Sensitivity to preference structures

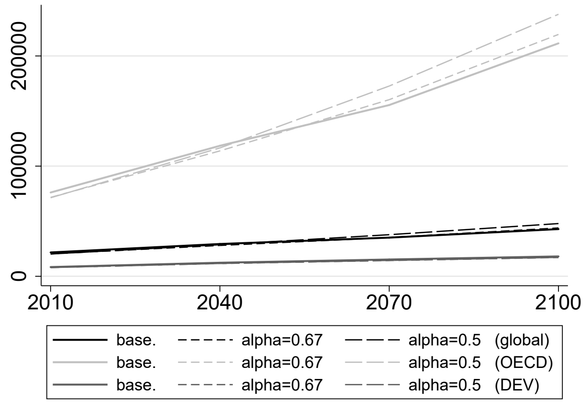
Notes: This figure reports the projected population size, the share of college educated workers, and the share of urban population for the baseline and the respective counterfactual scenario. The scenario "alpha=0.67" refers to the scenario with imperfectly substitutable goods and non homothetic preferences and a value of 0.67 for α. The scenario "alpha=0.5" refers to the scenario with imperfectly substitutable goods and non homothetic preferences and a value of 0.5 for α.



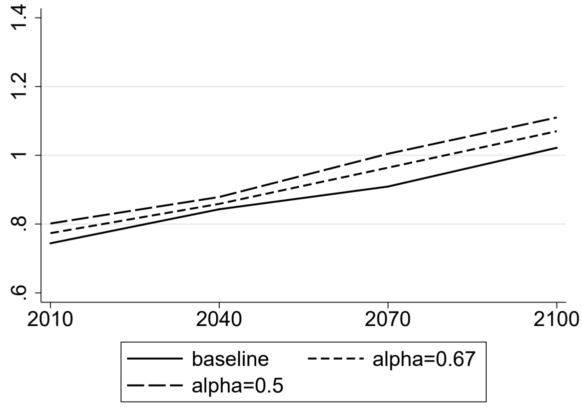
(a) Income per capita - externalities



(b) Theil index - externalities



(c) Income per capita - preferences



(d) Theil index - preferences

Figure 1.A7: Income inequality prospects under alternative modeling assumptions

Chapter 2

Climate change, inequality, and migration

Abstract[1]

This chapter investigates the long-term effects of climate change on labor migration at various spatial scales (local, interregional and international). Based on the model developed in the previous chapter, we build a two-sector, two-class, intertemporal model of the world economy that accounts for the effects of climate change. For each country, we endogenize the effect of rising temperature and sea levels on population and productivity growth, education decisions, income inequality, extreme poverty and mobility decisions. Climate change creates conditions that are conducive to increasing urbanization and international migration from developing to rich countries. In our median scenario ($+2.09°C$, $+1.1m$), we predict that climate change induces voluntary and forcibly displacements of about 120 million adult workers in the course of the 21st century. Nevertheless, under current migration laws and policies, most of these workers will move short distances, and only 19% of them will opt for long-haul migration to OECD destinations. Climate change has limited effects on international emigration and immigration rates, even when considering more extreme scenarios. Larger amounts of internal and international migrations can be obtained when adding direct utility losses and conflicts over resources, two effects that are more uncertain and harder to quantify.

Keywords: human capital, migration, climate change, inequality

JEL codes: E24, J24, O15

2.1 Introduction

There is strong evidence that the global mean surface temperature of the world has increased since the beginning of the 19th century, and that the process has accelerated since 1980. Temperatures are expected to increase by 1 to $3°C$ over the 21st century, and recent studies suggest that, once adding an increment from storm surge, the sea level is

[1]This chapter is coauthored with Michał Burzyński, Frédéric Docquier and Jaime de Melo. We thank the *Agence Française de Développement* for its financial support (convention IRS/ECO/437-2017) as well as Michel Beine, Simone Bertoli, François Gemenne, Fabio Mariani and Katrin Millock for their helpful suggestions and comments.

expected to rise by 1 to 2 metres by 2050 (e.g., Rigaud et al., 2018). Global warming and sea level rise are two major ingredients of long-term climate change (henceforth CLC), which will alter ecosystems and affect several economic outcomes such as productivity, health, drudgery of work, conflicts, and more (see Dell et al., 2014). Damages will vary across space because the economic effects of temperature are nonlinear (i.e., initial temperature matters) and countries are heterogeneously exposed to sea-level rise. Low-latitude countries that have contributed the least to CLC will be the most adversely affected. Hence, migratory pressures, both internal and international, will presumably be strongest in poor countries and are sometimes portrayed as a first-order adaptation mechanism to CLC. The scant evidence from past episodes suggests, however, that the scale and type of mobility responses are uncertain and context-specific.

This chapter studies the long-term effects of CLC on migration. For the first time, we use the state-of-the-art tools of the migration literature to model the long-term mobility responses to CLC at various spatial scales, and their interactions with global inequality and extreme poverty over the 21st century. The existing literature has mostly looked at the short-term impacts of fast-onset variables (e.g., storms, hurricanes, torrential rains, floods, landslides, etc.), as opposed to long-run CLC or slow-onset variables (e.g., temperature trends, desertification, rising sea level, coastal erosion, etc.).[2] Long-run extrapolation of these estimates is questionable,[3] and there is very little theoretical modeling of the population and economic consequences of CLC. Contrary to existing studies, our forward-looking, general equilibrium model covers the world economy and accounts for the economic and socio-demographic contexts in which mobility decisions are made. We model migration decisions as the outcome of a micro-founded, random utility model, and jointly account for the main migration mechanisms mentioned in the literature. Increases in temperature affect income and incentives to migrate (as in Desmet and Rossi-Hansberg, 2015, or Shayegh, 2017), and the rising sea level forces people and activities to move (as in Rigaud et al., 2018). In more extreme scenarios, we also consider that CLC may cause direct utility costs (linked to health or to the drudgery of work) and conflicts over resources. In addition, our migration technology is parameterized to match international and urbanization data of the last 30 years.[4] In our framework, geography matters: each one of 179 countries is populated by two types of agents (*college graduates and the less educated*) living in two regions (*agriculture and non-agriculture*) and heterogeneously affected by sea level rise (*flooded and unflooded areas*). The model also endogenizes the productivity, fertility, and education responses to CLC which, together with skill-specific migration decisions, govern the evolution of human capital and income inequality. Such a unified model is helpful for quantifying the long-run demographic and economic responses to CLC and their sensitivity.

We contribute to the growing literature on the linkages between CLC and migration. As explained above, existing studies are mostly empirical and focused on responses to extreme weather shocks. Recent reviews of the literature are provided in Perch-Nielsen

[2]Note that in the long-run, there is a correlation between the slow-onset indicators and the frequency of fast-onset shocks.

[3]Although it has been documented that the 2^0C rise in temperatures during the Medieval warm period between the 9^{th} and 14^{th} centuries resulted in large relocation of people and economic activity (Fagan, 2008), the world has changed and it is difficult to draw causal inference about long-run effects from the past 30 years because global warming has been modest and migration restrictions have gradually increased.

[4]Using backcast exercises, Dao et al. (2017) demonstrate that such a model fits the past international migration trends very well.

et al. (2008), Piguet et al. (2011), Millock (2015), Berlemann and Steinhardt (2017) or Cattaneo et al. (2018).[5] The meta-analysis in Beine and Jeusette (2018) reveals a diversity in methodological choices in empirical studies. They identify four important methodological choices, namely (i) the measurement of the dependent variable,[6] (ii) the decision to include or exclude indirect effects of CLC,[7] (iii) the analytical specification of the transmission technology,[8] (iv) and the identification strategy. Methodological diversity is reflected in the heterogeneity of findings. While CLC has consistently emerged as a potent driver of internal migration (Piguet et al., 2011; Barrios et al., 2006; Kubik and Maurel, 2016; Dallmann and Millock, 2013; Henderson et al., 2017), its effect on international migration is not consensual. Some studies find important international migration outflows that are directly associated to weather shocks (Coniglio and Pesce, 2015; Backhaus et al., 2015; Cai et al., 2016) or indirectly induced by CLC-driven pressures on income in urban areas (Marchiori et al., 2012, 2015; Beine and Parsons, 2015). Others attempt to explain why migration responses are small, and even why migration does not respond or responds negatively to climate shocks (Black et al., 2011; Black et al., 2013; Cattaneo et al., 2018).[9] Overall, using empirical approaches to predict the migration responses to global warming poses three major problems. Firstly, difficulties in identifying a clear-cut effect are due to the fact that climate variables closely interact with the other economic and political drivers of migration. Secondly, mobility decisions are context-specific and can be influenced by a large number of factors that vary across regions and countries (such as the country size, the level of economic development, the political context or some cultural characteristics). Thirdly, the effects of CLC have not yet fully materialized.

In light of these limitations, we propose an alternative, micro-founded approach that includes a spatial dimension. Our study is part of an incipient literature pioneered by Desmet and Rossi-Hansberg (2015) (henceforth DRH) who investigate the economic costs of CLC by modeling the interaction of mobility and production changes in the continuous space.[10] Unlike DRH, our approach distinguishes between two regions, agriculture and nonagriculture, to accommodate empirical estimates that show consistently that the im-

[5]Earlier studies show that millions of people will be forcibly displaced in the future as a result of climate change (Gemenne, 2011; Piguet et al., 2011). In response to the diversity of findings across studies, the paradigm has gradually changed with recent studies seeing migration as an adaptation strategy among several others (not the least costly one).

[6]Some studies focus on international migration (to all countries or to selected destinations) while others tackle internal migration and urbanization (Henderson et al., 2017)

[7]An indirect link is identified when climate variables affect mobility decisions through other variables such as changes in productivity and income (Marchiori et al., 2012; Beine and Parsons, 2015), or conflicts over resources (Miguel et al., 2004; Gleditsch, 2012).

[8]The literature distinguishes between monotonic or unconditional specifications (i.e., models capturing responses that are independent of the context), and conditional specifications that allow the eventual outcome to depend on socioeconomic and political characteristics of the individuals, households or regions exposed to climatic events.

[9]Cattaneo and Peri (2016) report that a gradual increase in the level of temperature reduces migration outflows from poor countries due to the presence of financial constraints. Bazzi (2017) finds similar results on Indonesia, as well as Findley (1994) on Mali. On the contrary, Jayachandran (2006), Gray and Mueller (2012), Mueller et al. (2014) find that landless households respond more than the wealthy ones in India, Pakistan and Bangladesh, respectively.

[10]In DRH all equilibria are spatially symmetric with prices and factor allocations identical for all locations at a given latitude. Desmet, Nagy and Rossi-Hansberg (2018) model the mobility of people and the dynamics of income inequality at a more detailed spatial scale (1x1 degree cells across the globe), but disregard CLC.

pact of CLC on productivity will be greater in agriculture than in manufacturing. We are looking for first-order effects of CLC on people and countries in a framework that takes into account that the (endogenous) geography of skills affects migration decisions through differences in incentives, fertility decisions, and migration costs. Another related study is Shayegh (2017), which models the effect of CLC on fertility rates, income inequality and human capital accumulation in developing countries. He assumes the probability to emigrate is skill-specific and increasing in temperature without microfoundations. As to the effects of CLC, DRH and Shayegh (2017) model the effect of the change in temperature on productivity. We also account for sea-level rise - about which scientific consensus is strong - which affects countries differentially, and we implement additional mechanisms of transmission such as direct utility losses and conflicts. The emphasis on migratory mechanisms comes at a cost. In our model, unlike the macro models of Nordhaus (2000) and DRH, CO2 emissions are exogenously subsumed in the simulation scenario rather than as a result of mitigation decisions included in the model. There are two reasons for this. Firstly, the effects of population change on the concentration of greenhouse gas and global mean temperature are highly uncertain. As discussed in the next section, projections of mean air temperature levels strongly vary across models for a given emissions scenario. Secondly, Shayegh (2017) shows that endogenizing the CLC response to migration has a negligible impact on the overall results given the small number of migrants compared to the whole population. We assume that CLC and its directs impacts are exogenous to the economies under investigation.

Our simulations reveal that CLC induces small positive effects on the worldwide average level of income per worker but makes the world distribution of income more unequal. Workers employed in countries located below the 35th parallel suffer income losses, particularly those employed in agriculture. CLC also increases world extreme poverty at both extensive and intensive margins. Coupled with the fact that the rising sea level induces forced displacements, CLC creates conditions that are conducive to increasing urbanization and international migration. Our *Intermediate* CLC scenario assumes $+2.09°C$ and a $1.1m$ rise in the sea level. It accounts for climate-driven productivity losses and forced displacements. Compared to a constant climate scenario, the worldwide number of working-age movers increases by 120 million in the course of the 21st century. Compared to Rigaud et al. (2018), we find similar levels of climate migration but offer additional insight on the type of migration. In particular, when considering forced displacements and productivity effects, we find that far more climate migrants will move within their own countries than across borders: 66% of movers relocate within their region and 15% migrate from rural areas to cities. Hence, only 19% opt for long-haul migration to an OECD destination country. CLC increases the world proportion of international migrants by 0.2 percentage points in the long-run. This only corresponds to 1/20 of the no-CLC worldwide migration rate, and to 1/5 of the gradual increase predicted for the 21st century. The latter trend is mostly driven by demographic imbalances between developing and rich countries, and by the education trends. These effects increase less than proportionately if the rise in temperature is twice as large (i.e., $+4°C$ in the 21st century): the number of movers reaches 185 millions, including 27% of long-haul migrants. In addition, a relaxation of immigration restrictions for migrants originating from the countries incurring the largest CLC-driven income losses has limited effects on extreme poverty headcounts and on poverty depth. Our results for international migration are highly robust to the scale of the sea level rise. This is due to the fact that forcibly displaced people essentially move locally. However, two major sources of uncertainty surround our projections. Our numerical experiments reveal that conflicts over resources could become a key determinant of climatic migration pressures, and that direct utility losses due to CLC have potentially important effects on internal and international migration.

The rest of this chapter is organized as follows. Section 2.2 illustrates the heterogeneous implications that CLC induces for the world economy. Section 2.3 describes our two-sector, two-class model and explains its parameterization. Section 2.4 presents our results. Finally, Section 2.5 concludes.

2.2 Heterogeneous effects of CLC

In this section, we show that low-latitude countries in general, and their rural regions in particular, will be the most adversely affected by CLC. This implies that CLC creates conditions that are conducive to increasing urbanization and international migration from developing to rich countries. In Section 2.2.1, we define three moderate climate scenarios that combine future variations in global temperature and sea levels. Then, Section 2.2.2 discusses two direct transmission channels - changes in total factor productivity and forced displacements - through which CLC affects the world economy and the migration decisions of people. These channels will be accounted for in the overlapping generations model described in Section 2.3. Note that more extreme climate scenarios and two additional channels of transmission - direct utility losses and conflicts, which are more uncertain and more difficult to quantify - will be considered in Section 2.4.2.

2.2.1 Moderate climate scenarios

Most analysts predict that CLC will lead to a gradual rise in the mean surface-temperature and in the sea level over the 21st century. Uncertainty about CLC, about damages, and about the interaction between CLC and damages is large.[11] To take this into account, we define three moderate scenarios referred to as:

- *CLC-Minimalist.* – This scenario involves a rise of $+0.09°C$ in temperature and $+0m$ in sea level over the 21st century.
- *CLC-Intermediate.* – This scenario involves a rise of $+2.09°C$ in temperature and $+1.1m$ in sea level over the 21st century.
- *CLC-Maximalist.* – This scenario involves a rise of $+4.09°C$ in temperature and $+1.3m$ in sea level over the 21st century.

We consider these changes as exogenous in our model. We thus disregard the endogeneity of CLC, which is comprised of uncertain links between CLC, economic activity and CO2 emissions. The scenario selection is discussed below.

[11] Stern (2013) reports that since an increase of $+3°C$ (likely to occur when concentrations increase from the current $400ppm$ to $750ppm$) has not been experienced for around 3 million years, we are in uncharted territory when it comes to modeling these likely effects. He lists the effects that might emerge strongly at $+3°C$. Schelling (2007) remarked about the climate sensitivity parameter (S) which defines the equilibrium surface warming from a doubling of the stock of CO2 emissions that "for a quarter of a century, the range of uncertainty [about S] has been a factor of 3". This uncertainty comes out clearly in the range of damage changes produced by the same warming scenario in the different climate models reviewed by Burke et al. (2015).

Projections of temperature. – We follow three steps to construct our projections of temperature levels. In a *first step*, we collect raw data on monthly temperature levels and projections from the Climate Change Knowledge Portal (CCKP) of the World Bank Group. Our variable of interest is the near surface monthly mean air temperature level. Figure 2.1a illustrates the cross-country relationship between mean surface-temperature and latitude in 2010. Bubble sizes are proportional to the working-age population in each of the 179 countries included in the model. Temperature levels are negatively correlated with latitude.

As for temperature projections, they are organized in 20-year climatological windows for the years 2020-2039, 2040-2059, 2060-2079, and 2080-2099. The CCKP projections are obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) distribution (Taylor et al., 2012) which distinguishes between several scenarios for the Representative Concentration Pathways (RCP) (Moss et al., 2010). The median-emission scenario is called RCP-4.5. In addition, for each RCP, the CCKP provides data for 16 models obtained from different research institutes. When these models are ranked by ascending order of the yearly temperature anomaly for the fourth 20-year climatological window of 2080-2099, the medium resolution model of the Institut Pierre Simon Laplace (the *ipsl_cm5a_mr* variant) takes the 8th (median) position in RCP-4.5. We select this *ipsl_cm5a_mr* variant as our *Intermediate* scenario.

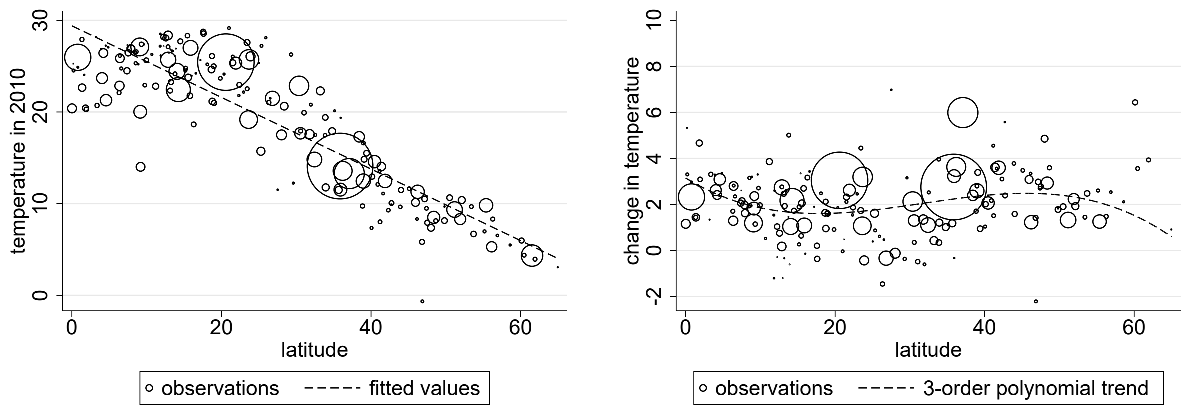
This *Intermediate* scenario predicts that the temperature levels increase gradually in all countries, and that the mean surface temperature of the world will increase by $2.09°C$ over the 21st century. Figure 2.1b plots the 2010-2100 variation in the average of our monthly levels of temperature by degree of latitude for the 179 countries. For most countries this difference takes a positive value between $0°C$ and $4°C$.[12] Overall, the correlation between latitude and the predicted temperature change is small. Hence, most countries will experience an increase in temperature, and all country types (small and large, rich and poor) will be affected with a similar intensity.[13]

In the *Minimalist* scenario, we start from the *Intermediate* and uniformly decrease the temperature by $2°C$ in all countries, which basically shifts the estimated curve downwards by $2°C$ in Figure 2.1b. Hence, this scenario predicts that the mean surface-temperature will increase by $0.09°C$ over the 21st century, virtually implying the absence of global warming. The *Minimalist* scenario roughly corresponds to the most optimistic variant under RCP-2.6. Similarly, the *Maximalist* scenario uniformly increases the temperature by $2°C$ in all countries, which shifts the estimated curve upwards by $2°C$. Hence, it predicts that the mean surface-temperature will increase by $4.09°C$. The *Maximalist* scenario roughly corresponds to the median variant under RCP-8.5.

Sea level rise (SLR). – Potentially, the second most serious impact of long-term CLC is the rise in the sea level. According to IPCC (2014), millions of individuals living at an altitude of less than one meter will be affected during the 21st century. Predicting changes in sea level is difficult, because the dynamics of ocean heat uptake and ice sheets/glaciers are poorly understood. Still, Vermeer and Rahmstorf (2009) developed a methodology that links global SLR (on time scales of decades to centuries) to global mean temperature.

[12]Figure 2.1b depicts the temperature difference for values between -2$°C$ and +10$°C$. Three outliers are not depicted: Russia and Canada include large territories in the northern hemisphere and exhibit high negative differences, Nepal has high levels of altitude and exhibits very large positive differences.

[13]In Appendix 2.A.1, we discuss how raw temperature levels are adjusted to account for within-country disparities in temperature and population density, and how climate windows are linked to the time periods of our overlapping generations model.



(a) Mean temperature level in 2010 and latitude

(b) Variation in mean temperature and latitude (2010-2100)

Figure 2.1: Intermediate CLC scenario (2010-2100)

Notes: Latitude (geographic coordinate) is measured on the X-axis and bubble sizes are proportional to the population aged 25-64 in the year 2010.

They estimate the SLR for each global temperature scenario of the IPCC involving a global temperature change above $2°C$. The estimated relationship between the sea-level variation (SLR) and the global change in the mean surface-temperature (ΔT) is concave if SLR is forced to be equal to zero for $\Delta T = 0$, and almost linear if $SLR(0)$ is not specified.[14]

In the *Intermediate* temperature scenario ($+2.09°C$), this curve implies that the sea level is expected to rise by $1.1m$. Given the gradual change in temperature in our baseline scenario, the sea level is predicted to rise by $0.78m$ in 2040, by $0.99m$ in 2070 and by $1.1m$ in 2100. In another study, DeConto and Pollard (2016) model the impact of Antarctic ice cap on overall SLR. In their reference estimation, they find changes which closely correspond to our projections: under the RCP-4.5 scenario, they predict a mean elevation of $1.05m$ and a confidence interval of $\pm 0.30m$, which is very similar to our *Intermediate* scenario.

In the *Minimalist* scenario, we assume a constant sea level. Remember this scenario also involves constant mean surface temperature. Although it can be considered as unrealistic and extreme, we use it as a no-CLC point of reference. In particular, the difference between the *Intermediate* and the *Minimalist* scenario gives valuable information about the mean expected effects of CLC.

In the *Maximalist* scenario, the mean surface temperature increases by $4.09°C$. Using the estimated relationship of Vermeer and Rahmstorf (2009), this involves a $1.3m$ SLR by 2100 ($0.97m$ in 2040 and $1.18m$ in 2070). More extreme scenarios will be considered in Section 2.4.2.

[14] It is very well proxied using a log-linear function: $SLR = 0.89 + 0.3\ln(\Delta T)$; the R-squared of this regression equals 0.985. The shape of the function and the proxied observations are depicted in Figure 2.A1b in the Appendix.

2.2.2 Damage functions

The "damage function" is central to estimating the potential economic implications of global temperature and sea-level variations. Two channels of transmission are systematically accounted for in our simulations. Firstly, we allow changes in temperature to affect the level of TFP in agriculture and in nonagricuture.[15] Secondly, SLR induces forced displacement of people. This leads to substantial costs as flooded areas are usually the most densely populated areas in a region.[16] More extreme scenarios involving direct utility losses and conflicts over resources will be considered later. Figure 2.2 illustrates the heterogeneous TFP responses to CLC, which are treated as exogenous shocks in our model. Figure 2.3 shows the country-specific shares of population living under $1.1m$ and between 1.1 and $1.3m$ as of the year 2010. Although these shares differ from the long-run (endogenous) population shares which will be impacted in the course of the 21st century, they give an indication of the scale of forced displacements induced by SLR.

Temperature and productivity. – To model the effect of temperature, we follow DRH who estimate an inverted-U shaped relationship between temperature (T) and total factor productivity in agriculture and in the manufacturing sector. They include a quadratic scale factor $G_r(T)$ in the TFP of sector r that depends on the level of temperature. It can be expressed as:

$$G_r(T) = \max\left\{g_{0r} + g_{1r}T + g_{2r}T^2; 0\right\}$$

where (g_{0r}, g_{1r}, g_{2r}) is a triplet of sector-specific parameters, and $r = (a, n)$ denotes agriculture (a) and nonagriculture (n). If $g_{1r} > 0$ and $g_{2r} < 0$, the ideal temperature in sector r is given by $T_r^* = -\frac{g_{1r}}{2g_{2r}}$. The level of TFP increases with temperature in regions with average temperature below T_r^*; it decreases with temperature in warmer regions.

Agronomic studies have been used to calibrate the quadratic relationship between TFP and temperature in agriculture (Mendelsohn et al., 1994; Le, 2010; Lobell and Burke, 2010). To account for the possibility of adapting to climate change by switching between crops, DRH estimate the envelope of the quadratic relationships obtained for different crops. This gives $(g_{0a}, g_{1a}, g_{2a}) = (-2.24, 0.308, -0.0073)$, which implies an optimal temperature T_a^* of $21.1°C$. It also implies that agricultural yields are nil when temperature T_a is below $9.4°C$ or greater than $32.9°C$. Figure 2.2a shows the relationship between temperature and agricultural productivity, after normalizing the maximal level of productivity to unity and smoothing $G_a(T)$ using a Gaussian function to avoid zero-productivity levels.

To estimate the quadratic relationship in the nonagricultural sector, DRH use data on population density (a proxy for economic development) by latitude. They consider 1,000 bands of $9.6km$ each, and estimate the relationship between (smoothed) levels of population density and temperature. They obtain $(g_{0n}, g_{1n}, g_{2n}) = (0.3, 0.08, -0.0023)$,

[15] In unreported results, we also accounted for the potential productivity losses due to the rising sea level. We used the NASA database and estimate of the fraction of land that could be flooded. Using population and land data, we compared the density of people in flood-risk areas and in the rest of the region and assume, in line with Desmet and Rossi-Hansberg (2015), that disparities in population density reflect disparities in total factor productivity. For each country, we produced region-specific estimates of the productivity loss caused by the sea-level rise. These productivity losses are small (in countries with access to the sea, we obtained an average loss of 1.2% in rural regions and of 0.7% in rural regions), either because the share of population located in flooded areas is small, or because productivity differences are small. For this reasons, this mechanism is not included in the model.

[16] On average, low elevation coastal zones (situated at an altitude of less than ten meters) account for 2.2% of dry land and 10.5% of the world population (see McGranahan et al., 2007).

which gives an optimal temperature T_n^* of 17.4°C. The quadratic is compatible with the findings of Dell and Jones (2014) who show that, on average, industrial output decreases by 2% for a 1°C increase in temperature; it is also compatible with specialization and trade patterns by level of latitude. Although the curve is flatter than in agriculture, nonagricultural productivity is nil when temperature T_n is below -3°C or greater than 38°C. Figure 2.2b shows the relationship between temperature and nonagricultural productivity, after normalizing the maximal level of productivity to unity and smoothing $G_n(T)$ using a Gaussian function to avoid zero-productivity levels. For each country and period, we plug the monthly population-weighted levels of temperature in the period t, $T_{m,t}$, in $G_a(.)$ and $G_n(.)$. We then compute the averages of these TFP levels for each period t:

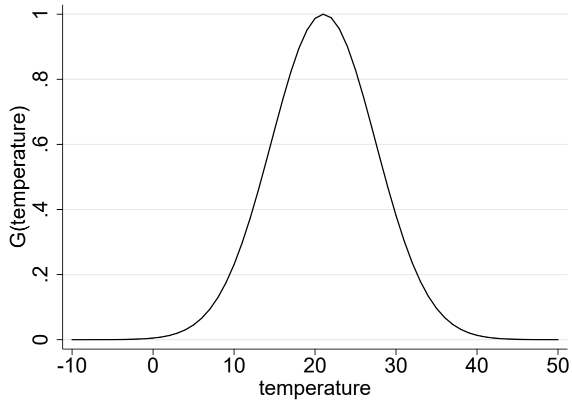
$$G_{r,t} = \frac{1}{12}\sum_{m=1}^{12} G_r(T_{m,t}).$$

Remember that expected variations in temperature are poorly correlated with latitude (see Figure 2.1b). Nevertheless, the current level of temperature is highly correlated with latitude (see Figure 2.1a): countries above the 35th parallel have average temperature levels under 20°C, while countries at lower latitude have a higher average temperature. Hence, the very same variation in temperature will induce dramatically different effects on productivity. Figure 2.2c depicts the predicted percentage variation in agricultural productivity by latitude caused by the change in temperature between 2010 and 2100 in the *Intermediate* scenario. On average, agricultural productivity decreases by 20-25% in countries close to the equator, and increases by 10-15% at high latitudes. Figure 2.2d shows the corresponding damage function in the nonagricultural sector. On average, nonagricultural productivity decreases by 10-15% in countries close to the equator, and slightly increases at high latitude levels.[17]

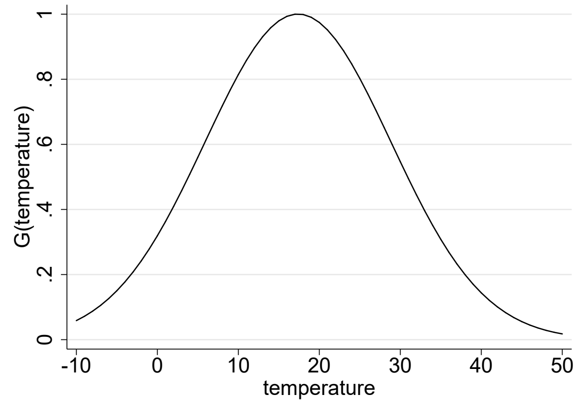
Figure 2.2e and 2.2f compare the variation in productivity implied by the *Maximalist* (with respect to the *Intermediate*) with those implied by the *Intermediate* scenario (with respect to the *Minimalist*). These pairwise comparisons allow visualizing the effect of a 2°C increase in temperature on productivity starting from different initial temperature levels. Figure 2.2e depicts the effect of the variations in temperature on agricultural productivity. Compared to the *Minimalist* (no CLC) scenario, the *Intermediate* (+2.09°C) induces a productivity loss of 20% in countries close to the equator, and a gain of 25% at high latitudes. And compared to the *Intermediate*, the *Maximalist* scenario (another +2°C) results in slightly greater losses. Figure 2.2f focuses on non-agricultural productivity. Compared to the *Minimalist* scenario, the *Intermediate* (+2°C) induces a productivity loss of 10-15% in countries close to the equator, and a gain of 5% for countries at high latitudes. Compared to the *Intermediate*, the *Maximalist* scenario results in similar damages.

SLR and forced displacements. – To proxy the number of people affected by SLR, we need to determine the fraction of the population living in low-lying coastal areas. We use the NASA database on the distribution of the population by elevation, by country and by region type (urban versus rural). We assume rural regions are totally specialized in agriculture and urban regions only produce nonagricultural goods. For each country, we produce region-specific estimates of the fraction of population living under 1.1m using a 4-parameter interpolation of the NASA data. The world map in Figure 2.3a illustrates

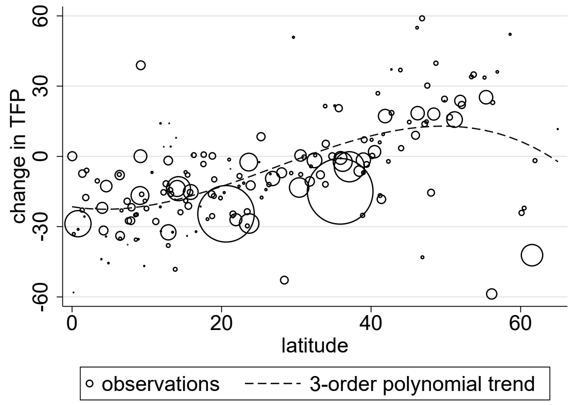
[17]Both graphs include the 3-order polynomial trend, which gives an R-squared of 0.33 for the agricultural sector and 0.41 for the nonagricultural sector.



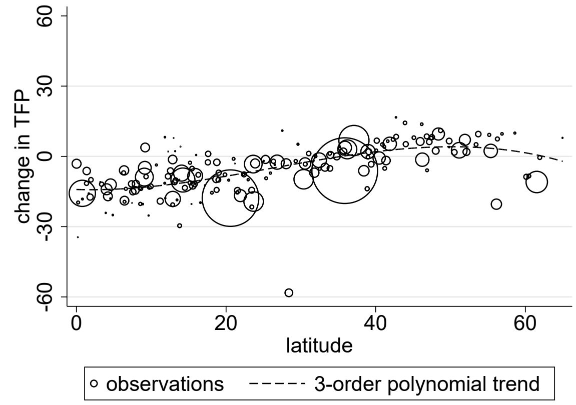
(a) $G_a(T)$: Agricultural TFP and temperature



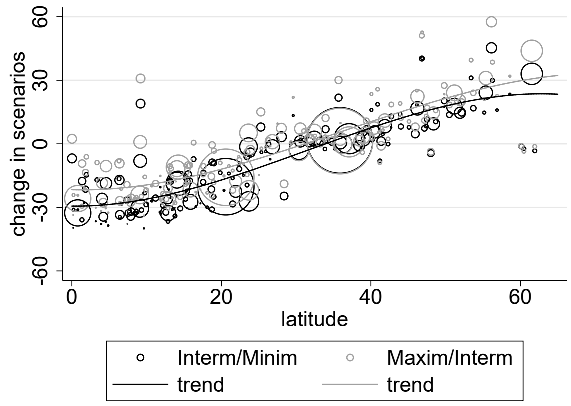
(b) $G_n(T)$: Nonagricultural TFP and temperature



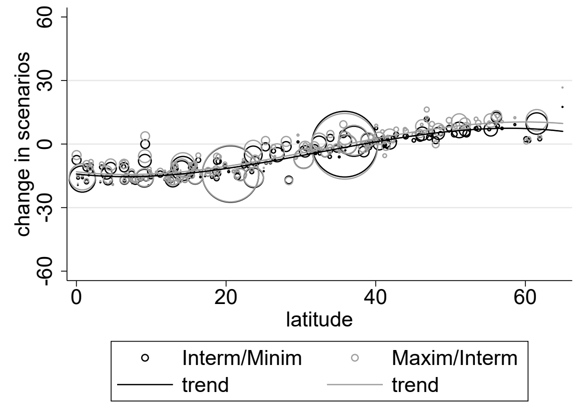
(c) dG_a/G_a (2100-2010) and latitude (Intermediate)



(d) dG_n/G_n (2100-2010) and latitude (Intermediate)



(e) dG_a/G_a and latitude (Maximalist/Minimalist)



(f) dG_n/G_n and latitude (Maximalist/Minimalist)

Figure 2.2: CLC and TFP by latitude

Notes: On Figure 2.2c to 2.2f, latitude (geographic coordinate) is measured on the X-axis, percentage deviations are measures on the Y-axis, and bubble sizes are proportional to the population aged 25-64 in the year 2010. We measure deviations as (Intermediate-Minimalist)/Minimalist on Figure 2.2e and (Maximalist-Intermediate)/Intermediate on Figure 2.2f.

the resulting percentage of the population by country in the year 2010 living in low-lying areas. About 70 million people aged 25 to 64 were living under $1.1m$ in that year. They will be close to 80 million in 2040. On the map, countries are grouped into ten bins, each bin corresponding to a population share living in low-lying areas. In a few countries the percentage of population living below $1.1m$ is larger than 10%. This is the case for less than 7.3% of the countries. For less than 19% of the countries the percentage value is larger than 5%.

Overall, the map shows that the more affected countries are not necessarily the poorest. SLR mostly affects countries with a large share of population located along the coasts of all seas and oceans, or in the major river deltas and estuaries. The percentage value equals 89.1% in the Netherlands. This share is large in South Asian and East Asian countries. Some Pacific islands situated a few centimeters above sea level (e.g., Tuvalu, Kiribati) are in a position of extreme vulnerability. This indicates that both rich and poor countries would be adversely affected by a SLR. It would certainly be an exaggeration to consider that these roughly 80 million individuals will all migrate internationally in the near future. Some of them will move to another region or country. Others will relocate within the same region or invest to build sea defences (especially in high-income countries).

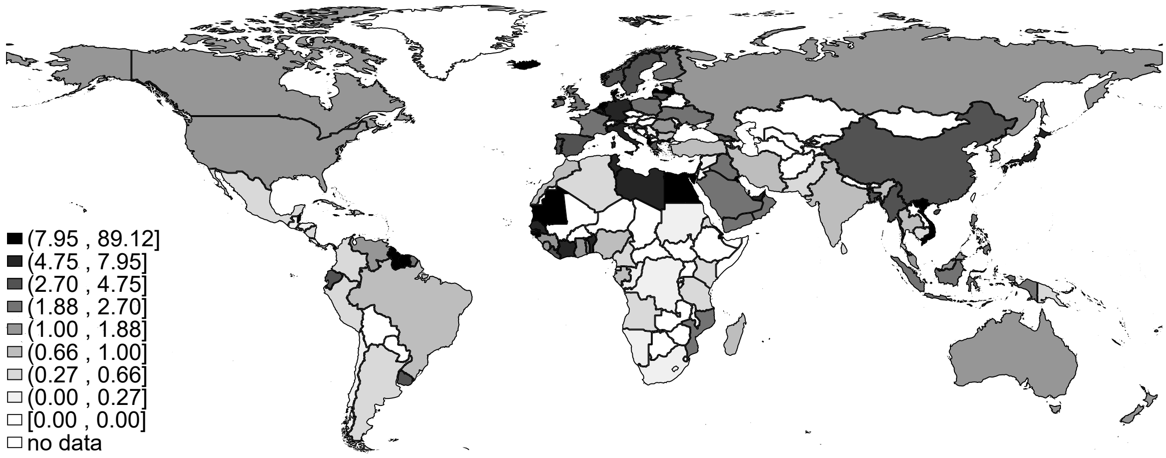
Finally, Figure 2.3b depicts the share of the population living between 1.1 and 1.3m of elevation in 2010. As in Figure 2.3a, countries are grouped by the size of their share into ten groups. Overall, the population share is small. The share is smaller than 10% in all countries, and exceeds 5% only in a handful of countries. The largest share is obtained in the Netherlands, with a value equal to 8%.

2.3 Model

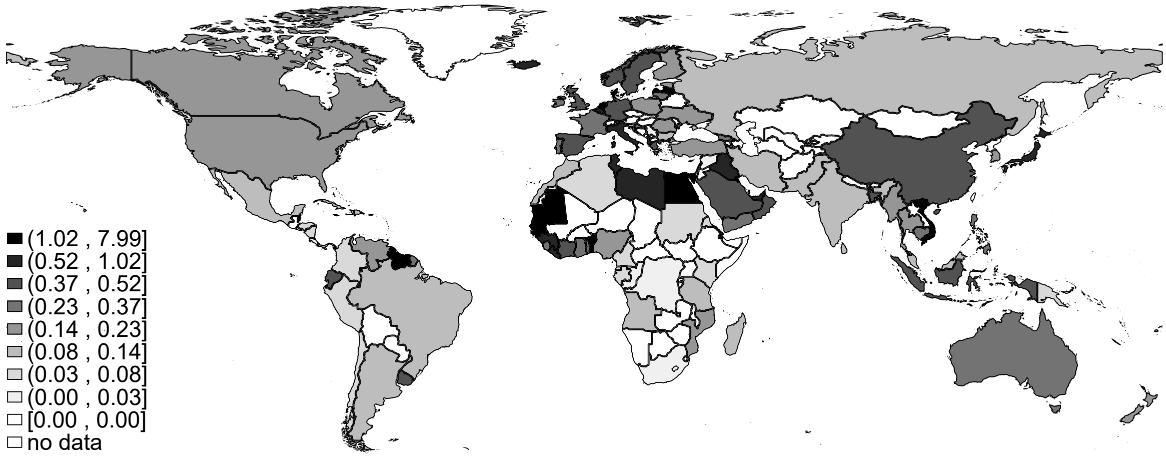
We construct an overlapping generations model of the world economy that depicts a set of countries and regions populated by two period-lived agents (children and adults). One period is meant to represent the active life of one generation (30 years) and we ignore the retirement period for simplicity. There are two types of adults at each period, with $s = (h, l)$ denoting college-educated workers (h) and the less educated (l). In virtually all countries, college graduates are more migratory than the less educated.

Our framework is similar to Delogu et al. (2018) but relies on different technological assumptions, and includes two sectors/regions with heterogeneous productivity, with $r = (a, n)$ denoting agriculture (a) and nonagriculture (n), in each country. For simplicity, we assume that firms in both sectors produce the same good. Contrary to DRH or Shayegh (2017), we thus disregard variations in the relative price of the agricultural good, and we normalize the price of the single good to unity. In theory, changes in relative price can mitigate or reinforce the effect of CLC. DRH show that CLC has uncertain effects on the relative price because it induces a rise in agricultural productivity in the North and a decline in the South.[18] In addition, the previous chapter shows that responses to productivity and migration policy reforms are quantitatively similar when considering

[18]Considering goods as heterogeneous in a small open economy context, variations in the relative price of the agricultural good can mitigate or reinforce the urbanization process. It mitigates it if CLC decreases the share of agriculture in the world total output (i.e., if the output loss in low-latitude countries exceeds the output gain in the North). In the benchmark scenario of DRH (Figure 4), changes in relative price are small. If the relative price of agricultural goods increases, the migration responsiveness predicted by our model can be considered as an upper-bound.



(a) Percentage of population living below 1.1m in 2010 (Intermediate)



(b) Percentage of population living between 1.1 and 1.3m in 2010 (Maximalist)

Figure 2.3: Forced displacements in the moderate scenarios

Notes: Own calculations based on NASA population data.

that agricultural and nonagricultural goods are identical or imperfect substitutes as in Boppart (2014).

Compared to Chapter 1, our model in this chapter formalizes the link between CLC and the productivity gap between regions. We add another source of heterogeneity. Each region consists of two areas of time-varying size, with $b = (f, d)$ denoting the flooded area (f) and the unflooded/dry area (d). The model endogenizes the levels of productivity of both sectors/regions as a function of the level of temperature, of rising sea level, and of the average level of schooling of the resident workers. There is no economic activity and no one can live in the flooded area.

Adults are the only decision makers. They maximize their well-being and decide where to live, how much to consume, and how much to invest in the quantity and quality of their children. As far as the location decision is concerned, each new adult decides whether to stay in the region where he grew up (if the area of birth does not get flooded), to move locally within the same region (if the area of birth gets flooded), to emigrate to the other region within the same country, or to emigrate abroad. This choice depends on economic disparities between regions and countries, on moving costs, on the area type, as well as on the direct effect of temperature on utility. Fertility and education decisions are governed by a warm-glow motive. Adults directly value the quality and quantity of children. It follows that the dynamic structure of the model is totally recursive. In this section, we describe our technological and preference assumptions, we derive the profit- and utility-maximization conditions, and we define the world-economy intertemporal equilibrium.

