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INTERGENERATIONAL MOBILITY IN AFRICA

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ABSTRACT

We examine intergenerational mobility (IM) in educational attainment in Africa since independence, using census data from 26 countries. First, we map and characterize the geography of IM. There is substantial variation both across and within countries with differences in literacy of the old generation being the strongest correlate of IM. Inertia is stronger for rural, as compared to urban, households and present for both boys and girls. Second, we explore the correlates of mobility across more than 2,800 regions. Colonial investments in the transportation network and missionary activity are associated with upward mobility. IM is also higher in regions close to the coast and national capitals as well as in rugged areas without malaria. Upward mobility is higher and downward mobility is lower in regions that were more developed at independence, with higher urbanization and employment in services and manufacturing. Third, we identify the effects of regions on educational mobility by exploiting within-family variation from children whose families moved during primary school age. While sorting is sizable, there are considerable regional exposure effects.

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An online appendix is available at <http://www.nber.org/data-appendix/w25534>

1 Introduction

There is rising optimism about Africa’s future, a continent with 1.2 billion opportunities, as the Economist (2016) recently touted. The formerly “hopeless continent” is gradually becoming the “hopeful” one (Economist (2000, 2011)). Educational attainment is rising, health is improving, and the income of many Africans is growing. Some speak about an African “growth miracle” (Young (2012)). However, anecdotal evidence indicates widespread inequalities in income, education, and social mobility. This suggests that the aggregate gains may not be broadly shared, but a comprehensive assessment is lacking.

In this paper, we take the first step toward mapping, exploring and explaining intergenerational mobility across the continent since independence. We look at educational attainment using census data covering more than 14 million individuals across 26 African countries and 2,800 regions. Reconstructing the joint distribution of parental and offspring educational outcomes since the 1960s, when most of Africa becomes independent, allows us to shed light on many questions. Where is the land of educational opportunity in Africa? Are differences in intergenerational mobility across countries and regions small, moderate or wide? How large are gender disparities? How big is the rural-urban gap? Which elements of a region’s history and geography correlate with educational mobility? Do regions matter for social mobility or do regions with higher mobility just attract families more eager to climb the social ladder?

Results Preview In the first part of the paper, we present new country and region level measures of educational opportunity in Africa. Following recent work on intergenerational mobility in income (Chetty et al. (2014); Chetty and Hendren (2018a), Chetty and Hendren (2018b)) and education (Card et al. (2018); Fletcher and Han (2018)) we construct measures of upward intergenerational mobility (IM) defined as the likelihood that children born to parents that have not completed primary schooling manage to do so. Similarly, we map downward mobility, defined as the probability that offspring of parents with completed primary education fail to do so. We use data from 14,149,328 children residing with at least one parent at the time of the census. To account for “selection on cohabitation”, we follow Card et al. (2018) and focus on children between 14 and 18 years. Children in that age bracket have largely finished primary school and at the same time they still reside overwhelmingly with their parents (cohabitation rates are approximately 94%).

We document large cross-country heterogeneity in upward and downward mobility rates. The likelihood that children born to parents with no education complete primary schooling exceeds 70% in South Africa and Botswana; the corresponding statistic in Sudan, Ethiopia, Mozambique, Burkina Faso, and Malawi hovers below 20%. The analysis also uncovers substantial within-country differences in IM. For example, in Kenya, a country with a close-to-average IM of 0.50, the likelihood that children of illiterate parents will complete primary education ranges from just 5% (in Turkana county in the Northwest of the country) to more than 85% (in Westlands, an administrative division and affluent neighborhood in Nairobi). Upward IM is higher (lower) in regions and countries with

relatively higher (lower) levels of parental literacy. Variation in literacy rates among the old generation accounts for half of the observed regional variability in intergenerational mobility. Downward mobility is also linked to the stock of literacy, though the association is less strong. These findings imply considerable persistence of initial conditions. Inertia is stronger for rural Africa. While there is a gender gap in educational levels, intergenerational mobility is similar for boys and girls.

In the second part, we characterize the geography of the *land of opportunity* in Africa. Upward IM is higher and downward IM is lower in malaria-free regions. Distance