2.3.1 Technology

Production is only feasible in the unflooded area of each region r. We assume that output is proportional to labor in efficiency units.[19] Each country is characterized by a pair of CES (constant elasticity of substitution) production functions with two types of labor (as in Gollin et al., 2014b, or Vollrath, 2009). The output level in region r at time t is given by:

$$Y_{r,t} = A_{r,t}\left(\sum_s \eta_{r,s,t}\ell_{r,s,t}^{\frac{\sigma_r-1}{\sigma_r}}\right)^{\frac{\sigma_r}{\sigma_r-1}} \qquad \forall t,r, \tag{2.1}$$

where $A_{r,t}$ denotes the productivity scale factor in sector r at time t (referred to as TFP henceforth), $\eta_{r,s,t}$ is a sector-specific variable governing the relative productivity of workers of type s (such that $\eta_{r,h,t} + \eta_{r,l,t} = 1$), and σ_r is the sector-specific elasticity of substitution between the two types of worker. The number of adult workers of type s employed in region r at time t is denoted by $\ell_{r,s,t}$, which differs from the total population, $L_{r,s,t}$ (as explained below)

Wage rates are determined by the marginal productivity of labor and there is no involuntary unemployment. This yields:

$$w_{r,s',t} = A_{r,t}\left(\sum_s \eta_{r,s,t}\ell_{r,s,t}^{\frac{\sigma_r-1}{\sigma_r}}\right)^{\frac{1}{\sigma_r-1}} \eta_{r,s',t}\ell_{r,s',t}^{\frac{-1}{\sigma_r}} \qquad \forall s',t,r. \tag{2.2}$$

It follows that the wage ratio between high-skilled and low-skilled workers in region r is given by:

$$\Gamma^w_{r,t} \equiv \frac{w_{r,h,t}}{w_{r,l,t}} = \Gamma^\eta_{r,t}\left(\Gamma^\ell_{r,t}\right)^{\frac{-1}{\sigma_r}} \qquad \forall t,r, \tag{2.3}$$

where $\Gamma^\ell_{r,t} \equiv \frac{\ell_{r,h,t}}{\ell_{r,l,t}}$ is the skill ratio in the labor force of region r at time t, and $\Gamma^\eta_{r,t} \equiv \frac{\eta_{r,h,t}}{\eta_{r,l,t}}$ measures the skill bias in relative productivity.

Two types of technological externality are factored in. First, we assume that the TFP level in each sector depends on the level of temperature and on the average level of schooling of workers. We have:

$$A_{r,t} = \gamma^t \overline{A}_r G(T_{r,t}) Z(\Gamma^\ell_{r,t}) \qquad \forall t,r, \tag{2.4}$$

where γ^t is a time trend in productivity which is common to all countries ($\gamma > 1$), $\overline{A}_r$ is the exogenous component of TFP in region r (reflecting exogenous factors such as the proportion of arable land, soil fertility, land ruggedness, etc.), $G(T_{r,t})$ is the inverted-U shaped function of temperature described in Section 2.2.2, and $Z(\Gamma^\ell_{r,t})$ a simple Lucas-type aggregate externality (see Lucas 1988) capturing the fact that college-educated workers facilitate innovation and the adoption of advanced technologies. We assume $Z(\Gamma^\ell_{r,t}) =$

[19] Such a model without physical capital features a globalized economy with a common international interest rate. This hypothesis is in line with Kennan (2013) or Klein and Ventura (2009) who assume that capital "chases" labor.

$\left(\Gamma^{\ell}_{r,t}\right)^{\epsilon_r}$ is a concave function of the skill-ratio in the resident labor force, where $\epsilon_r \in (0,1)$ is the sector-specific elasticity of TFP to the skill-ratio in sector r.

Second, we assume a directed, skill-biased technical change. As the technology improves, the relative productivity of college-educated workers increases, and this is particularly the case in the nonagricultural sector (Acemoglu, 2002; Restuccia and Vandenbroucke, 2013). For example, Autor et al. (2003) show that computerization is associated with declining relative industry demand for routine manual and cognitive tasks, and increased relative demand for nonroutine cognitive tasks. The observed relative demand shift favors college versus non-college labor. We write:

$$\Gamma^{\eta}_{r,t} = \overline{\Gamma}^{\eta}_{r} \left(\Gamma^{\ell}_{r,t}\right)^{\kappa_r} \qquad \forall t, r, \tag{2.5}$$

where $\overline{\Gamma}^{\eta}_{r}$ is an exogenous term, and $\kappa_r \in (0,1)$ is the sector-specifc elasticity of the skill-bias to the skill-ratio in sector r.

2.3.2 Preferences

The number of new native adults of type s at time t is denoted by $N_{r,s,t}$. Depending on the elevation structure of the region and on the sea-level rise, part of the region may be flooded at the beginning of the period. If so, a fraction $\Theta_{r,t}$ of the native population is forced to leave. We denote the number of forcibly displaced people by $N^{f}_{r,s,t} = \Theta_{r,t} N_{r,s,t}$, and the rest of the native population as $N^{d}_{r,s,t} = (1-\Theta_{r,t}) N_{r,s,t}$. Only the latter may decide not to move. New adults make consumption, fertility, education and migration decisions in early adult life. As illustrated on Figure 2.4, those who grew up in the unflooded area of the region have the choice between staying in the region (at no cost), emigrating to another region r' within the same country (requiring an effort $x_{rr'}$), or emigrating to an OECD country (requiring an effort x_{rF}). Individuals who grew up in the flooded area have the possibility to relocate in the same region (from the flooded to the unflooded area). They lose their residential capital and incur a monetary cost that corresponds to a fraction B of their lifetime income. They can also emigrate to another region or to another country at the same cost as those who grew up in the unflooded area.

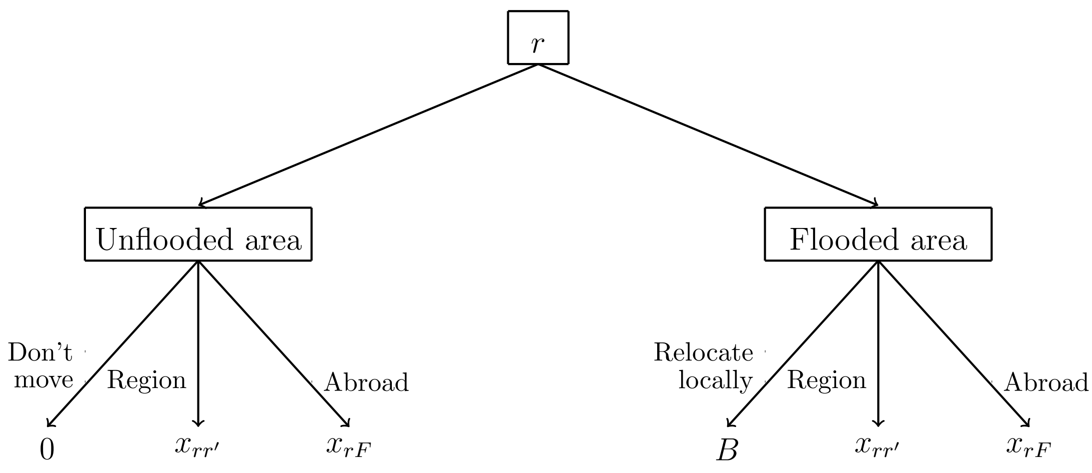


Figure 2.4: Movement decisions

Individuals raised in unflooded areas

We first focus on individuals who grew up in the unflooded area (d) of their region of birth. Individual decisions to emigrate result from the comparison of discrete alternatives, staying in the region of birth, emigrating to the other region, or to a foreign country. To model these decisions, we use a logarithmic *outer utility function* with a deterministic and a random component. The utility of an adult of type s, born in the unflooded area of region r^*, moving to the unflooded area of region/country r is given by:

$$U^d_{r^*r,s,t} = \ln v^d_{r,s,t} + \ln(1 - x_{r^*r,s,t}) + \xi^d_{r^*r,s,t} \qquad \forall s, t, r^*, r \tag{2.6}$$

where $v^d_{r,s,t} \in \mathbb{R}$ is the deterministic level of utility that can be reached in the location r at period t (governed by the inner utility function described below), $x_{r^*r,s,t} \leq 1$ captures the effort required to migrate from region r^* to location r (such that $x_{r^*r^*,s,t} = 0$). Migration costs are exogenous; they vary across location pairs, across education levels, and over time. The individual-specific random taste shock for moving from country r^* to r is denoted by $\xi^d_{r^*r,s,t} \in \mathbb{R}$ and follows an iid Type-I Extreme Value distribution with a common scale parameter $\mu > 0$ (this scale parameter governs the responsiveness of migration decisions to changes in $v^d_{r,s,t}$ and $x_{r^*r,s,t}$). Although $\xi^d_{r^*r,s,t}$ is individual-specific, we omit individual subscripts for notational convenience.

In line with Galor and Weil (2000), Galor (2011), de la Croix and Doepke (2003, 2004), the *inner utility* $\ln v^d_{r,s,t}$ is a function of the climate conditions in region r at time t ($T_{r,t}$),[20] consumption ($c^d_{r,s,t}$), fertility ($n^d_{r,s,t}$) and the probability that each child becomes highly skilled ($p^d_{r,s,t}$):

$$\ln v^d_{r,s,t} = \ln(1 - \tau_{r,t}) + \ln c^d_{r,s,t} + \theta \ln \left(n^d_{r,s,t} p^d_{r,s,t}\right) \quad \forall s, t, r, \tag{2.7}$$

where $\theta \in (0, 1)$ is a preference parameter for the quantity and quality of children, and $\tau_{r,t}$ is a possible utility loss directly caused by CLC (see Section 2.4.2).

The probability that a child becomes high-skilled increases with the share of time that is spent in education ($q^d_{r,s,t}$):

$$p^d_{r,s,t} = \left(\pi_r + q^d_{r,s,t}\right)^\lambda \quad \forall s, t, r, \tag{2.8}$$

where π_r is an exogenous parameter that is region-specific and λ governs the elasticity of knowledge acquisition to education investment.

A type-s adult in region r receives a wage rate $w_{r,s,t}$ per unit of time worked. Raising a child requires a time cost ϕ (thereby reducing the labor market participation rate), and each unit of time spent by a child in education incurs a cost equal to $E_{r,t}$. The budget constraint writes as:

$$c^d_{r,s,t} = w_{r,s,t}(1 - \phi n^d_{r,s,t}) - n^d_{r,s,t} q^d_{r,s,t} E_{r,t}. \tag{2.9}$$

It follows that the labor supply of each type-s adult in region r at time t is given by:

$$\ell^d_{r,s,t} = 1 - \phi n^d_{r,s,t}. \tag{2.10}$$

In the following sub-sections, we solve the optimization problem backward. We first determine the optimal fertility rate and investment in education in a given location r,

[20] E.g., the effect of temperature on health, drudgery of work, etc.

which characterizes the optimal level of utility, $v^d_{r,s,t}$, that can be reached in any location. We then characterize the choice of the optimal location.

Education and fertility. – Each adult in region r maximizes her utility (2.7) subject to the constraints (2.8) and (2.9). Solving the system of first-order conditions for an interior solution gives:

$$\begin{cases} q^d_{r,s,t} = \frac{\lambda\phi w_{r,s,t} - \pi_r E_{r,t}}{(1-\lambda)E_{r,t}} \\ n^d_{r,s,t} = \frac{\theta(1-\lambda)}{1+\theta} \cdot \frac{w_{r,s,t}}{\phi w_{r,s,t} - \pi_r E_{r,t}} \end{cases} \quad \forall s,t,r. \tag{2.11}$$

The cost of education is assumed to be proportional to the wage of high-skilled workers in the region, multiplied by a fixed, region-specific factor $\psi_{r,t}$ (capturing education policy/quality, population density, average distance to schools, etc.):

$$E_{r,t} = \psi_{r,t} w_{r,h,t} \quad \forall r, s. \tag{2.12}$$

The deterministic indirect utility function can be obtained by substituting the first-order conditions into (2.7). This yields:

$$\begin{cases} \ln v^d_{r,h,t} = \chi_{r,t} + \ln(w_{r,h,t}) - \theta\lambda \ln(\psi_{r,t}) - \theta(1-\lambda)\ln(\phi - \pi_r\psi_{r,t}) \\ \ln v_{r,l,t} = \chi_{r,t} + \ln(w_{r,l,t}) - \theta\lambda \ln(\psi_{r,t}) - \theta(1-\lambda)\ln\left(\phi - \pi_r\psi_{r,t}\Gamma^w_{r,t}\right) \\ \qquad + \ln\left(\frac{\phi\left(1+\theta\lambda\left(1-1/\Gamma^w_{r,t}\right)\right) - \pi_r\psi_{r,t}\Gamma^w_{r,t}\left(1+\theta\left(1-1/\Gamma^w_{r,t}\right)\right)}{\phi - \pi_r\psi_{r,t}\Gamma^w_{r,t}}\right) \end{cases} \tag{2.13}$$

where $\chi_{r,t} = \ln(1-\tau_{r,t}) + \theta\ln\left(\frac{\theta}{1+\theta}(1-\lambda)^{1-\lambda}\lambda^\lambda\right) - \ln(1+\theta)$ include the direct effect of CLC on utility ($\tau_{r,t}$).

Migration. – Given their taste characteristics (captured by ξ), each individual chooses the location that maximizes her/his utility, defined in Equation (2.6). Under the Type I Extreme Value distribution with scale μ for ξ, McFadden (1974) shows that the emigration rate from region r^* to a particular destination r is governed by a logit expression. The emigration rate is given by:

$$\frac{M^d_{r^*r,s,t}}{N^d_{r^*,s,t}} = \frac{\exp\left(\frac{\ln v^d_{r,s,t} + \ln(1-x_{r^*r,s,t})}{\mu}\right)}{\sum_k \exp\left(\frac{\ln v^d_{k,s,t} + \ln(1-x_{r^*k,s,t})}{\mu}\right)} = \frac{(v^d_{r,s,t})^{1/\mu}(1-x_{r^*r,s,t})^{1/\mu}}{\sum_k (v^d_{k,s,t})^{1/\mu}(1-x_{r^*k,s,t})^{1/\mu}}.$$

Skill-specific emigration rates are endogenous and comprised between 0 and 1. Individuals that grew up in region n (respectively a) have the choice between staying in their region of origin n (respectively a), moving to the other region a (respectively n), or emigrating to a foreign country F. The emigration rates from r^* to a particular destination r depend on the utiliy levels attainable in all regions k of the world. The choice to emigrate internally or internationally are thus interdependent.

Staying rates ($M^d_{r^*r^*,s,t}/N^d_{r^*,s,t}$) are governed by the same logit model. It follows that the emigrant-to-stayer ratio ($m_{r^*r,s,t}$) is governed by the following expression:

$$m^d_{r^*r,s,t} \equiv \frac{M^d_{r^*r,s,t}}{M^d_{r^*r^*,s,t}} = \left(\frac{v^d_{r,s,t}}{v^d_{r^*,s,t}}\right)^{1/\mu} (1-x_{r^*r,s,t})^{1/\mu}. \tag{2.14}$$

Equation (2.14) is a gravity-like migration equation, which states that the ratio of emigrants from region r^* to location r to stayers in region r^* (i.e., individuals born in r^* who remain in r^*), is an increasing function of the utility achievable in the destination location r and a decreasing function of the utility attainable in r^*. The proportion of migrants from r^* to r also decreases with the bilateral migration cost $x_{r^*r,s,t}$. Labor is not perfectly mobile across sectors/regions; internal migration costs ($x_{an,s,t}$ and $x_{na,s,t}$) capture all private costs that migrants must incur to move between regions. In line with Young (2013), internal mobility is driven by self-selection (i.e., skill-specific disparities in utility across regions as well as heterogeneity in individual unobserved characteristics). Similarly, international migration costs ($x_{aF,s,t}$ and $x_{nF,s,t}$) capture private costs and the legal/visa costs imposed by the destination countries. They are also assumed to be exogenous. Heterogeneity in migration tastes implies that emigrants select all destinations for which $x_{r^*r,s,t} < 1$ (if $x_{r^*r,s,t}$=1, the corridor is empty).

Forcibly displaced people

Individuals raised in the flooded area of region r^* (denoted by the superscript f) are forced to move. If they relocate into the unflooded area of their region of birth r^*, they face a relocation cost equivalent to a fraction B of their lifetime income. Hence, their budget constraints write as:

$$c^f_{r^*,s,t} = (1-B)w_{r^*,s,t}(1-\phi n^f_{r^*,s,t}) - n^f_{r^*,s,t}q^f_{r^*,s,t}E_{r,t}.$$

This relocation cost affects their fertility rate ($n^f_{r^*,s,t}$), investment in education ($q^f_{r^*,s,t}$) and consumption level ($c^f_{r^*,s,t}$). Their labor supply is given by $\ell^f_{r,s,t} = 1-\phi n^f_{r,s,t}$. Hence, the utility of staying in the region becomes:

$$\begin{cases} \ln v^f_{r^*,h,t} = \chi_{r^*,t} + \ln\left(w_{r^*,h,t}\right) + \ln(1-B) - \theta\lambda\ln\left(\psi_{r^*,t}\right) - \theta(1-\lambda)\ln\left(\phi - \pi_{r^*}\psi_{r^*,t}\right) \\ \ln v^f_{r^*,l,t} = \chi_{r^*,t} + \ln\left(w_{r^*,l,t}\right) + \ln(1-B) - \theta\lambda\ln\left(\psi_{r^*,t}\right) - \theta(1-\lambda)\ln\left(\phi - \pi_r\psi_{r,t}\frac{\Gamma^w_{r,t}}{1-B}\right) \\ \qquad + \ln\left(\frac{\phi\left(1+\theta\lambda\left(1-(1-B)/\Gamma^w_{r,t}\right)\right)-\pi_r\psi_{r,t}\left(1+\theta\left(1-(1-B)/\Gamma^w_{r,t}\right)\right)\Gamma^w_{r,t}/(1-B)}{\phi-\pi_r\psi_{r,t}\Gamma^w_{r,t}/(1-B)}\right). \end{cases}$$

It follows that the emigrant-to-stayer ratio ($m^f_{r^*r,s,t}$) for forcibly displaced people is governed by:

$$m^f_{r^*r,s,t} \equiv \frac{M^f_{r^*r,s,t}}{M^f_{r^*r^*,s,t}} = \left(\frac{v^d_{r,s,t}}{v^f_{r^*,s,t}}\right)^{1/\mu}\left(1-x_{r^*r,s,t}\right)^{1/\mu}$$

Since $v^f_{r^*,s,t} < v^d_{r^*,s,t}$, forcibly displaced people tend to migrate more than those who grew up in unflooded regions.

2.3.3 Dynamics and intertemporal equilibrium

We can characterize the equilibrium structure of the resident population in the unflooded area of the region $\forall s,t,r$:[21]

$$\begin{cases} L_{n,s,t} = \frac{N^d_{n,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{N^f_{n,s,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} + \frac{m_{an,s,t}N^d_{a,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{m^f_{an,s,t}N^f_{a,s,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} \\ L_{a,s,t} = \frac{N^d_{a,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{N^f_{a,s,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} + \frac{m_{na,s,t}N^d_{n,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{m^f_{na,s,t}N^f_{n,s,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} \end{cases}. \quad (2.15)$$

[21] In the OECD member states, these variables should be supplemented by the the inflow of immigrants, $I_{r,s,t}$. For simplicity, we assume that the distribution of immigrants by destination is time-invariant, calibrated on the year 2010. Equation (2.14) also determines the outflow of international migrants by education level.

The total labor supply is given by:

$$\begin{cases} \ell_{n,s,t} = \frac{N^d_{n,s,t}\ell^d_{n,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{N^f_{n,s,t}\ell^f_{n,s,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} + \frac{m_{an,s,t}N^d_{a,s,t}\ell^d_{n,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{m^f_{an,s,t}N^f_{a,s,t}\ell^d_{n,s,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} \\ \ell_{a,s,t} = \frac{N^d_{a,s,t}\ell^d_{a,s,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{N^f_{a,s,t}\ell^f_{a,s,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} + \frac{m_{na,s,t}N^d_{n,s,t}\ell^d_{a,s,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{m^f_{na,s,t}N^f_{n,s,t}\ell^d_{a,s,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} \end{cases} . \quad (2.16)$$

Together with the number and structure of the resident population at time t, fertility and education decisions ($n^b_{r,s,t}, q^b_{r,s,t}\ \forall r, b, s$) determine the size and structure of the native population before migration ($N_{r,s,t+1}\ \forall r, s$) at time $t+1$. For all t, r, we have:

$$\begin{cases} N_{n,h,t+1} = \\ \sum_s \left[\frac{N^d_{n,s,t}n^d_{n,s,t}p^d_{n,h,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{N^f_{n,s,t}n^f_{n,s,t}p^f_{n,h,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} + \frac{m_{an,s,t}N^d_{a,s,t}n^d_{n,s,t}p^d_{n,h,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{m^f_{an,s,t}N^f_{a,s,t}n^d_{n,s,t}p^d_{n,h,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} \right] \\ N_{a,h,t+1} = \\ \sum_s \left[\frac{N^d_{a,s,t}n^d_{a,s,t}p^d_{a,h,t}}{1+m_{an,s,t}+m_{af,s,t}} + \frac{N^f_{a,s,t}n^f_{a,s,t}p^f_{a,h,t}}{1+m^f_{an,s,t}+m^f_{af,s,t}} + \frac{m_{na,s,t}N^d_{n,s,t}n^d_{a,s,t}p^d_{a,h,t}}{1+m_{na,s,t}+m_{nf,s,t}} + \frac{m^f_{na,s,t}N^f_{n,s,t}n^d_{a,s,t}p^d_{a,h,t}}{1+m^f_{na,s,t}+m^f_{nf,s,t}} \right] \end{cases} \quad (2.17)$$

Similar expressions characterize the evolution of the low-skilled population, except that $p^b_{r,s,t}$ must be replaced by $(1-p^b_{r,s,t})$ on the numerator of each term.

An intertemporal equilibrium for the world economy can be defined as following:

Definition 2.1 *For a set* $\{\gamma, \theta, \lambda, \phi, \mu, B\}$ *of common parameters, a set* $\{\sigma_r, \epsilon_r, \kappa_r\}$ *of sector-specific elasticities, a set* $\left\{\overline{A}_{r,t}, \overline{\Gamma}^\eta_{r,t}, x_{r^*r,s,t}, \psi_r, \pi_r\right\}$ *of country- and region-specific exogenous characteristics, and a set* $\{N_{r,s,0}\}$ *of predetermined variables, an intertemporal equilibrium is a set* $\{A_{r,t}, \eta_{r,h,t}, w_{r,s,t}, n_{r,s,t}, q_{r,s,t}, v_{r,s,t}, E_{r,t}, m_{r^*r,s,t}, N_{r,s,t+1}, L_{r,s,t}, \ell_{r,s,t}\}$ *of endogenous variables, which simultaneously satisfies technological constraints (2.4), (2.5) and (2.12), profit maximization conditions (2.2), utility maximization conditions (2.11), (2.13) and (2.14) in all countries and regions of the world, and such that the equilibrium structure and dynamics of population satisfy (2.15), (2.16) and (2.17).*

The equilibrium level of the other variables described above (in particular, $\Gamma^\ell_{r,t}$, $\Gamma^\eta_{r,t}$, $\Gamma^w_{r,t}$ as well as urbanization rates and international migration outflows and inflows) can be computed as a by-product of the reduced set of endogenous variables. Note that equilibrium wage rates are obtained by substituting the labor force variables into the wage equation (2.2), thereby assuming full employment. By the Walras law, the market for goods is automatically balanced.

2.3.4 Parameterization

In this section, we describe our parameterization strategy for 145 developing countries and for the entire set of 34 OECD countries modeled as a single entity.[22] We use socio-demographic and economic data for 1980 and 2010, as well as socio-demographic prospects for the year 2040. For each country, our baseline trajectory matches the recent trends in human capital accumulation, income disparities, and population movements (including internal and international migrations). Table 2.1 summarizes the calibration outcomes.

[22]With the exceptions of Macao, North-Korea, Somalia and Taiwan, all countries that are not covered by our sample have less than 100,000 inhabitants.

Data. – We collect data on the socio-demographic and economic characteristics of 179 countries in the years 1980 and 2010. We use data on national Gross Domestic Product (GDP) for all countries from the Economic Research Service of the United States Department of Agriculture (USDA).[23] Data on the agriculture share in the value added are taken from the Food and Agriculture Organization of the UN (FAOSTAT). As for the structure of the resident labor force by education level and by sector, we use the estimates described in detail in the previous chapter. Data on wages by education level are obtained from Biavaschi et al. (2016) for the nonagricultural sector, and from the Gallup World Polls for the agricultural sector.

We model international migration to OECD countries only. From the Database on Immigrants in OECD and non-OECD countries (DIOC), we extract the number of emigrants by education level to OECD countries for all countries in our sample and for the year 2010. The DIOC does not identify the region of origin of migrants (urban versus rural). However, for the majority of countries in our sample, skill- and region-specific information on the desire to emigrate can be extracted from the Gallup World Polls. Assuming the structure of migration aspirations is identical to the structure of actual emigration stocks, we split the number of emigrants to OECD countries by region of origin and by education level. As for urbanization, net internal migration is then the difference between the "before-migration" population ($N_{r,s,2010}$) in 2010 and the sum of the resident population and the international migrants ($\sum_{r,s}(L_{r,s,2010} + M_{rf,s,2010})$) in 2010.

To proxy the average fertility rate ($\overline{n}_{1980}$), we divide the total native population of adults in 2010 ($\sum_{r,s} N_{r,s,2010}$) by the resident population of adults in 1980 ($\sum_{r,s} L_{r,s,1980}$).[24] Moreover, our calibration requires data on the skill- and region-specific fertility for each country. By construction, we have $\overline{n}_t \equiv \sum_{r,s} L_{r,s,t} n_{r,s,t} / \sum_{r,s} L_{r,s,t}$. We use the Gallup World Polls and extract the Gallup-based average number of children per household in urban and rural regions by skill level for 2010. We compute the fertility of the college educated workers by fitting the sector-specific, low/high-skilled fertility differentials from the Gallup database. In this way, we obtain the fertility rates for each country for the year 1980. From 2010 onwards, the number of children is endogenous.

Technological parameters. – Output in each sector depends on the size and skill structure of employment. To calibrate the set of technological parameters, we proceed in two steps.

First, we calibrate the parameters affecting the private returns to higher education. For each sector, we combine our estimates for $\ell_{r,s,t}$ with cross-country data on the income gap between college graduates and the less educated. We calibrate the elasticity of substitution between college graduates and less educated workers relying on existing studies. As for the nonagricultural sector, there is a large number of influential papers that propose specific estimates for industrialized countries (i.e., countries where the employment share of agriculture is small). Ottaviano and Peri (2012) suggest setting σ_n close to 2.0. As for the agricultural sector, it is usually assumed that the elasticity of substitution is much larger. For example, Vollrath (2009) or Lucas (2009) assume perfect substitution between skill groups. In line with the existing literature, we assume $\sigma_n = 2$ and $\sigma_a = \infty$. Once the elasticities are chosen, we use our proxies for $\Gamma^w_{r,t}$ and $\Gamma^\eta_{r,t}$ using (2.3). Regressing the log of $\Gamma^\eta_{r,t}$ on the log of $\Gamma^\ell_{r,t}$ yields an insignificant effect in agri-

[23]For a few missing observations we impute values by making use of the Maddison database and data from the World Bank.

[24]There is no mortality in the model. The average fertility rate at time t, $\overline{n}_t$, should be seen as a net population growth rate.

culture, and a correlation of 0.38 in nonagriculture. We thus rule out the possibility of skill-biased technical change in agriculture ($\kappa_a = 0$), and assume a linear technology with a constant $\Gamma^{\eta}_{a,t} = \overline{\Gamma}^{\eta}_{a,t} = 1.3$ for all countries and all periods. The value of Γ^{ϖ}_{a} is given by the population-weighted average of Γ^{w}_{a}, leading to $\varpi_a = 0.57$. In nonagriculture, we assume that half the correlation is due to the skill-bias externality (i.e., $\kappa_n = 0.19$), and we calibrate $\overline{\Gamma}^{\varpi}_{n}$ as a residual from (2.5).

In the second step, we use data on income by sector in the year 2010 and identify the TFP levels ($A_{r,t}$) as a residual from Equation (2.1). There is a clear positive relationship between TFP and the skill ratio in both sectors. Indeed, regressing the log of $A_{r,t}$ on the log of $\Gamma^{\ell}_{r,t}$ gives a coefficient of 0.57 in the nonagricultural sector, and 0.66 in agriculture. We assume that half the correlation between TFP and the share of college-educated workers is due to the schooling externality (i.e., $\epsilon_n = 0.28$ and $\epsilon_a = 0.33$). We calibrate $\overline{A}_n$ as a residual from (2.4).

Preference parameters. – The literature indicates some common values of several preference parameters. We assign the following values to the parameters that are time-invariant and equal for all countries: $\theta = 0.25$, $\lambda = 0.5$ and $\phi = 0.14$.[25] From (2.13) and (2.14), the scale parameter of the distribution of migration tastes (μ) is the inverse of the elasticity of bilateral migration to the wage rate. Bertoli and Fernández-Huertas Moraga (2013) find a value between 0.6 and 0.7 for this elasticity. Hence, we use $\mu = 1.4$.

The parameters π_r and $\psi_{r,t}$ affect the fertility and education decisions. We calibrate them to match the population dynamics between the years 1980 and 2010, i.e., the transition from the resident population in 1980 and the native population in 2010. From Equations (2.11) and (2.12), the fertility rate in the model depends on the product of $\pi_r\psi_{r,t}$. Once fertility rates are matched we are able to identify the product $\pi_r\psi_{r,t}$. We then calibrate π_r and $\psi_{r,t}$ in order to match the educational structure of the native population in 2010, imposing the given value to the ratio of probabilities of becoming high-skilled across regions.

As for internal migration costs, we assume there is only migration from rural to urban regions (i.e., $x_{an,s,t} < 1$ and $x_{na,s,t} = 1$). We obtain internal migration costs for rural-urban migration from Equation (2.14). In order to determine the international migration costs ($x_{af,s,t}$ and $x_{nf,s,t}$), we begin by retrieving the utilities achievable abroad. We set these utilities equal to the skill-specific weighted average utilities of the OECD countries. The weights consist in the respective population sizes of the OECD countries. We then obtain the international migration costs from Equation (2.14).

To the best of our knowledge, there is no information on the relative income loss experienced by individuals which are displaced by floods. However, in cases of armed conflicts, Fiala (2015) finds that displaced households incur a loss of consumption ranging between 28% and 35%. For Columbia, Ibanez and Moya (2006) find that a displacement is associated with a loss of 50% of income. Kellenberg and Mobarak (2011) characterize the willingness to pay for investments in disaster prevention to around 24% of income. We use these studies to proxy the expected income loss due to a climate-driven froced displacement. Given this micro evidence, we pessimistically assume $B = 0.5$ (i.e., relocating within the region of birth induces an income loss equal to 50% of the lifetime income).

[25] Given the expression in (2.9), this assumption reflects setting the bound of the maximal number of children equal to 7 (i.e., 14 children per couple). See Docquier et al. (2016) for a brief review of studies using similar parameter values.

Table 2.1: Common and country-specific parameters

	Description	Mean	s.d.	Source/Moment matches
Parameters without country variations				
σ_n	Elast. subst. in nonagr.	2.00	-	Ottaviano & Peri (2012)
σ_a	Elast. subst. in agr.	∞	-	Vollrath (2009) or Lucas (2009)
ϵ_n	Aggregate externality in nonagr.	0.28	-	Half correl. betw. $\ln A_{n,t}$ & $\ln\Gamma^{\ell}_{n,t}$
ϵ_n	Aggregate externality in agr.	0.33	-	Half correl. betw. $\ln A_{a,t}$ & $\ln\Gamma^{\ell}_{a,t}$
κ_n	Skill-biased externality in nonagr.	0.19	-	Half correl. betw. $\ln\Gamma^{\eta}_{n,t}$ & $\ln\Gamma^{\ell}_{n,t}$
κ_a	Skill-biased externality in agr.	0.00	-	Half correl. betw. $\ln\Gamma^{\eta}_{a,t}$ & $\ln\Gamma^{\ell}_{a,t}$
θ	Preference for children	0.25	-	Docquier et al. (2016)
λ	Elast. training technology	0.50	-	Docquier et al. (2016)
ϕ	Time to raise a child	0.14	-	Docquier et al. (2016)
μ	1/Elast. mig. to wages	1.40	-	Bertoli & Fernández-Huertas Moraga (2013)
B	Income loss due to forced displ.	0.50	-	Fiala (2015) or Ibanez & Moya (2006)
Parameters with some country variations				
$\overline{A}_n$	Scale factor in TFP	216,969	267,723	Residual from (2.4)
$\overline{A}_a$	Scale factor in TFP	89,025	320,698	Residual from (2.4)
$\overline{\Gamma}^{\eta}_n$	Scale factor in skill bias	1.878	-	Residual from (2.3)
$\overline{\Gamma}^{\eta}_a$	Scale factor in skill bias	1.326	-	Residual from (2.3)
π_n	Scale factor training technology	0.025	0.041	Match fertility/educ. in (2.11)
π_a	Scale factor training technology	0.043	0.142	Match fertility/educ. in (2.11)
ψ_n	Education cost	13.74	67.27	Match fertility/educ. in (2.11)
ψ_a	Education cost	46.22	148.98	Match fertility/educ. in (2.11)
$x_{an,h}$	Internal mig. cost, high-skilled	0.712	1.989	Match urbanization (WDI)
$x_{an,l}$	Internal mig. cost, low-skilled	0.928	0.163	Match urbanization (WDI)
$x_{nf,h}$	International mig. cost, high-skilled	0.416	4.422	Match migration data (DIOC)
$x_{af,h}$	International mig. cost, high-skilled	0.829	1.065	Match migration data (DIOC)
$x_{nf,l}$	International mig. cost, low-skilled	0.947	0.281	Match migration data (DIOC)
$x_{af,l}$	International mig. cost, low-skilled	0.985	0.066	Match migration data (DIOC)

Projections. – The philosophy of our baseline projection exercise is to predict the future trends in income, population and human capital if all parameters remain constant, with the exception of the parameters governing access to education. More precisely, we constrain our baseline trajectory to be compatible with medium-term official demographic projections, as reflected by the UN projections of the national adult population and proportion of college graduates for the year 2040. Hence, we allow for country-specific proportional adjustments in $\psi_{r,t}$ $(r = a, n)$ (i.e., the same relative change in both sectors) that minimizes the sum of squared differences in population and human capital between the baseline simulations and the UN projections for the year 2040. Remember $\psi_{r,t}$ determines the cost of education in the region. Comparing the new levels of $\psi_{r,2010}$ with those obtained in 1980 (i.e., $\psi_{r,1980}$), we identify a conditional convergence process in the access to education. We see it as a likely consequence of the *Millennium Development* policy. We estimate two quadratic, region-specific convergence equations considering the US as the benchmark frontier: $\ln\left(\psi_{r,t+1}/\psi_{r,t}\right) = \alpha_r + \beta_r \ln\left(\psi^{USA}_{r,t}/\psi_{r,t}\right) + \gamma_r \left(\ln\left(\psi^{USA}_{r,t}/\psi_{r,t}\right)\right)^2$.

We obtain $\gamma_a = 0.032$, $\gamma_n = 0.046$, $\beta_a = -0.195$ and $\beta_n = -0.223$, where all parameters are highly significant.

For subsequent years, our baseline scenario assumes a continuation of this quadratic convergence process, in line with the new *Sustainable Development Agenda*. Under this assumption, the previous chapter shows that the model simulations fit the official socio-demographic projections very well. This is a proof of concept that such a stylized model does a good job in generating realistic projections of population, human capital, and urbanization.

2.4 Results

In Section 2.4.1, we focuses on the three moderate CLC scenarios and study their economic and demographic impacts. Then, Section 2.4.2 discusses the results obtained under more extreme CLC scenarios. Finally, Section 2.4.3 discusses the role of international migration policies in limiting the inequality and poverty implications of CLC.

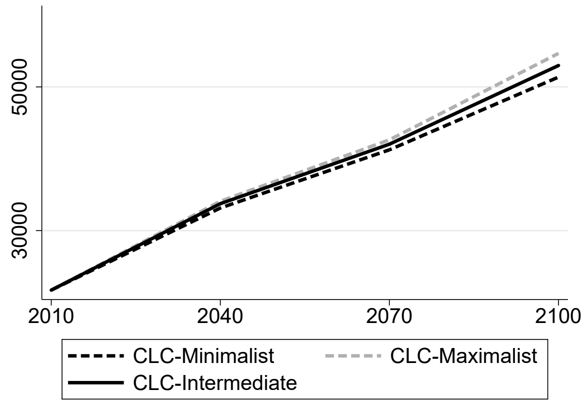
2.4.1 Impact under moderate scenarios

We first consider the three moderate scenarios (*Intermediate*, *Minimalist* and *Maximalist*) defined in Section 2.2.1, and discuss the worldwide effects of CLC on income per capita, income inequality, population, human capital, urbanization and international migration. Then, we highlight the cross-country heterogeneity in the effect of CLC before quantifying internal and international migration responses.

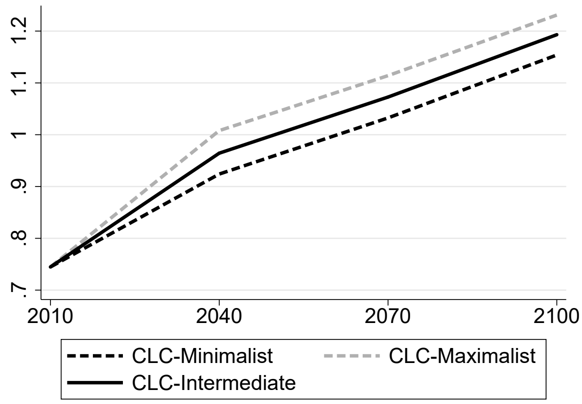
Aggregate effects on the world economy. – The effects on the world economy are depicted in Figure 2.5. The worldwide responses are the weighted averages of the positive and negative effects observed in high-income and developing countries.

We first compare our *Intermediate* scenario (continuous black curve) to the *Minimalist* (dotted black curve) and to the *Maximalist* (dotted grey curve). CLC slightly increases the worldwide level of income per worker (Figure 2.5a), but makes the world distribution of income more unequal (Figure 2.5b). The former result is due to multiple factors. First, higher temperature levels induce positive changes in TFP at high levels of latitude (where income per worker is initially higher) and negative changes in TFP close to the equator (where income per worker initially is lower). Second, in developing countries, CLC reallocates people from lower-productivity rural regions to higher-productivity urban regions, as illustrated in Figure 2.5e. Third, CLC reallocates people from poorer countries to richer countries, as illustrated in Figure 2.5f. The effects on the world population size and on the share of college graduates are small, as illustrated in Figure 2.5c and 2.5d. The mobility responses to CLC are slightly non linear: the difference between the *Maximalist* and *Intermediate* scenarios slightly exceeds the difference between the *Intermediate* and the *Minimalist* ones. On the contrary, the effects on income per worker and inequality are almost identical.

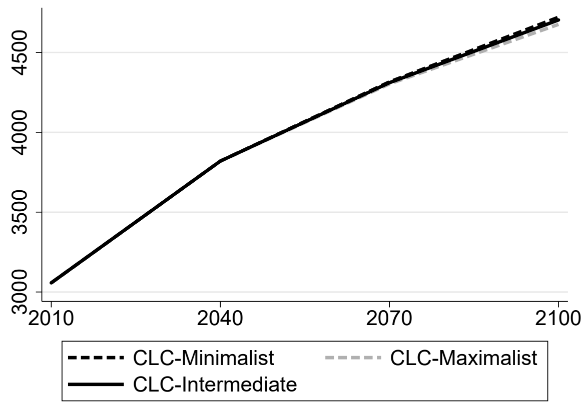
Country-specific effects. – The country-specific effects of CLC are depicted in Figure 2.6. For the projected numbers in the year 2100 we report the relative differences between the *Intermediate* and the *Minimalist* scenarios (black bubbles), as well as the relative differences between the *Maximalist* and the *Intermediate* scenarios (grey bubbles). Third-degree polynomial trends are represented in black and grey, respectively. Bubble sizes are proportional to the adult population size of each country in 2010. Figure 2.6a shows that



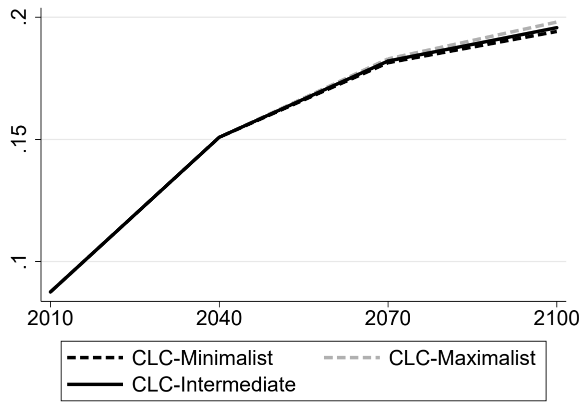
(a) Income per worker



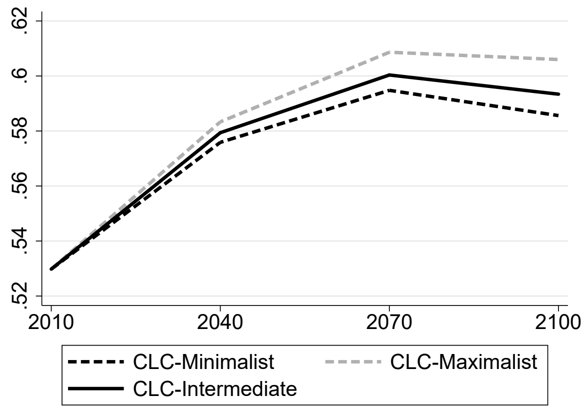
(b) Theil index of income inequality



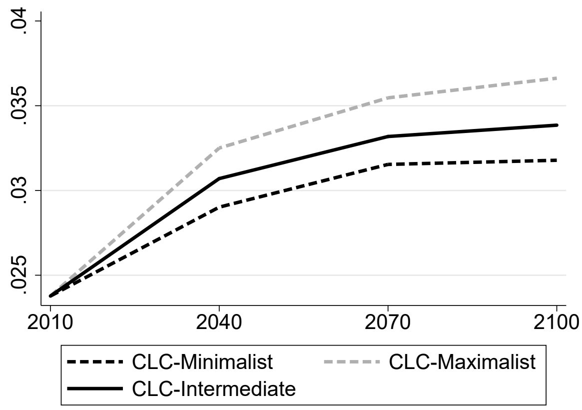
(c) Population (in million of people)



(d) Share of college educated workers



(e) Urbanization



(f) Share of international migrants to OECD

Figure 2.5: Aggregate effects of CLC on the world economy

Notes: Simulation results based on the moderate CLC scenarios defined in Section 2.2.1.

CLC decreases income per worker by 15% in countries close to the equator, and increases it by 10% at high levels of latitude. Hence, the income gap between the richest and poorest countries increases by 25% in the course of the 21st century. Given the assumed timing of CLC, unreported results reveal that most of the effect occurs in the first half of the century. Assuming more gradual CLC, results would be different.

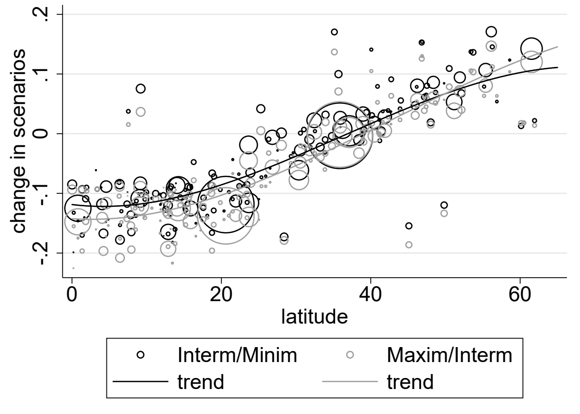
In developing countries, the negative effect on income is resulting from three mechanisms (in line with worldwide aggregate effects). The first one is the fall in TFP in both sectors, documented in Figure 2.2. The second effect is the rise in urbanization in Figure 2.6c, which attenuates the TFP shocks since the average level of labor productivity is greater in manufacturing than in agriculture. The third effect is the slight decrease in human capital illustrated on Figure 2.6b. Although urbanization increases the access to education in poor countries, rising international emigration (see Figure 2.6d) reduces human capital accumulation. The reason is that high-skilled people face smaller migration cost, which implies that migration is skill biased. In poor countries, college graduates migrate 20 times more than the less educated. CLC reduces the intensity of positive selection by 10% only, as shown on Figure 2.6f. Hence, the positive effect of CLC on emigration rates tends to reduce the share of college graduates in the origin country. For the sake of comparability, the effect of CLC on the skill bias in internal migration is similar to that of long-haul migration, as illustrated in Figure 2.6e. Overall, CLC has a greater impact on low-skilled mobility than on high-skilled mobility.

Comparing the *Maximalist* to the *Intermediate* scenario, and comparing the *Intermediate* to the *Minimalist* give very similar results. The negative effect on income is slightly more pronounced in countries close to the equator when considering the *Maximalist* scenario. In addition, Figure 2.6c and 2.6d demonstrate that under the *Maximalist* scenario, urbanization and emigration responses are slightly greater. The human capital responses are on average almost identical. Table 2.A1 in Appendix 2.A.1 reports the effect of CLC on the country-wide level of income per worker for the 20 most adversely affected countries in the year 2100. Countries close to the equator experience a long-run decrease in income per worker which varies between 14% and 22% when the temperature increases by $2°C$. The most affected countries include Sao Tome and Principe, The Gambia, Venezuela, Nepal, Grenada, Nicaragua, Malaysia, the Dominican Republic, Ghana, the Philippines, and several African countries and Pacific islands.

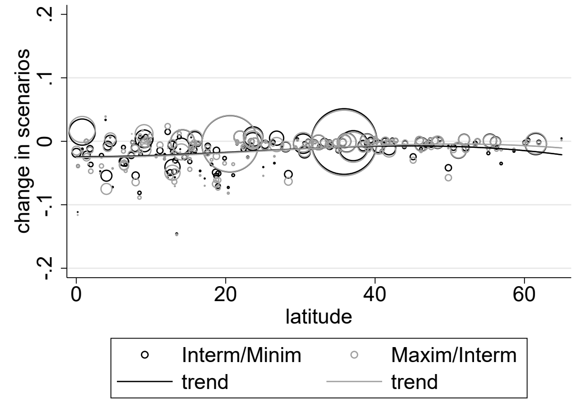
The income loss is even greater for the poorest workers trapped in the poorest or falling regions (i.e., rural regions). Extreme poverty is usually measured as the percentage of population living with less than $1.90 per day in PPP value. Nevertheless, in our secular context with a constant rate of productivity growth and two skill groups only, we need to use a relative poverty line. We measure extreme poverty as the world percentage of adults below a relative poverty line that corresponds to 2% of the worldwide average level of income per worker.

Comparing the CLC scenarios, Figure 2.7a shows that CLC adversely impacts extreme poverty. In the *Intermediate* scenario, poverty headcounts mechanically increase over time. This is essentially due to the differential in population growth between poor and rich countries/regions. By the year 2100, we identify 621 million individuals in extreme poverty in the *Intermediate* scenario (about 13.2% of the world population). Under the *Minimalist* and *Maximalist* scenarios, the numbers amount to 517 and 835 million (i.e., 11.0% and 17.9% of the world population), respectively.[26] In addition, Figure 2.7b shows

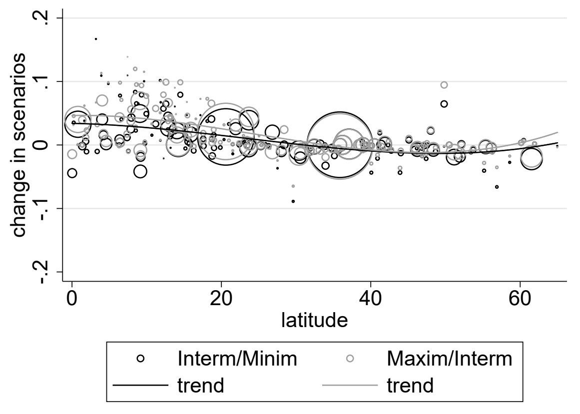
[26]If the poverty line equals 1% of the worldwide average income level, 202 million workers will live in extreme poverty in 2100 under the *Intermediate* scenario (4.2% of the world population). This compares



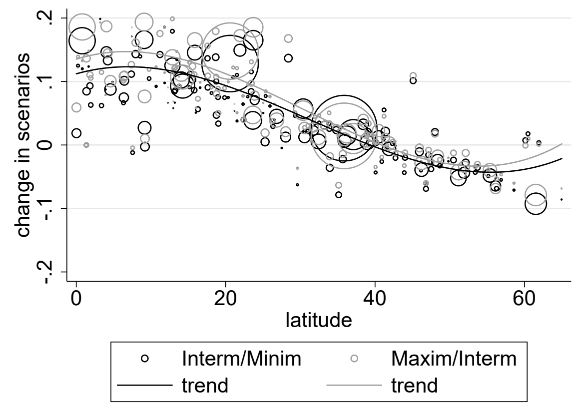
(a) Income per worker



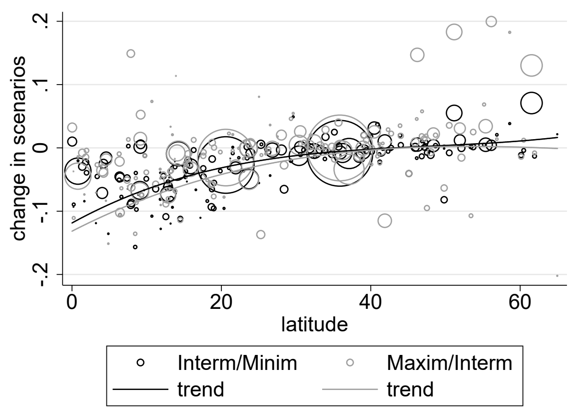
(b) Share of college graduates



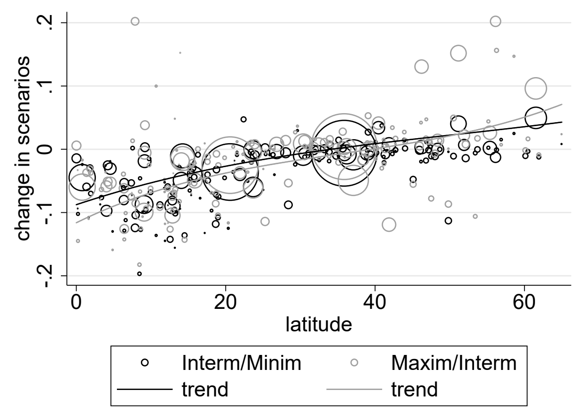
(c) Urbanization



(d) Emigration rate



(e) Skill bias in internal migration



(f) Skill bias in international migration

Figure 2.6: Country-specific effects by level of latitude

Notes: Simulation results based on the moderate CLC scenarios defined in Section 2.2.1. Latitude (geographic coordinate) is measured on the X-axis, percentage deviations are measures on the Y-axis, and bubble sizes are proportional to the population aged 25-64 in the year 2010. A few outliers are not depicted on Figures 2.6a, 2.6d and 2.6e.

that the intensity/depth of extreme poverty increases. The ratio of average income of the extreme poor to the worldwide average income decreases with CLC in all years. Hence, CLC influences extreme poverty at both extensive and intensive margins.

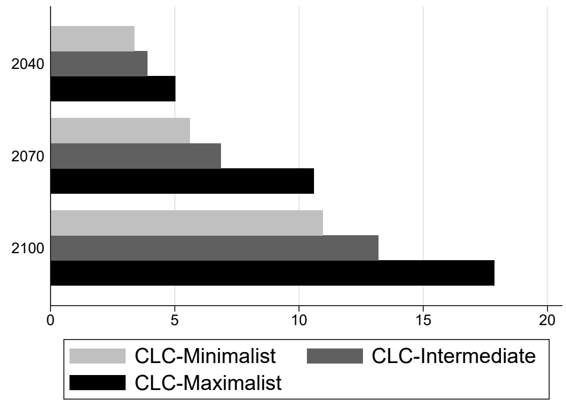
Figure 2.7c shows the effect of CLC on the relative income of the ten poorest groups on earth. We rank all classes of worker with respect to the ratio between their income level and the worldwide average level. The poorest people are low-skilled workers living in the rural region of the poorest countries. For instance, low-skilled workers in rural regions of Burundi earned around 0.54% of the global average income in the *Intermediate* scenario. This ratio reaches 0.65 in the *Minimalist* scenario and 0.42 in the *Maximalist* one. On average, the index of relative income of the poorest workers is divided by 1.5 when the temperature increases by $2°C$.

Migration responses. – It is frequently claimed that CLC will create the world's biggest international refugee crisis of all ages. In line with Figure 2.5f, our results in Table 2.2 suggest that this is unlikely to be the case. We predict that CLC will induce large displacements of people from vulnerable to more viable areas on Earth. However, most of them will move within their country. Compared to the *Minimalist* (no-CLC) scenario, rising temperature and sea level increases the number of adult movers by 78.4, 24.6 and 16.9 million people in 2040, 2170 and 2100 (i.e., by 2.1%, 0.6% and 0.4% of the world adult population, respectively). In the course of the 21st century, this amounts to a total of 120 million adults in the *Intermediate* scenario (we obtain 185 millions in the *Maximalist* scenario). Far more people are migrating within their own countries than across borders. In the *Intermediate* scenario, 66% of these movements are local displacements within the region of birth, 15% are movements between regions (from agriculture to nonagriculture), and only 19% are long-haul international movements from developing to OECD countries.

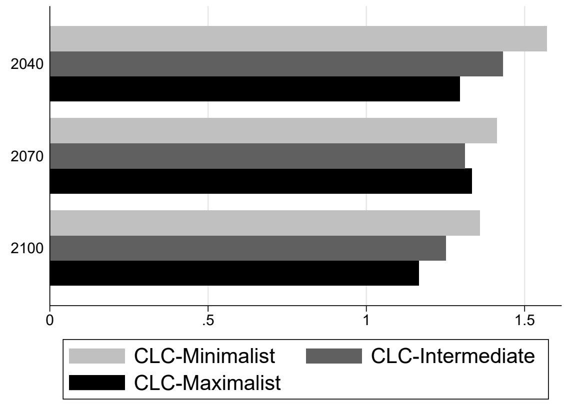
Hence, CLC increases the number of internal adult migrants by 97 millions (with 81% of internal displacements). In the *Maximalist* scenario, we obtain 135 millions (with 67% of local displacements). The numbers are very much in line with those reported in Rigaud et al. (2018), who predict that 65 to 145 million people of all ages could migrate within their own countries to escape slow-onset impacts of climate change by the year 2050. Compared to this study, we offer additional insight on the international migration responses to CLC. We show that CLC increases the number of international adult migrants by 22.5 millions in the *Intermediate* scenario and by 51.3 millions in the *Maximalist* scenario. Although these numbers are non-negligible, they are small compared to the global changes in migration stocks.

Table 2.A2 in Appendix 2.A.2 reports emigration and immigration rates by region. As far as emigration is concerned, we show that CLC multiplies emigration rates by a factor of 1.05, which is a small fraction (between 1/10 and 1/20) of the total rise in emigration rates. Total changes in emigration rates are mostly explained by the changing educational attainment in the developing world: education makes people more migratory. As for immigration, the average share of immigrants should be multiplied by a factor of 1.5 in settlement countries (the US, Canada and Australia), and should increase twofold in Europe over the 21st century. However, the contribution of CLC to increasing immigration is small. CLC explains about 1/20 of the total change in the worldwide share of immigrants in the population. Total changes are mostly explained by demographic imbalances between rich and poor countries, and by education trends.

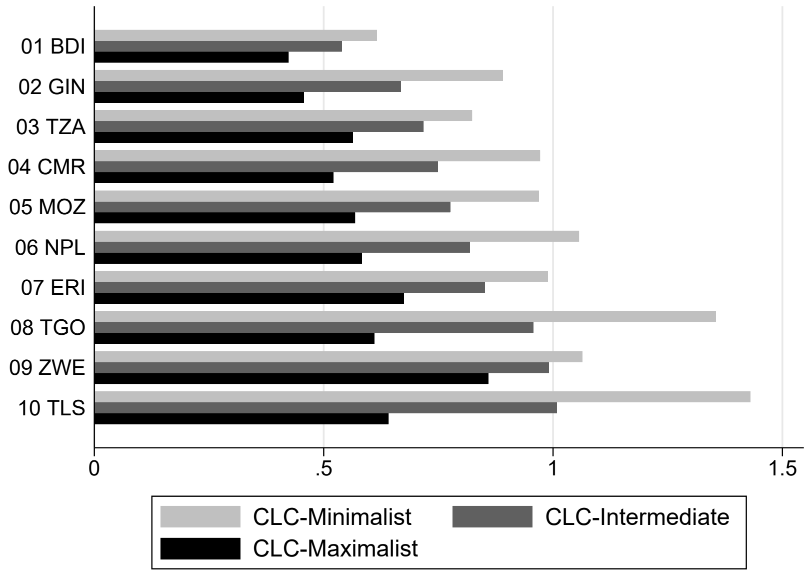
to 181 and 272 million workers (3.9% and 6.0%) under the more optimistic and pessimistic scenarios, respectively.



(a) Effect on poverty headcounts



(b) Effect on poverty depth



(c) Effect on the ten poorest groups

Figure 2.7: Effect of CLC on extreme poverty in 2100

Notes: Simulation results based on the moderate scenarios defined in Section 2.2.1. The reported countries in Figure 2.7c include Burundi (BDI), Cameroon (CMR), Eritrea (ERI), Guinea (GIN), Mozambique (MOZ), Nepal (NPL), Tanzania (TZA), Timor-Leste (TLS), Togo (TGO), and Zimbabwe (ZWE).

2.4.2 Robustness to extreme CLC scenarios

It has been argued that we are in uncharted territory when predicting CLC as the effects of CO2 emissions on temperature and sea level are highly uncertain (Stern, 2003; Schelling, 2007). It is thus important to consider more extreme scenarios. This section defines four alternative scenarios and analyzes the sensitivity of our results to more extreme changes.

Definition of extreme scenarios. – Uncertainty about SLR is large as climate models have been unable until recently to replicate the estimated sea level swings reconstructed from geological data during the Pliocene (about 100,000 years ago) when concentrations were about the same as now, temperatures were 0-2°C higher and the sea level was 6-9m

Table 2.2: Global numbers and shares of movers in 2040, 2070 and 2100
(Numbers in million of people and shares as % of world adult population)

	Number (in million)			As % world pop.		
	2040	2070	2100	2040	2070	2100
	Intermediate minus Minimalist					
Total	78.4	24.6	16.9	2.05	0.57	0.36
Rural-Urban	13.1	4.1	1.1	0.34	0.10	0.02
International	6.4	6.9	9.2	0.17	0.16	0.20
Local	58.8	13.6	6.6	1.54	0.31	0.14
Flooded	69.4	15.5	7.5	1.82	0.36	0.16
	Maximalist minus Minimalist					
Total	109.7	42.6	33.2	2.58	1.01	0.69
Rural-Urban	26.5	13.5	4.5	0.69	0.32	0.09
International	13.6	16.5	21.2	0.35	0.38	0.46
Local	69.8	12.7	7.5	1.83	0.29	0.16
Flooded	82.5	14.5	8.5	2.16	0.34	0.18

Notes: Simulation results based on the moderate CLC scenarios defined in Section 2.2.1.

higher.[27] The World Bank predicts a sea-level rise of $2m$ for the year 2050. For the purpose of comparison, we also consider an extreme SLR variant with a $2.7m$ rise by the end of the century, and a no-SLR scenario as a point of comparison.

Furthermore, two additional channels of transmission are frequently accounted for in the literature. Firstly, temperature variations may also cause direct utility effects through their impact on health or on the drudgery of work. Secondly, CLC can affect economic performance and migration decisions through conflicts over resources. We model these two additional channels as following:

- To account for potential direct utility losses (due to the effect of temperature on health or on the drudgery of work), we follow Dell et al. (2014) who report estimates that output per worker decreases by 2% per $1°C$ increase when temperature exceeds $20°C$. We assume that this effect is due to a decrease in effective labor supply driven by a greater disutility of labor. In a simple model with quasi-linear utility function and a constant elasticity of labor supply to the disutility of labor, relative variations in utility are proportional to relative variations in labor supply. As shown in Appendix 2.A.3, assuming an elasticity of labor supply to income of 1/3, the optimal utility level decreases by 8% per $1°C$ increase in all regions where temperature exceeds $20°C$. Although our model disregards the disutility of labor, we model utility losses similarly and assume $\tau_{r,t} = 0.08(T_{r,t} - T_{r,2010})$ if $T_{r,t} > 20$ and zero otherwise.

- In contexts of high political and social instability, CLC can contribute to the onset and propagation of (violent) conflicts driven by the deterioration of governance capacities and by the increase in inequality among groups (Miguel et al., 2004; Gleditsch, 2012). The relationship between CLC and conflict has been investigated in a number of studies, which have produced mixed results (Cattaneo et al.,

[27] De Conto and Pollard (2016) have calibrated the sea level swings of the Pliocene, projecting an increase in the sea level above $1m$ in 2100. They estimate that the Antarctica ice sheet cannot be saved even with extraordinary success at cutting emissions. This would lead to a locking of the sea level rise of more than $5m$.

2018). Using a hierarchical meta-analysis of 55 studies, Burke et al. (2015) find that deviations from moderate temperatures and precipitation patterns systematically increase conflict risk (including interpersonal conflict, such as assault and murder, and intergroup conflict, including riots and civil war). On average, one standard-deviation increase in temperature increases interpersonal conflict by 2.4% and intergroup conflict by 11.3%. In turn, conflicts lead to forced displacements. Dao et al. (2017) find that severe armed conflicts increase the dyadic stock of migrants twofold in the long-term.[28] In our simulations, we assume that conflicts decrease net international migration costs in the poorest countries in such a way that their emigration stocks increase by a factor of 2, as explained in Appendix 2.A.3.

In sum, to investigate the sensitivity of our results to extreme scenarios and additional channels of transmission, we consider four alternative scenarios:

- *Extreme-No SLR.* – Assuming constant seal level and a global increase in temperature of $2.09°C$, this scenario neutralizes forced displacements. It can be considered as unrealistic and extreme, but we use it as a no-SLR point of reference.
- *Extreme-Greater SLR.* – While keeping a global increase in temperature of $2.09°C$, we now assume a sharper sea-level rise over the 21st century. In line with Rigaud et al. (2018), our Greater SLR variant assumes that the sea level reaches $2m$ in 2040. For subsequent periods, we assume the same relative changes as in the Intermediate scenario; this gives $2.4m$ in 2070 and $2.7m$ in 2100. This scenario induces a larger number of forcibly displaced people.
- *Extreme-Utility.* – In this scenario, we start from the *Maximalist* scenario and supplement it with direct utility losses. As stated above, we assume a direct utility loss of 8% per $1°C$ increase in all regions where temperature exceeds $20°C$.
- *Extreme-Conflict.* – Here, we start from the *Extreme-Utility* scenario and assume that a long-term conflict arises in the ten countries with the highest povery headcounts (i.e., Burundi, Cameroon, Eritrea, Guinea, Mozambique, Nepal, Tanzania, Timor-Leste, Togo, and Zimbabwe).

Results. – Aggregate implications for the world economy are depicted in Figure 2.A2 in Appendix 2.A.4. We focus here on the mobility responses to more extreme scenarios. Compared to the *Intermediate* scenario, considering extreme SLR (i.e., no SLR or a $2.7m$ SLR by the end of the century) has a limited impact on worldwide migration responses, both at the internal and international level. This means that variations in SLR mostly induce local displacements. In other words, the variations between the moderate scenarios reported in Table 2.2 are overwhelmingly explained by the effect of temperature on productivity. On the contrary, compared to the *Maximalist* scenario, accounting for direct utility losses (8% per $1°C$ increase above $20°C$) or conflicts over resources (in ten countries with the greatest poverty headcounts) has a drastic impact on internal and international migration.

Table 2.3 characterizes the effect of direct utility losses and conflict on mobility patterns. The numbers can easily be compared with those of the *Maximalist* scenario in

[28]It increases the dyadic stock of migrants by a factor of 4 in the medium-term.

Table 2.2. Remember the *Maximalist* scenario predicts a total number of movers of 185 millions, including 51 million international migrants to the OECD member states. When adding the direct utility losses, we obtain 305 million movers (i.e., an increment of 120 millions) and 74 million international migrants (i.e., an increment of 23 millions). Table 2.A4 in Appendix 2.A.4 shows that, by the year 2100, the proportion of emigrants increases by 0.9 percentage point in Latin America, and by 0.6 percentage point in sub-Saharan Africa. As far as OECD destinations are concerned, the proportion of immigrants increases by 0.9 percentage point in the US and in the European Union.

When adding the conflict effect, we obtain 320 million movers (i.e., a new increment of 15 millions) and 89 million international migrants (i.e., a new increment of 15 millions). Severe conflicts impact international migration flows. By the year 2100, the proportion of emigrants increases by additional 0.4 percentage point in sub-Saharan Africa, where most conflict-affected countries are located. The resulting shares of immigration increase by 0.4 percentage point in the US and in the European Union. These numerical experiments reveal that conflicts over resources are likely to become a key determinant of climatic migration pressures, and that direct utility effects of CLC imply rather high uncertainty about their scale and their type.

Table 2.3: Global numbers and shares of movers under extreme scenarios
(Numbers in million of people and shares as % of world adult population)

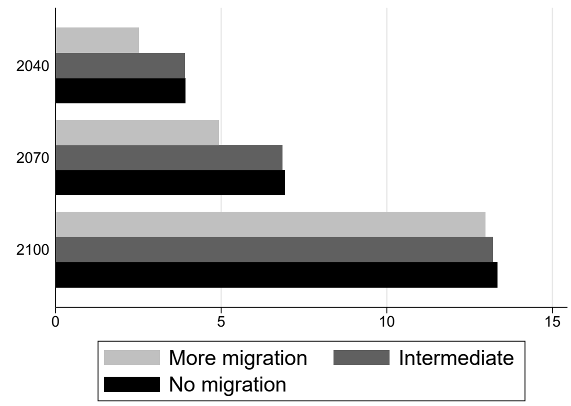
	Number (in million)			As % world pop.		
	2040	2070	2100	2040	2070	2100
	Extreme-Utility minus Minimalist					
Total	158.8	87.5	59.0	4.2	2.0	1.3
Rural-Urban	71.0	50.1	20.6	1.9	1.2	0.4
International	18.1	24.7	30.9	0.5	0.6	0.7
Local	69.7	12.7	7.5	1.8	0.3	0.2
Flooded	82.7	14.5	8.5	2.2	0.3	0.2
	Extreme-Conflict minus Minimalist					
Total	162.1	92.1	65.5	4.2	2.1	1.4
Rural-Urban	72.0	49.8	18.9	1.9	1.2	0.4
International	20.3	29.7	39.1	0.5	0.7	0.8
Local	69.7	12.7	7.5	1.8	0.3	0.2
Flooded	82.7	14.6	8.5	2.2	0.3	0.2

Notes: Simulation results based on the extreme scenarios defined in this section.

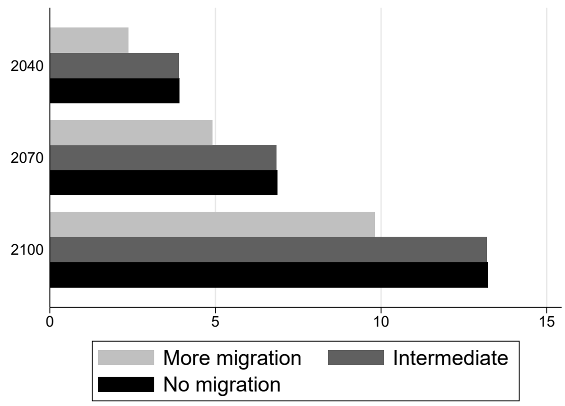
2.4.3 Role of migration policies

We now investigate whether a change of immigration policies can help limiting the effect of CLC on extreme poverty. Starting from the *Intermediate* scenario, we simulate the effect of two policy options for two sets of origin countries. The first option consists of preventing people to emigrate from 2040 onwards ($x_{r^*F,s,t} = 1$); the second one consists of reducing international migration cost by 5% ($x_{r^*F,s,t} \to 0.95 \cdot x_{r^*F,s,t}$). Figure 2.8 shows the effect of these two policy reforms on the world proportion of people whose income is smaller than the relative poverty line (i.e., 2% of the world average level of income per worker). As far as the target group is concerned, Figure 2.8a shows the effect obtained when the policy affects all workers living in the ten countries with the largest shares of population in extreme poverty (those reported in Figure 2.7c). Figure 2.8b shows the effect obtained when the policy is restricted to low-skilled workers living in the rural region of the same ten poorest countries. Figure 2.8c shows the effect obtained when the policy affects all workers living in the twenty most affected countries by CLC (those listed in Table 2.A1 in Appendix 2.A.2). Figure 2.8d shows the effect obtained when the policy affects low-skilled workers living in the rural region of the same twenty most affected countries.

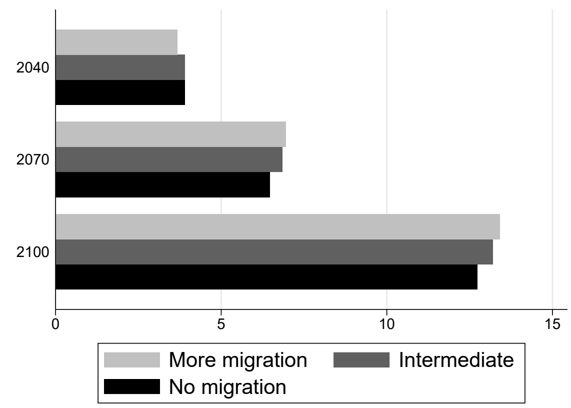
In all cases, reinforcing migration restrictions has little effects on extreme poverty, which means that the current laws and policies are already highly restrictive. As for the relaxation of migration restrictions, its effectiveness is highly sensitive to the target group. When the policy affects the poorest individuals from the poorest countries, it decreases sensibly the worldwide extreme poverty headcounts. If the policy affects all workers, the effect is negligible. This is due to skill-selection in international migration responses. The relaxation policy mostly benefits high-skilled workers in the urban sector. The resulting "brain drain" reduces the low-skilled wage rate in this sector, which slows down urbanization and increases the number of low-skilled workers in the rural sector. When targeting countries that are strongly impacted by CLC, the effect of relaxing migration restrictions on extreme poverty is detrimental if affecting all groups of workers, and very slightly beneficial if affecting low-skilled workers in agriculture.



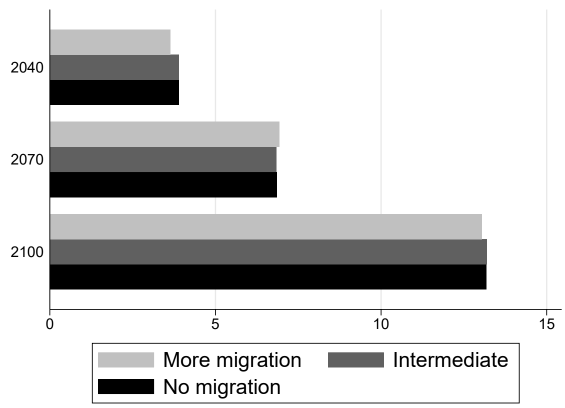
(a) Ten poorest countries, all workers



(b) Ten poorest regions, LS rural



(c) Twenty greatest CLC impacts, all workers



(d) Twenty greatest CLC impacts, LS rural

Figure 2.8: Poverty effects of relaxing immigration restrictions

Notes: Simulation results based on the Intermediate scenario.

2.5 Conclusion

In the course of the 21st century, climate change will increase the income gap between the richest and poorest countries by about 25%. It will also influence extreme poverty at both extensive and intensive margins, and force millions of adults to flee their flooded area of residence. These are favorable conditions for increasing the international mobility of workers. In this chapter, we endogenize the migration responses to climate change at various spatial scales. Our model relies on consensus micro-foundations, and is calibrated to match international and urbanization data of the last 30 years. Assuming a moderate scenario, we predict that climate change will lead to voluntary and forced movements of about 120 million working-age individuals and their children (i.e., around 200 individuals) during the 21st century. Nevertheless, more than 80% of them will move internally while 19% will opt for long-haul migration to an OECD destination. Under current migration laws and policies, far more climate migrants will move within their own countries than across borders. These migrants are mostly originating from countries that have contributed the least to climate change, but experience the most damaging effects. However, our results also reveal that international migration is a costly adaptation strategy of last resort. This results hold when considering more extreme temperature and SLR scenarios: the number of displaced people increases but most of them move locally. Larger amounts of internal and international migration can be obtained when adding direct utility losses - which is a difficult mechanism to quantify - or conflicts over resources - which are more uncertain.

As far as policy implications are concerned, our results illustrate the difficulty to define a status of climate refugee. In our median scenario, about 85% of forcibly displaced persons will move internally. In addition, half of non-local movements - and 95% of international movements - are caused by climate-driven deterioration of economic and social conditions. Things look clearer when CLC induces conflicts although in practice, the link between CLC and conflict can be hard to establish. For example, the thesis of a Syrian "climate war" has been challenged in the literature (Fröhlich, 2016; Selby et al., 2017). Hence, CLC is an additional factor that calls for better coherence between migration, development and environmental policies. Given people's difficulty to emigrate from the poorest countries, preventive measures are needed to encourage climate change adaptation, local disaster-risk reduction, sustainable development in general, and urban sustainable development in particular.

2.A Appendix

2.A.1 Temperature scenarios

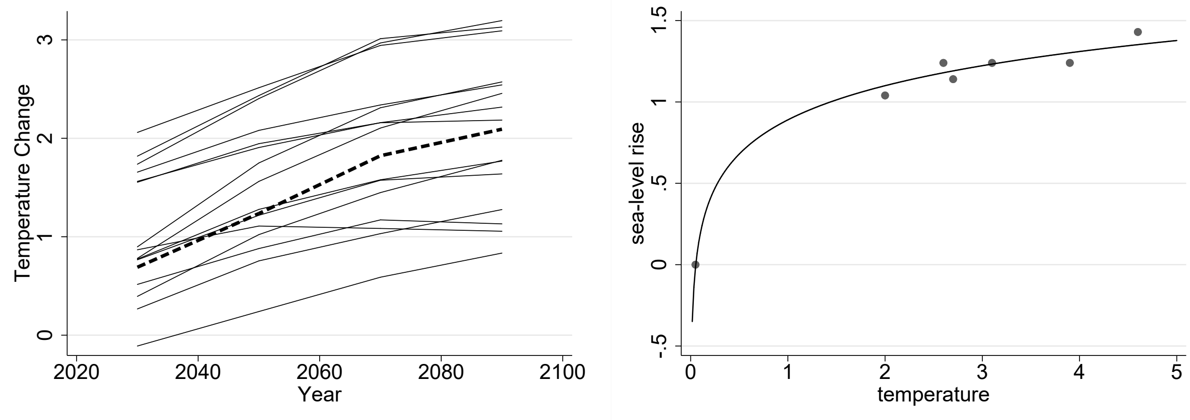
The CCKP projections are organized in 20-year climatological windows for the years 2020-2039, 2040-2059, 2060-2079, and 2080-2099. These projections are obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) distribution (Taylor et al., 2012) which distinguishes between several scenarios for the Representative Concentration Pathways (RCP) (Moss et al., 2010). The median-emission scenario is called RCP-4.5. In addition, for each RCP, the CCKP provides data for 16 models obtained from different research institutes. Figure 2.A1a depicts the evolution of the worldwide mean surface-temperature predicted by each of the 16 models of the median (RCP-4.5) package. The dashed black curve describes our *baseline* scenario. Overall, all models under RCP-4.5 predict an increase in temperature levels.

We proceed to two adjustments before plugging the temperature data into our model:

- Firstly, the climate literature suggests that aggregate (unweighted) country levels of temperature may not reflect accurately the impact of CLC (Dell et al., 2014). Particularly in large countries with regions of heterogeneous population densities, the aggregate measure poorly captures the intensity of the phenomenon. Hence, in a second step, we weight the monthly future temperature levels by population. To do this, we extract from the CCKP the monthly mean air temperature levels for the climatological window for the years 1991-2015. We weight equally the monthly observations to obtain a yearly temperature level for each country. Furthermore, Dell et al. (2012) provide a data set with population-weighted data on temperature levels. We compute the country-specific averages of these temperature levels for the years between 1995 and 2005. We then construct a scale factor for each country by dividing these population-weighted temperature levels by the temperature levels from the CCKP. In order to obtain future population-weighted measures, we multiply each of the monthly temperature levels for the future 20-year climatological windows with the country-specific scale factor.

- Secondly, the OLG model described in Section 2.3 must be fed with data in 30-year intervals (a period that is meant to represent the length of one generation), starting in 2010. Therefore, our third step consists in allocating the 20-year climatological windows to fit the temporal structure of the model. We assimilate the 2040-2059 climatological window to the year 2040, the 2060-2079 climatological window to the year 2070, and the 2080-2099 climatological window to the year 2100, respectively. In this way we obtain monthly population-weighted levels of temperature for the 179 countries in our data set. When averaged over all countries and months, our baseline temperature data predicts an increase in global temperature of $2.09°C$ by the end of the 21st century.[29]

[29] Under the RCP-4.5 scenario the projected anomalies range from $0.83°C$ for the minimalist model of the 16 models to $3.20°C$ for the maximalist model as illustrated on Figure 2.A1a.



(a) Worldwide mean temperature in RCP-4.5 (b) Variation in temperature and in sea level

Figure 2.A1: CLC scenarios (2010-2100)

Sources: CCPK for Figure 2.A1a, and Vermeer and Rahmstorf (2009) for Figure 2.A1b

2.A.2 Additional results for moderate scenarios

Table 2.A1 gives the effect of CLC on the country-wide level of income per worker for the 20 most adversely affected countries (the ranking is based on the effect in the year 2100). It documents the relative difference in income per worker between the *Intermediate* and the *Minimalist* scenarios, and between the *Maximalist* and the *Intermediate* scenarios. The table shows that poorer countries close to the equator experience a sustantial decrease in income per worker in the long-term.

Table 2.A2 reports emigration and immigration rates by region. The top panel shows that the mean emigration rates from the developing world will increase during the 21st century. The regional emigration rates will be multiplied by a factor of 1.5 to 2. This can be explained by the rise in education (highly educated people are more mobile) and by CLC. To identify the effect of CLC, the last two columns compare the predictions of the two alternative CLC scenarios in the year 2100. Comparing the *Intermediate* to the *Minimalist* and *Maximalist* scenarios, CLC affects the emigration rates from Latin America and, to a lesser extent, from Asia and sub-Saharan Africa. However, on average, CLC multiplies emigration rates by a factor of 1.05, which is a small fraction of the total rise in emigration rates.

The bottom panel documents the change in the proportion of immigrants in selected OECD countries. Remember we assume emigrants to the OECD aggregate entity are allocated across countries on the basis of the dyadic shares of the year 2010. Over the 21st century and at current migration policies and laws, the average share of immigrants should be multiplied by a factor of 1.5 in settlement countries (the US, Canada and Australia), and should increase twofold in Europe. These changes are mostly explained by demographic imbalances and by the progress in education. Comparing the CLC scenarios for the year 2100, we show that the contribution of CLC to increasing immigration is small. CLC explains about 1/20 of the total change in the share of immigrants in the population. The rise in the sea level induces minor effects on international migration, as most of the forcibly displaced people will relocate locally.

Table 2.A3 lists the countries with the highest emigration responses to CLC for the years 2040 and 2100. In 2040, countries that send the greatest numbers of emigrants

Table 2.A1: Most adversely affected countries in 2040 and 2100 (as % of dev.)
(Ranking based on income per worker in 2100)

	Country	Interm/Minim 2040	Interm/Minim 2100	Country	Maxim/Interm 2040	Maxim/Interm 2100
1	Sao Tome and Principe	-17.8	-19.9	Sao Tome and Principe	-20.1	-22.5
2	The Gambia	-11.7	-18.2	The Gambia	-15.1	-21.7
3	Venezuela	-13.8	-17.8	Venezuela	-16.4	-20.8
4	Nepal	-15.9	-17.3	Malaysia	-16.8	-19.7
5	Grenada	-13.4	-17.1	Dominican Republic	-16.0	-19.6
6	Nicaragua	-15.3	-16.8	Ghana	-18.9	-19.4
7	Malaysia	-14.3	-16.7	Philippines	-18.1	-19.3
8	Dominican Republic	-13.5	-16.6	Nicaragua	-17.5	-18.9
9	Ghana	-15.9	-16.5	Cuba	-15.3	-18.6
10	Philippines	-15.3	-16.4	El Salvador	-16.1	-18.4
11	El Salvador	-13.9	-16.0	Nepal	-18.1	-17.9
12	Cuba	-12.6	-15.4	Liberia	-21.7	-17.6
13	Liberia	-18.6	-15.3	Gabon	-15.2	-17.5
14	Fiji	-11.9	-15.0	Brunei Darussalam	-17.0	-17.2
15	Brunei Darussalam	-14.4	-14.8	Fiji	-14.4	-17.2
16	Gabon	-12.5	-14.6	Guinea-Bissau	-15.0	-16.7
17	Guyana	-14.2	-14.3	Equatorial Guinea	-18.6	-16.6
18	Belize	-14.2	-14.1	Belize	-18.0	-16.2
19	Equatorial Guinea	-14.5	-14.0	Panama	-15.6	-16.1
20	Barbados	-12.5	-13.8	Maldives	-15.2	-16.0

Notes: Simulation results based on the moderate CLC scenarios defined in Section 2.2.1.

Table 2.A2: International migration rates under moderate scenarios
(Emig. as % of native pop., Immig. as % of resident pop. 25-64)

	Intermediate 2010	Intermediate 2040	Intermediate 2070	Intermediate 2100	Minim. 2100	Maxim. 2100
Emigration rates						
Latin America	3.8	5.3	6.1	6.7	6.3	6.7
Sub-Saharan Africa	1.3	1.8	2.1	2.2	2.0	2.2
MENA	2.8	4.0	4.3	4.6	4.4	4.6
Asia	1.1	1.9	2.5	3.0	2.8	3.0
OECD	4.7	5.6	5.2	4.7	4.8	4.7
Immigration rates						
United States	16.0	21.4	23.0	23.1	22.7	23.6
Canada	18.7	26.5	28.5	28.4	28.2	28.6
Australia	24.9	29.4	29.2	28.1	27.8	28.5
European Union	12.1	18.6	21.9	23.6	23.2	24.1
EU15	13.6	20.3	23.3	24.6	24.2	25.1
Germany	15.0	22.5	25.4	26.4	26.1	26.8
France	12.2	18.8	20.5	22.1	21.6	22.6
United Kingdom	14.6	22.2	25.4	26.6	26.3	26.9
Italy	10.9	17.2	20.6	22.5	21.9	23.1
Spain	14.0	20.6	23.3	24.3	23.8	24.8

Notes: Simulation results based on the moderate scenarios defined in Section 2.2.1.

abroad under the more pessimistic scenarios are usually those with higher fractions of forcibly displaced workers and/or those located close to the equator. By the end of the century, these general results do not markedly change. Some of the small Caribbean islands are among the group of the most adversely affected economies in the year 2100.[30]

Table 2.A3: Largest changes in the stock of emigrants (as % of dev.)
(Ranking based on 2100)

	Country	Interm/Minim		Country	Maxim/Interm	
		2040	2100		2040	2100
Bot 01	Guyana	17.0	-15.6	Guyana	15.5	-22.3
Bot 02	Suriname	17.3	-13.1	Suriname	12.7	-15.0
Bot 03	Grenada	13.5	-9.5	Samoa	12.3	-11.0
Bot 04	Tonga	7.8	-8.9	Tonga	7.7	-10.3
Bot 05	Russia	-10.3	-8.0	Jamaica	11.3	-10.0
Bot 06	Micronesia	23.8	-6.5	Micronesia	17.0	-8.8
Bot 07	Samoa	10.6	-6.5	El Salvador	12.0	-7.3
Bot 08	Jamaica	10.9	-6.3	Russia	-8.9	-6.9
Bot 09	Mongolia	-9.4	-5.2	Grenada	7.4	-5.8
Bot 10	Lesotho	-6.5	-4.3	Mongolia	-8.0	-5.0
Bot 11	El Salvador	11.4	-4.2	Fiji	11.8	-3.9
Bot 12	Cape Verde	11.0	-4.2	St Vinc & Gren	8.5	-3.6
Bot 13	Albania	6.1	-3.7	Cape Verde	7.4	-3.4
Bot 14	St Vinc & Gren	10.4	-3.4	Lesotho	-4.0	-2.3
Bot 15	Afghanistan	-4.3	-3.0	Belarus	-4.4	-2.1
Bot 16	Belarus	-5.4	-2.4	Afghanistan	-2.3	-1.4
Bot 17	Ukraine	-2.3	-1.7	Bosnia Herz	-3.6	-1.2
Bot 18	Fiji	10.9	-1.6	Ukraine	-2.6	-1.1
Bot 19	Bosnia Herz	-4.9	-1.4	Albania	1.6	-0.9
Bot 20	Serbia	-3.3	-1.1	Serbia	-2.1	-0.6

Notes: Simulation results based on the moderate scenarios defined in Section 2.2.1.

2.A.3 Modeling utility losses and conflicts

To account for *potential direct utility losses due to the effect of temperature* on health or on the drudgery of work, we follow Dell et al. (2014) who report estimates that output per worker decreases by 2% per 1°C increase when temperature exceeds 20°C. We assume that this effect is due to a decrease in effective labor supply driven by a greater disutility of labor.

In a model with a quasi-linear utility function:

$$U = wl - \frac{\varrho l^{1+\vartheta}}{1+\vartheta},$$

we have:

$$\begin{aligned} l &= \left(\frac{w}{\varrho}\right)^{1/\vartheta} \\ \frac{\Delta U}{U} &= (1+\vartheta)\frac{\Delta l}{l}. \end{aligned}$$

[30]Interestingly, Micronesia is among the top positively affected countries in the short-run and the top negatively affected countries in the long-run.

Assuming a conservative value of 3 for ϑ (a labor supply elasticity to income of 1/3), we have $\frac{\Delta U}{U} = 4\frac{\Delta l}{l} = 8\Delta T$ when temperature exceeds $20°C$.

To account for the *effect of conflicts over ressources*, we follow Dao et al. (2017) who show that severe armed conflicts increase the emigration stock twofold in the long-term. In our model, migration decisions from region r^* are governed by:

$$\begin{aligned} N_{r^*,s,t} &= M_{r^*r^*,s,t} + M_{r^*r,s,t} + M_{r^*f,s,t} \\ &= M_{r^*r^*,s,t}(1 + m_{r^*r,s,t} + m_{r^*f,s,t}), \end{aligned}$$

where $m_{r^*f,s,t} = (v_{f,s,t}/v_{r^*,s,t})^{1/\mu}(1 - x_{r^*f,s,t})^{1/\mu}$ denotes the migrant-to-stayer ratio, and $N_{r^*,s,t}$ is the native (pre-migration) population (given at the beginning of each period). We can express the emigrant stock as:

$$M_{r^*f,s,t} = m_{r^*f,s,t}M_{r^*r^*,s,t} = \frac{m_{r^*f,s,t}N_{r^*,s,t}}{1 + m_{r^*r,s,t} + m_{r^*f,s,t}}.$$

Everything else equal, we constrain $M_{r^*f,s,t}$ to increase by a factor of 2 after the conflict (i.e., $\overline{M}_{r^*f,s,t} = 2M_{r^*f,s,t}$). Assuming (i) it affects high- and low-skilled workers symmetrically, and (ii) it affects all regions symmetrically, the conflict does not impact the relative attractiveness of rural and urban areas (i.e., $m_{r^*r,s,t}$ is constant). We have to find the new level of $\overline{m}_{r^*f,s,t}$ that is compatible with $\overline{M}_{r^*f,s,t}$. The solution is:

$$\begin{aligned} \frac{\overline{m}_{r^*f,s,t}N_{r^*,s,t}}{1 + m_{r^*r,s,t} + \overline{m}_{r^*f,s,t}} &= \frac{2m_{r^*f,s,t}N_{r^*,s,t}}{1 + m_{r^*r,s,t} + m_{r^*f,s,t}} \\ \Longrightarrow \overline{m}_{r^*f,s,t} = \frac{2m_{r^*f,s,t}(1 + m_{r^*r,s,t})}{1 + m_{r^*r,s,t} - m_{r^*f,s,t}} &= Z_{r^*f,s,t}m_{r^*f,s,t} \end{aligned}$$

Considering that the effect of the conflict is governed by a change in migration costs and net amenities ($x_{r^*f,s,t} \rightarrow \overline{x}_{r^*f,s,t}$), this requires:

$$(1 - \overline{x}_{r^*f,s,t}) = (1 - x_{r^*f,s,t})Z^{\mu}_{r^*f,s,t}.$$

2.A.4 Additional results for extreme scenarios

The effects on the world economy are depicted in Figure 2.A2, which reports results from the Intermediate scenario of Section 2.2.1 and those of the extreme scenarios defined in Section 2.4.2. The worldwide responses are the weighted averages of the positive and negative effects observed in high-income and developing countries.

Overall, considering extreme SLR scenarios (i.e., no SLR or a $2.7m$ SLR) has negligible impacts on worldwide responses. Changes in SLR slightly influence the share of international migrants in the year 2040. On the contrary, accounting for direct utility losses (8% per $1°C$ increase above $20°C$) or conflicts over resources (in ten countries with the greatest CLC-driven changes in poverty headcounts: Burundi, Cameroon, Eritrea, Guinea, Mozambique, Nepal, Tanzania, Timor-Leste, Togo, and Zimbabwe) has a drastic impact on urbanization, international migration and income. Greater propensity to move, internally or internationally, increases the share of people living in cities and OECD countries. This explains why income per capita increases.

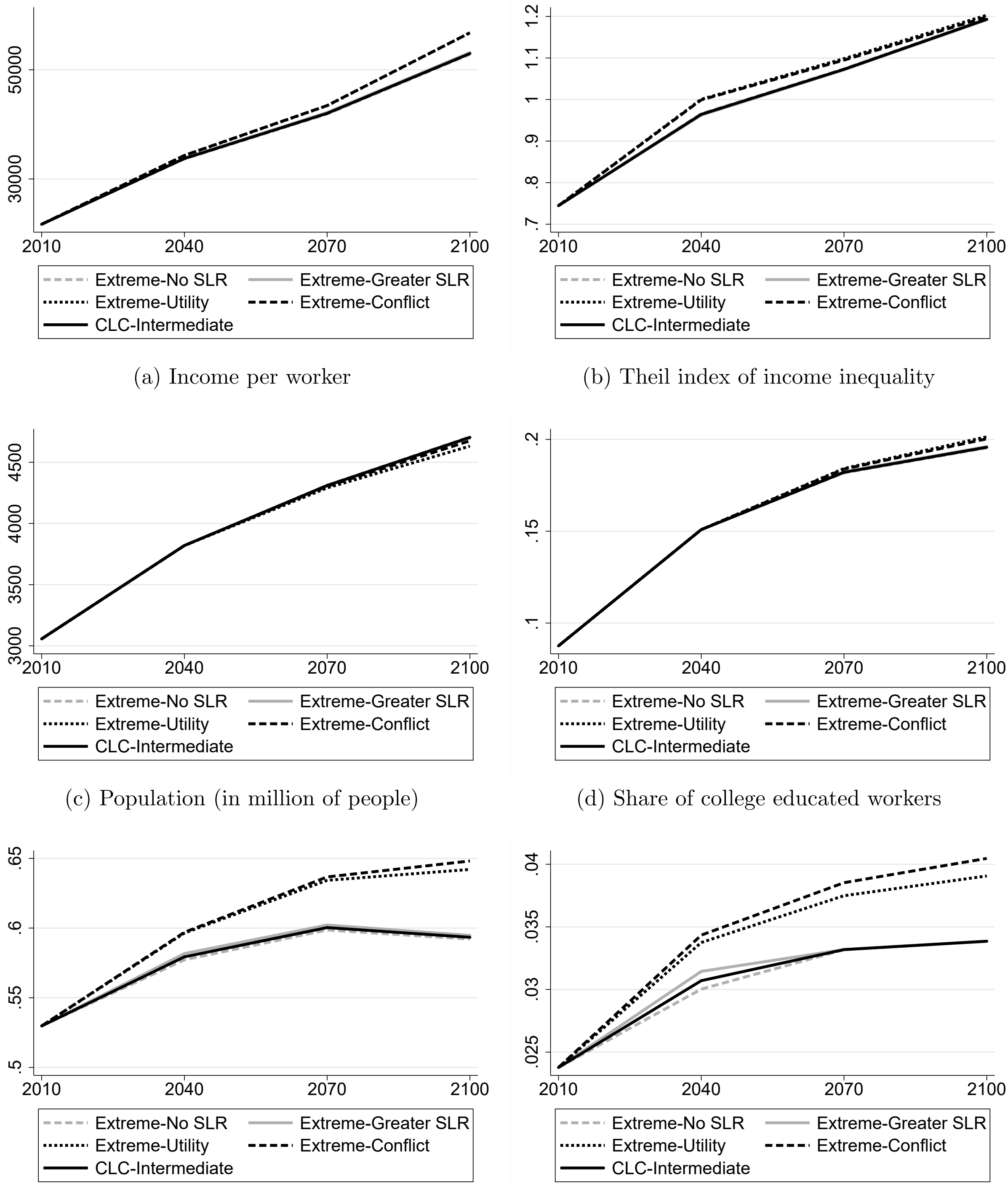
Table 2.A4 reports emigration and immigration rates by region by the year 2100. The top panel shows that direct utility losses and conflict increase emigration rates by

0.9 percentage points in Latin America and between 0.6 and 1 percentage point in sub-Saharan Africa. The effect of SLR is negligible, confirming that forcibly displaced people migrate internally or locally. The bottom part of the table shows that immigration rates in OECD countries are very robust to SLR. On the contrary, they increase by 0.5 to 1 percentage point when direct utility losses and conflicts are accounted for.

Table 2.A4: International migration rates under extreme scenarios
(Emig. as % of native pop., Immig. as % of resident pop 25-64)

	Interm. 2100	No SLR 2100	Great SLR 2100	Utility 2100	Conflict 2100
Emigration rates					
Latin America	6.7	6.7	6.7	7.6	7.6
Sub-Saharan Africa	2.2	2.2	2.2	2.8	3.2
MENA	4.6	4.6	4.6	4.7	4.7
Asia	3.0	3.0	3.1	3.6	3.7
OECD	4.7	4.7	4.7	4.5	4.5
Immigration rates					
United States	23.1	23.2	23.1	24.0	24.4
Canada	28.4	28.4	28.3	28.8	29.0
Australia	28.1	28.2	28.1	28.8	29.1
European Union	23.6	23.6	23.6	24.5	24.9
EU15	24.6	24.6	24.6	25.4	25.9
Germany	26.4	26.4	26.4	27.0	27.5
France	22.1	22.1	22.0	23.0	23.4
United Kingdom	26.6	26.6	26.5	27.2	27.5
Italy	22.5	22.5	22.4	23.6	24.2
Spain	24.3	24.3	24.2	25.2	25.7

Notes: Simulation results based on the more extreme scenarios defined in Section 2.4.2.



(a) Income per worker

(b) Theil index of income inequality

(c) Population (in million of people)

(d) Share of college educated workers

(e) Urbanization

(f) Share of international migrants to OECD

Figure 2.A2: Aggregate effects of CLC under extreme scenarios

Notes: Simulation results based on the more extreme scenarios defined in Section 2.4.2.

Chapter 3

Climate change and human capital in Africa

Abstract[1]

What is the relationship between climate change and human capital accumulation? Through which mechanisms do weather changes affect tertiary educational outcomes in African economies? This chapter investigates the potential link between climate change and high-skilled human capital formation in Africa. In order to do so, a two-sector, world economy model that endogenizes education decisions and internal migration decisions is developed. This stylized model predicts that negative climatic conditions increase the share of people moving internally from rural to urban areas. This in turn increases the future share of individuals investing in tertiary education, because the access and returns to education are higher in urban areas. These theoretical predictions are empirically validated by a panel data analysis at the country level, and a cross-sectional data analysis at the province level. The panel data set includes 37 African countries and covers the time period from 1960 to 2010. The cross-sectional data set includes 111 provinces in 17 African economies. A linear regression analysis shows that there is a correlation between weather changes and educational attainment. A Two-Stage least squares regression analysis indicates that this effect results from the impact of climatic variation on internal migration. The research leads to the conclusion that adverse weather changes may have the unexpected effect of increasing high-skilled educational attainment in African economies.

Keywords: human capital, migration, climate change

JEL codes: E24, O15, Q54

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3.1 Introduction

The analysis of the consequences of global warming and climate change has gained increasing interest by economists over the past decades. The potentially adverse impact of climate variables on economic growth and sustainable development has been numerously documented within the economics literature. For instance, beginning from the late nineties, several studies focused on cross-sectional analyses of the connection between climate and economic outcomes (Sachs and Warner, 1997; Gallup et al., 1999; Nordhaus, 2006). They have in common that they find a negative relationship between temperature and economic development. Countries with higher temperatures are characterized by lower aggregate economic outcomes.

More recently, panel data analyses using weather data for several decades addressed the shortcoming that a high correlation between temperature and institutional quality potentially drives the results in the cross sectional analyses (Acemoglu et al., 2002; Sachs, 2003; Rodrik et al., 2004). By identifying changes or shocks in climate variables over time, these studies find statistically significant impacts of climatic conditions on economic outcome variables. In terms of economic output, there is evidence of a negative impact of lower precipitation and temperature increases for a given year on income in poor countries, particularly in sub-Saharan Africa (Dell et al., 2012; Hsiang, 2010). In addition, windstorms have a negative impact on local economic output. Moreover, climate variables disproportionally affect the output in the agricultural sector (Dell et al., 2014). Most panel data studies find a negative effect of lower rainfall or higher temperature levels on agricultural production in developing countries.

At the same time, it is well-established that human capital plays a key role for development and long-run growth. In particular, highly educated workers are crucial for facilitating innovation and technology diffusion when knowledge becomes economically useful. The literature shows that this was the case during the industrial revolution (Mokyr, 2005; Scquicciarini and Voigtländer, 2015) and it is still important in the modern world (Castelló-Climent and Mukhopadhyay, 2013; Jones, 2014; Kerr et al., 2016). Given that growth and development are affected by both factors, climate variables and high-skilled educational attainment, the question whether climate variation itself impacts on educational attainment is apparent.

Indeed several studies explicitly address the connection between weather and educational variables, demonstrating the relevance of such an analysis. Most of these studies investigate the matter from a micro-level perspective. For instance, Maccini and Yang (2009), Marchetta et al. (2017), and Randell and Gray (2016) conclude for Indonesia, Madagascar, and Ethiopia that positive rainfall shocks increase educational attainment of female adults, school enrollment, or school completion rates, particularly in the agricultural sector. At the same time, Groppo and Krähnert (2017) show that negative weather shocks in Mongolia decrease the likelihood of students to complete mandatory schooling in the future.

While these analyses provide informative results at the micro-level, the long-run conclusions at the macro-level remain rather speculative. Little seems to be known about the adaptation mechanisms of economies to weather changes over time. For the United States, Burke and Emerick (2016) conclude that farmers have failed to adapt to productivity losses caused by higher temperatures by adjusting production methods. Similarly, Fishman (2011) finds that irrigation has a limited impact as an adaptation strategy to climate variation in the Indian agricultural production sector. In terms of human capital investment, there is evidence of an impact of weather shocks on school enrollment via an effect on wages. Shah and Steinberg (2017) show that positive rainfall shocks in India increase wages. This in turn leads to less school enrollment and weaker test performances of students, because the opportunity cost of schooling increases. These findings indicate that rural households react to negative weather shocks by increasing the investment in the offspring's education. Furthermore, Beine and Parsons (2015) investigate whether international migration is a channel of medium- or long-run adaptation to adverse weather changes. In their panel data study they do not find evidence of a direct effect of long-run climatic factors on international migration rates. However, they show that natural disasters create higher urbanization rates and conclude, in line with numerous other studies (Piguet et al., 2011; Barrios et al., 2006; Kubik and Maurel, 2016; Dallmann and Millock, 2013; Henderson et al., 2017), that unfavorable climatic factors may trigger internal migration movements. This is also in line with one of the main conclusions derived in the previous chapter, namely that the predominant majority of movements induced by climate change are at the local scale. Dell et al. (2014) reach a similar conclusion by stating that emigration from climate-affected areas seems to be a common result of negative shocks in agricultural production.

Finally, various analyses of the brain drain and brain gain phenomena emphasize the role of the incentive mechanism of educational attainment. As outlined in detail in the following chapter, the well-established principal theoretical argument is that higher returns to education in the destination country increase the individual incentives of potential migrants to invest in education (Mountford, 1997; Stark et al., 1997; Vidal, 1998; Beine et al., 2001). This argument is confirmed by the empirical evidence in numerous studies (Chand and Clemens, 2008; Gibson and McKenzie, 2011; Batista et al., 2012; Shrestha, 2017; Theoharides, 2017). In addition to the studies discussed above, this indicates that the analysis of the relationships between climatic conditions, adaptation mechanisms, human mobility, and educational attainment needs to address individual incentive mechanisms.

The supposition that negative environmental conditions impact on individual movement decisions is further confirmed by the Gallup World Polls. Figure 3.1 reports for 26 African economies the country-specific shares of respondents who anticipate a necessity to move because of severe environmental problems in the next five years.[2] This share is higher than 0.1 in 19 countries. In addition, Figure 3.1 indicates that this share is positively correlated with the share of the rural population in 2010.

These findings point to the importance of analyzing the channels through which (particularly developing) economies adapt to changing climatic conditions. How does climatic variability affect educational attainment? In particular, do higher temperatures or lower rainfall have a positive or negative impact on high-skilled education? Do weather changes result in a medium or long-run substitution away from low-skilled tasks, particularly in the agricultural sector, to more human capital intensive tasks? Is this process connected with more internal migration from rural to urban regions? These are the questions addressed in this chapter. To do so, a simple two-sector partial equilibrium model is developed. This model incorporates the crucial findings of the literature outlined above. It provides key predictions that are empirically validated by a panel data and cross-sectional data analysis focusing on African countries. By using two data sets, it is shown that adverse weather changes are correlated with higher tertiary educational attainment in

[2]The question in the Gallup World Polls reads: "In the next five years, do you think you will need to move because of severe environmental problems?"

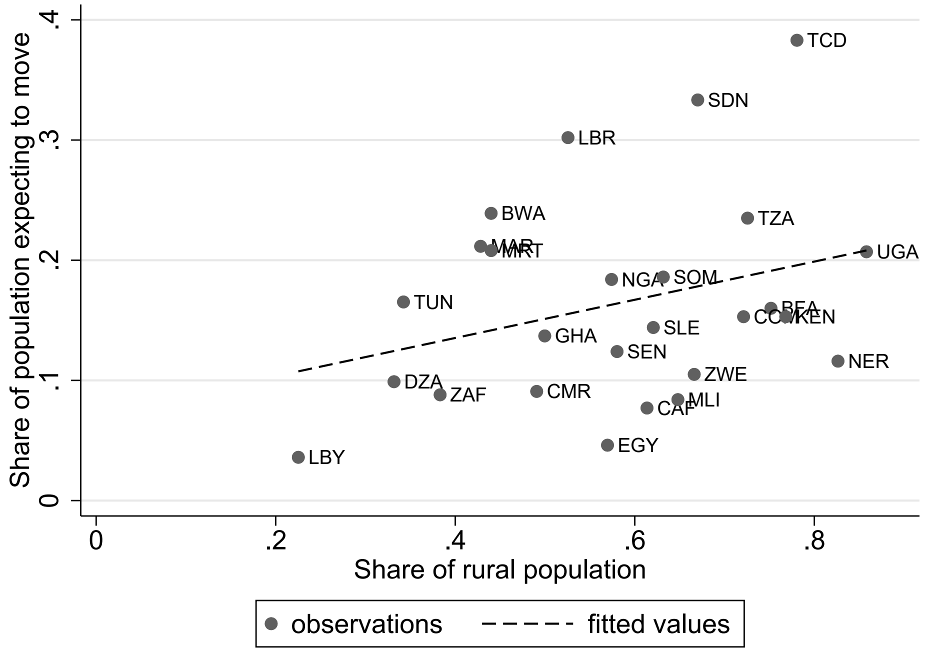


Figure 3.1: Rural population and expectation to move in Africa

Notes: This figure reports for 26 African countries the share of the rural population in 2010 and the share of respondents in the Gallup World Polls that expect a necessity to move because of severe environmental problems in the next five years.

Africa. In addition, a Two-Stage least squares regression analysis indicates that internal migration seems to be a key mechanism linking climate change and education. Hence, the empirical validation reveals indirect causality between climate change and education via the moderating variable of internal migration. The study demonstrates that adverse weather changes might promote internal migration and in turn high-skilled educational attainment in Africa.

As opposed to the previous chapter, this chapter focuses exclusively on African countries. There are mainly four reasons for this: First, the impact of weather variation is highly region-specific as illustrated in Chapter 2. A climatic anomaly or deviation in the global and generally humid North has entirely different effects than in hotter regions closer to the equator.[3] Second, this chapter analyzes the impact of climatic variation on agricultural production. In general, developed countries are characterized by far more advanced agricultural production technologies than African economies. For instance, the capacity to construct effective adaptation or protection mechanisms to rainfall deviations, such as irrigation systems, might be far more developed in richer countries. Third, our projections derived and described in Chapter 1 illustrate that future global socio-demographic variables will be increasingly determined by African countries. For example, we project that the share of sub-Saharan Africa in the worldwide working-age population increases from 7.2% in 1980 to 34.0% in 2100 and emphasize that the speed of urbanization will be faster in Africa than in the rest of the world over the 21st century

[3]This might also explain the partly conflicting conclusions of the micro-level studies on the climate-education nexus outlined above.

(see Appendix 1.A.3 in Chapter 1). Finally, the analysis presented in the previous chapter finds rather limited effects of climate change on high-skilled human capital accumulation at the global scale. The country-specific effects depicted in Chapter 2 are characterized by some degree of variation, particularly for the developing countries. This indicates that an analysis aiming to understand the mechanisms behind the dynamics of high-skilled human capital accumulation and climate change might need to specifically focus on a particular subgroup of countries. For these reasons it appears most reasonable to focus on less-developed economies in Africa only.

The rest of this chapter is organized as follows. Section 3.2 describes the model. Section 3.3 contains the empirical validation exercise of key predictions derived from the theoretical framework. This section describes the data sets and the approach to the estimation. Section 3.4 concludes.

3.2 Model

The model describes a set of economies with two sectors/regions $r = (a, n)$, denoting agriculture/rural region (a) and nonagriculture/urban region (n). Goods are produced in both sectors and are assumed to be perfect substitutes from the point of view of consumers. The price of goods is normalized to unity. The productivity in the agricultural sector is a function of climatic conditions. Each economy is populated by individuals that supply the labor for the production process. An individual λ earns a wage payment according to the inelastically supplied efficiency units of labor. Individuals have the option to increase their supply of efficiency units of labor by acquiring education. Hence, individuals can be attributed to one of two skill groups $s = (h, l)$, with $s = h$ for the high-skilled individuals and $s = l$ for the low-skilled individuals. Individuals maximize their well-being by first deciding in which region to live and second whether to invest in own education. Hence, the dynamic structure of the model is recursive. This section describes the model assumptions.

3.2.1 Technology

The production sector in each region is characterized by a simple production function. In the urban sector a single composite good is produced in each time period t according to a constant returns to scale production function:

$$Y_{n,t}(H_{n,t}) = A_{n,t} H_{n,t} \quad \forall t, \tag{3.1}$$

where $A_{n,t}$ denotes the total factor productivity and $H_{n,t}$ denotes the labor input measured in efficiency units at time t. The agricultural output is assumed to depend on weather variables such as temperature or precipitation.[4] In the rural sector a single composite good is produced in each time period t according to a constant returns to scale production function:

$$Y_{a,t}(H_{a,t}) = G(C_t) A_{a,t} H_{a,t} \quad \forall t, \tag{3.2}$$

where $A_{a,t}$ denotes the total factor productivity and $H_{a,t}$ denotes the labor input measured in efficiency units at time t. The function $G(C_t) \leq 1$ captures the dependence of agricultural output on climatic conditions C_t at time t, which are determined by rainfall

[4]Dell et al. (2014) review the studies that stress the impact of the climate on agricultural production.

or temperature levels. This function is assumed to be decreasing in the severity of the adverse climatic conditions (i.e., $\frac{\partial G(C_t)}{\partial C_t} < 0$). This means this function gives a lower value for more severe adverse climatic conditions.

Labor is the only production factor in this economy.[5] High-skilled and low-skilled labor are assumed to be perfect substitutes. In the urban sector the average and marginal product of one efficiency unit of labor is given by $A_{n,t}$. In the rural sector the average and marginal product of one efficiency unit of labor is given by $G(C_t)A_{a,t}$. All existing markets are assumed to be perfectly competitive in this economy. The wage paid per efficiency unit of labor in each region and period $w_{r,t}$ equals the marginal product of labor:

$$\begin{aligned} w_{n,t} &\equiv \frac{\partial Y_{n,t}(H_{n,t})}{\partial H_{n,t}} = A_{n,t} \quad \forall t, \\ w_{a,t} &\equiv \frac{\partial Y_{a,t}(H_{a,t})}{\partial H_{a,t}} = G(C_t)A_{a,t} \quad \forall t. \end{aligned} \tag{3.3}$$

The total factor productivity levels are assumed to be exogenous in each time period t. This means they may vary between time periods and will probably increase over time illustrating technological change. For simplicity, this type of technological change is not captured explicitly in the model. It is, however, assumed in the following that the total factor productivity is higher in the urban sector (i.e., $A_{n,t} > A_{a,t}$). This assumption reflects real-world productivity and wage differences between both sectors with a higher productivity in the urban than in the rural sector (Gollin et al., 2014b).

3.2.2 Preferences

Individuals derive utility from the wage payment they obtain for their inelastically supplied units of labor.[6] These wage payments are determined by the amount of efficiency units of labor $E_{s,t}$ that individuals supply on the labor market. In addition, individuals derive disutility from the effort of moving between regions and the effort of acquiring education. This is reflected by the individual-specific movement cost $x^{\lambda}_{r^*r,t} \in [0,1]$ and the individual-specific cost of education $e^{\lambda}_{s,t} \in [0,1]$. The former parameter captures the costs of moving from region r^* to region r, where $x^{\lambda}_{r^*r^*,t} = 0$. Hence, individuals have heterogeneous abilities to acquire education and heterogeneous preferences over the region where they want to live. The utility of an individual with skill-level s born in region r^* and moving to region r is denoted by:

$$U^{\lambda}_{r^*r,s,t} = \ln(w_{r,t}E_{s,t}) + \ln(1 - x^{\lambda}_{r^*r,t}) + \ln(1 - e^{\lambda}_{s,t}) \quad \forall r^*, r, s, t. \tag{3.4}$$

The amount of efficiency units of labor low-skilled individuals supply is normalized to unity ($E_{l,t} = 1$). As stated above, individuals increase the efficiency units of labor they can supply by acquiring high-skilled education ($E_{h,t} > 1$). Consequently, investments in education increase the wage payments obtained on the labor market.

However, education investments are not costless. Individual λ incurs a strictly positive cost of investing in high-skilled education ($e^{\lambda}_{h,t} > 0$). The cost parameter $e^{\lambda}_{s,t}$ reflects

[5]A model without physical capital features a globalized economy with a common international interest rate. This hypothesis is in line with Kennan (2013) or Klein and Ventura (2009) who assume that capital "chases" labor.

[6]This formulation implicitly accounts for the consumption of goods by assuming that the earned wages are exclusively spent on buying consumption goods.

the innate ability of individuals to acquire education. It is assumed that staying uneducated is effortless. In this case the cost of acquiring low-skilled education is equal to zero for all individuals ($e^{\lambda}_{l,t} = 0 \quad \forall\lambda$). The individual-specific cost of education for the high-skilled individuals is distributed on $[0, 1]$ according to the following cumulative distribution function:

$$F_1(e_{h,t}) = e^{z+1}_{h,t}, \tag{3.5}$$

where the parameter z governs the slope of the density function $f_1(e_{h,t}) = (1 + z)e^{z}_{h,t}$. This function is increasing in $e_{h,t}$. The fraction of individuals with a high ability to become high-skilled (i.e., with low high-skilled education cost) is decreasing in the size of z. The parameter z determines the abundance of highly educated individuals.[7]

Furthermore, an additional simplifying assumption is made at this stage. College education is predominantly obtained in urban regions. Hence, it is assumed that individuals in the rural region do not have the option to invest in high-skilled educational attainment. This type of education can only be attained in the urban sector.[8]

As stated above, the wage payments per efficiency unit of labor in each sector is determined by the marginal product of labor. By assumption, this marginal product is higher in the nonagricultural sector than in the agricultural sector. With positive movement costs (i.e., $x^{\lambda}_{r^*r,t} \geq 0 \quad \forall r^*, r, t$) there are only one-directional movements of individuals from the agricultural to the nonagricultural sector. It is simply not beneficial for individuals to move from the urban to the rural region, since wage payments are higher at the origin. Therefore, we focus only on the group of individuals born in the agricultural sector when analyzing the movement decision. For some of these individuals moving internally may be optimal. This depends on the individual-specific movement cost parameter $x^{\lambda}_{an,t}$. This parameter can be broadly interpreted as the effort required to move between regions. It also captures individual preferences for living in urban or rural regions and other causes of internal migration (Bryan et al., 2014). In addition, the cost could also be interpreted as reflecting the ability of individuals to provide funds for the moving process. Similarly to the education cost, it is assumed that the movement cost $x^{\lambda}_{an,t}$ is distributed on $[0, 1]$ according to the following cumulative distribution function:

$$F_2(x_{an,t}) = x^{v+1}_{an,t}, \tag{3.6}$$

where v governs the slope of the density function $f_2(x_{an,t}) = (1 + v)x^{v}_{an,t}$. This function is increasing in $x_{an,t}$. The higher the value of the parameter v, the lower the fraction of individuals for which moving becomes beneficial.[9]

3.2.3 Individual decisions

The timing of individual decisions is according to the following pattern: First, individuals discover their movement cost $x^{\lambda}_{r^*r,t}$ and decide on moving between sectors. At this stage individuals do not know their education cost $e^{\lambda}_{s,t}$ but know how it is distributed. Hence, it is assumed that individuals have complete information about wage payments but may not have complete information about all their individual-specific cost characteristics. This

[7] Note that for $z = 0$ the distribution is equal to the uniform distribution.

[8] In principle, it could also be assumed that education is simply more accessible in urban regions. In this case high-skilled education would also be available in rural regions. It is key, however, that education is more accessible in urban regions which is in line with the observation that the educational infrastructure is usually more developed in urban areas.

[9] As before, the distribution is equal to the uniform distribution for $v = 0$.

assumption can be interpreted as reflecting that individuals have complete information about markets but may not have detailed knowledge about specific abilities required to adjust to these markets. After the movement decision is made, those individuals that live in the urban sector decide in a second step on education. Both decisions follow a discrete choice in order to maximize the utility function given by Equation (3.4).

To better illustrate the decision structure, Figure 3.2 portrays a timeline of the decision process in period t. Climatic changes influence the productivity level in the rural sector. This affects the wage payments. Consequently, climatic changes have the potential to change individual decisions via the impact on wages. Individual moving decisions are made in the first stage. In the second stage, individuals decide on acquiring higher education. In order to determine the optimal individual decisions, the problem is solved backward in the following.

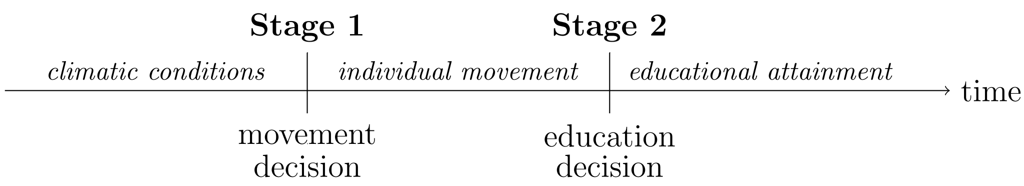


Figure 3.2: Timeline

Education decisions. – After individuals moved and settled in the region where they prefer to live, the education decision is made. By assumption, individuals living in the rural sector do not have the option to invest in high-skilled education. However, individuals in the urban region decide on such an investment. Urban individuals decide on acquiring education by maximizing Equation (3.4). The individual-specific cost of high-skilled education $e^{\lambda}_{h,t}$ determines whether an individual acquires high-skilled education. From transforming Equation (3.4) a threshold level of education cost can be derived:

$$\hat{e}_{h,t} \equiv \frac{E_{h,t} - 1}{E_{h,t}} \quad \forall t. \tag{3.7}$$

Individuals with a high-skilled education cost parameter lower than $\hat{e}_{h,t}$ invest in education, whereas individuals with an education cost higher than $\hat{e}_{h,t}$ do not acquire education. The threshold education cost is increasing in the efficiency units of labor high-skilled individuals can supply on the labor market (i.e., $\frac{\partial \hat{e}_{h,t}}{\partial E_{h,t}} > 0$). This means more individuals invest in high-skilled education if the rise in wage payments generated by higher efficiency is higher.

Given the distribution specified in Equation (3.5), the share of individuals that live in the urban region and invest in high-skilled education is described by:

$$h_{n,t} \equiv \left(\frac{E_{h,t} - 1}{E_{h,t}} \right)^{z+1} \quad \forall t. \tag{3.8}$$

The share $h_{n,t}$ is increasing in the efficiency units of labor high-skilled individuals can supply on the labor market (i.e., $\frac{\partial h_{n,t}}{\partial E_{h,t}} > 0$) and decreasing in the parameter z (i.e., $\frac{\partial h_{n,t}}{\partial z} < 0$).

Movement decisions. – Before individuals decide on acquiring high-skilled education, individuals in the rural sector decide on moving to the urban sector.[10] The decision to

[10]Note that as emphasized above, the assumption on the wage differential between both sectors impedes movements from the urban to the rural sector.

move between both regions depends on the difference in the future generated income in both sectors and the individual specific movement cost $x^{\lambda}_{r^*r,t}$. Individuals do not have information on their exact education cost. However, they anticipate the probability that their realized individual-specific high-skilled education cost $e^{\lambda}_{h,t}$ is below the threshold level $\hat{e}_{h,t}$. This means individuals know they will invest in education with probability p_t if they live in the urban region. Following Equation (3.5), the probability p_t is equal to $h_{n,t}$ and given by Equation (3.8). Individuals born in the rural sector decide on moving to the urban sector by maximizing their expected utility. From transforming Equation (3.4) a threshold level of an individual moving cost from a to n can be derived:

$$\hat{x}_{an,t} \equiv 1 - \frac{w_{a,t}}{w_{n,t}} (E_{h,t}\chi_t)^{-p_t} \quad \forall t, \tag{3.9}$$

where $\chi_t \equiv e^{\mathbb{E}_t\left[\ln\left(1-e^{\lambda}_{h,t}\right)\right]}$ is a term that captures the expected disutility from an investment in high-skilled education. Since there is no uncertainty about wages, the uncertainty about future utility arises from the lack of information about the individual-specific education cost. Individuals with a moving cost higher than $\hat{x}_{an,t}$ stay in the rural region, whereas individuals with a moving cost lower than $\hat{x}_{an,t}$ move to the urban region.

The threshold parameter $\hat{x}_{an,t}$ is inversely proportional to the ratio of wages in both sectors. If the difference between current wages in both sectors is higher, more individuals move from rural to urban areas. This difference is higher if either the wage in the urban sector is higher or the wage in the rural sector is lower (i.e., $\frac{\partial \hat{x}_{an,t}}{\partial w_{n,t}} > 0$ and $\frac{\partial \hat{x}_{an,t}}{\partial w_{a,t}} < 0$).[11] Finally, the threshold moving cost is increasing in the size of the parameter capturing education-induced efficiency (i.e., $\frac{\partial \hat{x}_{an,t}}{\partial E_{h,t}} > 0$) and decreasing in the size of the expected disutility (i.e., $\frac{\partial \hat{x}_{an,t}}{\partial \chi_t} > 0$).[12] This means more individuals move internally if the expected payoff of education investments is higher.

Given the distribution specified in Equation (3.6), the share of individuals that are born in the rural region and decide to move to the urban region is described by:

$$m_{an,t} \equiv \left(1 - \frac{w_{a,t}}{w_{n,t}} (E_{h,t}\chi_t)^{-p_t}\right)^{v+1} \quad \forall t. \tag{3.10}$$

The share $m_{an,t}$ is decreasing in the parameter v (i.e., $\frac{\partial m_{an,t}}{\partial v} < 0$).

3.2.4 Educational attainment

The individual decisions determine the size of the group of individuals that acquire high-skilled education. The share of individuals born in the rural sector in period t is denoted by r_t. Consequently, the share of individuals born in the urban sector is given by $1 - r_t$. The share of individuals that decide to acquire high-skilled education H_t is given by:

$$H_t = \left[(1 - r_t) + r_t m_{an,t}\right] h_{n,t} \quad \forall t. \tag{3.11}$$

Combining Equations (3.3), (3.8), (3.10) and (3.11) leads to the following term:

$$H_t = \left[(1 - r_t) + r_t \left(1 - \frac{G(C_t)A_{a,t}}{A_{n,t}} (E_{h,t}\chi_t)^{-p_t}\right)^{v+1}\right] \left(\frac{E_{h,t} - 1}{E_{h,t}}\right)^{z+1} \quad \forall t. \tag{3.12}$$

[11] Note that if the movement cost is interpreted as reflecting individual abilities to secure funds for the moving process, climatic changes affect the moving decisions of those individuals that are in the middle of this distribution. This is in line with the conclusion of Kubik and Maurel (2016) that individuals in the middle of the wealth distributions react to weather shocks by moving internally.

[12] The disutility is higher for smaller χ_t.

This expression explicitly links the climatic conditions in period t to the share of individuals that invest in high-skilled education. It simply states that the share of individuals moving from the rural region is higher, the more severe the adverse climatic condition. The share of individuals living in the urban region is higher if the share of individuals moving from the rural region is higher. The future share of tertiary educated individuals is higher if the share of individuals living in the urban region is higher.[13]

Formally this can be concluded by analyzing the signs of the partial derivatives of Equation (3.12). The threshold level $\hat{x}_{an,t}$, that determines the share of individuals migrating internally, is decreasing in the function $G(C_t)$ which captures the climatic conditions C_t (i.e., $\frac{\partial \hat{x}_{an,t}}{\partial G(C_t)} < 0$). Therefore, the share of individuals investing in high-skilled education in t is decreasing in the function that reflects the size of adverse climatic conditions in period t (i.e., $\frac{\partial H_t}{\partial G(C_t)} < 0$). Since $G(C_t)$ is decreasing in C_t, the share of individuals investing in high-skilled education is increasing in the size of adverse climatic conditions (i.e., $\frac{\partial H_t}{\partial C_t} > 0$).

Proposition 3.1 *For given values of r_t, $A_{r,t}$, $E_{h,t}$, χ_t, for exogenous parameters z, v, and for a negative impact of adverse climatic conditions on agricultural productivity $\left(\frac{\partial G(C_t)}{\partial C_t} < 0\right)$, adverse climatic conditions (C_t) increase the share of highly educated individuals (H_t).*

3.3 Empirical validation

The theoretical framework provides key predictions. This section aims at validating these predictions by means of an empirical investigation drawing on two data sets. The first sub-section describes the data sources and the construction of some additional variables. The following sub-sections outline different estimation approaches to validate the key theoretical predictions of the model.

3.3.1 Data

The first data set used for the empirical validation is an unbalanced panel data set for 37 African countries. The variables in this data set are provided at the country level in intervals of five years (i.e., the difference between period t and $t + 1$ amounts to five years). The second data set provides data at the province level for 111 provinces in 17 African countries. Collecting data at the province level for African economies is more difficult than obtaining data at the country level. Data for provinces are accessible only for recent years. Therefore, the second data set has a cross-sectional character.

Panel data

The crucial dependent variable in Equation (3.12) is the share of individuals investing in high-skilled education within an economy.[14] Data on the shares of people with completed tertiary education are provided by Barro and Lee (2013). These data are available for

[13]Higher returns to education in the destination region (the urban sector) promote individual educational attainment. Hence, the theoretical prediction of the model is akin to the central argument of the brain gain literature that is described above.

[14]In this section and the following sections we focus on the percentage shares for expositional convenience.

38 African countries in five-year intervals from 1950 until 2010. Note that this variable captures the stocks of highly educated individuals. Since there is a time gap between the decision to invest in education and the completion of education, the share of individuals investing in tertiary education in period t is proxied by the stock of college educated individuals in period $t+1$.[15]

Moreover, Equation (3.12) builds on the share of individuals born in the rural region. The World Bank database on the World Development Indicators 2017 contains yearly data on the share of the rural population for 52 African economies from 1960 to 2015. The shares of the population in the urban sector are simply obtained as the reciprocal shares. To be in line with the variable reflecting high-skilled educational attainment, the quinquennial averages of the urban and rural shares are obtained by computing the average of the yearly values five years around the year of interest.[16]

Following the approach of Beine and Parsons (2015), the impact of long-run environmental factors is analyzed. In other words, the following analysis focuses on slow-onset variables as opposed to addressing the impact of fast-onset shocks.[17] Rainfall and temperature data are obtained from the TS4.0 data set which is provided by the Climatic Research Unit of the University of East Anglia. This data set contains monthly weather observations on high-resolution 0.5° x 0.5° grids. The country level annual observations are the averages of the area weighted monthly observations. Quinquennial values are obtained by computing the mean of the five annual observations before the year of interest. The approach differs from the approach taken above, because it is assumed that individuals adapt their decisions to climatic conditions they observed in the recent past. The effect of the absolute levels of rainfall or temperature might simply reflect the educational attainment for wetter or warmer countries.[18] Hence, the way in which adverse weather impacts are measured is very important. As in Beine and Parsons (2015) or Dallmann and Millock (2013), several different measures of the weather conditions are computed.

First, deviations are characterized by the difference between the country level quinquennial mean and the long-run mean given by:

$$Dev_{i,t}(Clim) = \mu_{i,t}^{5}(Clim) - \mu_{i}^{LR}(Clim), \tag{3.13}$$

where the index i denotes the country, $\mu_{i,t}^{5}(Clim)$ denotes the quinquennial means of the climate variable ($Clim \in \{Pre, Tem\}$), that can be precipitation (Pre) or temperature (Tem), five years before time t and $\mu_{i}^{LR}(Clim)$ denotes the long-run mean of the climate variable for the 20th century. Hence, the long-run refers in this context to the period 1901 until 2000.

Second, anomalies are obtained by normalizing the deviations by dividing through

[15]In general, there is no specific restriction or prediction on the time it takes for internal migration to have an impact on stocks of tertiary educated individuals. Given that most college degrees take around three years to complete, it is reasonable to assume a time gap of five years for the analysis.

[16]Note that the model relies on the stock of individuals in urban areas in order to capture internal migration movements. Different fertilities between sectors are not accounted for in the theoretical framework. The literature has shown that for the period between 1960 and 1990 around half of African urbanization can be explained by internal migration movements (Zachariah and Conde, 1981; Kelley, 1991; Barrios et al., 2006). If this share is constant, fertility differentials should have no qualitative impact on the results of the empirical analysis.

[17]As argued in the previous chapter, the slow-onset indicators and the frequency of fast-onset shocks are positively correlated.

[18]Note that there is arguably a high correlation between temperature and institutional quality (Acemoglu et al., 2002; Sachs, 2003; Rodrik et al., 2004).

the long-run standard deviations:

$$Ano_{i,t}(Clim) = \frac{\mu_{i,t}^{5}(Clim) - \mu_i^{LR}(Clim)}{\sigma_i^{LR}(Clim)}, \tag{3.14}$$

where $\sigma_i^{LR}(Clim)$ denotes the long-run standard deviation of temperature or rainfall for the the 20th century. As argued by Marchiori et al. (2012), this measure corrects for scale effects.

Third, similarly to Iyer and Topalova (2014), a non-linear measure of the climatic conditions is constructed. For this measure positive and negative climatic conditions are simply counted. A positive rainfall (respectively temperature) shock is defined as a yearly rainfall (respectively temperature) level that is one standard deviation above (respectively below) the long-run mean for the 20th century. Equivalently, a negative rainfall (respectively temperature) shock is characterized as a yearly rainfall (respectively temperature) level that is one standard deviation below (respectively above) the long-run mean. For each year a variable is constructed which takes the value of one if a positive and minus one if a negative rainfall or temperature shock occurred:[19]

$$Dum_{i,t'}(Pre) = \begin{cases} 1 & Pre_{i,t'} > \mu_i^{LR}(Pre) + \sigma_i^{LR}(Pre) \\ -1 & Pre_{i,t'} < \mu_i^{LR}(Pre) - \sigma_i^{LR}(Pre) \\ 0 & otherwise \end{cases} \tag{3.15}$$

$$Dum_{i,t'}(Tem) = \begin{cases} 1 & Tem_{i,t'} < \mu_i^{LR}(Tem) - \sigma_i^{LR}(Tem) \\ -1 & Tem_{i,t'} > \mu_i^{LR}(Tem) + \sigma_i^{LR}(Tem) \\ 0 & otherwise \end{cases} \tag{3.16}$$

These variables are then summed for the five years before time period t in order to obtain the non-linear measure:

$$Nlin_{i,t}(Clim) = \sum_{t'=t-5}^{t} Dum_{i,t'}(Clim). \tag{3.17}$$

The non-linear variable capturing the climatic conditions can take a value between minus five and five. The higher the value of this variable, the more positive are the climatic conditions five years before time period t.

Finally, some control variables are used in the empirical investigation. Data on the gross domestic product per capita are taken from the World Bank database on the World Development Indicators 2017. The yearly data are given in constant 2010 US Dollars for the period between 1960 and 2016. Moreover, as in Castelló-Climent and Mukhopadhyay (2013), the adult population is defined as the sum of individuals that are older than 15 years. Yearly population data by age group are provided by the United Nations Population Division for the period between 1950 and 2015. From these data, the share of population that is older than 15 years is computed. To be in line with the other variables of the data set, quinquennial averages of both variables are computed as the average of the yearly values five years around the year of interest.

[19] Unreported results show that using dummy variables for positive and negative weather shocks separately in the regression analysis leads to similar results. For this reason, the analysis focuses on a variable that jointly captures positive and negative weather events.

Table 3.1 reports some descriptive statistics for the variables of the data set. The merged data set is unbalanced and provides information for 37 economies in Africa from 1960 to 2010.[20]

Table 3.1: Descriptive statistics - panel data

	count	mean	s.d.	min	max
Tertiary completed	370	1.63	1.94	0.0	11.7
Urban population	370	29.49	17.00	2.1	83.4
Pre. Deviation	370	-0.99	6.93	-40.5	21.8
Tem. Deviation	370	0.15	0.39	-0.7	1.5
Pre. Anomaly	370	-0.09	0.59	-1.7	1.5
Tem. Anomaly	370	0.37	1.02	-1.5	6.1
Non-linear Pre.	370	-0.20	1.49	-4.0	3.0
Non-linear Tem.	370	-0.78	2.23	-5.0	4.0
ln(GDP per capita)	335	6.89	0.93	4.9	9.6
Adult population	370	56.16	4.19	50.0	75.4

Notes: This table reports some descriptive statistics for the share of individuals with completed tertiary education (tertiary completed), the share of people living in urban regions (urban population), the logarithm of the GDP per capita (ln(GDP per capita)), the share of people that are older than 15 years (adult population), as well as the temperature and precipitation deviation ($Dev_{i,t}(Clim)$), anomaly ($Ano_{i,t}(Clim)$), and non-linear measures ($Nlin_{i,t}(Clim)$). Depicted shares are percentage shares.

Cross-sectional data

The Gallup World Polls provide data on individual educational attainment. For each of 111 African provinces the provincial share of high-skilled individuals is computed as the weighted sum of tertiary educated individuals divided by the weighted sum of all individuals living in the respective province. As stated above, the individual decision to invest in high-skilled education is not immediately reflected in the stocks of tertiary educated individuals. The share of individuals investing in tertiary education in a certain period is proxied by the provincial stock of college educated individuals between two and nine years later.[21]

Henderson et al. (2017) use weather variables at the province level for their analysis of the connection between climate change and urbanization in African provinces. Their data is used to analyze the impact of climatic conditions at the province level. Following the approach of Henderson et al. (2017), the change in climatic conditions is defined as:

$$Change_j(Clim) = \frac{\ln(Clim_{j,t}) - \ln(Clim_{j,t-4})}{4}, \tag{3.18}$$

where the index j denotes the province, $Clim_{j,t}$ is the climate variable at time t, that can be precipitation (Pre) or temperature (Tem). The change in rainfall or temperature is measured in a four-year interval. This comes closest to the approach applied for the panel data analysis which consists of computing the differences over five years. The variable

[20]Table 3.A1 in Appendix 3.A.1 lists the countries of the panel data set. Figure 3.A1 in Appendix 3.A.1 provides a map of Africa which illustrates the countries for which panel data is used in the linear regression.

[21]Restrictions in the availability of data only allow to match the provincial data on the basis of this wide time frame.

$Change_j(Clim)$ reflects the assumption that the change in the climatic conditions in the recent past impacts on individual decisions.

Finally, three control variables are used in the empirical analysis. Two of these variables are only available at the country level. As before, the country-specific share of the population that is older than 15 years is computed from data provided by the United Nations Population Division. For this control variable the averages of the yearly values five years around the year 2005 are computed. In addition, similarly to Castelló-Climent and Mukhopadhyay (2013) a country-specific control variable on the government expenditures is used in the cross-sectional regression analysis. The UNESCO Institute for Statistics provides data on the government expenditures on education as a share of total government expenditures. These shares for the year 2005 are included in the cross-sectional specification as an additional control variable.[22] The control variable on the economic capacity can be computed at the province level. The Gallup World Polls provide data on household income. Similarly to the approach for the province-specific high-skilled shares described above, the average of the household income levels are computed for each of the 111 provinces. The logarithmic values of these province-specific income levels are used as a proxy for the GDP per capita in each province.[23]

Table 3.2 reports some descriptive statistics for the variables in the cross-sectional data set. Data are available for one time period per country only. The time periods match years between 2000 and 2009.[24]

Table 3.2: Descriptive statistics - cross-sectional data

	count	mean	s.d.	min	max
Tertiary completed	111	1.81	2.14	0.1	10.7
Pre. Change	111	0.0017	0.0111	-0.0368	0.0420
Tem. Change	111	0.0012	0.0019	-0.0062	0.0074
ln(income)	111	6.42	0.57	5.0	7.7
Adult population	111	55.86	3.48	50.8	64.9
Expenditures	111	19.26	6.27	7.7	32.4

Notes: This table reports some descriptive statistics for the share of individuals with completed tertiary education (tertiary completed), the change in precipitation and temperature at province level ($Change_j(Clim)$), the logarithm of the household income levels (ln(income)) at province level, the share of people that are older than 15 years at the country level (adult population), and the government expenditures on education as a share of total government expenditures. Depicted shares are percentage shares.

[22]Due to data limitations, information on the government expenditures on education of the year 2006 is used for Niger.

[23]For Zimbabwe no province-specific income levels could be computed from the Gallup World Polls. Therefore, the GDP per capita from the World Development Indicators 2017 is taken as a proxy for the income levels in the provinces of Zimbabwe.

[24]Table 3.A2 in Appendix 3.A.1 lists the countries and provinces of the cross-sectional data set. Figure 3.A2 in Appendix 3.A.1 provides a map of Africa which illustrates the provinces for which the cross-sectional data set is used in the linear regression. The cross-sectional data set is corrected in some ways. First, data for Kenya are available at a more detailed scale, so that data on several administrative regions are merged at the province level. Second, for other countries of the data set some provinces are merged. Third, data on educational attainment appear unreasonably high in very few cases, so that provinces with a share of high-skilled individuals above 0.11 are dropped from the data set. This leads to the exclusion of three observations.

3.3.2 Linear regression - reduced form

In a first step, this sub-section investigates whether there is a correlation between educational attainment and adverse climatic changes in Africa.[25] The approach consists of estimating the reduced form of the model in order to analyze whether climatic conditions and human capital accumulation are related. Equation (3.12) illustrates the dependence of the share of high-skilled individuals on the climatic conditions. The main prediction of the model is that the share of tertiary educated workers is higher if the adverse weather impact is more severe.[26] The data sets allow to estimate a linear dependence of this form.

Panel data

The regression analysis for the panel data set focuses on two estimable equations. The first part of this sub-section analyzes the simplest specification to assess the potential correlation between climate change and high-skilled educational attainment. The following equation is estimated:

$$H_{i,t} = \beta_0^{l.p.A} + \beta_1^{l.p.A} C_{i,t} + \beta_2^{l.p.A} \ln(y_{i,t}^c) + \beta_3^{l.p.A} pop_{i,t}^a + k_i + \epsilon_{i,t}^{l.p.A}, \tag{3.19}$$

where the index i denotes the country, $H_{i,t}$ is the share of individuals with completed tertiary education (at time $t+1$), $C_{i,t}$ is a measure for the climate variable at time t, $\ln(y_{i,t}^c)$ is the logarithm of the GDP per capita at time t, $pop_{i,t}^a$ is the share of individuals older than 15 years at time t, k_i is a country fixed effect, and $\epsilon_{i,t}^{l.p.A}$ is the error term.

Similarly to Castelló-Climent and Mukhopadhyay (2013), the linear regression analysis controls for the GDP per capita and the size of the adult population. Both measures are expected to impact on the share of individuals obtaining high-skilled education.[27] Furthermore, country fixed effects capture the role of idiosyncrasies at the country level. Finally, one could also think of adding time fixed effects to the specification. However, the empirical analysis focuses on one continent. Overall, the weather conditions analyzed here (rainfall and temperature) could potentially be correlated across regions. For instance, exceptionally hot or cold years might affect a whole continent in a similar manner. If this is the case, time fixed effects would absorb some of the variation in the weather conditions. For this reason, the analysis refrains from including time fixed in the specification.

Table 3.3 gives the results of the estimation. Columns (1), (3), and (5) contain the results for the estimations in which the rainfall data is used. Columns (1) and (3) show that there is a negative correlation between precipitation deviations as well as anomalies and the share of tertiary educated individuals five years later. Column (5) indicates that a higher number of positive rainfall shocks occurring in the recent past is correlated with a lower future share of college educated workers.

[25] For additional illustration, Appendix 3.A.2 provides graphs which depict the correlation between the climate variables contained in the data sets and the variables capturing future educational attainment. Note that the slopes of the curves illustrating the linear fit have the expected signs.

[26] Remember that the partial derivative of Equation (3.12) with respect to the measure of the adverse weather impact is positive (i.e., $\frac{\partial H_t}{\partial C_t} > 0$).

[27] The use of additional control variables may further increase the precision of the empirical analysis. For instance, Castelló-Climent and Mukhopadhyay (2013) use total or development expenditures as additional control variables. However, including such measures comes at the severe cost of drastically decreasing the number of observations for the panel data analysis. Data on government expenditures are only available for 91 observations of the data set used in this section. In the cross-sectional analysis a control variable on government expenditures can be included.

Table 3.3: Linear fixed effects regression

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Tertiary completed (5 years later)					
Pre. Deviation	-0.0564***					
	(0.0160)					
Tem. Deviation		1.805***				
		(0.225)				
Pre. Anomaly			-0.843***			
			(0.127)			
Tem. Anomaly				0.592***		
				(0.101)		
Non-linear Pre.					-0.336***	
					(0.0582)	
Non-linear Tem.						-0.288***
						(0.0386)
ln(GDP per capita)	0.904**	0.906**	0.944**	1.047***	0.945**	1.002***
	(0.388)	(0.375)	(0.388)	(0.387)	(0.382)	(0.376)
Adult population	0.221***	0.116**	0.217***	0.142**	0.219***	0.138**
	(0.058)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)
Constant	-9.025**	-3.406	-9.675**	-6.190	-9.603**	-5.733
	(4.413)	(4.306)	(4.283)	(4.368)	(4.398)	(4.387)
Observations	335	335	335	335	335	335
Number of countries	37	37	37	37	37	37
R-squared	0.646	0.681	0.660	0.670	0.661	0.675

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the linear fixed effects regression. The independent variables include the deviation in precipitation and temperature ($Dev_{i,t}(Pre)$ and $Dev_{i,t}(Tem)$), the precipitation and temperature anomalies ($Ano_{i,t}(Pre)$ and $Ano_{i,t}(Tem)$), and the non-linear measure of precipitation and temperature ($Nlin_{i,t}(Pre)$ and $Nlin_{i,t}(Tem)$). The control variables include the logarithm of the GDP per capita (ln(GDP per capita)) and the share of the population older than 15 years (adult population). Country fixed effects are not depicted. The dependent variable is the share of individuals with completed tertiary education five years after period t. Shares are measured in percentage.

Columns (2), (4), and (6) depict the results for the estimations using the temperature data. The results indicate that temperature deviations or anomalies occurring in Africa are positively correlated with the share of individuals investing in high-skilled education. Column (6) shows that higher numbers of positive temperature shocks are negatively correlated with the shares of tertiary educated individuals five years later.

Furthermore, a second specification for the reduced form estimation of the model is analyzed. Many of the macroeconometric analyses addressing high-skilled educational attainment propose a dynamic specification of human capital accumulation. Commonly a β-convergence specification is estimated.[28] The second part of this sub-section follows

[28] For instance, Beine et al. (2008) use a β-convergence equation for their analysis of the brain drain phenomenon. In addition, the following proposed specification is fully in line with the specification applied in Chapter 4.

this approach and focuses on the following estimable equation:

$$\ln\left(\frac{H_{i,t}}{H_{i,t-1}}\right) = \beta_0^{l.p.B} + \beta_1^{l.p.B}C_{i,t} + \beta_2^{l.p.B}\ln\left(H_{i,t-1}\right) + \beta_3^{l.p.B}\ln(y_{i,t}^c) + \beta_4^{l.p.B}pop_{i,t}^a + k_i + \epsilon_{i,t}^{l.p.B}, \tag{3.20}$$

where the index i denotes the country, $H_{i,t}$ is the share of individuals with completed tertiary education (at time $t+1$), $H_{i,t-1}$ is the share of individuals with completed tertiary education (at time t), $C_{i,t}$ is a measure for the climate variable at time t, $\ln(y_{i,t}^c)$ is the logarithm of the GDP per capita at time t, $pop_{i,t}^a$ is the share of individuals older than 15 years at time t, k_i is a country fixed effect, and $\epsilon_{i,t}^{l.p.B}$ is the error term. This specification focuses on the change in the shares of high-skilled individuals. It departs from equation (3.12) which is derived in the theoretical section and links climatic conditions to the share of individuals living in urban areas and the share of individuals investing in tertiary education.[29]

Table 3.4 provides the results of the estimation with the dynamic specification. In line with the literature (see Beine et al., 2008), there is a statistically significant negative effect of the share of tertiary educated individuals in the previous period. This indicates a catching-up process in terms of human capital.

Equivalently to Table 3.3, columns (1), (3), and (5) of Table 3.4 give the results for the estimations in which the rainfall data is used while columns (2), (4), and (6) depict the results for the estimations using the temperature data. Columns (1) and (3) show that there is a negative correlation between precipitation deviations as well as anomalies and the change in human capital. For the other climate variables no statistically significant effect can be recorded. Nevertheless, the signs of the coefficients are in line with the previous results depicted in Table 3.3. This further indicates that unfavorable climatic conditions are positively correlated with a change in human capital accumulation.

Cross-sectional data

Similarly to the analysis at the country level, the correlation between climatic conditions and educational attainment can be investigated at the province level. The regression analysis for the cross-sectional data set focuses on the following estimable equation:

$$H_j = \beta_0^{l.c} + \beta_1^{l.c}C_j + \beta_2^{l.c}\ln(y_j^c) + \beta_3^{l.c}pop_i^a + \beta_4^{l.c}exp_i + \epsilon_j^{l.c}, \tag{3.21}$$

where the index i denotes the country, the index j denotes the province, H_j is the share of individuals with tertiary education, C_j is a measure for the climate variable, $\ln(y_j^c)$ is the logarithm of the income levels, pop_i^a is the share of individuals older than 15 years, exp_i is the share of educational government expenditures, and $\epsilon_j^{l.c}$ is the error term.

Table 3.5 shows the results for the linear estimation of the reduced form of the model at the province level. Column (1) contains the result for the estimation in which the change in rainfall is used as a proxy of the climatic conditions. The result points to a negative correlation between precipitation and the share of tertiary educated individuals

[29] Many studies addressing internal migration analyze a similar change in the shares of individuals living in urban areas in different time periods. For instance, Henderson et al. (2017) focus on the annualized growth of the urban population share. In general, the current analysis could follow a similar strategy by including a specification with the change in the shares of individuals living in urban areas. However, a specification focusing on the change in the urban population shares departs further from the main theoretical prediction derived from the model. Therefore, it is not included in the current analysis.

Table 3.4: Linear fixed effects regression - dynamic specification

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Change in tertiary completed (in 5 years)					
Pre. Deviation	-0.0157*					
	(0.00823)					
Tem. Deviation		0.177				
		(0.170)				
Pre. Anomaly			-0.180**			
			(0.0883)			
Tem. Anomaly				0.0455		
				(0.0555)		
Non-linear Pre.					-0.0579	
					(0.0356)	
Non-linear Tem.						-0.0228
						(0.0271)
ln(tertiary completed)	-0.206***	-0.209**	-0.220***	-0.197**	-0.210***	-0.198**
	(0.0663)	(0.0915)	(0.0725)	(0.0878)	(0.0752)	(0.0884)
ln(GDP per capita)	0.105	0.121	0.128	0.125	0.123	0.124
	(0.0915)	(0.106)	(0.0951)	(0.115)	(0.0971)	(0.111)
Adult population	-0.0019	-0.0141*	-0.0025	-0.0100	-0.0029	-0.0106
	(0.009)	(0.008)	(0.009)	(0.007)	(0.009)	(0.007)
Constant	0.255	0.805	0.00239	0.511	0.111	0.550
	(1.149)	(0.977)	(1.199)	(1.099)	(1.232)	(1.076)
Observations	331	331	331	331	331	331
Number of countries	37	37	37	37	37	37
R-squared	0.220	0.183	0.215	0.177	0.200	0.178

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the linear fixed effects regression in the dynamic specification. The independent variables include the deviation in precipitation and temperature ($Dev_{i,t}(Pre)$ and $Dev_{i,t}(Tem)$), the precipitation and temperature anomalies ($Ano_{i,t}(Pre)$ and $Ano_{i,t}(Tem)$), and the non-linear measure of precipitation and temperature ($Nlin_{i,t}(Pre)$ and $Nlin_{i,t}(Tem)$). The control variables include the logarithm of the share of individuals with completed tertiary education in period t (ln(tertiary completed)), the logarithm of the GDP per capita (ln(GDP per capita)), and the share of the population older than 15 years (adult population). Country fixed effects are not depicted. The dependent variable is the logarithm of the share of individuals with completed tertiary education five years after period t divided by the share of individuals with completed tertiary education in period t. Shares are measured in percentage.

several years later. However, the coefficient is not precisely estimable. Column (2) illustrates the result for the estimation in which the temperature change is used. It indicates that an increase in temperature levels occurring in the recent past is correlated with a higher future share of college educated workers. The depicted coefficient is statistically significant at the ten percent level. These results are in line with the results of the linear country fixed effects regression analysis for the panel data set. The coefficients have the expected signs but are only significant when the temperature data is used.

Overall, the results of the linear regression analysis might only reflect correlations between different variables. They are results of a reduced form estimation. However, these results align with the model prediction on the sign of the partial derivative of Equation (3.12) with respect to the climatic variation. In this light, the linear regression analysis

Table 3.5: Linear regression - province data

	(1)	(2)
VARIABLES	Tertiary completed (2-9 years later)	
Pre. Change	-25.06	
	(23.36)	
Tem. Change		219.2*
		(121.1)
ln(income)	1.455***	1.443***
	(0.423)	(0.387)
Adult population	-0.0104	0.0676
	(0.0625)	(0.0686)
Expenditures	-0.0495	-0.0822
	(0.0458)	(0.0496)
Constant	-5.958**	-9.909***
	(2.497)	(3.301)
Number of provinces	111	111
Number of countries	17	17
R-squared	0.120	0.128

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the linear regression for the cross-sectional province data. The independent varibale include the change in precipitation ($Change_j(Pre)$) and the change in temperature ($Change_j(Tem)$) between period t and four years before period t. These variables are region-specific. The control variables include the province-specific logarithm of the household income levels (ln(income)), the country-specific share of the population older than 15 years (adult population), and the country-specific government expenditures on education as a share of total government expenditures. The dependent variable is the region-specific share of individuals with tertiary education between two and nine years after period t. Shares are measured in percentage.

can be understood as a first step in empirically validating the theoretical predictions of the model. In the next sub-section another approach is taken to reinforce the results.

3.3.3 Two-Stage least squares regression - structural form

The main claim of the theoretical model is that climatic changes impact on tertiary educational attainment via their effect on internal migration. A Two-Stage least squares regression analysis based on the panel data set allows to isolate and test this effect. This aims at estimating the structural form of the model and is considered as the main empirical validation of the predictions derived from the theoretical framework.

Column (1) of Table 3.6 shows that there is a significant positive effect of the share of people living in urban areas on the share of individuals with completed tertiary education five years later. In an analogous manner to columns (1) to (6) of Table 3.3, this column provides the coefficients of a country fixed effects estimation with the usual control variables. Column (2) provides the results for the estimation using the dynamic specification. The coefficient of interest is not statistically significant but has the expected sign.

A Two-Stage least squares country fixed effects regression analysis is conducted to investigate whether the correlation between higher shares of the urban population and future tertiary educational attainment may result from the impact of weather changes.

Table 3.6: Correlation between urban population and tertiary educational attainment

VARIABLES	(1) Tertiary completed (5 years later)	(2) Change in tertiary completed (in 5 years)
Urban population	0.119***	0.0137
	(0.0107)	(0.00908)
ln(GDP per capita)	-0.0640	0.0486
	(0.232)	(0.0731)
Adult population	0.194***	-0.0052
	(0.0411)	(0.0081)
ln(tertiary completed)		-0.275**
		(0.119)
Constant	-7.459*	0.0813
	(4.173)	(1.295)
Observations	335	331
Number of Countries	37	37
R-squared	0.791	0.201

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the linear fixed effects regression with the simple and the dynamic specification. The control variables include the logarithm of the share of individuals with completed tertiary education in period t (ln(tertiary completed)), the logarithm of the GDP per capita (ln(GDP per capita)), and the share of the population older than 15 years (adult population). Country fixed effects are not depicted. The dependent variable is the share of individuals with completed tertiary education five years after period t (column (1)) and the logarithm of the share of individuals with completed tertiary education five years after period t divided by the share of individuals with completed tertiary education in period t (column (2)). Shares are measured in percentage.

The regression analysis is based on the following two stages. First stage:

$$u_{i,t} = \alpha_0^{2SLS} + \alpha_1^{2SLS} C_{i,t}^p + \alpha_1^{2SLS} C_{i,t}^t + k_i + v_{i,t}^{2SLS}, \tag{3.22}$$

where $u_{i,t}$ is the share of the urban population at time t in country i, $C_{i,t}^p$ is the variable capturing rainfall variation at time t in country i, $C_{i,t}^t$ is the variable capturing temperature variation at time t in country i, k_i is a country fixed effect, and $v_{i,t}^{2SLS}$ is the error term.[30] In line with the linear regression analysis, two variations of the estimation of the second stage are analyzed. The second stage for the simplest version is given by:

$$H_{i,t} = \beta_0^{2SLS.A} + \beta_1^{2SLS.A} \hat{u}_{i,t} + \beta_2^{2SLS.A} \ln(y_{i,t}^c) + \beta_3^{2SLS.A} pop_{i,t}^a + k_i + e_{i,t}^{2SLS.A}, \tag{3.23}$$

where $H_{i,t}$ is the share of highly educated individuals (i.e., the stocks of individuals with completed tertiary education five years after time t) in country i, $\ln(y_{i,t}^c)$ is the logarithm of the GDP per capita at time t, $pop_{i,t}^a$ is the share of individuals older than 15 years at time t, k_i is a country fixed effect, and $e_{i,t}^{2SLS.A}$ is the error term.

[30] Two instrumental variables are used jointly in the first stage regression to test the validity of the instrumental variables used in the Two-Stage least squares regression analysis. This differs slightly from the expression of the theoretical model. Using only one of the instruments at a time gives very similar and significant results as shown by unreported results.

In addition, a dynamic specification of the second stage is analyzed. This is given by:

$$\ln\left(\frac{H_{i,t}}{H_{i,t-1}}\right) = \beta_0^{2SLS.B} + \beta_1^{2SLS.B}\hat{u}_{i,t} + \beta_2^{2SLS.B}\ln\left(H_{i,t-1}\right) \quad (3.24)$$

$$+ \beta_3^{2SLS.B}\ln(y_{i,t}^c) + \beta_4^{2SLS.B}pop_{i,t}^a + k_i + e_{i,t}^{2SLS.B}, \quad (3.25)$$

where $H_{i,t}$ is the share of individuals with completed tertiary education five years after time t in country i, $H_{i,t-1}$ is the share of individuals with completed tertiary education at time t in country i, $\ln(y_{i,t}^c)$ is the logarithm of the GDP per capita at time t, $pop_{i,t}^a$ is the share of individuals older than 15 years at time t, k_i is a country fixed effect, and $e_{i,t}^{2SLS.B}$ is the error term.

Table 3.7 depicts the coefficients for the first stage of the Two-Stage least squares country fixed effects estimation. Negative rainfall and positive temperature deviations have a positive effect on urbanization rates as depicted in column (1). Similarly, column (2) shows that negative rainfall and positive temperature anomalies have a positive effect on urbanization rates. Finally, column (3) indicates that a higher number of years with positive rainfall and temperature shocks is associated with a lower urbanization rate. This means the coefficients have the expected signs. All results are significant at the one percent level.

Table 3.7: 2SLS fixed effects regression - first stage

	(1)	(2)	(3)
VARIABLES	Urban population		
Pre. Deviation	-0.320***		
	(0.0659)		
Tem. Deviation	12.98***		
	(1.184)		
Pre. Anomaly		-4.486***	
		(0.801)	
Tem. Anomaly		4.112***	
		(0.470)	
Non-linear Pre.			-1.868***
			(0.312)
Non-linear Tem.			-1.922***
			(0.213)
Constant	27.24***	27.61***	27.61***
	(0.455)	(0.462)	(0.457)
Observations	335	335	335
Number of Countries	37	37	37
R-squared	0.384	0.349	0.359

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the results for the first stage of the Two-Stage least squares country fixed effects estimation. The independent variables include the deviation in precipitation and temperature ($Dev_{i,t}(Pre)$ and $Dev_{i,t}(Tem)$), the precipitation and temperature anomalies ($Ano_{i,t}(Pre)$ and $Ano_{i,t}(Tem)$), and the non-linear measure of precipitation and temperature ($Nlin_{i,t}(Pre)$ and $Nlin_{i,t}(Tem)$). Country fixed effects are not depicted. The dependent variable is the share of individuals living in urban areas in period t. Shares are measured in percentage.

Table 3.8 depicts the results for the second stage regression. The left panel of the table reports the result for the simple specification, while the right panel provides the results for the dynamic specification. Column (1) and (4) depict the results if rainfall and temperature deviations are used in the first stage. Column (2) and (5) show the equivalent results for rainfall and temperature anomalies. Finally, column (3) and (6) depict the results if the non-linear measures of rainfall and temperature are used in the first stage. The coefficients have the expected signs and are significant at the one percent level. Furthermore, the reported F statistics are high and above ten in all cases. This indicates that the instrumental variables are not weak. Moreover, for the simple specification the instrumental variables seem not to be orthogonal to the error term in the second stage. The reported Sargan p-values are high, so that the null hypothesis that the instrumental variables are uncorrelated with the error term in the second stage cannot be rejected at the one percent level. This indicates statistical validity of the instrumental variables when the specification most closely related to the theoretical model is considered. For the dynamic specification the Sargan p-values are lower and only close to 0.2 when the non-linear measures of precipitation and temperature are included in the first stage regression.

Table 3.8: 2SLS fixed effects regression - second stage

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Tertiary completed (5 years later)			Change in tertiary completed (in 5 years)		
	(*Dev*)	(*Ano*)	(*Nlin*)	(*Dev*)	(*Ano*)	(*Nlin*)
Urban population	0.117***	0.118***	0.122***	0.0482***	0.0511***	0.0444***
	(0.0123)	(0.0126)	(0.0126)	(0.0140)	(0.0170)	(0.0154)
ln(GDP per capita)	-0.0433	-0.0519	-0.0898	-0.0905	-0.102	-0.0752
	(0.243)	(0.245)	(0.244)	(0.103)	(0.111)	(0.105)
Adult population	0.1948***	0.1947***	0.1940***	-0.0067	-0.0068	-0.0065
	(0.0253)	(0.0253)	(0.0253)	(0.0100)	(0.0101)	(0.0098)
ln(tertiary completed)				-0.539***	-0.562***	-0.510***
				(0.111)	(0.134)	(0.121)
Observations	335	335	335	331	331	331
R-squared	0.552	0.552	0.552	-0.050	-0.086	-0.008
Number of Countries	37	37	37	37	37	37
Craig-Donald Wald F statistic	94.26	86.7	88.35	17.68	11.91	13.66
Sargan p-value	0.935	0.52	0.849	0.04	0.046	0.185

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the results for the second stage of the Two-Stage least squares country fixed effects estimation. The dependent variable in columns (1)-(3) is the share of individuals with completed tertiary education five years after period t. The dependent variable in columns (4)-(6) is the logarithm of the share of individuals with completed tertiary education five years after period t divided by the share of individuals with completed tertiary education in period t. Temperature and precipitation deviations (Dev), anomalies (Ano), and non-linear measures of temperature and rainfall ($Nlin$) are used as variables in the first stage. The control variables include the logarithm of the GDP per capita (ln(GDP per capita)), the share of the population older than 15 years (adult population), and the logarithm of the share of individuals with completed tertiary education in period t (ln(tertiary completed)). Country fixed effects are not depicted. Shares are measured in percentage.

In addition to the results of the linear estimation, the results obtained by estimating the structural form of the model confirm the predictions of the theoretical framework.

These results show that climatic variations affect the level of internal migration, as measured by the share of people living in urban areas. Increased urbanization in turn impacts on the proportion of highly educated workers within each country.

3.4 Conclusion

This chapter investigates the link between tertiary educational attainment and variation of climate variables in Africa. Recent analyses of this connection do not provide long-run conclusions at the macro-level. Numerous contributions to the literature find that adverse weather changes have a negative impact on production, particularly in the agricultural sector. Moreover, several studies show that the agricultural sector seems to be unable to adjust to these changes which potentially induces more people to leave rural areas. This chapter incorporates these findings in a theoretical model. This model predicts that unfavorable weather changes in the past generate higher shares of individuals moving from rural to urban regions. This will increase the future share of individuals investing in high-skilled education, because the access and returns to education are higher in urban regions. In this light, the model addresses the capacities of economies to adapt to weather changes via increasing their share of highly educated workers.

The empirical section of the chapter validates the key predictions of the model. By drawing on a panel data set for 37 African countries and a cross-sectional data set for 111 African provinces, the empirical analysis confirms that there is a positive correlation between adverse weather changes and future shares of tertiary educated individuals. In addition, a Two-Stage least squares regression analysis indicates that the correlation between urbanization and future tertiary educational attainment results from the impact of rainfall or temperature changes. The conclusion that climate change might have beneficial effects on high-skilled human capital accumulation may be somewhat unexpected. Nevertheless, this shows that climate change potentially affects economies through multiple and complex channels and that the overall effects of weather changes are not always purely one-directional. These findings further underline the importance of policies targeting education quality and sustainable urban development as advocated by the findings of the previous chapters. If there are indeed some beneficial effects of weather changes on human capital accumulation, it is vital to harness these potentially beneficial effects by ensuring that effective policy environments exist.

3.A Appendix

3.A.1 African countries and provinces

Table 3.A1: African countries in the panel data set

Algeria (DZA), Benin (BEN), Botswana (BWA), Burundi (BDI), Cameroon (CMR), Central African Republic (CAF), Congo (COG), Cote d'Ivoire (CIV), Democratic Republic of the Congo (COD), Egypt (EGY), Gabon (GAB), The Gambia (GMB), Ghana (GHA), Kenya (KEN), Lesotho (LSO), Liberia (LBR), Libya (LBY), Malawi (MWI), Mali (MLI), Mauritania (MRT), Mauritius (MUS), Morocco (MAR), Mozambique (MOZ), Namibia (NAM), Niger (NER), Rwanda (RWA), Senegal (SEN), Sierra Leone (SLE), South Africa (ZAF), Sudan (SDN), Swaziland (SWZ), Tanzania (TZA), Togo (TGO), Tunisia (TUN), Uganda (UGA), Zambia (ZMB), Zimbabwe (ZWE)

Table 3.A2: African countries and provinces in the cross-sectional data set

Benin (BEN): Atacora and Donga, Mono and Couffo, Borgou and Alibori, Zou and Collins, Atlantique and Littoral, Oueme and Plateau
Botswana (BWA): North-East, Kgatleng, South-East, Ghanzi, Ngamiland-old, Central, Kweneng
Burkina Faso (BFA): Nord, Centre Nord, Centre Sud, Centre Est, Centre, Sud-Ouest, Hauts Bassins
Cameroon (CMR): Nord-Ouest, Est, Ouest, Centre Sud, Nord and Adamoua and Extreme Nord, Sud-Ouest, Littoral
Central African Republic (CAF): Ouaka, Basse-Kotto, Ombella-M'Poko and Bangui
Chad (TCD): Tandjile, Lac, Mayo-Kebbi, West Logone (Occidental), East Logone (Oriental), Kanem and Bahr el Gazal, Guera, Chari-Baguirmi and N'Djamena and Hadjer Lamis
Ghana (GHA): Eastern, Ashanti, Northern, Volta, Brong Ahafo, Greater Accra, Western
Kenya (KEN): Eastern, North Eastern, Rift Valley, Central, Nyanza, Nairobi, Western, Coast
Lesotho (LSO): Maseru, Quthing, Mohale's Hoek, Leribe, Mafeteng, Berea
Mali (MLI): Koulikoro, Segou, Kayes, Bamako, Gao and Kidal, Sikasso
Mozambique (MOZ): Niassa, Cabo Delgado, Province of Maputo, Sofala
Niger (NER): Agadez, Zinder, Diffa, Niamey/Tillaberi, Maradi
Senegal (SEN): Fleuve/Saint-Louis and Matam, Sine-Saloum (Fatick and Kaolack and Kaffrine), Cap-Vert/Dakar, Thies, Louga, Casamance (Kolda and Ziguinchor and Sedhiou), Senegal Oriental/Tambacounda and Kedougou, Diourbel
Sierra Leone (SLE): Western, Northern, Southern, Eastern
Tanzania (TZA): Mbeya, Mwanza, Mara, Tabora, Kigoma, Morogoro, Kagera, Dar es Salaam, Iringa, Kilimanjaro, Shinyanga, Ruvuma
Zambia (ZMB): Western, Central and Lusaka, Southern, Eastern, Copperbelt, Northern, North-Western
Zimbabwe (ZWE): Mashonaland East, Mashonaland West, Mashonaland Central, Matabeleland South, Matabeleland North, Midlands

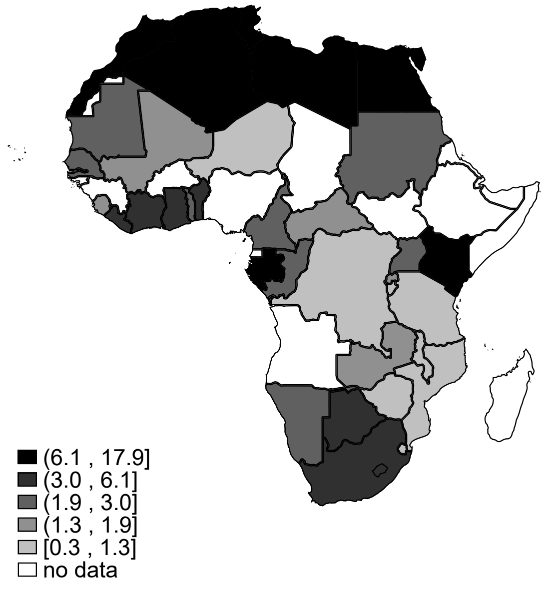


Figure 3.A1: Share of college educated individuals in 2010 in African countries

Notes: This figure reports the percentage share of college educated individuals for the year 2010 in African countries in the panel data set. Countries are grouped into five bins, each bin representing a quintile of the distribution of tertiary educated individuals.

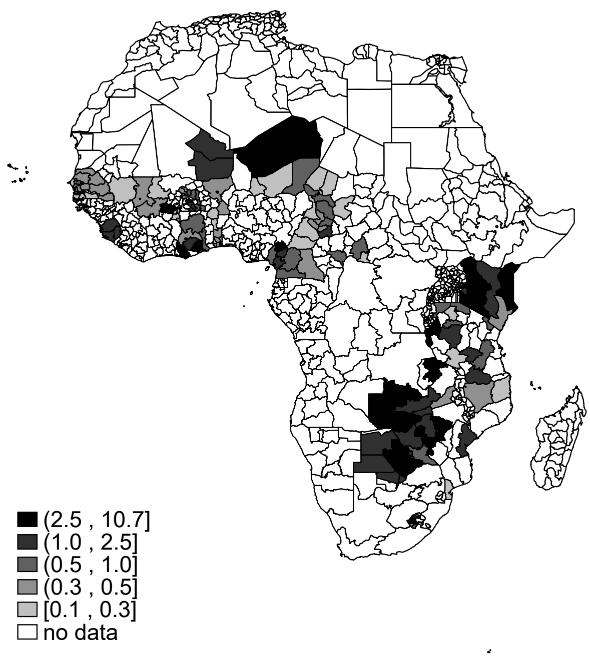
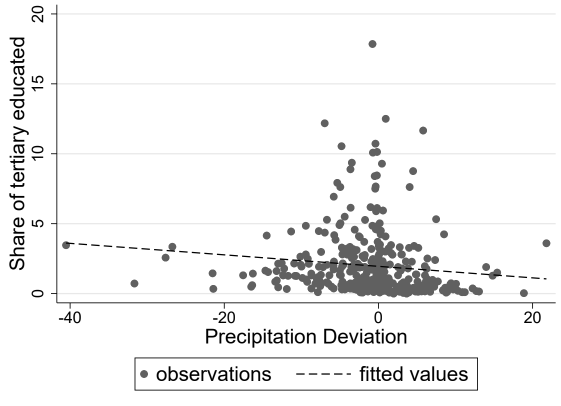


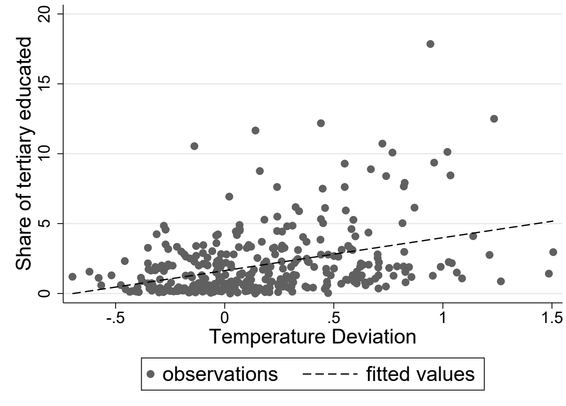
Figure 3.A2: Share of college educated individuals in African provinces

Notes: This figure reports the percentage share of college educated individuals for the provinces in Africa in the cross-sectional data set. Provinces are grouped into five bins, each bin representing a quintile of the distribution of tertiary educated individuals.

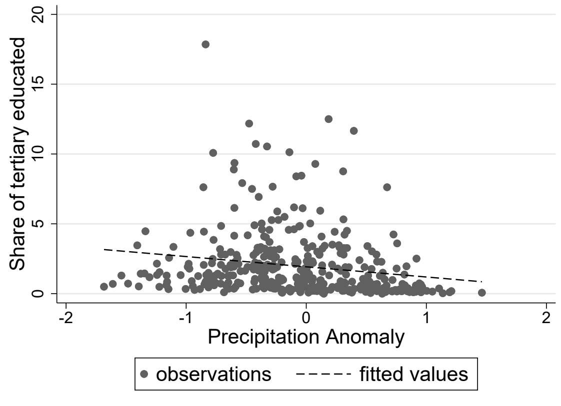
3.A.2 Correlation between climate variables and human capital accumulation



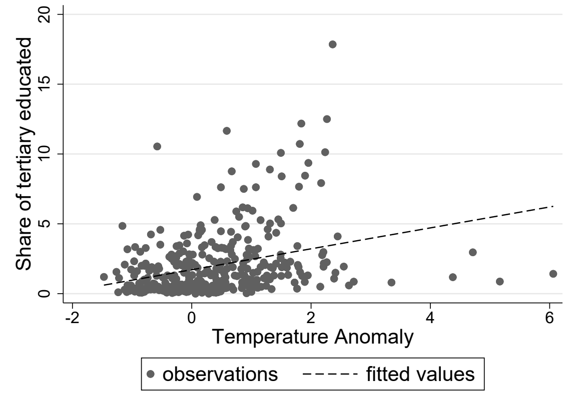
(a) Precipitation Deviation



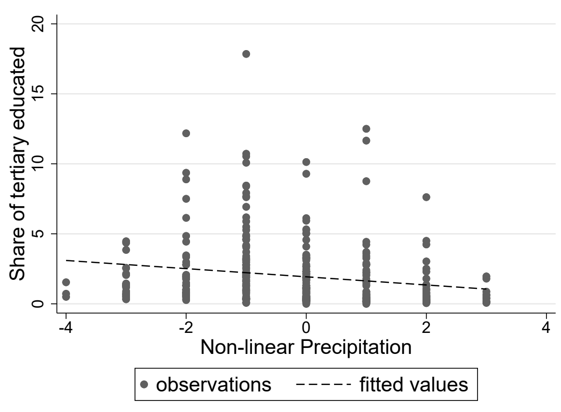
(b) Temperature Deviation



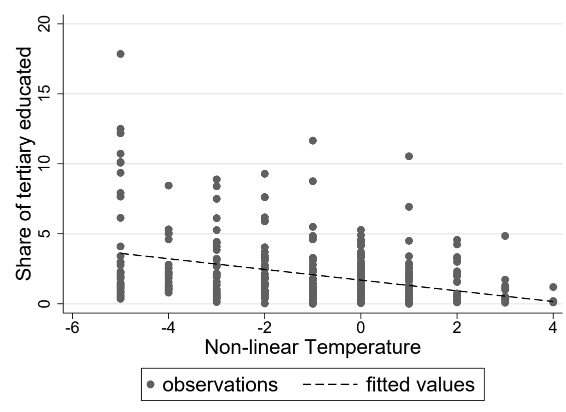
(c) Precipitation Anomaly



(d) Temperature Anomaly



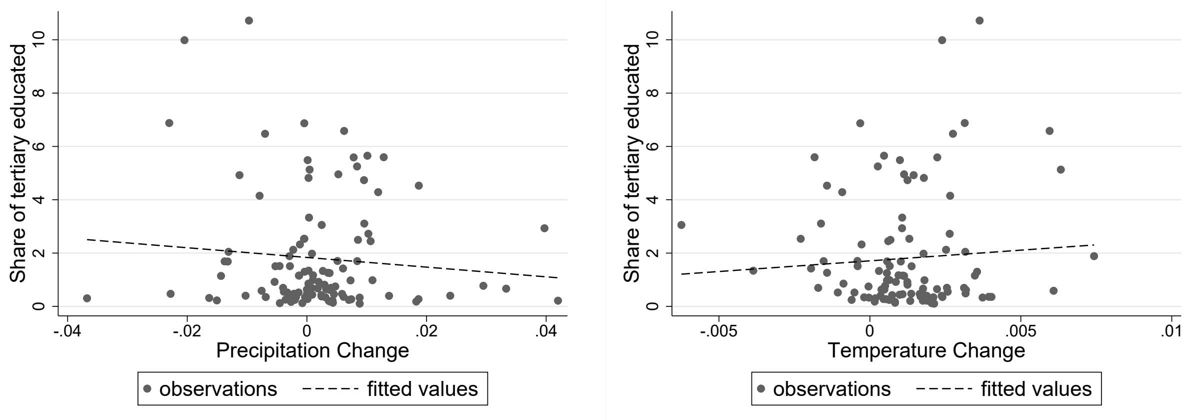
(e) Non-linear Precipitation



(f) Non-linear Temperature

Figure 3.A3: Pooled panel data

Notes: This figure reports the correlation between the country-specific precipitation and temperature variables and the country-specific percentage shares of individuals with completed tertiary education five years later. Observations are pooled.



(a) Precipitation Change (b) Temperature Change

Figure 3.A4: Cross-sectional data

Notes: This figure reports the correlation between the province-specific precipitation and temperature changes and the province-specific percentage shares of individuals with completed tertiary education several years later.

Chapter 4

Migration and human capital inequality: a dyadic approach

Abstract[1]

This chapter revisits the implications of (selective) international migration for upper-tail human capital accumulation and inequality. After reviewing and updating the existing literature, we propose a new approach that establishes the micro-foundations of the relationship between higher education and migration decisions in a dyadic context. We parameterize our model for 174 countries and for the year 2010. Contrary to the standard approach, this allows us to investigate the country-specific effects of international migration on higher education decisions, on human capital accumulation, and on the effectiveness of public education policies. Human capital responses to skilled emigration vary with the characteristics of origin and destination countries, as well as with low-skilled emigration prospects/rates. On average, the net effect on human capital accumulation is small in low-income and middle-income countries. There are a few exceptions to this rule. As opposed to earlier findings, we show that a net brain gain emerges in some small, poor countries, while a net brain loss is observed in countries where emigrants are negatively selected. We also demonstrate that international migration hardly affects the effectiveness of public education policies in developing countries. Overall, our results suggest that international migration has a limited impact on the world distribution of human capital. The responses are even smaller when general equilibrium effects are accounted for.

Keywords: upper-tail human capital, migration, selection, brain drain/gain, education policy, human capital inequality

JEL codes: E24, J24, O15

4.1 Introduction

Human capital is usually perceived as a proximate cause of development (Glaeser et al., 2004; Acemoglu et al., 2014; Jones, 2014). Although there are different ways to measure it (literacy rates, mean years of schooling, or population shares by educational attain-

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ment), recent contributions in the growth literature show, in line with the findings of the previous chapters, that the role of workers with completed tertiary/college education is key for development. These highly educated workers exhibit the greatest levels of productivity, generate positive labor market complementarities with the less educated, and are instrumental to facilitating innovation and technology diffusion when knowledge becomes economically useful. This was the case during the Industrial Revolution (Mokyr, 2005; Squicciarini and Voigtländer, 2015) and it is still relevant in the modern world (Castelló-Climent and Mukhopadhyay, 2013; Jones, 2014; Kerr et al., 2016). The size of the college-educated labor force is endogenous as higher education investments are costly, returns to schooling are endogenous, and college-educated workers are highly mobile across nations. Over the last 25 years, education policies have led to an absolute convergence in the share of college graduates between countries. However, cross-country disparities remain significant and it is imperative to understand the factors that affect upper-tail human capital accumulation, in particular in the context of developing countries. This chapter focuses on the role of (skill-biased) international migration flows to OECD countries and contributes to the growing literature on skilled emigration and human capital formation.

We provide an update of the macroeconometric findings on skilled emigration and human capital formation, and a generalization of the theoretical framework that relates human capital disparities to higher education and migration decisions. In particular, we propose a new dyadic approach that establishes the micro-foundations of these relationships. Compared to the existing literature, this is the substantial novelty of this chapter. The standard macroeconometric approach of Beine et al. (2008, 2010) relies on a simple human capital accumulation technology that endogenizes the share of college-educated natives at time $t+1$ ($H_{i,t+1}$) as a function of its lags ($H_{i,t}$), of the lagged high-skilled emigration rate ($m_{i,h,t}$), and of a set of additional control variables ($A_{i,t}$). The empirical specification boils down to a Cobb-Douglas training technology, $H_{i,t+1} = A_{i,t}H_{i,t}^{\phi}m_{i,h,t}^{\alpha}$, which suffers from three main limitations. It is incompatible with a closed economy context; it disregards the role played by low-skilled emigration; and it assumes that the elasticity of education to emigration prospects (α) is common to all countries. The latter is independent of the size of emigration and of the characteristics of the origin and destination countries. On the contrary, our dyadic framework is compatible with all levels of openness (including the total absence of openness) and fully accounts for the characteristics of each origin country and of all its potential destinations. The dyadic model can be parameterized to match 2010 migration and education data for 174 countries, as well as the average education responses identified in the standard macroeconometric literature. This new model enables to produce migration backcasts by education level, to identify the country-specific effects of international migration on higher education decisions and on human capital accumulation, and to gain an understanding of the factors governing the effectiveness of education policies.

Our quantitative analysis reveals that high-skilled emigration rates to OECD countries decreased between 1990 and 2010, a phenomenon that is due to the progress in education and to human capital convergence across countries. Indeed, in line with Docquier et al. (2007), we find that changes in education among natives generate a less than proportional change in the education level of emigrants. Using new data for 2010, we follow the standard macroeconometric literature and confirm the existence of a positive and significant relationship between skilled emigration prospects and higher education decisions. However, compared to existing studies (which use data for 1990 and 2000 only), the elasticity is sensitive to the choice of human capital indicators. When the effect is significant, the updated short-run elasticity is greater, while the long-run elasticity is slightly smaller. The standard model predicts that low levels of high-skilled emigration generate large education (or brain gain) responses, that high levels of emigration generate large human capital losses, and that the maximal brain gain response is obtained when the skilled emigration rate is around 14%.

We then use our dyadic approach to refine and generalize these results. After showing that our dyadic model replicates the historical migration trends of the last 20 years well, we use it to predict country-specific responses to skilled emigration. In the vast majority of cases (90% of the sample), we find that emigration prospects stimulate the expected returns to schooling and natives' investments in higher education. Then, we identify the net effect of emigration on human capital accumulation. A net brain gain emerges in 90 countries, while a brain loss emerges in the remaining 84 countries. Contrary to the standard approach, we find that the net effect need not be positive at low levels of emigration, and need not be negative at high levels of emigration. The size of the net effect varies with the characteristics of origin and destination countries, as well as with low-skilled emigration prospects/rates. On average, the net effect is small in low-income and middle-income countries. There are a few exceptions to this rule. Contrary to the standard approach, a net brain gain emerges in some small, poor countries, while a net brain loss is observed in countries where emigrants are negatively selected. We also demonstrate that international migration has little effect on the effectiveness of public education policies. Larger effects are obtained for the richest countries; selective emigration reduces their stock of human capital and the effectiveness of education policies. Nonetheless, our results suggest that international migration to OECD countries has a limited impact on the world distribution of human capital.

The rest of this chapter is organized as follows. Section 4.2 summarizes the existing empirical cross-country literature and the standard approach, and updates the findings of the literature. Section 4.3 establishes the micro-foundations of the relationship between education decisions and international migration in a dyadic context. This section presents the predictions of the dyadic model and discusses its policy implications. Finally, Section 4.4 concludes.

4.2 Standard macroeconometric approach: literature and updates

Existing studies suggest that the effect of international migration on human capital disparities is ambiguous. *On the one hand*, two salient features of international labor mobility are that well-educated people exhibit a much greater propensity to emigrate than the less educated, and tend to agglomerate in countries/regions with high rewards to skill (Grogger and Hanson, 2011; Belot and Hatton, 2012; Docquier and Rapoport, 2012; Kerr et al., 2016). Positive selection is due to migrants' self-selection (high-skilled people are more responsive to economic opportunities and political conditions abroad, have more transferable skills and a greater ability to gather information, or finance emigration costs, etc.), and to the skill-selective immigration policies implemented in the major destination countries (Docquier et al., 2009). Some of the early contributions to this literature emphasize the worldwide inegalitarian effects induced by positive selection (e.g., Bhagwati and Hamada, 1974; Miyagiwa, 1991; Haque and Kim, 1995; Wong and Yip, 1999).

On the other hand, skill-biased emigration prospects impact on the expected return to investments in human capital. Starting with Mountford (1997), Stark et al. (1997), Vidal (1998), and Beine et al. (2001), the link between skill-biased emigration rates and pre-migration human capital formation has been theoretically investigated in a two-country setting with a (poor) origin country and a (rich) destination country. Emigration prospects are shown to raise the expected return to human capital, thus leading more people to invest (or people to invest more) in education at home before deciding whether to emigrate or not.

A growing strand of literature shows empirically that incentives for human capital accumulation in developing countries are based to a significant extent on migration opportunities. Micro-level evidence of a positive impact of emigration on the *net* stock of human capital in the source country has been provided in many studies. They include Chand and Clemens (2008) on Fiji, Gibson and McKenzie (2011) on Tonga and Papua New Guinea, Batista et al. (2012) on Cape Verde, Shrestha (2017) on Nepal, and Theoharides (2017) on the Philippines. To identify causation, these studies exploit survey data on education choices and migration intentions, micro data on education and exposition to migration by region, or quasi-natural experimental methods.

Macro-level evidence of the same relationship can be found in the literature. Using 1990 emigration data for 127 developing countries, Beine et al. (2008) estimate that a doubling of a country's emigration rate of highly-skilled workers is associated with a 20% increase in the long-run stock of human capital possessed by its nationals (including emigrants), and with a 5% increase in the short run (in the 1990-2000 decade). Their findings suggest that under certain conditions the stimulus to skill formation may be strong enough to bring the economy's stock of human capital to a higher level in the post-migration equilibrium. Beine et al. (2010) find that the brain gain mechanism holds when using alternative brain drain measures controlling for whether migrants acquired their skills in the home or host country, or when using alternative specifications and/or indicators of human capital formation. Beine et al. (2011) confirm these effects in a panel setting covering 147 origin countries and 6 destinations during the period 1975-2000.

In this section, we use new and updated databases described in detail in Appendix 4.A.1 to examine empirically whether the conclusions of Beine et al. (2008) also apply to the period 2000-2010.[2] We follow the β-convergence empirical specification of Beine et al. (2008). The regression model is written:

$$\ln\left(\frac{H_{i,t+1}}{H_{i,t}}\right) = \alpha_0 + \alpha_1 \ln(H_{i,t}) + \alpha_2 \ln(m_{i,h,t}) + \beta X_{i,t} + \epsilon_{i,t}, \tag{4.1}$$

where $\ln(H_{i,t+1}/H_{i,t})$ is the log change in the proportion of college graduates in the native labor force of country i between t and $t+1$, $\ln(H_{i,t})$ is the log of the initial level, $\ln(m_{i,h,t})$ is the log of the skilled emigration rate at the beginning of period t, $X_{i,t}$ is a vector of additional control variables used in Beine et al. (2008) - this includes population density ($DENS_{i,t}$), a dummy for sub-Saharan African countries ($SSAD_i$) and for Latin American countries ($LATD_i$) - and $\epsilon_{i,t}$ is the error term.

As stated in the introduction, this β-convergence specification boils down to a Cobb-Douglas relationship between human capital and emigration: $H_{i,t+1} = A_{i,t}H_{i,t}^{1+\alpha_1}m_{i,h,t}^{\alpha_2}$ where $A_{i,t} = \exp(\alpha_0 + \beta X_{i,t})$. The short-run elasticity of human capital to emigration

[2] Appendix 4.A.1 discusses migration trends by education level. Comprehensive tables are provided in Appendix 4.A.3.

equals α_2. If $-1 < \alpha_1 < 0$, the model is stable, and the human capital stock converges towards $H_i = A_i^{-1/\alpha_1} m_{i,h}^{-\alpha_2/\alpha_1}$, so that the long-run elasticity of human capital to emigration equals $-\alpha_2/\alpha_1$.

This β-convergence specification suffers from three main limitations. Firstly, it is incompatible with a closed economy context ($H_{i,t+1} = 0$ if $m_{i,h,t} = 0$). Secondly, it disregards the role played by low-skilled emigration.[3] Thirdly, it assumes a constant elasticity of education to emigration prospects (α_2). The latter is independent of the size of emigration and of the characteristics of the origin and destination countries. Nevertheless, this specification has been used to empirically explore the link between skilled emigration prospects and higher education decisions.

Our empirical results are provided in Table 4.1. The results reported in column (1) are based on the same data set, the same specification and the same sample as in Beine et al. (2010). For the sake of comparability with other regressions, we exclude remittances from the set of control variables.[4] Nevertheless, the results obtained in column (1) are very similar to those described in Beine et al. (2010). There are two main parameters of interest. Firstly, we are interested in the short-run impact of emigration prospects on human capital formation. This is captured by the coefficient on the log of the high-skilled emigration rate (α_2). This coefficient is given in the first row of the table. Secondly, we are also interested in the long-run effect of skilled emigration, which can be obtained by dividing the short-run coefficient (α_2) by the convergence coefficient ($-\alpha_1$). The latter captures the inertia in human capital responses to emigration. The long-run effect is reported in the bottom of the table (Long Run). Column (1) gives a short-run elasticity of 0.045 and a long-run elasticity of 0.209. This evidences a positive association between the high-skilled emigration rate in 1990 and the change in human capital between 1990 and 2000. Since Beine et al. (2010) find rather robust results (by age of entry and across specifications), we consider these results as our reference levels, and compare them with those obtained when conducting the regression for different data sources and periods.

Column (2) presents the results of the regression for the same period as in column (1), but uses the revised version of the migration database described in *ADOP*. The effect of emigration remains significant albeit smaller in size. With respect to our first parameter of interest, the coefficient on the share of high-skilled migrants is significant at the 5% level. The short-run elasticity amounts to 0.024, while the long-run elasticity is similar to that of column (1) (we obtain a value of 0.173 as compared to 0.209 in column (1)). The human capital data used in columns (1) and (2) combine census data available in *ADOP*, data from Barro and Lee's database (Barro and Lee, 2013), and data from Cohen and Soto (2007). When restricting the sample to countries available in Barro and Lee (2013), we lose about 25 observations. Conducting the regression on 96 countries changes the significance of coefficients, as shown in column (3). The short-run and long-run effects have the same magnitude as in column (1) but become insignificant. In addition, we can also use human capital proxies from the more recent database of the *Wittgenstein Centre*. Column (4) presents the results for the analysis using this data set for the years 1990 to 2000. The short-run elasticity becomes negative and insignificant. This demonstrates that the education response to emigration prospects is sensitive to the choice of the database used to proxy the proportion of college graduates in the resident population.

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[3]Beine et al. (2010) consider a specification with the ratio of emigration rates ($m_{i,h,t}/m_{i,l,t}$) but find less significant results. They also consider a specification with $1 + m_{i,h,t}$, which is compatible with a no-migration situation.

[4]This increases the number of countries included in the sample from 103 to 123.

In column (5) and (6), we turn our attention to the period 2000-2010. Column (5) uses the 96 countries available in the data set of Barro and Lee (2013), while column (6) uses the data set of the *Wittgenstein Centre*. In line with previous results, the effect obtained in column (5) is insignificant.[5] On the contrary, a positive and significant effect is found in column (6). Compared to the previous period, the short-run elasticity is greater (0.099) but the long-run effect does not change (0.173).

Finally, columns (7) and (8) provide the results obtained when pooling both decades, and when using human capital proxies from Barro and Lee (2013) or from the *Wittgenstein Centre*, respectively. Column (7) shows that the coefficient for the short-run impact is not significant, albeit positive when using Barro and Lee (2013). The short-run elasticity is positive (0.0977) and highly significant when using the *Wittgenstein Centre* data. The corresponding long-run effect amounts to 0.165, which is very similar to the values obtained in columns (2) and (6).

Overall, our estimates suggest that the long-run elasticity of ex-ante human capital to high-skilled emigration is around 0.165 (and the short-run elasticity is around 0.098). Figure 4.1 illustrates the effect of skilled emigration on the share of college graduates in the resident labor force. We denote this share by h. Our numerical example assumes an economy where the low-skilled emigration rate is nil, and where $H \simeq h = 0.05$ if the high-skilled emigration rate is close to zero. In the absence of low-skilled migration, we have $h = \frac{(1-m_h)H}{1-m_h H}$. Figure 4.1 reports the *predicted relative deviation from the closed economy*, $\Delta h/h$, when the high-skilled emigration rate (m_h) varies between 0 and 1. Figure 4.1a shows the effect obtained using the estimates from Beine et al. (2008). In the short-run, high-skilled emigration increases human capital if the brain drain is below 14%; the cost of the brain drain is exponential for larger emigration rates. In the long-run, the brain drain is beneficial if the high-skilled emigration rate is below 62%. Figure 4.1b is based on the pooled 1990-2010 estimates. The short-run effect is more beneficial (a brain gain emerges when emigration rates are below 33%), but the long-run effect is smaller (a brain gain emerges when emigration rates are below 54%). The maximal brain gain response is obtained when the brain drain equals 14%. High-skilled emigration leads to a share of college graduates of 7.4% (i.e., +2.4 percentage points compared to the closed economy). We show below that our dyadic approach allows refining and generalizing these results.

4.3 New dyadic approach

In this section, we establish the micro-foundation for the link between emigration rates and human capital formation in a multi-destination or dyadic framework. We begin by outlining the theoretical model in Section 4.3.1. Once calibrated, the dyadic model can be used to quantify the effect of immigration and education policies on human capital formation and global inequality, and to backcast the skill structure of international migration. We produce three sets of results in a partial equilibrium context with exogenous wages. Firstly, in Section 4.3.2, we assess the predictive power of the model by comparing emigration backcasts and data by education level for the years 1990 and 2000. Then, in Section 4.3.3, we calibrate the training technology of the dyadic model and quantify the country-specific effects of migration on human capital accumulation. Section 4.3.4 investigates the effect of migration prospects and realizations on the effectiveness of education

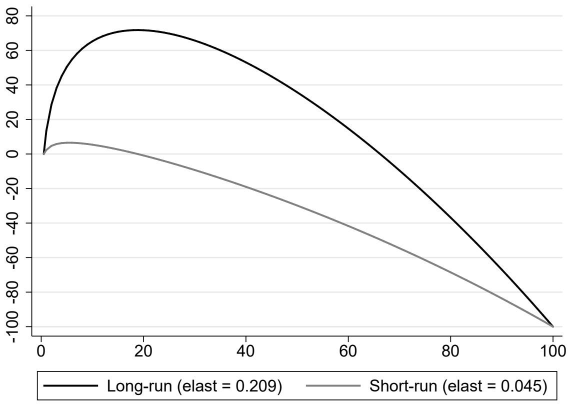
[5] In Barro and Lee (2013), the growth rate in human capital between 1990-2000 is uncorrelated to that observed between 2000 and 2010.

Table 4.1: Standard approach - updated estimation results

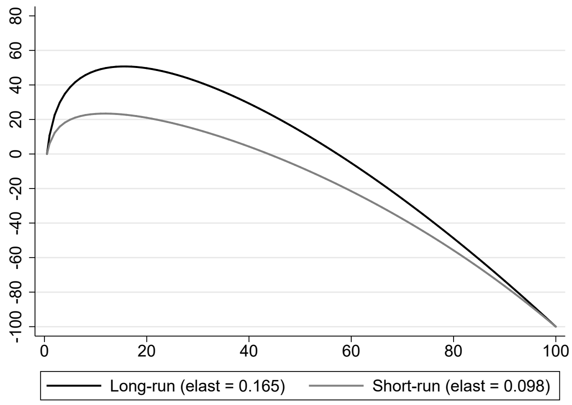
	(1) 1990-2000	(2) 1990-2000	(3) 1990-2000	(4) 1990-2000	(5) 2000-2010	(6) 2000-2010	(7) 1990-2010	(8) 1990-2010
$\ln(m_{i,h,t})$	0.0454**	0.0244**	0.0400	-0.0141	-0.00438	0.0993***	0.0181	0.0977***
	(0.0221)	(0.0109)	(0.0513)	(0.0453)	(0.0317)	(0.0347)	(0.0307)	(0.0321)
$\ln(H_{i,t})$	-0.217***	-0.141***	-0.188***	-0.169**	-0.0929**	-0.573***	-0.157***	-0.591***
	(0.0349)	(0.0250)	(0.0504)	(0.0745)	(0.0425)	(0.0583)	(0.0326)	(0.0454)
$SSAD_i$	-0.336***	-0.182***	-0.168*	-0.164	-0.0786	-0.816***	-0.142*	-0.747***
	(0.0930)	(0.0521)	(0.0986)	(0.148)	(0.107)	(0.136)	(0.0730)	(0.117)
$LATD_i$	-0.0628	0.00727	-0.0786	-0.179	-0.139*	-0.0295	-0.104*	-0.0109
	(0.0549)	(0.0386)	(0.0836)	(0.124)	(0.0810)	(0.102)	(0.0605)	(0.0984)
$DENS_{i,t}$	-0.000154	2.92e-05	-0.000636	-0.000102	-3.43e-05	-5.22e-05	-0.000317*	-0.000227
	(0.0001)	(8.7e-05)	(0.0004)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0332	-0.00635	-0.196	0.380	-0.119	-1.058***	-0.204	-0.833***
	(0.0901)	(0.0855)	(0.241)	(0.278)	(0.130)	(0.159)	(0.126)	(0.170)
Long Run	0.209	0.173	ins.	ins.	ins.	0.173	ins.	0.165
Obs.	123	120	96	120	96	120	192	240
R-sq.	0.380	0.306	0.231	0.111	0.128	0.566	0.179	0.458

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports updated estimation results for the standard macroeconometric approach. The independent variables include the logarithm of the skilled emigration rate at the beginning of period t ($\ln(m_{i,h,t})$) and the logarithm of the initial proportion of college graduates in the native labor force ($\ln(H_{i,t})$). The control variables include the population density ($DENS_{i,t}$), a dummy for sub-Saharan African countries ($SSAD_i$) and for Latin American countries ($LATD_i$). The dependent variable is the logarithm change in the proportion of college graduates in the native labor force between period t and $t+1$ ($\ln(H_{i,t+1}/H_{i,t})$).



(a) Specification of Beine et al. (2008)



(b) Pooled estimates 1990-2010

Figure 4.1: Effect of brain drain on human capital
(Relative deviation from the closed economy = $(h - h^{NM})/h^{NM}$)

Notes: This numerical example assumes an economy where $H \simeq h = 0.05$ if $m_h \rightarrow 0$, and where the low-skilled emigration rate is nil.

policies. Finally, we illustrate the implications of a general equilibrium extension with endogenous wages in Section 4.3.5.

4.3.1 Theory

We depict a world-economy model with J countries. We consider an origin country i with a working-age native population denoted by N_i. We divide the population into two skill groups $s = (h, l)$, with $s = h$ for college graduates and $s = l$ for the less educated, and we denote by $N_{i,s}$ the endogenous size of the type-s native population. Hence, the fraction of college graduates in the native population is written:

$$H_i \equiv \frac{N_{i,h}}{N_{i,l} + N_{i,h}}. \tag{4.2}$$

Individuals have the choice between staying in their home country or emigrating to a foreign country $j \in J$. We denote by $N_{ij,s}$ the number of type-s individuals deciding to move from i to j. Hence, the skill-specific emigration rate is given by:

$$m_{i,s} \equiv \frac{\sum_{j \neq i} N_{ij,s}}{N_{i,s}}. \tag{4.3}$$

Our multi-country model jointly endogenizes H_i and $m_{i,s}$, and extracts some static comparative properties. To do so, we model migration and education choices as outcomes of a random utility model (RUM). The RUM is becoming the consensus tool to model dyadic migration decisions. The standard RUM assumes that the utility of a type-s individual λ born in country i and moving to a destination country j is made of a deterministic component that accounts for the average income at destination ($w_{j,s} \in \Re^+$) and the average level of moving costs ($c_{ij,s} < 1$), and of a random component ($\varepsilon^{\lambda}_{ij,s} \in \Re$) that captures heterogeneity between individuals (i.e., heterogeneity in preferences, in the ability to assimilate, in moving costs, etc.). To model interdependencies between migration and education decisions, we extend the standard RUM and introduce a second source of heterogeneity in the cost of college education, $e^{\lambda}_h \in [0, 1]$, in line with Delogu et al. (2018). There is no such cost if the individual chooses not to invest in human capital ($e^{\lambda}_l = 0$).

We also allow the individual-specific effort to acquire education to decrease with the (exogenous) provision of public education and to vary with other country characteristics (reflected in the scale variable G_i). Highlighting the complementarity between public education and individual efforts to accumulate human capital is particularly relevant when considering the problem of investment in education in poor developing countries, where credit markets for the purpose of funding private education are underdeveloped, as noted by the World Bank (2000). Higher education systems are heavily dominated by public universities with the costs falling predominantly to the state.

Hence, working-age individuals have heterogeneous abilities to acquire higher education, and heterogeneous preferences concerning destination countries. The utility function of an individual choosing the education type s and moving from i to j has a logarithmic form and is written:

$$U^{\lambda}_{ij,s} = \ln(w_{j,s}) + \ln(1 - c_{ij,s}) + \ln\left(1 - \frac{e^{\lambda}_s}{G_i}\right) + \varepsilon^{\lambda}_{ij,s}. \tag{4.4}$$

As is standard in the migration literature, we assume that the random component of utility $\varepsilon^{\lambda}_{ij,s}$ follows a Type I Extreme Value distribution, also known as the double-exponential cumulative distribution function:

$$\varepsilon^{\lambda}_{ij,s} \rightsquigarrow F_1(\varepsilon) = \exp\left[-\exp\left(-\frac{\varepsilon}{\mu} - \gamma\right)\right] \quad \forall i, j, s, t, \tag{4.5}$$

where $\mu > 0$ is a common scale parameter governing the responsiveness of migration decisions to income disparities, and $\gamma \approx 0.577$ is Euler's constant.

As far as the higher education cost is concerned, no effort is required if the individual does not acquire higher education (as stated above, $e_l^\lambda = 0$). On the contrary, investing in higher education requires a positive level of effort ($e_h^\lambda \geq 0$). We assume e_h^λ is distributed on $[0, 1]$ according to the following cumulative distribution function:

$$F_2(e_h) = e_h^{z+1}, \tag{4.6}$$

where $z \in \Re^+$ is a parameter governing the slope of the density function, $f_2(e_h) = (1 + z)e_h^z$, which is increasing in e_h. The greater z, the smaller the fraction of individuals with a high ability to educate (i.e., with a low education cost). In other words, z determines the scarcity of talent. The scale factor $(1 + z)$ in $f_2(e_h)$ ensures that $\int f_2(e_h^z) = 1$.[6]

The timing of the decisions is the following. First, each individual discovers her education type (e_h^λ). She does not know her migration type ($\varepsilon_{ij,s}^\lambda$) but she knows its distribution. Given her expectations about $w_{j,s}$ and $c_{ij,s}$, she decides whether to acquire higher education or not. Second, she discovers her migration type ($\varepsilon_{ij,s}^\lambda$) and decides whether to emigrate or to stay in her home country.

Higher education decisions. – In the first stage, individuals acquire higher education if the expected utility gain from being college educated exceeds the effort cost. Under the Type I Extreme Value distribution for $\varepsilon_{ij,s}^\lambda$, de Palma and Kilani (2007) derive the expression for the ex-ante expected utility. Using their theorem, the expected utility of choosing type s is given by:

$$\begin{aligned}
E(U_{i,s,t}) &= E\left[\ln(w_{j,s}) + \ln(1 - c_{ij,s})\right] + \ln\left(1 - \frac{e_s^\lambda}{G_i}\right) \\
&= \ln \sum_{j=1}^{I} e^{[\ln(w_{j,s}) + \ln(1 - c_{ij,s})]/\mu} + \ln\left(1 - \frac{e_s^\lambda}{G_i}\right) \\
&= \ln \sum_{j=1}^{I} (w_{j,s})^{1/\mu} (1 - c_{ij,s})^{1/\mu} + \ln\left(1 - \frac{e_s^\lambda}{G_i}\right).
\end{aligned} \tag{4.7}$$

Investing in college education is optimal if $E(U_{i,h}) > E(U_{i,l})$. This condition is written:

$$\left(1 - \frac{e_s^\lambda}{G_i}\right) \sum_{j=1}^{I} (w_{j,h})^{1/\mu} (1 - c_{ij,h})^{1/\mu} \geq \sum_{j=1}^{I} (w_{j,l})^{1/\mu} (1 - c_{ij,l})^{1/\mu}. \tag{4.8}$$

A variable that plays a key role in this condition is the expected return to higher education investment, which is defined as:

$$\begin{aligned}
\Lambda_i &\equiv \frac{\sum_{j=1}^{I} (w_{j,h})^{1/\mu} (1 - c_{ij,h})^{1/\mu}}{\sum_{j=1}^{I} (w_{j,l})^{1/\mu} (1 - c_{ij,l})^{1/\mu}} \\
&\equiv \frac{(w_{i,h})^{1/\mu} + (W_{i,h})^{1/\mu}}{(w_{i,l})^{1/\mu} + (W_{i,l})^{1/\mu}}.
\end{aligned} \tag{4.9}$$

where $(W_{i,s})^{1/\mu} \equiv \sum_{j \neq i} (w_{j,s})^{1/\mu} (1 - c_{ij,s})^{1/\mu}$ $\forall s$ is the expected-income component related to emigration prospects. The expected return to higher education investments is fully

[6] If $z = 0$, there is a uniform distribution. When $z > 0$, the density is strictly increasing in z: there are more individuals facing large education costs than individuals facing low education costs.

determined by the local wage ratio ($\Lambda_i^{NM} = (w_{i,h}/w_{i,l})^{1/\mu}$) in a no-migration (or closed) economy. The influence of emigration prospects is large if the levels of $W_{i,s}/w_{i,s}$ are large. This is the case if foreign wages are large and migration costs are low. In an open economy (i.e., when $W_{i,s} > 0$), the expected return to higher education investment is clearly affected by emigration prospects.

From (4.8) and (4.9), investing in college education is optimal when:

$$e_h^\lambda \leq G_{i,t} \left[\frac{\Lambda_i - 1}{\Lambda_i} \right] \equiv \chi_i, \tag{4.10}$$

where χ_i is the (endogenous) critical level of ability below which investing in higher education is optimal. As in the two-country setting of Djajić et al. (2017), this critical level increases with the provision of public education (G_i) and with the expected college premium, which accounts here for the wage structure in all potential destination countries.

The fraction of natives deciding to invest in higher education is given by $F_2(\chi_{i,t})$, which can be expressed as:

$$H_i = G_i^{1+z} \left[\frac{\Lambda_i - 1}{\Lambda_i} \right]^{1+z}, \tag{4.11}$$

where $w_{i,s}$ and G_i are the components of the expected utility affected by the home country characteristics (i.e., domestic wages and education policy), and $W_{i,s}$ is the component driven by emigration prospects. Again, this is the case if the origin country is poor relative to other countries and if emigration costs are small. In a closed economy framework ($c_{ij,s} = 1 \; \forall s, j \neq i$), the critical level of effort below which college education is beneficial is determined locally; it increases with G_i and with the local skill premium ($w_{i,h}/w_{i,l}$).

Proposition 4.1 *For a given education policy ($G_{i,t}$), emigration prospects stimulate incentives to acquire higher education if the expected education premium abroad is greater than in the country of origin* $\frac{W_{i,h}}{W_{i,l}} > \frac{w_{i,h}}{w_{i,l}}$.

The condition $\frac{W_{i,h}}{W_{i,l}} > \frac{w_{i,h}}{w_{i,l}}$ is equivalent to $\Lambda_i > \Lambda_i^{NM}$.

Emigration decisions. – In the second stage, education has been determined and individuals choose to emigrate to a country j if $\ln(w_{j,s}) + \ln(1 - c_{ij,s}) + \varepsilon_{ij,s}^\lambda$ exceeds the level attainable in any other location. Following McFadden (1974), under the Type I Extreme Value distribution, the probability that a type-s individual born in country i moves to country j is given by a multinomial logit expression:

$$\frac{N_{ij}^s}{N_i^s} = \frac{e^{[\ln(w_{j,s})+\ln(1-c_{ij,s})]/\mu}}{\sum_{k=1}^J e^{\left[\ln\left(w_{k,s}\right)+\ln\left(1-c_{ik,s}\right)\right]/\mu}} = \frac{(w_{j,s})^{1/\mu}(1-c_{ij,s})^{1/\mu}}{\sum_{k=1}^J (w_{k,s})^{1/\mu}(1-c_{ik,s})^{1/\mu}}. \tag{4.12}$$

Skill-specific emigration rates are endogenous and comprised between 0 and 1. The multinomial logit expression also implies that the emigration rate from i to j depends on the characteristics of all potential destinations k (i.e., a crisis in Greece affects the emigration rate from Romania to Germany). However, the staying rates (N_{ij}^s/N_i^s) are governed by the same multinomial logit expression. The emigrant-to-stayer ratio in Equation (4.13) and the aggregation constraint in Equation (4.14) fully characterize the equilibrium distribution of the population:

$$n_{ij,s} \equiv \frac{N_{ij,s}}{N_{ii,s}} = \frac{e^{[\ln w_{j,s} + \ln(1-c_{ij,s})]/\mu}}{e^{[\ln w_{i,s}]/\mu}} = \left(\frac{w_{j,s}}{w_{i,s}}\right)^{1/\mu} (1-c_{ij,s})^{1/\mu}, \ \forall j \neq i, \tag{4.13}$$

$$N_{i,s} = \sum_{j=1}^{J} N_{ij,s} = \left(1 + \sum_{j \neq i} n_{ij,s}\right) N_{ii,s}. \tag{4.14}$$

From Equation (4.13), it comes out that $1/\mu$ can now be interpreted as the elasticity of migration to wage disparities. The ratio of emigrants to stayers only depends on the characteristics of the destination and origin countries: it increases with the income gap between the two countries, and it decreases with dyadic migration costs. Heterogeneity in migration tastes implies that emigrants select all destinations for which $c_{ij,s} < 1$. If $c_{ij,s} = 1$, the corridor is empty. All corridors such that $c_{ij,s}, c_{ji,s} < 1$ exhibit bidirectional migration flows.[7]

Brain gain in a dyadic context. – The aggregate emigration rate ($m_{i,s}$) and the ratio of emigration rates (ρ_i) from country i (an index of skill selection) are jointly determined and are given by the following expressions:

$$m_{i,s} \equiv \frac{\sum_{j\neq i} N_{ij,s}}{N_{i,s}} = \frac{(W_{i,s})^{1/\mu}}{(w_{i,s})^{1/\mu} + (W_{i,s})^{1/\mu}}, \tag{4.15}$$

$$\rho_i \equiv \frac{m_{i,h}}{m_{i,l}} = \frac{(W_{i,h})^{1/\mu}}{(W_{i,l})^{1/\mu}} \left[\frac{(w_{i,h})^{1/\mu} + (W_{i,h})^{1/\mu}}{(w_{i,l})^{1/\mu} + (W_{i,l})^{1/\mu}}\right]^{-1}. \tag{4.16}$$

The ratio of emigration rates increases with $W_{i,h}$ and decreases with $W_{i,l}$. From (4.11) and (4.16), we have $sgn\left(\frac{\partial H_i}{\partial W_{i,s}}\right) = sgn\left(\frac{\partial \rho_i}{\partial W_{i,s}}\right)$ and $sgn\left(\frac{\partial H_i}{\partial w_{i,s}}\right) \neq sgn\left(\frac{\partial \rho_i}{\partial w_{i,s}}\right)$:

Proposition 4.2 *Emigration-driven expected utility shocks ($\Delta W_{i,s}$) induce a positive correlation between human capital formation (H_i) and the ratio of emigration rates (ρ_i). Local expected utility shocks ($\Delta w_{i,s}$) induce a negative correlation between H_i and ρ_i.*

In particular, shocks increasing the expected utility of college graduates abroad (e.g., greater skill selection in the major destination countries) have a positive effect on human capital formation (H_i) and on the positive selection of emigrants (as reflected by the ratio of emigration rates ρ_i). Shocks increasing the expected utility of the less educated abroad have a negative effect on both variables. This establishes the micro-foundation for the link between emigration rates and pre-migration human capital formation in a multi-destination framework.

4.3.2 Predictive power

We parameterize the dyadic model of Section 4.3.1 for 174 countries and for the year 2010. Equation (4.13) and (4.14) show that dyadic migration stocks depend on wage disparities between countries ($w_{j,s}/w_{i,s}$), on migration costs ($c_{ij,s}$), and on the size and structure of

[7] Note that the previous chapters intensively discussed the important implications of internal migration. In this chapter, we do not explicitly address internal migration. However, the dyadic approach allows accounting for country-specific characteristics (i.e., international migration net costs) that implicitly account for internal migration opportunities. This is shown in Appendix 4.A.4.

the native population ($N_{i,s}$). To calibrate skill-specific wages, we use data on the size and structure of the labor force from the *Wittgenstein Centre* ($L_{i,s}$), and data on the wage ratio between college graduates and less educated workers ($WR_i \equiv w_{i,h}/w_{i,l}$) from Hendricks (2004). GDP per capita in PPP values is taken from the Maddison project described in Bolt and Zanden (2014). The data are available for 143 out of the 174 countries in our larger sample. We obtain the GDP in PPP by simply multiplying the GDP per capita by the population size given by the *Wittgenstein Centre*. For missing observations, we use rescaled GDP data from the *World Development Indicators* (WDI) provided by the World Bank.[8] Assuming total labor income (W_i) equals 2/3 of the GDP, we have $W_i = L_{i,h}w_{i,h} + L_{i,l}w_{i,l} = w_{i,l}(L_{i,h}WR_i + L_{i,l})$. In line with Dao et al. (2017), we identify $w_{i,l}$ from this equation and use $w_{i,h} = w_{i,l}WR_i$ for the high-skilled wage. Finally, to calibrate migration costs ($c_{ij,s}$), we use the *DIOC* data on dyadic migration stocks and assume an elasticity of bilateral migration to the wage ratio, $1/\mu$, equal to 0.7 (in line with Bertoli and Fernández-Huertas Moraga, 2013). Dyadic migration costs are calibrated as a residual from Equation (4.13).

To gauge the ability of our micro-founded model to replicate past emigration rates, we parameterize the model of Section 4.3.1 and use it to backcast the size and structure of emigration stocks in the years 1990 and 2000. For these two years, wage and labor force proxies by education level are obtained from Dao et al. (2017), who follow the same calibration as ours for all years prior to 2010. Plugging them into Equation (4.13) and (4.14), we predict the allocation of the native labor force, compute emigration rates by education level, and compare the backcasts with the data. Figure 4.2 presents the correlation between the observed and simulated stocks of emigrants for 2000 and 1990. The 45° line is added to better visualize the prediction errors.

Figure 4.2a and 4.2b show that the square of the correlation between actual and predicted stocks equals 0.907 for college graduates and 0.905 for the less educated in the year 2000. For the year 1990, Figure 4.2c and 4.2d show that these correlations are equal to 0.766 for college graduates and to 0.803 for the less educated. The correlation unsurprisingly decreases with the distance from the year 2010. This is because our model identifies neither past variations in migration policies (e.g., the Schengen agreement in the European Union, changes in the H1B visa policy in the US, etc.), nor past changes in net amenities and non-pecuniary push/pull factors (e.g., conflicts, political unrest, etc.) between 1990 and 2010. Nevertheless, the correlations are large, a proof of concept that our model does a good job at explaining migration patterns.

4.3.3 Emigration and human capital

Furthermore, we now use the dyadic model to assess the educational response to international migration prospects/rates. The empirical analysis of Section 4.2 captures the average education response to emigration prospects in a large set of developing countries. It might be the case that the mean response hides large differences across countries. Once properly calibrated, our dyadic model of Section 4.3.1 enables to account for country-specific characteristics and to predict specific responses. To do so, we now parameterize the human capital technology of the dyadic model to assess the country-specific effects of

[8] The data is rescaled in a way that matches the GDP in the United States. For this, the GDP obtained from the Maddison project is divided by the GDP obtained from the WDI for the United States. The GDP from the WDI is then multiplied by this quotient for the missing observations in order to retrieve comparable GDP measures.

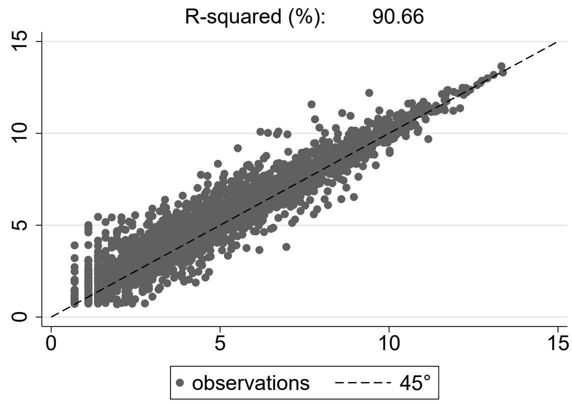
emigration shocks. We use the dyadic migration costs, the wage rates calibrated in Section 4.3.2, and the share of college graduates among natives in the year 2010, H_i. When wage and migration cost proxies are available, Equation (4.11) shows that the ex-ante proportion of college graduates depends on two unknown parameters, z and G_i.

We calibrate these two parameters iteratively. We arbitrarily allocate alternative values (e.g., 0, 0.05, 0.10, 0.15, ... ,) to z and, for each z, we calibrate the scale variable G_i to the level that perfectly matches H_i as a residual of Equation (4.11). Let us denote by $G_i(z)$ the scale factor that corresponds to the arbitrary level of z. We then simulate several skilled migration shocks (i.e., changes in $m_{i,h}$) and identify the education responses (i.e., the change in H_i). These shocks consist in reducing the high-skilled migration cost by one, five, and ten percentage points. For each of these shocks and for each pair of z and $G_i(z)$, we compute the human capital responses as the log variations in the share of college graduates, $\Delta \ln H_i$. We then regress $\Delta \ln H_i$ on the corresponding log changes in the high-skilled emigration rate, $\Delta \ln m_{i,h}$, using the same sample of countries as in the standard macroeconometric literature (see Section 4.2). Finally, we choose a value for the parameter z for which the simulated elasticity of education to emigration is the closest to the average of the empirical estimates of the long-run elasticity reported in Table 4.1 (i.e., 0.18). As shown on Figure 4.3a, we find that $z^* = 0.7$ is the most relevant value, whatever the size of the migration shock.

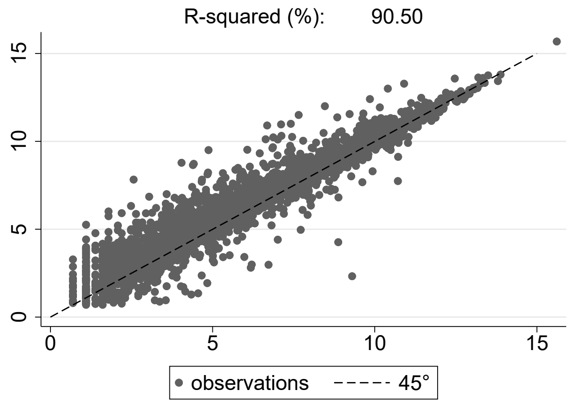
Having calibrated the value of z allows us to quantify the education response to emigration and selection. Figure 4.3 illustrates the effect of shocks in migration costs on higher education investment for constant wages (i.e., in partial equilibrium). Figure 4.3b compares the open economy expected return to higher education investment (Λ_i) with the no-migration (closed) economy level (Λ_i^{NM}). We identify 16 countries (9.2% of the sample) where international migration reduces Λ_i. These are countries where low-skilled emigration rates are large and/or for which the main destinations are less developed than the origin.[9] In these countries, emigration prospects reduce the optimal investment of the natives (H_i); these countries are below the 45° line on Figure 4.3c. For example, the share of college graduates among natives decreases from 12.1% to 11.9% in Turkey or from 14.0% to 13.2% in Mexico. In the other 158 countries, emigration prospects increase Λ_i and H_i. On average, the Λ_i and H_i increase by a factor of 1.17 and 1.16, respectively. The greatest effects on Λ_i are observed in small and poor countries. The open economy level of Λ_i is twice as large as the closed economy level in 9 countries (The Gambia, Grenada, Guyana, Haiti, Jamaica, Mauritius, Saint-Vincent and Grenadines, Sao Tome and Principe, and Trinidad and Tobago). In these countries (above the 45° line on Figure 4.3b and 4.3c), emigration prospects increase the optimal investment of the natives. For example, the share of college graduates among natives increases from 3.5% to 5.3% in Haiti or from 12.0% to 18.6% in Jamaica. Finally, Figure 4.3d compares the observed share of college graduates in the resident population (h_i on the vertical axis) with the no-migration (closed) economy level (h_i^{NM} on the horizontal axis). Out of our 174 countries, 84 countries experience a decrease in human capital (48.3% of the sample), while the remaining 90 countries experience a net brain gain.

Contrary to the long-run and short-run predictions of the standard model, the net effect of emigration on human capital accumulation need not be positive at low levels

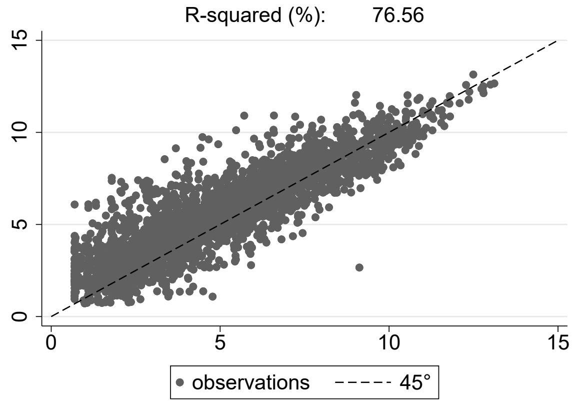
[9] They include Albania (-2.1%), Bolivia (-1.7%), Bulgaria (-1.7%), Canada (-1.0%), Croatia (-0.6%), Dominican Republic (-0.4%), Ecuador (-1%), El Salvador (-6.2%), Finland (-2.3%), Kazakhstan (-3.8%), Lithuania (-4.9%), Mexico (-5.6%), Portugal (-2.4%), Serbia (-1.0%), Macedonia (-8.7%), and Turkey (-1.1%).



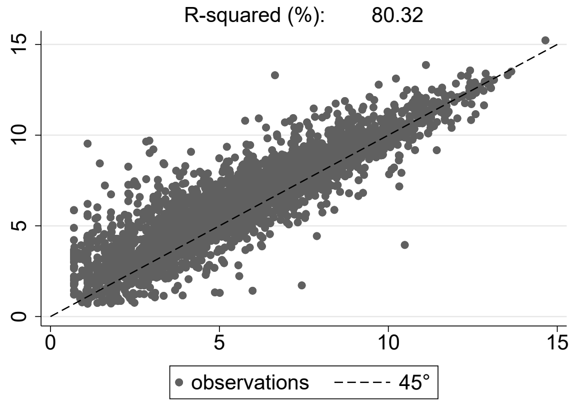
(a) College graduates, year 2000



(b) Less educated, year 2000



(c) College graduates, year 1990

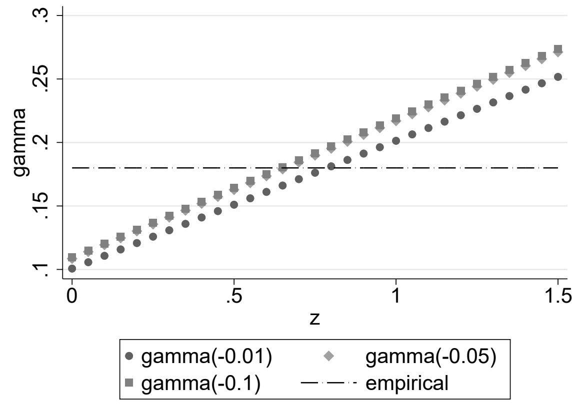


(d) Less educated, year 1990

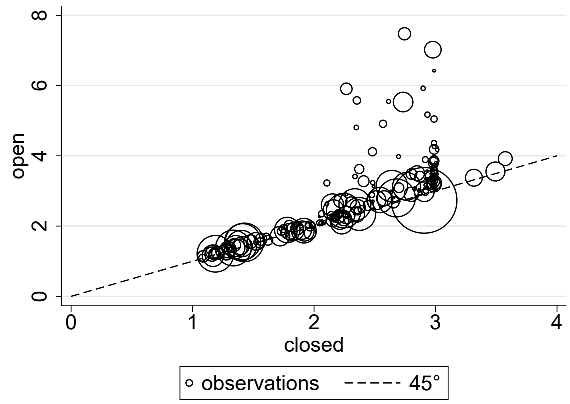
Figure 4.2: Actual (X-axis) and predicted (Y-axis) migrant stocks by dyad in 1990 and 2000 (in logs)

of emigration, and need not be strongly negative at high levels of emigration. For a given emigration rate, the net effect varies across countries, due to the dyadic heterogeneity across destination characteristics and to the level of the low-skilled emigration rate. Figure 4.4 shows the effect of international migration on human capital. On Figure 4.4a and 4.4b, the change in human capital, in relative terms or in absolute terms (i.e., $\Delta h_i/h_i$ or $\Delta h_i = h_i - h_i^{NM}$), is plotted against the migration rate differential between high- and low-skilled natives ($m_{i,h} - m_{i,l}$). On average and despite the fact that our model matches the long-run average elasticity of education to skilled emigration, the net effect is smaller than under the standard approach (with the exception of a few small countries). Overall, the coefficient of variation in the share of college graduates equals 0.763 in the current open economy context and 0.758 in the hypothetical closed economy context. This strongly suggests that international migration has limited effects on the world distribution of human capital.

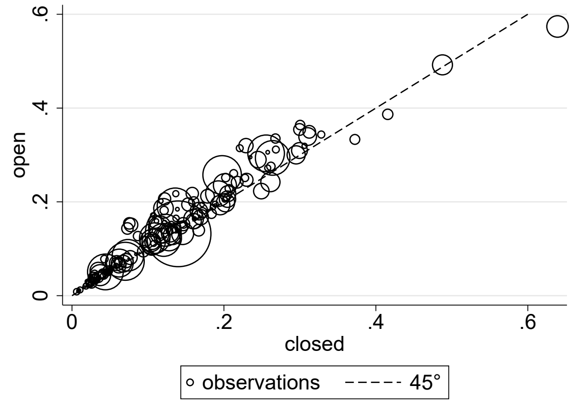
On Figure 4.4c, we rank countries by increasing order of their observed level of h (i.e., the X-axis is ordinal), and we compare the observed level of h (thin grey curve) with three counterfactuals: no high-skilled emigration in dots ($m_{i,h} = 0$), no low-skilled migration in dashed ($m_{i,l} = 0$), and no migration in bold black ($m_{i,s} = 0\ \forall s$). The effect of migration is usually negative but negligible in the bottom 33% of the sample (i.e., in the poorest



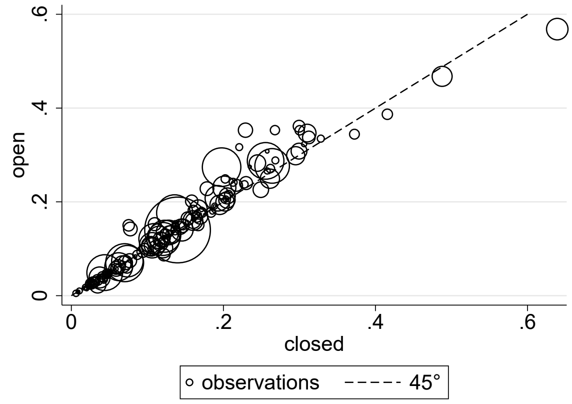
(a) Calibration of z



(b) Effect on the expected income ratio (Λ_i)



(c) Effect on native human capital (H_i)



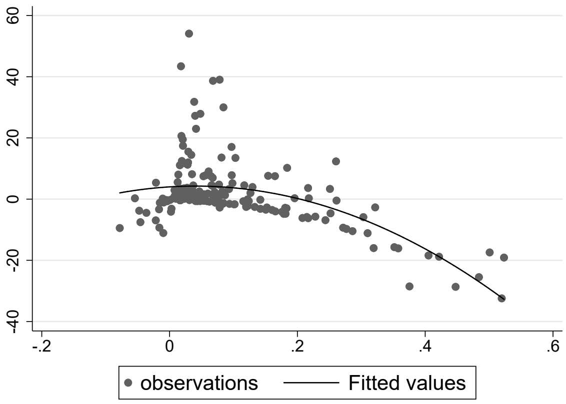
(d) Effect on residents' human capital (h_i)

Figure 4.3: Country-specific responses to migration

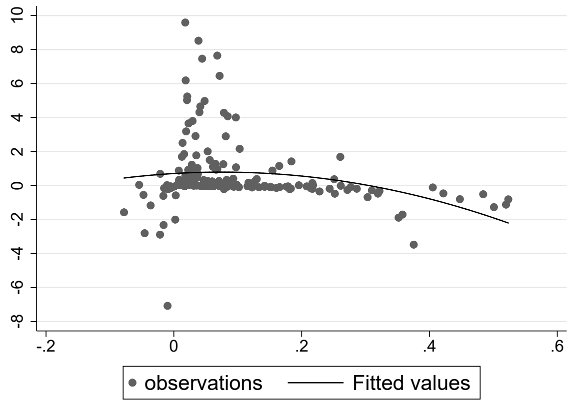
countries with less than 10% of college graduates), and there are small effects in the next 33%. The effect is larger in the top 33%: stopping skilled migration is usually good for human capital accumulation, while stopping low-skilled migration is bad. Overall, the net effect is ambiguous but generally positive in these richer countries. There are a few exceptions to the rule. Contrary to the standard approach, a net brain gain emerges in about 20 small, poor countries where both emigration rates are large. In addition, a net brain loss is observed in 5 to 10 countries where emigrants are negatively selected (i.e., $m_{i,l} > m_{i,h}$).

4.3.4 Emigration and education policy

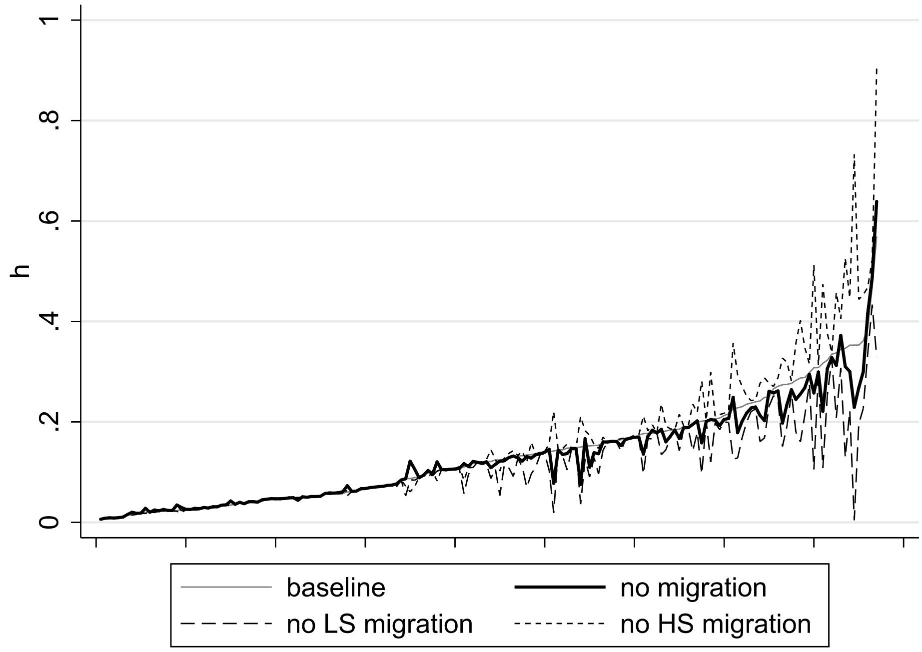
In this section we investigate whether international migration affects the effectiveness of public education policies of the origin country. We calibrated z^* and $G_i(z^*)$ so as to match the long-run elasticity of human capital to high-skilled migration and the observed share of college graduates in the native population of 2010. The mean and standard errors of G_i equal 0.747 and 0.819, respectively. Regressing G_i (in logs) on the level of public expenditures as a percentage of GDP gives a significant and positive coefficient equal



(a) Relative dev. ($\Delta h/h$) against $m_h - m_l$



(b) Absolute dev. (Δh) against $m_h - m_l$



(c) Observed and counterfactual levels of h

Figure 4.4: Global implications of international migration
(Relative and absolute deviations from the closed economy)

Notes: In Figure 4.4c countries are ranked on the horizontal axis by increasing order of observed h. The observed level is depicted in grey, $m_s = 0$ in bold black, $m_l = 0$ in dashed, and $m_h = 0$ in dots.

to 0.094.[10] Hence, increasing the ratio of public education expenditures to GDP by 1 percentage point leads to $\Delta G_i/G_i = \exp(0.094) - 1 \simeq 0.10$. In partial equilibrium, Λ_i is constant. From Equation (4.11), it implies that $\Delta H_i/H_i = (1+z)\Delta G_i/G_i \simeq 0.17$. In addition, $m_{i,s}$ are also constant for all s in the partial equilibrium framework. This

[10]Note that the log of G_i is also positively correlated with the income per capita (in logs) and with the urbanization rate (G_i is a good proxy for the access to education).

implies that $\Delta H_i/H_i \simeq \Delta h_i/h_i$.[11]

Hence, a one-percentage-point increase in public education expenditures generates a variation in the domestic share of college graduates that is almost proportional to the initial share, $\Delta h_i \simeq 0.17 h_i$, which is itself an ambiguous function of international migration rates, $m_{i,h}$ and $m_{i,l}$. In countries where international migration reduces (respectively increases) domestic human capital (h_i), migration also reduces (respectively increases) the effectiveness of public education policies. In other words, the effect of migration on the effectiveness of public education policies moves in the same direction as the effect of migration on human capital accumulation. Djajić et al. (2017) find a similar result in a two-country setting. Again, our dyadic model generalizes previous findings. In addition, given Figure 4.3d and 4.4a, we show that international migration has little effect on h_i in the bottom 2/3 of the sample, and a small positive effect in high-income countries. We conclude that international migration has very little effect on the effectiveness of public education policies in developing countries. On the contrary, it slightly increases the effectiveness of public education policies in the majority of high-income countries.

4.3.5 General equilibrium extension

In the dyadic model of Section 4.3.1, the condition under which migration to a destination country j is profitable for type-s workers born in country i depends on wage disparities. Through the production technology, the latter are affected by the allocation of labor which depends itself on the size and structure of migration flows. The combination of endogenous migration decisions and equilibrium wages jointly determines the world distribution of income and the allocation of the world population. The resident labor force in country i is given by:

$$L_{i,s} = \sum\nolimits_j N_{ji,s}. \tag{4.17}$$

Assume output in country i, Y_i, is a multiplicative function of total factor productivity (TFP), A_i, and total quantity of labor in efficiency units, $L_{i,T}$.[12] In the recent labor market, immigration and growth literatures, labor in efficiency units is usually modeled as a CES function of the number of college-educated and less educated workers employed. We have:

$$Y_i = A_i L_{i,T} = A_i \left[\theta_{i,h} L_{i,h}^{\frac{\sigma-1}{\sigma}} + \theta_{i,l} L_{i,l}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{4.18}$$

where $\theta_{i,s}$ is the country and time-specific value share parameter for workers of type s (such that $\theta_{i,h} + \theta_{i,l} = 1$), and σ is the common elasticity of substitution between the two groups of workers.

Firms maximize profits and the labor market is competitive. The equilibrium wage rate for type-s workers in country j is equal to the marginal productivity of labor:

$$w_{i,s} = \theta_{i,s} A_i \left(\frac{L_{i,T}}{L_{i,s}}\right)^{1/\sigma}. \tag{4.19}$$

Hence, the wage ratio between college graduates and less educated workers is given by:

$$\frac{w_{i,h}}{w_{i,l}} = \frac{\theta_{i,h}}{\theta_{i,l}} \left(\frac{L_{i,h}}{L_{i,l}}\right)^{-1/\sigma}. \tag{4.20}$$

[11]The effect is slightly greater in countries with large emigration rates. We have $\Delta h_i/h_i \in [0.18, 0.20]$ in countries such as Belize, Fiji, Grenada, Guyana, Haiti, Jamaica, Mauritius, Suriname, etc..

[12]Such a model without physical capital features a globalized economy with a common international interest rate.

As long as this ratio is greater than one, a rise in human capital increases the average productivity of workers. Furthermore, greater contributions of human capital to productivity can be obtained by assuming technological externalities. In particular, as discussed in the previous chapters, skill-biased technical changes affect the relative productivity of high-skilled workers (see Acemoglu, 2002; Restuccia and Vandenbroucke, 2013). For example, Autor et al. (2003) show that computerization is associated with a declining relative industry demand for routine manual and cognitive tasks, and increased relative demand for non-routine cognitive tasks. The observed relative demand shift favors college versus non-college labor. We write:

$$\frac{\theta_{i,h}}{\theta_{i,l}} = \Phi_i \left(\frac{L_{i,h}}{L_{i,l}} \right)^{\kappa}, \tag{4.21}$$

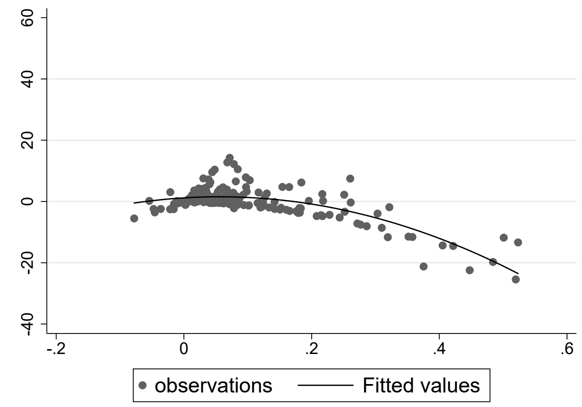
where Φ_i is the exogenous country-specific component of the skill bias in productivity in country i, and κ is the elasticity of the skill bias to the skill ratio. Plugging (4.21) into (4.20), the elasticity of the college premium to the skill ratio ($L_{i,h}/L_{i,l}$) is now equal to $\kappa - 1/\sigma$.

In the general equilibrium setting, the world economy equilibrium is characterized by:

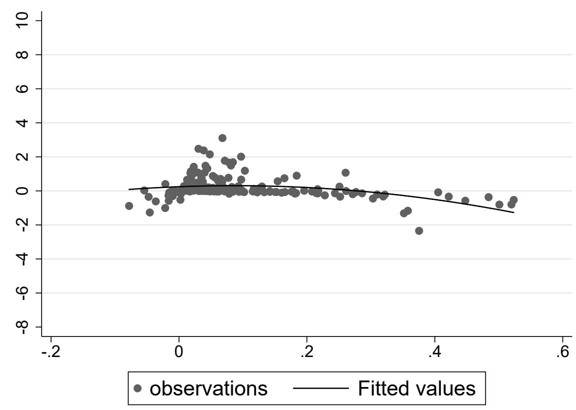
Definition 4.1 *For a set $\{\mu, \sigma, \kappa, z\}$ of common parameters, a set $\{\Phi_i, G_i\}_{\forall i}$ of country-specific parameters, a set $\{c_{ij,s}\}_{\forall i,j,s}$ of dyadic migration costs, and for given distribution of the native population $\{N_{i,s}\}_{\forall i,s}$, a competitive equilibrium is an allocation of labor $\{N_{ij,s}\}_{\forall i,j,s}$ and a vector of wages $\{w_{j,s}\}_{\forall j,s}$ satisfying (i) the utility maximization condition, Equation (4.13), (ii) the profit maximization condition, Equation (4.19), (iii) the skill-biased technological constraint, Equation (4.21), and (iv) the aggregation constraints, Equations (4.14) and (4.17).*

It is thus interesting to check whether the partial equilibrium results discussed in the previous sections resist a general equilibrium analysis. We parameterize the technology for 174 countries and for the year 2010. We use the wage and labor force data of the year 2010. Assuming $\sigma = 2$ (in line with Ottaviano and Peri, 2012) and using Equation (4.20), we first calibrate the technological skill bias, $\theta_{i,h,2010}/\theta_{i,l,2010}$, to perfectly match the skill premium data. Note that the cross-country elasticity of $\frac{\theta_{i,h,2010}}{\theta_{i,l,2010}}$ to the skill ratio is equal to 0.214 (our proxy for κ), suggesting the existence of directed technical changes. Then, using Equation (4.18), we calibrate $A_{i,2010}$ to perfectly match the aggregate GDP data. Finally, we use Equation (4.19) to predict the wages.

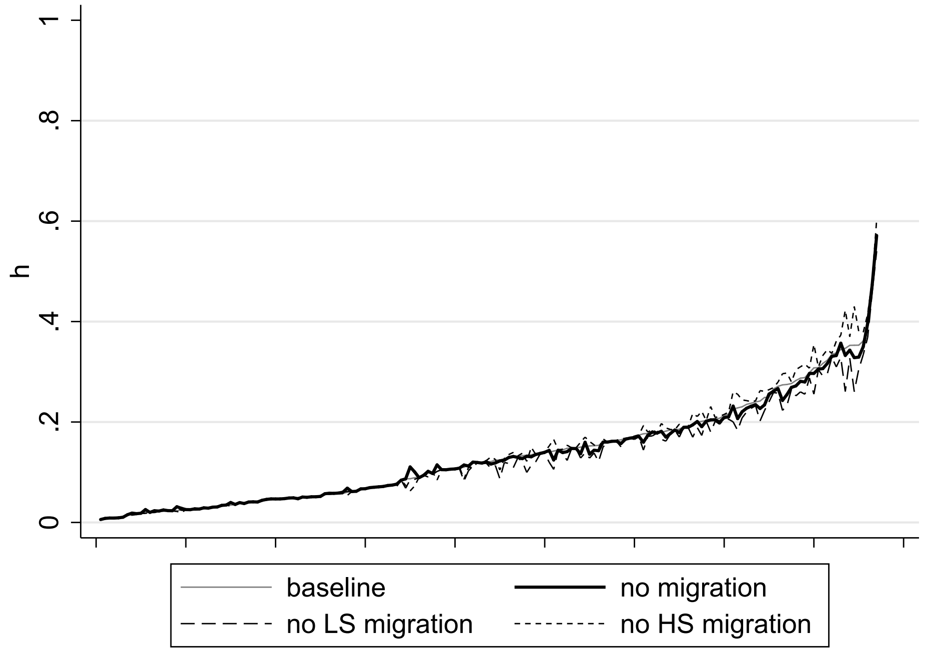
Figure 4.5 shows the effect of international migration on upper-tail human capital accumulation in a general equilibrium context with endogenous wages. Compared to the partial equilibrium results of Figure 4.4, the effects are much smaller. On Figure 4.5c, we rank countries by increasing order of their observed level of h (i.e., the X-axis is ordinal), and we compare the observed level of h (thin grey curve) with three counterfactuals: no high-skilled emigration in dots ($m_{i,h} = 0$), no low-skilled migration in dashed ($m_{i,l} = 0$) and no migration in bold black ($m_{i,s} = 0 \; \forall s$). When low-skilled emigration is prohibited, the proportion of college graduates (h_i) decreases in most countries. This effect is attenuated by an increase in Λ_i: without emigration prospects for the low-skilled, the expected return to higher education investment increases. This mitigation effect is small because migration costs are large. In the general equilibrium setting, the decrease in h_i leads to a rise in the domestic skill premium, which leads to a larger increase in Λ_i. This in turn triggers investments in high-skilled human capital. The opposite effects are found when high-skilled emigration is prohibited. Repatriating college-educated migrants increases h_i mechanically. This effect is attenuated by a moderate decrease in Λ_i due to lower emigration prospects for the highly skilled. In the general equilibrium setting, the rise in h_i leads to a decrease in the domestic skill premium, which leads to a larger decrease in Λ_i. This confirms that international migration has a limited impact on the world distribution of human capital.



(a) Relative dev. ($\Delta h/h$) against $m_h - m_l$



(b) Absolute dev. (Δh) against $m_h - m_l$



(c) Observed and counterfactual levels of h

Figure 4.5: Global implications of international migration - general equilibrium effects (Relative and absolute deviations from the closed economy)

Notes: In Figure 4.5c countries are ranked on the horizontal axis by increasing order of observed h. The observed level is depicted in grey, $m_s = 0$ in bold black, $m_l = 0$ in dashed, and $m_h = 0$ in dots.

4.4 Conclusion

International migrants are positively selected in terms of skills and education, and the movement of highly educated workers from developing to advanced countries has been the subject of extensive research over the last four decades. This brain drain has long been viewed as detrimental to the growth potential of the home country and to the welfare of those left behind. It is usually expected to be even more harmful for the least developed countries where positive selection is greatest. This view has been challenged by the recent literature, which demonstrates that limited high-skilled emigration can be beneficial for growth and development. In relative terms, the standard macroeconometric approach suggests that large brain gain effects can be obtained at low levels of emigration, and large costs are observed at high levels of emigration. While these findings are globally confirmed when pooling old and recent data on skill-specific emigration rates, we argue here that the standard approach fails to capture the cross-country heterogeneity in migration opportunities and development differentials.

We propose a new dyadic approach that fully accounts for the characteristics of each origin country and of all its potential destinations. Our structural model jointly endogenizes higher education decisions, as well as the skill and dyadic structures of emigration. Parameterized on the year 2010, our model predicts the migration data of the previous decades well, a proof of concept that it does a good job at explaining migration patterns. Our analysis reveals that the effect of international migration on upper-tail human capital accumulation is much smaller than the effect predicted by standard macroeconometric models. On average, the net effect on human capital accumulation is very small in low-income and middle-income countries. Despite positive selection, we argue that international migration has a limited impact on the world distribution of human capital. The effects are even smaller in a general equilibrium framework with endogenous wages. In addition, the exodus of high-skilled workers is usually seen as a factor reducing the effectiveness of education policies and the optimal provision of public education. Given that the cost of education and training represents a disproportionate financial burden for poor economies, a number of studies argue that high-skilled migration reduces the net benefits from public investments in education (see Justman and Thisse, 1997; Stark and Wang, 2002; Docquier et al., 2008). On the contrary, our quantitative analysis shows that international migration has little effect on the effectiveness of public education policies in developing countries. Significant negative effects are found in some high-income countries only. This implies that international migration is unlikely to jeopardize the achievement of education-related development goals, and should not be cited as an argument to curb efforts for improving the quantity and quality of education.

4.A Appendix

4.A.1 Migration trends by education level

Although many aspects of migration have been analyzed by demographers, economists, sociologists, and other social scientists, data constraints have long obstructed some important research avenues. Fortunately, several databases have been recently constructed to document dyadic migration stocks and their skill structure.[13] They all rely on census and administrative data which are usually available in ten-year intervals. Expanding on Docquier et al. (2009), Artuç et al. (2015) provide comprehensive matrices of dyadic migration stocks for the years 1990 and 2000 (referred to as the *ADOP* database). The *DIOC* database of the OECD (Database on Immigrants in OECD Countries) is described in Arslan et al. (2014) and provides data for the 2000 and 2010 census rounds. Finally, the *IAB* database (Brücker et al., 2013) provide data in five-year intervals from 1980 to 2010 but for a restricted set of 20 OECD destination countries only. The authors have to deal with inevitable gaps in the data. This is particularly the case in the *IAB* database where many interpolations and/or imputations were used when census data were missing or were not sufficiently detailed. This is also the case in the *ADOP* database for some non-OECD destinations.

We combine the *ADOP* and *DIOC* databases to characterize the evolution of emigration rates between 1990 and 2010. We focus on emigration to 34 OECD countries, which is the best documented, growing component of international migration; migration to non-OECD countries is ignored. We restrict our sample to emigrants aged 25 and over, who emigrated to one of the OECD member states. Data on emigration for the year 1990 are taken from the *ADOP* database. For the years 2000 and 2010, we extract data on dyadic migration numbers from *DIOC*. In order to obtain the emigration rates, we have to proxy the size of the native populations. For this purpose, we combine data on the population aged 25 years and above, with data on the share of college-educated individuals from different data sources.[14] For 174 origin countries, the skill-specific emigration rates ($m_{i,s}$) are proxied as the ratio of emigrants to OECD destination countries ($M_{i,s}$) to the sum of the emigrant and resident populations ($L_{i,s}$). We write:

$$m_{i,s} = \frac{M_{i,s}}{M_{i,s} + L_{i,s}}.$$

Figure 4.A1 illustrates the evolution of emigration rates by education level and by period. Figure 4.A1a and 4.A1b describe the evolution observed over 20 years. On average, skilled emigration rates decreased by 23%, while low-skilled emigration rates increased by 17%. These trends must be related to the worldwide evolution of human capital. A strong regularity in migration data is that the proportion of the educated among emigrants increases with the general level of education of the native population. The most educated migrants originate from countries with the highest level of human capital. However, an increase in human capital generates a less than proportional increase

[13]Özden et al. (2011) provide dyadic data from 1960 to 2000 in ten-year intervals for the whole population of migrants (including children), but with no disaggregation between age and skill groups. They can be supplemented by the matrices of the United Nations Population Division for the years 2010 and 2015.

[14]For the years 1990 and 2000, we use population data by education level from Docquier et al. (2009). For the year 2010, we use a combination of data from Docquier et al. (2009) and the *Wittgenstein* database.

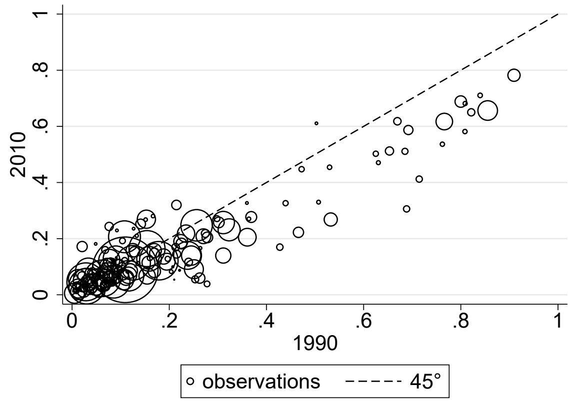
in the education level of emigrants (Docquier et al., 2007). As illustrated in Appendix 4.A.2 (see Figure 4.A2), human capital indicators evidence a general increase in virtually all countries, and an absolute convergence process (the human capital growth rate is greater in initially poor countries). This translates into a less than proportional increase in the stock of college-educated emigrants, and a more than proportional increase in the stock of low-skilled emigrants. Disentangling the 20-year change by decade, Figure 4.A1c and 4.A1e show that half of the change in skilled emigration rates occurred between 1990 and 2000, and the other half occurred between 2000 and 2010. As far as low-skilled emigration rates are concerned, most of the changes occurred between 1990 and 2000, as illustrated on Figure 4.A1d and 4.A1f.

Table 4.A1 provides emigration stocks and skill-specific rates for the years 1990, 2000, 2010 by income group, by country size, and by region. It shows that high-skilled emigration rates strongly decrease with economic development and population size. On the contrary, low-skilled emigration rates increase with economic development. Regions with the greatest skilled emigration rates include small, poor countries (e.g., Caribbean and Pacific islands). Overall, skilled emigration rates decreased between 1990 and 2010 in all groups. Exceptions are Eastern Europe, Eastern Asia, and South-Central Asia. The worldwide average emigration rate has been quite stable for the last 20 years, which is due to the increasing demographic share of low-income countries (the group exhibiting the greatest emigration rates). On the contrary, low-skilled emigration rates increased in virtually all groups.

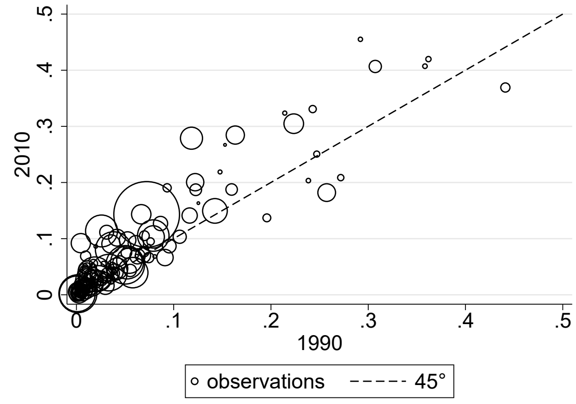
Table 4.A2 shows the evolution of migration stocks and rates in the countries most and least affected by emigration. Countries with less than one million inhabitants are excluded from the list of 174 countries. The first part of Table 4.A2 lists the ten countries with the greatest *stocks* of college-educated emigrants in 1990, 2000, and 2010. The top countries include rich countries with highly educated populations (the UK, Germany, Canada, etc.) and large developing countries such as the Philippines, India, or China. The second part of the table displays the ten countries with the greatest *rates* of college-educated emigrants in 1990, 2000, and 2010. In line with Table 4.A1, small, poor countries exhibit large emigration rates. The brain drain reaches more than 60% of the population in countries such as Jamaica, Haiti, Trinidad and Tobago, or Mauritius. Finally, the third part gives the high-skilled emigration rates for the ten countries with the lowest rates in 1990, 2000, and 2010. This set includes rich countries from the Persian Gulf, as well as ex-Soviet block countries sending their emigrants to Russia (a non-OECD destination country).

4.A.2 Human capital and migration

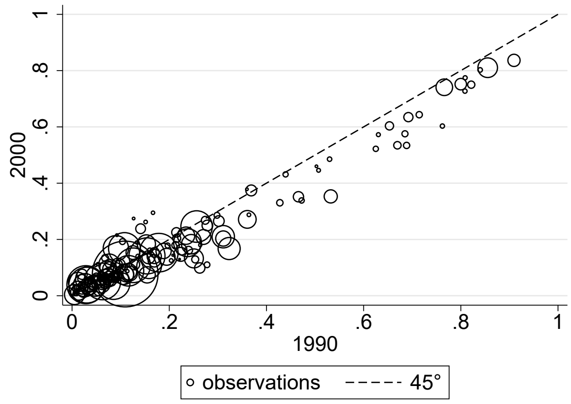
Figure 4.A2 describes the evolution of human capital (proxied by the share of college-educated adults) between 1990 and 2010, and the relationship between the change in human capital and the changes in emigration rates. Figure 4.A2a and 4.A2b show that the shares of college graduates in the resident and native populations increased by a factor of 1.5 between 1990 (on the X-axis) and 2010 (on the Y-axis). Figure 4.A2c and 4.A2d compare the 1990-2010 average annual growth rates in the share of college graduates (on the X-axis) with the initial (1990) shares in logs (on the Y-axis). This β-convergence analysis evidences an absolute convergence in residents' and natives' human capital. In both cases, the annual speed of convergence is around 1.1%. Finally, Figure 4.A2e and 4.A2f show the relationship between the growth rate of the share of college graduates



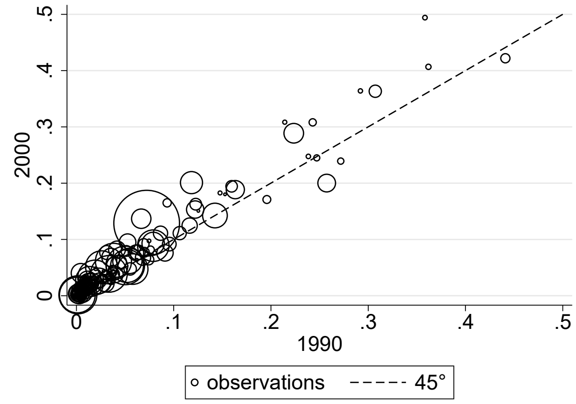
(a) College graduates, 1990 (X) versus 2010 (Y)



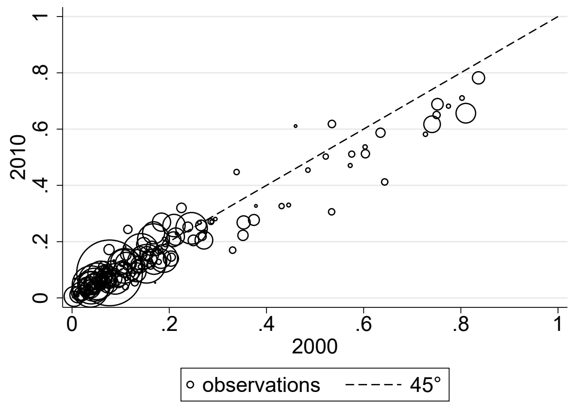
(b) Less educated, 1990 (X) versus 2010 (Y)



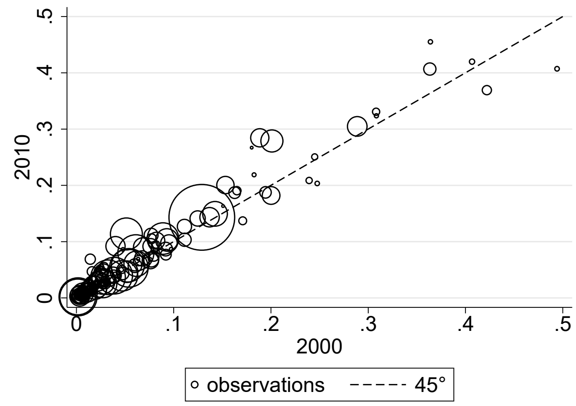
(c) College graduates, 1990 (X) versus 2000 (Y)



(d) Less educated, 1990 (X) versus 2000 (Y)



(e) College graduates, 2000 (X) versus 2010 (Y)



(f) Less educated, 2000 (X) versus 2010 (Y)

Figure 4.A1: Emigration rates to OECD destination countries
(Data by education level and for the years 1990, 2000 and 2010)

Notes: Figure 4.A1 focuses on emigration to OECD destination countries only. Bubble sizes are proportional to the stock of emigrants.

Table 4.A1: Emigration stocks and rates to OECD destination countries
(Data by group of countries, by education level and for the years 1990, 2000 and 2010)

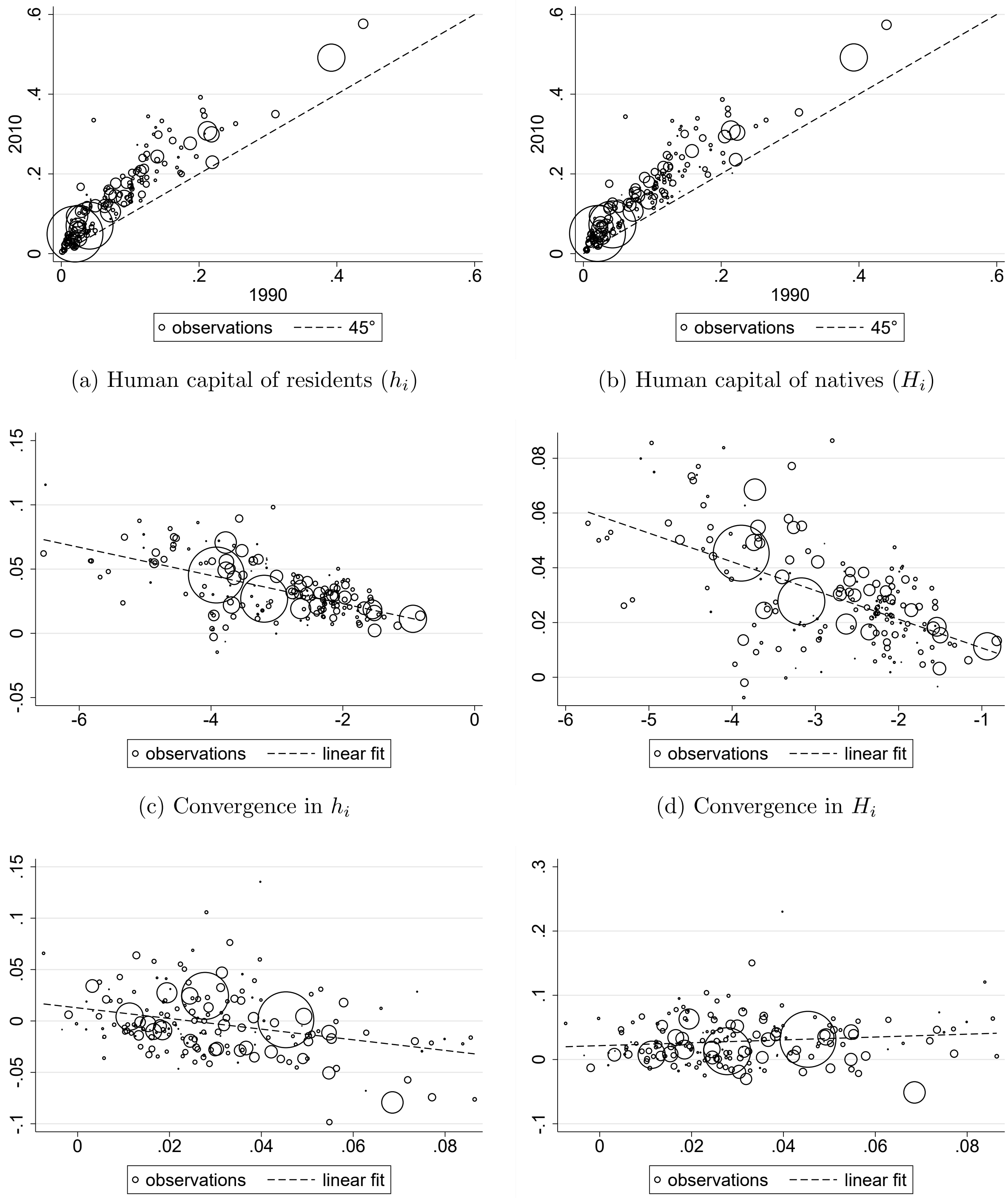
	Total stock (in thousand)			Rate low-skilled (as %)			Rate high-skilled (as %)		
Year	1990	2000	2010	1990	2000	2010	1990	2000	2010
World	40,717	58,585	81,449	1.3	1.5	1.7	5.2	4.7	5.1
By income group									
High-income	19,570	22,369	26,286	2.7	3.0	3.0	3.9	3.3	3.7
Upper-middle	11,708	20,238	30,229	0.9	1.3	1.6	6.4	5.5	5.1
Lower-middle	8,791	14,739	22,679	0.9	1.1	1.3	8.5	8.4	8.1
Low-income	649	1,240	2,255	0.5	0.8	1.1	16.4	16.2	18.0
By country size									
High-pop.	25,603	37,997	52,565	0.9	1.1	1.2	4.0	3.8	4.2
Upper-middle	6,919	9,714	14,204	2.9	3.6	4.3	10.2	8.8	9.4
Lower-middle	6,683	8,880	12,064	4.7	5.5	6.2	12.1	10.5	10.4
Low-pop.	1,511	1,994	2,617	8.0	9.3	9.9	28.2	24.5	22.1
By region									
Africa									
Northern	2,016	3,274	4,687	3.1	3.6	4.0	10.8	10.7	9.2
Sub-Saharan	1,375	2,414	4,250	0.5	0.7	0.9	14.1	13.0	11.9
Americas									
Caribbean	1,951	3,055	3,926	9.3	13.2	13.8	43.6	34.6	32.7
Central	3,484	8,166	12,221	6.8	12.2	13.8	13.6	9.4	10.2
South	1,628	3,100	5,214	0.8	1.4	1.9	4.8	4.0	4.5
USA & CAN	1,428	1,660	1,905	0.6	0.9	0.7	1.0	0.8	0.9
Asia									
Eastern	1,288	2,248	3,399	0.1	0.1	0.2	2.0	2.4	2.3
South-Cent.	1,726	3,302	6,353	0.2	0.3	0.4	3.2	4.4	5.2
South-East	2,583	4,207	5,979	0.8	1.1	1.2	10.8	7.4	6.2
Middle East	2,760	3,840	5,230	2.6	2.8	2.7	10.4	7.4	6.4
Europe									
Eastern	6,644	8,558	12,488	4.3	5.4	7.4	9.5	9.5	11.6
Western	13,304	13,972	14,742	4.5	4.4	4.1	8.4	7.4	7.1
Oceania									
Australia & NZ	397	565	753	2.6	3.4	3.4	4.3	4.3	5.2
Pacific islands	133	223	303	4.1	5.5	5.6	47.2	39.7	27.5

Notes: Table 4.A1 focuses on emigration to OECD destination countries only. For income groups and regions, we follow the World Bank classification. For country size, we distinguish between countries with a population above 25 million (High-pop.), between 10 and 25 million (Upper-middle), between 2.5 and 10 million (Lower-middle), and below 2.5 million (Low-pop.).

(on the X-axis) and the growth rate of emigration rates (on the Y-axis). High-skilled emigration rates decrease with human capital, while low-skilled emigration rates increase with h.

4.A.3 Emigration data and backcasts by country

Table 4.A3 reports the emigration rates by education and by country for the years 1990, 2000 and 2010 for the partial equilibrium. We supplement these observations with backcasts from the dyadic model for the years 1970 and 1980. To do so, we use proxies for



(a) Human capital of residents (h_i)

(b) Human capital of natives (H_i)

(c) Convergence in h_i

(d) Convergence in H_i

(e) High-skilled emigration and h (Δh_i and $\Delta m_{i,h}$)

(f) Low-skilled emigration and h (Δh_i and $\Delta m_{i,l}$)

Figure 4.A2: Human capital and emigration between 1990 and 2010

Notes: Bubble sizes are proportional to the stock of emigrants.

Table 4.A2: Most and least affected countries in 1990, 2000 and 2010

Highest stocks of college-educated migrants					
1990		2000		2010	
UK	1,149,411	UK	1,299,901	India	2,087,376
Germany	807,612	India	933,289	Philippines	1,494,127
Philippines	635,129	Philippines	859,974	UK	1,450,392
India	447,409	Germany	823,956	China	1,361,434
Canada	401,812	China	777,671	Germany	1,169,076
Mexico	366,838	Poland	451,781	Poland	941,028
China	359,692	Mexico	433,892	Mexico	825,502
Poland	334,190	Canada	403,201	Ukraine	642,428
Italy	321,953	USA	395,759	France	551,245
USA	316,353	Italy	360,108	USA	548,750
Highest emigration rates for college graduates (as %)					
1990		2000		2010	
Jamaica	85.5	Jamaica	81.0	Trin & Tob	68.8
Trin & Tob	80.0	Trin & Tob	75.2	Jamaica	65.7
Haiti	76.6	Haiti	74.1	Mauritius	61.8
The Gambia	76.2	Mozambique	64.3	Haiti	61.7
Mozambique	71.4	The Gambia	60.3	The Gambia	53.7
Mauritius	66.9	Mauritius	53.5	Liberia	44.7
Lebanon	53.2	Guinea-Bissau	44.6	Mozambique	41.2
Guinea-Bissau	50.7	Sierra Leone	43.1	Guinea-Bissau	33.0
Liberia	47.2	Ghana	37.4	Sierra Leone	32.6
Kenya	46.6	Lebanon	35.3	Somalia	32.0
Lowest emigration rates for college graduates (as %)					
1990		2000		2010	
Oman	0.3	USA	0.4	USA	0.5
USA	0.5	Oman	0.5	Turkmenistan	0.7
UAE	0.6	Turkmenistan	0.7	Tajikistan	0.8
Tajikistan	0.9	UAE	0.7	Japan	1.1
Uzbekistan	0.9	Saudi Arabia	0.9	Indonesia	1.1
Saudi Arabia	0.9	Japan	1.2	Oman	1.2
Turkmenistan	1.0	Tajikistan	1.2	Thailand	1.4
Kyrgyzstan	1.0	Thailand	1.7	Saudi Arabia	1.4
Azerbaijan	1.2	Brazil	1.8	Kyrgyzstan	1.6
Kazakhstan	1.2	Indonesia	2.0	UAE	1.6

Notes: Table 4.A2 focuses on emigration to OECD destination countries only. It excludes countries with a population below one million.

skill-specific wages and native labor force data from Dao et al. (2017), and simulate the equilibrium allocation of the world labor force using Equations (4.13) and (4.14).

Table 4.A4 illustrates the country-specific effects of international migration on human capital in partial and general equilibrium. This table reports the proportions of college graduates in the native labor force and the resident population, as well as the proportions of college graduates under a no migration scenario for the year 2010.

Table 4.A3: Emig. rate by skill group and by country, 1970-2010 (1/4)

	Low-skilled emig. rates					**High-skilled emig. rates**				
Iso	**Backcasts**		**Observations**			**Backcasts**		**Observations**		
	1970	**1980**	**1990**	**2000**	**2010**	**1970**	**1980**	**1990**	**2000**	**2010**
AFG	0.014	0.017	0.006	0.010	0.020	0.094	0.122	0.128	0.111	0.153
ALB	0.240	0.272	0.163	0.189	0.285	0.252	0.281	0.153	0.184	0.269
DZA	0.038	0.036	0.054	0.062	0.061	0.068	0.070	0.090	0.169	0.129
AGO	0.015	0.028	0.026	0.030	0.025	0.089	0.169	0.169	0.154	0.149
ARG	0.013	0.015	0.006	0.013	0.017	0.037	0.040	0.034	0.030	0.045
ARM	0.038	0.044	0.009	0.028	0.044	0.106	0.119	0.096	0.113	0.112
AUS	0.013	0.014	0.011	0.015	0.013	0.032	0.033	0.021	0.027	0.032
AUT	0.050	0.046	0.055	0.048	0.043	0.098	0.085	0.169	0.124	0.083
AZE	0.008	0.009	0.005	0.006	0.010	0.029	0.034	0.012	0.029	0.035
BHS	0.030	0.061	0.075	0.097	0.087	0.116	0.214	0.364	0.288	0.270
BHR	0.005	0.007	0.005	0.006	0.008	0.028	0.036	0.042	0.050	0.044
BGD	0.003	0.003	0.002	0.003	0.004	0.023	0.029	0.036	0.038	0.039
BRB	0.180	0.225	0.247	0.245	0.251	0.399	0.501	0.685	0.576	0.511
BLR	0.034	0.038	0.014	0.022	0.035	0.065	0.078	0.046	0.049	0.070
BEL	0.042	0.040	0.038	0.038	0.038	0.055	0.051	0.052	0.050	0.052
BLZ	0.155	0.161	0.238	0.248	0.203	0.349	0.371	0.530	0.485	0.454
BEN	0.003	0.003	0.002	0.003	0.004	0.109	0.119	0.084	0.109	0.124
BTN	0.012	0.014	0.000	0.000	0.012	0.040	0.058	0.004	0.006	0.067
BOL	0.031	0.034	0.008	0.016	0.047	0.023	0.024	0.068	0.043	0.031
BIH	0.202	0.194	0.122	0.153	0.201	0.224	0.214	0.235	0.213	0.218
BWA	0.015	0.008	0.001	0.002	0.008	0.140	0.074	0.040	0.047	0.092
BRA	0.004	0.003	0.001	0.004	0.005	0.017	0.015	0.013	0.018	0.022
BRN	0.003	0.007	0.016	0.020	0.020	0.012	0.028	0.221	0.130	0.087
BGR	0.087	0.088	0.061	0.076	0.092	0.075	0.074	0.068	0.066	0.076
BFA	0.002	0.002	0.001	0.001	0.002	0.032	0.040	0.020	0.030	0.043
MMR	0.003	0.003	0.001	0.001	0.002	0.024	0.024	0.043	0.032	0.021
BDI	0.002	0.002	0.001	0.002	0.004	0.042	0.041	0.114	0.087	0.083
KHM	0.045	0.043	0.030	0.034	0.030	0.213	0.219	0.225	0.164	0.183
CMR	0.007	0.007	0.003	0.004	0.009	0.100	0.113	0.213	0.179	0.170
CAN	0.047	0.045	0.042	0.052	0.047	0.036	0.035	0.049	0.036	0.037
CPV	0.426	0.386	0.243	0.308	0.331	0.723	0.697	0.821	0.750	0.650
CAF	0.003	0.003	0.002	0.003	0.005	0.084	0.113	0.049	0.108	0.181
TCD	0.001	0.002	0.000	0.001	0.001	0.057	0.109	0.207	0.144	0.100
CHL	0.016	0.019	0.012	0.016	0.018	0.033	0.038	0.069	0.043	0.036
CHN	0.004	0.004	0.001	0.001	0.002	0.057	0.057	0.030	0.038	0.031
COL	0.019	0.020	0.013	0.022	0.030	0.032	0.036	0.106	0.075	0.053
COM	0.036	0.052	0.020	0.048	0.086	0.107	0.145	0.151	0.262	0.268
COD	0.001	0.001	0.004	0.003	0.003	0.049	0.071	0.215	0.204	0.145
COG	0.019	0.018	0.009	0.029	0.029	0.073	0.081	0.160	0.160	0.131
CRI	0.022	0.022	0.017	0.028	0.027	0.033	0.034	0.083	0.046	0.042
CIV	0.005	0.005	0.003	0.006	0.012	0.039	0.043	0.050	0.067	0.105
HRV	0.123	0.113	0.116	0.125	0.141	0.125	0.112	0.188	0.159	0.136
CUB	0.082	0.078	0.079	0.093	0.103	0.196	0.200	0.311	0.210	0.257
CYP	0.157	0.144	0.196	0.171	0.137	0.218	0.211	0.274	0.268	0.218
CZE	0.027	0.027	0.016	0.019	0.029	0.069	0.067	0.105	0.060	0.073

Table 4.A3: Emig. rate by skill group and by country, 1970-2010 (cont'd 2/4)

Iso	Low-skilled emig. rates					High-skilled emig. rates				
	Backcasts		Observations			Backcasts		Observations		
	1970	1980	1990	2000	2010	1970	1980	1990	2000	2010
DNK	0.026	0.027	0.036	0.028	0.027	0.067	0.069	0.074	0.061	0.069
DJI	0.004	0.006	0.008	0.009	0.010	0.065	0.090	0.091	0.086	0.132
DOM	0.150	0.134	0.067	0.137	0.143	0.139	0.126	0.245	0.183	0.140
ECU	0.054	0.052	0.035	0.068	0.091	0.045	0.044	0.074	0.064	0.081
EGY	0.006	0.005	0.005	0.006	0.005	0.034	0.030	0.062	0.045	0.035
SLV	0.203	0.216	0.118	0.201	0.279	0.151	0.165	0.323	0.168	0.231
GNQ	0.136	0.127	0.028	0.044	0.040	0.547	0.522	0.127	0.274	0.236
ERI	0.022	0.024	0.009	0.026	0.027	0.226	0.241	0.298	0.286	0.271
EST	0.056	0.061	0.028	0.026	0.055	0.071	0.079	0.068	0.057	0.068
ETH	0.005	0.005	0.002	0.004	0.006	0.041	0.054	0.091	0.070	0.089
FJI	0.105	0.097	0.093	0.165	0.191	0.317	0.290	0.653	0.604	0.512
FIN	0.070	0.069	0.074	0.064	0.066	0.042	0.043	0.073	0.059	0.045
FRA	0.017	0.017	0.016	0.019	0.018	0.044	0.046	0.026	0.038	0.052
GAB	0.007	0.006	0.003	0.008	0.013	0.120	0.136	0.092	0.215	0.229
GMB	0.039	0.037	0.016	0.025	0.052	0.442	0.415	0.762	0.603	0.537
GEO	0.023	0.029	0.008	0.029	0.045	0.037	0.046	0.020	0.060	0.067
DEU	0.040	0.038	0.033	0.039	0.040	0.061	0.056	0.062	0.051	0.059
GHA	0.010	0.014	0.010	0.012	0.016	0.224	0.265	0.369	0.374	0.277
GRC	0.077	0.070	0.091	0.076	0.066	0.069	0.063	0.154	0.074	0.067
GRD	0.404	0.410	0.358	0.494	0.407	0.690	0.708	0.840	0.802	0.710
GTM	0.087	0.080	0.042	0.082	0.102	0.096	0.089	0.195	0.138	0.118
GIN	0.007	0.007	0.003	0.004	0.009	0.059	0.070	0.037	0.061	0.080
GNB	0.023	0.030	0.038	0.043	0.044	0.166	0.247	0.507	0.446	0.330
GUY	0.264	0.271	0.307	0.363	0.407	0.661	0.669	0.909	0.836	0.782
HTI	0.051	0.044	0.053	0.095	0.097	0.374	0.333	0.766	0.741	0.617
HND	0.081	0.076	0.031	0.077	0.111	0.132	0.127	0.224	0.147	0.190
HUN	0.034	0.034	0.032	0.033	0.036	0.106	0.106	0.157	0.137	0.115
ISL	0.055	0.051	0.062	0.063	0.069	0.131	0.122	0.264	0.180	0.166
IND	0.002	0.003	0.001	0.002	0.002	0.053	0.059	0.028	0.039	0.046
IDN	0.002	0.001	0.004	0.002	0.001	0.011	0.010	0.056	0.020	0.011
IRN	0.006	0.007	0.010	0.012	0.010	0.045	0.059	0.251	0.133	0.091
IRQ	0.007	0.005	0.023	0.027	0.030	0.022	0.017	0.095	0.107	0.100
IRL	0.243	0.227	0.257	0.200	0.182	0.252	0.236	0.361	0.271	0.205
ISR	0.031	0.029	0.027	0.029	0.029	0.068	0.063	0.086	0.064	0.068
ITA	0.040	0.037	0.058	0.047	0.039	0.067	0.062	0.116	0.089	0.068
JAM	0.165	0.212	0.223	0.289	0.305	0.456	0.539	0.855	0.810	0.657
JPN	0.004	0.003	0.002	0.003	0.003	0.010	0.010	0.013	0.012	0.011
JOR	0.018	0.013	0.022	0.019	0.019	0.040	0.030	0.090	0.056	0.050
KAZ	0.070	0.082	0.005	0.040	0.092	0.041	0.049	0.012	0.049	0.056
KEN	0.005	0.005	0.011	0.010	0.008	0.127	0.132	0.466	0.352	0.223
KWT	0.003	0.007	0.003	0.008	0.012	0.024	0.051	0.062	0.064	0.077
KGZ	0.002	0.002	0.003	0.003	0.004	0.009	0.010	0.010	0.021	0.016
LAO	0.084	0.081	0.069	0.092	0.077	0.293	0.277	0.302	0.265	0.258
LVA	0.041	0.046	0.017	0.022	0.049	0.090	0.101	0.068	0.070	0.102
LBN	0.064	0.066	0.106	0.111	0.103	0.148	0.162	0.532	0.353	0.268

Table 4.A3: Emig. rate by skill group and by country, 1970-2010 (cont'd 3/4)

Iso	Low-skilled emig. rates					High-skilled emig. rates				
	Backcasts		Observations			Backcasts		Observations		
	1970	1980	1990	2000	2010	1970	1980	1990	2000	2010
LSO	0.002	0.002	0.001	0.000	0.002	0.047	0.042	0.082	0.055	0.045
LBR	0.012	0.015	0.007	0.019	0.026	0.286	0.354	0.472	0.339	0.447
LBY	0.005	0.007	0.022	0.028	0.023	0.009	0.014	0.061	0.062	0.069
LTU	0.077	0.088	0.070	0.077	0.105	0.039	0.047	0.094	0.076	0.060
LUX	0.079	0.095	0.081	0.076	0.068	0.108	0.124	0.091	0.073	0.089
MKD	0.141	0.130	0.123	0.163	0.187	0.080	0.075	0.075	0.066	0.109
MDG	0.004	0.005	0.002	0.008	0.009	0.089	0.110	0.068	0.134	0.160
MWI	0.002	0.002	0.002	0.002	0.002	0.170	0.167	0.133	0.189	0.210
MYS	0.009	0.007	0.005	0.007	0.006	0.060	0.054	0.263	0.099	0.060
MDV	0.003	0.002	0.001	0.002	0.002	0.021	0.020	0.013	0.017	0.024
MLI	0.016	0.015	0.008	0.010	0.013	0.229	0.220	0.104	0.192	0.192
MLT	0.236	0.204	0.272	0.239	0.209	0.311	0.279	0.688	0.534	0.306
MRT	0.009	0.011	0.009	0.011	0.014	0.038	0.049	0.053	0.112	0.068
MUS	0.129	0.126	0.076	0.082	0.095	0.699	0.694	0.669	0.535	0.618
MEX	0.102	0.092	0.072	0.129	0.143	0.054	0.052	0.109	0.077	0.089
FSM	0.173	0.145	0.153	0.180	0.267	0.203	0.156	0.360	0.378	0.327
MDA	0.029	0.036	0.009	0.014	0.069	0.081	0.098	0.021	0.076	0.172
MNG	0.005	0.004	0.001	0.001	0.008	0.042	0.039	0.095	0.071	0.061
MAR	0.081	0.080	0.079	0.089	0.106	0.159	0.174	0.256	0.246	0.248
MOZ	0.005	0.008	0.008	0.009	0.007	0.318	0.448	0.714	0.643	0.412
NAM	0.004	0.004	0.001	0.001	0.006	0.038	0.043	0.030	0.045	0.068
NPL	0.001	0.001	0.001	0.001	0.001	0.014	0.016	0.062	0.034	0.020
NLD	0.038	0.041	0.040	0.038	0.040	0.068	0.072	0.116	0.086	0.070
NZL	0.108	0.113	0.086	0.111	0.127	0.141	0.147	0.169	0.140	0.157
NIC	0.029	0.038	0.051	0.080	0.075	0.077	0.107	0.278	0.250	0.205
NER	0.001	0.001	0.000	0.001	0.001	0.029	0.045	0.082	0.082	0.081
NGA	0.002	0.002	0.001	0.002	0.003	0.036	0.038	0.078	0.095	0.062
NOR	0.032	0.027	0.036	0.026	0.025	0.053	0.045	0.080	0.060	0.043
OMN	0.002	0.002	0.001	0.000	0.003	0.007	0.009	0.003	0.005	0.012
PAK	0.008	0.008	0.006	0.007	0.008	0.124	0.120	0.077	0.111	0.125
PAN	0.036	0.035	0.037	0.047	0.051	0.077	0.077	0.240	0.162	0.116
PNG	0.004	0.003	0.004	0.006	0.006	0.058	0.047	0.204	0.125	0.082
PRY	0.015	0.014	0.004	0.017	0.023	0.033	0.028	0.039	0.052	0.045
PER	0.029	0.032	0.011	0.028	0.044	0.035	0.038	0.060	0.043	0.052
PHL	0.026	0.025	0.019	0.033	0.037	0.078	0.077	0.126	0.108	0.114
POL	0.079	0.081	0.038	0.061	0.080	0.161	0.162	0.154	0.142	0.164
PRT	0.164	0.148	0.142	0.143	0.149	0.133	0.120	0.159	0.105	0.128
QAT	0.001	0.002	0.002	0.002	0.004	0.008	0.009	0.016	0.026	0.022
ROU	0.091	0.089	0.026	0.051	0.114	0.186	0.177	0.108	0.167	0.207
RWA	0.003	0.003	0.001	0.002	0.004	0.209	0.211	0.167	0.295	0.280
LCA	0.172	0.179	0.148	0.183	0.219	0.386	0.410	0.630	0.572	0.471
VCT	0.236	0.270	0.214	0.308	0.324	0.588	0.635	0.809	0.775	0.682
WSM	0.302	0.284	0.362	0.407	0.420	0.374	0.361	0.625	0.522	0.503
STP	0.098	0.099	0.125	0.151	0.163	0.445	0.479	0.503	0.460	0.611
SAU	0.001	0.001	0.001	0.001	0.002	0.004	0.004	0.009	0.009	0.014

Table 4.A3: Emig. rate by skill group and by country, 1970-2010 (cont'd 4/4)

	Low-skilled emig. rates					**High-skilled emig. rates**				
Iso	**Backcasts**		**Observations**			**Backcasts**		**Observations**		
	1970	**1980**	**1990**	**2000**	**2010**	**1970**	**1980**	**1990**	**2000**	**2010**
SEN	0.024	0.030	0.019	0.026	0.035	0.196	0.233	0.141	0.238	0.252
SRB	0.043	0.039	0.068	0.068	0.070	0.040	0.036	0.111	0.076	0.061
SLE	0.008	0.009	0.004	0.011	0.016	0.179	0.204	0.439	0.431	0.326
SGP	0.021	0.018	0.016	0.017	0.018	0.050	0.046	0.253	0.129	0.055
SVK	0.088	0.089	0.095	0.092	0.087	0.166	0.166	0.125	0.153	0.158
SVN	0.043	0.038	0.038	0.040	0.041	0.050	0.041	0.086	0.061	0.044
SLB	0.003	0.002	0.004	0.005	0.005	0.029	0.021	0.210	0.171	0.054
SOM	0.027	0.032	0.011	0.025	0.048	0.183	0.229	0.215	0.225	0.320
ZAF	0.005	0.005	0.004	0.006	0.008	0.060	0.061	0.120	0.079	0.085
ESP	0.021	0.019	0.030	0.022	0.016	0.037	0.032	0.035	0.035	0.032
LKA	0.027	0.028	0.010	0.016	0.025	0.166	0.153	0.270	0.209	0.208
SDN	0.003	0.003	0.001	0.001	0.004	0.034	0.041	0.076	0.060	0.051
SUR	0.236	0.240	0.441	0.422	0.369	0.439	0.441	0.692	0.635	0.587
SWZ	0.004	0.004	0.002	0.001	0.005	0.031	0.038	0.037	0.043	0.058
SWE	0.020	0.022	0.017	0.018	0.021	0.041	0.044	0.042	0.040	0.042
CHE	0.045	0.052	0.044	0.060	0.057	0.092	0.099	0.071	0.101	0.106
SYR	0.012	0.009	0.016	0.014	0.013	0.038	0.029	0.077	0.050	0.044
TJK	0.001	0.001	0.003	0.005	0.002	0.003	0.003	0.009	0.012	0.008
TZA	0.002	0.002	0.003	0.003	0.002	0.078	0.089	0.108	0.103	0.122
THA	0.009	0.008	0.002	0.004	0.007	0.015	0.014	0.024	0.017	0.014
TGO	0.004	0.004	0.004	0.005	0.010	0.043	0.054	0.136	0.140	0.111
TON	0.331	0.317	0.292	0.364	0.455	0.428	0.427	0.809	0.727	0.582
TTO	0.174	0.161	0.160	0.194	0.188	0.680	0.660	0.800	0.752	0.688
TUN	0.068	0.061	0.063	0.077	0.069	0.099	0.105	0.311	0.203	0.140
TUR	0.054	0.055	0.052	0.053	0.057	0.041	0.043	0.085	0.045	0.047
TKM	0.001	0.001	0.003	0.002	0.002	0.005	0.005	0.010	0.007	0.007
UGA	0.003	0.005	0.007	0.006	0.004	0.125	0.181	0.428	0.330	0.170
UKR	0.017	0.020	0.023	0.026	0.029	0.052	0.061	0.033	0.059	0.086
ARE	0.002	0.002	0.001	0.001	0.005	0.006	0.008	0.006	0.007	0.016
GBR	0.055	0.056	0.050	0.054	0.053	0.126	0.128	0.178	0.153	0.121
USA	0.003	0.004	0.003	0.003	0.003	0.006	0.006	0.005	0.004	0.005
URY	0.051	0.052	0.018	0.029	0.056	0.118	0.117	0.079	0.080	0.117
UZB	0.003	0.004	0.003	0.005	0.005	0.025	0.026	0.009	0.024	0.032
VUT	0.009	0.008	0.006	0.011	0.014	0.060	0.059	0.130	0.101	0.101
VEN	0.007	0.009	0.004	0.011	0.015	0.024	0.033	0.035	0.038	0.052
VNM	0.032	0.035	0.013	0.027	0.025	0.162	0.183	0.238	0.188	0.140
YEM	0.007	0.005	0.010	0.010	0.008	0.028	0.020	0.278	0.110	0.039
ZMB	0.003	0.004	0.002	0.004	0.006	0.068	0.090	0.197	0.178	0.128
ZWE	0.006	0.007	0.003	0.007	0.015	0.111	0.114	0.076	0.115	0.244

Table 4.A4: Effect of intl. migration on human capital in 2010 (1/4)

Iso	**Observations**			**No mig. (par. eq.)**		**No mig. (gen. eq.)**	
	$\mathbf{\Lambda}$	**H**	**h**	$\mathbf{\Lambda}$	**H = h**	$\mathbf{\Lambda}$	**H = h**
AFG	3.4	0.046	0.040	3.0	0.041	2.9	0.041
ALB	2.2	0.128	0.130	2.2	0.132	2.2	0.131
DZA	2.7	0.115	0.107	2.5	0.106	2.6	0.107
AGO	3.1	0.053	0.047	2.7	0.047	2.7	0.047
ARG	1.8	0.218	0.213	1.8	0.205	1.8	0.209
ARM	2.4	0.251	0.237	2.2	0.228	2.2	0.231
AUS	1.2	0.354	0.361	1.2	0.300	1.2	0.350
AUT	1.3	0.218	0.201	1.2	0.158	1.2	0.191
AZE	2.3	0.195	0.191	2.3	0.189	2.3	0.189
BHS	2.6	0.184	0.153	2.1	0.139	2.2	0.144
BHR	2.1	0.179	0.174	2.1	0.169	2.1	0.171
BGD	2.9	0.064	0.062	2.8	0.062	2.8	0.062
BRB	3.2	0.217	0.153	2.1	0.137	2.2	0.143
BLR	1.6	0.242	0.235	1.6	0.217	1.6	0.227
BEL	1.2	0.349	0.337	1.2	0.312	1.2	0.332
BLZ	3.4	0.159	0.115	2.3	0.111	2.4	0.112
BEN	3.3	0.026	0.023	2.9	0.024	2.9	0.023
BTN	3.1	0.055	0.052	2.9	0.052	2.9	0.052
BOL	1.6	0.175	0.178	1.6	0.184	1.6	0.180
BIH	2.3	0.133	0.130	2.3	0.129	2.3	0.129
BWA	3.3	0.055	0.050	3.0	0.051	3.0	0.051
BRA	3.6	0.106	0.105	3.5	0.105	3.5	0.105
BRN	2.0	0.154	0.145	1.9	0.135	1.9	0.139
BGR	1.3	0.223	0.226	1.3	0.249	1.3	0.232
BFA	3.1	0.021	0.020	3.0	0.020	3.0	0.020
MMR	3.0	0.068	0.067	2.9	0.067	2.9	0.067
BDI	3.2	0.039	0.036	2.9	0.036	2.9	0.036
KHM	3.4	0.039	0.033	2.9	0.034	2.8	0.034
CMR	3.6	0.046	0.039	3.0	0.040	3.0	0.040
CAN	1.2	0.574	0.568	1.2	0.639	1.2	0.571
CPV	4.9	0.047	0.025	2.6	0.030	2.5	0.028
CAF	3.6	0.018	0.015	2.9	0.016	2.9	0.015
TCD	2.3	0.010	0.009	2.0	0.009	2.1	0.009
CHL	2.0	0.177	0.177	2.0	0.171	2.0	0.174
CHN	1.4	0.051	0.049	1.3	0.044	1.4	0.047
COL	3.0	0.163	0.160	2.9	0.160	2.9	0.160
COM	3.7	0.053	0.043	3.0	0.045	2.9	0.044
COD	3.5	0.027	0.023	3.0	0.024	3.0	0.024
COG	3.3	0.063	0.057	3.0	0.058	3.0	0.058
CRI	2.0	0.209	0.206	2.0	0.203	2.0	0.205
CIV	3.3	0.050	0.045	3.0	0.046	3.0	0.046
HRV	2.2	0.159	0.160	2.2	0.160	2.2	0.160
CUB	2.6	0.146	0.124	2.2	0.115	2.2	0.119
CYP	1.9	0.260	0.242	1.7	0.213	1.8	0.227
CZE	1.1	0.154	0.150	1.1	0.075	1.1	0.137

Table 4.A4: Effect of intl. migration on human capital in 2010 (cont'd 2/4)

Iso	**Observations**			**No mig. (par. eq.)**		**No mig. (gen. eq.)**	
	Λ	**H**	**h**	**Λ**	**H = h**	**Λ**	**H = h**
DNK	1.4	0.252	0.249	1.3	0.202	1.3	0.234
DJI	3.0	0.056	0.049	2.6	0.049	2.6	0.049
DOM	1.7	0.193	0.194	1.7	0.195	1.7	0.194
ECU	1.9	0.198	0.200	1.9	0.202	1.9	0.201
EGY	2.3	0.153	0.149	2.2	0.146	2.2	0.147
SLV	2.1	0.133	0.140	2.2	0.146	2.2	0.144
GNQ	3.1	0.062	0.050	2.5	0.050	2.5	0.050
ERI	3.9	0.033	0.025	2.9	0.027	2.9	0.027
EST	1.5	0.320	0.323	1.5	0.306	1.5	0.317
ETH	3.3	0.027	0.025	3.0	0.026	3.0	0.026
FJI	4.1	0.182	0.118	2.5	0.121	2.5	0.120
FIN	1.5	0.387	0.387	1.6	0.416	1.5	0.397
FRA	1.4	0.236	0.230	1.4	0.201	1.4	0.220
GAB	2.9	0.053	0.042	2.3	0.040	2.3	0.041
GMB	5.9	0.030	0.015	2.9	0.020	2.7	0.019
GEO	1.8	0.276	0.271	1.8	0.262	1.8	0.266
DEU	1.2	0.304	0.287	1.2	0.256	1.2	0.281
GHA	3.3	0.038	0.028	2.4	0.029	2.4	0.028
GRC	1.3	0.206	0.204	1.3	0.205	1.3	0.204
GRD	4.8	0.202	0.110	2.3	0.117	2.3	0.115
GTM	3.4	0.068	0.067	3.3	0.067	3.3	0.067
GIN	3.2	0.037	0.034	3.0	0.035	3.0	0.035
GNB	4.3	0.023	0.016	3.0	0.018	2.9	0.018
GUY	7.5	0.206	0.087	2.7	0.122	2.5	0.111
HTI	7.0	0.053	0.023	3.0	0.035	2.7	0.031
HND	3.9	0.081	0.075	3.6	0.077	3.5	0.076
HUN	1.5	0.158	0.152	1.3	0.110	1.4	0.136
ISL	1.9	0.295	0.275	1.7	0.235	1.8	0.255
IND	2.8	0.073	0.070	2.7	0.070	2.7	0.070
IDN	2.7	0.095	0.094	2.7	0.094	2.7	0.094
IRN	2.7	0.114	0.106	2.5	0.105	2.5	0.105
IRQ	2.5	0.128	0.120	2.4	0.117	2.4	0.118
IRL	1.6	0.339	0.347	1.5	0.310	1.6	0.333
ISR	1.3	0.335	0.353	1.3	0.268	1.3	0.329
ITA	1.4	0.123	0.121	1.4	0.109	1.4	0.116
JAM	5.5	0.186	0.102	2.7	0.120	2.6	0.115
JPN	1.4	0.309	0.308	1.4	0.299	1.4	0.305
JOR	2.0	0.272	0.266	2.0	0.258	2.0	0.261
KAZ	1.8	0.242	0.249	1.9	0.261	1.9	0.256
KEN	3.8	0.035	0.028	3.0	0.030	2.9	0.029
KWT	2.0	0.194	0.184	1.8	0.171	1.9	0.177
KGZ	1.9	0.193	0.191	1.9	0.188	1.9	0.190
LAO	3.5	0.070	0.057	2.8	0.059	2.8	0.058
LVA	1.7	0.312	0.288	1.6	0.268	1.6	0.280
LBN	2.7	0.194	0.165	2.2	0.153	2.3	0.157

Table 4.A4: Effect of intl. migration on human capital in 2010 (cont'd 3/4)

Iso	**Observations**			**No mig. (par. eq.)**		**No mig. (gen. eq.)**	
	Λ	**H**	**h**	**Λ**	**H = h**	**Λ**	**H = h**
LSO	3.1	0.032	0.031	3.0	0.031	3.0	0.031
LBR	5.2	0.035	0.020	2.9	0.025	2.8	0.023
LBY	2.3	0.137	0.132	2.2	0.128	2.2	0.130
LTU	1.7	0.333	0.344	1.8	0.372	1.8	0.357
LUX	1.2	0.306	0.308	1.2	0.258	1.2	0.297
MKD	1.8	0.140	0.151	2.0	0.167	1.9	0.160
MDG	3.5	0.029	0.025	3.0	0.026	3.0	0.026
MWI	3.8	0.010	0.008	3.0	0.008	3.0	0.008
MYS	2.6	0.175	0.168	2.4	0.165	2.5	0.166
MDV	2.2	0.092	0.090	2.2	0.089	2.2	0.089
MLI	3.6	0.012	0.010	3.0	0.011	2.9	0.010
MLT	2.4	0.165	0.148	2.1	0.137	2.1	0.141
MRT	3.1	0.051	0.049	2.9	0.049	2.9	0.049
MUS	5.6	0.078	0.034	2.4	0.043	2.2	0.040
MEX	2.7	0.132	0.140	2.9	0.140	2.9	0.140
FSM	2.7	0.147	0.137	2.5	0.135	2.5	0.135
MDA	2.0	0.200	0.182	1.8	0.160	1.8	0.170
MNG	3.0	0.089	0.084	2.9	0.084	2.9	0.084
MAR	3.1	0.086	0.074	2.6	0.074	2.6	0.074
MOZ	5.0	0.008	0.005	3.0	0.006	2.8	0.006
NAM	3.2	0.060	0.057	3.0	0.057	3.0	0.057
NPL	2.9	0.048	0.047	2.9	0.048	2.9	0.048
NLD	1.3	0.290	0.283	1.3	0.245	1.3	0.272
NZL	1.2	0.320	0.353	1.2	0.229	1.2	0.328
NIC	2.7	0.115	0.100	2.3	0.096	2.3	0.098
NER	3.2	0.010	0.009	3.0	0.009	3.0	0.009
NGA	3.2	0.075	0.071	3.0	0.071	3.0	0.071
NOR	1.1	0.314	0.317	1.1	0.221	1.1	0.306
OMN	2.1	0.170	0.169	2.1	0.167	2.1	0.168
PAK	2.4	0.044	0.039	2.2	0.037	2.2	0.038
PAN	2.3	0.228	0.216	2.1	0.207	2.2	0.210
PNG	3.1	0.055	0.051	2.8	0.051	2.8	0.051
PRY	2.1	0.111	0.109	2.0	0.108	2.1	0.108
PER	1.9	0.300	0.298	1.8	0.295	1.8	0.297
PHL	2.4	0.294	0.277	2.2	0.264	2.3	0.269
POL	1.6	0.191	0.177	1.4	0.136	1.5	0.160
PRT	1.9	0.122	0.135	1.9	0.128	1.9	0.131
QAT	2.0	0.166	0.163	2.0	0.161	2.0	0.162
ROU	2.6	0.140	0.127	2.3	0.123	2.4	0.124
RWA	4.2	0.011	0.008	3.0	0.009	2.9	0.009
LCA	4.0	0.139	0.098	2.7	0.103	2.7	0.102
VCT	5.5	0.172	0.089	2.6	0.106	2.5	0.101
WSM	2.9	0.153	0.134	2.5	0.131	2.5	0.132
STP	6.4	0.042	0.020	3.0	0.028	2.7	0.026
SAU	2.1	0.205	0.203	2.1	0.201	2.1	0.202

Table 4.A4: Effect of intl. migration on human capital in 2010 (cont'd 4/4)

Iso	**Observations**			**No mig. (par. eq.)**		**No mig. (gen. eq.)**	
	$\boldsymbol{\Lambda}$	**H**	**h**	$\boldsymbol{\Lambda}$	**H = h**	$\boldsymbol{\Lambda}$	**H = h**
SEN	3.9	0.037	0.029	3.0	0.031	2.9	0.031
SRB	2.3	0.167	0.169	2.4	0.170	2.3	0.169
SLE	4.4	0.033	0.023	3.0	0.026	2.9	0.025
SGP	2.5	0.344	0.335	2.4	0.328	2.4	0.331
SVK	1.3	0.151	0.142	1.2	0.078	1.2	0.124
SVN	1.3	0.189	0.180	1.3	0.186	1.3	0.181
SLB	3.1	0.075	0.071	3.0	0.072	3.0	0.072
SOM	4.2	0.035	0.025	3.0	0.028	2.9	0.027
ZAF	3.2	0.128	0.119	3.0	0.120	3.0	0.119
ESP	1.4	0.180	0.186	1.4	0.167	1.4	0.179
LKA	3.5	0.070	0.057	2.8	0.059	2.8	0.059
SDN	3.1	0.049	0.047	3.0	0.047	3.0	0.047
SUR	3.6	0.127	0.087	2.4	0.087	2.4	0.087
SWZ	2.8	0.078	0.075	2.7	0.074	2.7	0.074
SWE	1.2	0.364	0.353	1.2	0.300	1.2	0.343
CHE	1.6	0.212	0.228	1.5	0.178	1.5	0.207
SYR	2.2	0.143	0.139	2.2	0.136	2.2	0.137
TJK	2.4	0.179	0.178	2.3	0.178	2.3	0.178
TZA	3.4	0.020	0.018	3.0	0.018	3.0	0.018
THA	2.2	0.145	0.144	2.2	0.144	2.2	0.144
TGO	3.3	0.051	0.046	3.0	0.047	3.0	0.047
TON	3.2	0.156	0.124	2.5	0.122	2.5	0.123
TTO	5.9	0.143	0.060	2.3	0.073	2.2	0.068
TUN	2.8	0.115	0.107	2.6	0.106	2.6	0.106
TUR	2.3	0.119	0.121	2.4	0.121	2.4	0.121
TKM	2.3	0.185	0.184	2.3	0.184	2.3	0.184
UGA	3.6	0.026	0.022	3.0	0.023	3.0	0.023
UKR	1.9	0.218	0.208	1.8	0.193	1.8	0.200
ARE	2.1	0.164	0.162	2.1	0.161	2.1	0.162
GBR	1.5	0.257	0.274	1.4	0.198	1.5	0.243
USA	1.4	0.492	0.468	1.4	0.488	1.4	0.473
URY	1.9	0.141	0.133	1.7	0.122	1.8	0.127
UZB	2.4	0.152	0.148	2.4	0.147	2.4	0.147
VUT	2.7	0.076	0.070	2.5	0.069	2.5	0.069
VEN	1.9	0.247	0.240	1.9	0.230	1.9	0.235
VNM	3.1	0.070	0.062	2.8	0.062	2.8	0.062
YEM	3.0	0.042	0.041	2.9	0.041	2.9	0.041
ZMB	3.4	0.057	0.050	3.0	0.051	3.0	0.051
ZWE	3.9	0.074	0.058	3.0	0.061	2.9	0.060

4.A.4 Internal migration in the dyadic model

The model described above could be extended by assuming that agents in country i additionally have the option to migrate internally to a number of m regions, which is an increasing function of the country size S_i (i.e., $\frac{\partial m(S_i)}{\partial S_i} > 0$). For expositional convenience, we assume that the other regions are characterized by similar economic conditions (same wage rates, etc.) and internal migration costs $\tilde{c}_{ii,s}$ to all regions are identical. We assume $\mu = 1$ for tractability. Actual international migration costs are denoted by $\tilde{c}_{ij,s}$. The multinomial logit expression (4.12) described above then becomes:

$$\begin{aligned} \frac{N_{ij}^s}{N_i^s} &= \frac{w_{j,s}(1-\tilde{c}_{ij,s})}{w_{i,s} + m w_{i,s}(1-\tilde{c}_{ii,s}) + \sum_{k\neq i} w_{k,s}(1-\tilde{c}_{ik,s})} \\ &= \frac{w_{j,s}(1-\tilde{c}_{ij,s})}{w_{i,s}(1+m(1-\tilde{c}_{ii,s})) + \sum_{k\neq i} w_{k,s}(1-\tilde{c}_{ik,s})}, \end{aligned} \tag{4.22}$$

which can be rewritten as a standard logit model:

$$\frac{N_{ij}^s}{N_i^s} = \frac{w_{j,s}\frac{1-\tilde{c}_{ij,s}}{1+m(1-\tilde{c}_{ii,s})}}{w_{i,s} + \sum_{k\neq i} w_{k,s}\frac{1-\tilde{c}_{ik,s}}{1+m(1-\tilde{c}_{ii,s})}}. \tag{4.23}$$

We do not observe internal migration and directly calibrate $1 - c_{ij,s}$, which is negatively affected by m. It clearly appears that our calibrated international migration costs implicitly accounts for internal migration costs:

$$1 - c_{ij,s} = \frac{1-\tilde{c}_{ij,s}}{1+m(1-\tilde{c}_{ii,s})}. \tag{4.24}$$

In large countries with more internal migration opportunities, m is large. This means the calibrated international migration costs $c_{ij,s}$ are larger: other things equal, large countries send less emigrants abroad.

Conclusion

This thesis discusses human migration at all spatial scales. It analyzes how local, regional and international migration are connected with and affected by high-skilled human capital accumulation, global inequality and climate change. In particular, the analysis addresses the education-migration nexus by specifically investigating the connection between high-skilled educational attainment and mobility. In addition, the analysis focuses on the climate-migration nexus by evaluating the impact of slow-onset effects of climate change on human mobility. The thesis proposes models that allow quantitatively assessing these connections. With the exception of the third chapter, which addresses the development in Africa, the discussion focuses on the world economy. Furthermore, while our models are micro-founded, results are provided at the macro-level.

The thesis starts by investigating the geography of skills in Chapter 1. This chapter analyzes how high-skilled human capital is spatially distributed and linked with global inequality. As opposed to many existing studies, the analysis jointly assesses the effects of international and internal migration. We show that the geography of skills has important implications for global inequality. Furthermore, our projections indicate that - with the continuation of current migration and education policies - inequality in the distribution of skills will persist over the 21st century. Our results highlight the impact of education and urbanization on future inequality and demographic pressures.

Based on the finding that high-skilled capital accumulation and urbanization are key determinants of future development, Chapter 2 further extends the model developed in Chapter 1. It incorporates the effects of climate change on human mobility at the local, regional and international scale. The analysis accounts for the effect of projected temperature increases on productivity and on sea-level rise. We find that climate change has a limited impact on international migration and predominantly induces movements at the local level over the 21st century.

This conclusion is crucial for the analysis conducted in Chapter 3 which aims at further specifying the results by focusing on the development in Africa. This chapter explicitly addresses the impact of climate change on high-skilled educational attainment in African economies. The focus of this chapter lies on the adaptation mechanisms to climate change. The proposed theoretical model accounts for internal mobility only. The findings derived from this model are validated by an empirical analysis and lead to the conclusion that adverse climatic conditions may have an unexpected beneficial effect on high-skilled educational attainment in Africa.

Finally, the focus of the analysis remains on high-skilled human capital accumulation in the last chapter but returns to the global scale and to international migration. Chapter 4 analyzes the brain drain phenomenon and updates the findings of the many previous studies on this topic. We propose a new theoretical dyadic approach. This allows us to assess the country-specific effects of international migration prospects on human capital accumulation and the efficiency of public education policies. We find smaller average effects of international migration on high-skilled education than the standard macroeconometric models. Furthermore, we show that the impact of international migration on the effectiveness of public education is rather limited.

In terms of policy implications, this thesis emphasizes the importance of policies that improve the access to all levels of education, enhance the quality of education and contribute to sustainable urban development. Moreover, the analysis illustrates that international migration does not have a detrimental impact on the effectiveness of public education policies. Hence, international migration cannot serve as an argument to limit the access to or the quality of public education. Finally, we show that the expected adverse effects of climate change call for coherent policy frameworks targeting sustainable development and migration at all spatial scales.

Overall, this thesis demonstrates that the links between mobility, inequality, human capital accumulation, and climate change are complex. This indicates that a multidimensional analysis of the connections between these different factors is very important. Migration at the local, regional and international scale are linked with global development through a variety of channels that are shown to be frequently interconnected. While this certainly explains the mixed and often conflicting findings of the literature on the economics of migration, it also calls for more sophisticated and careful studies of the phenomenon of human mobility. The world is becoming increasingly interconnected and human migration is closely tied to the international integration process. This thesis, therefore, aspires to provide and refine some important findings in order to contribute to a better informed debate about human migration.

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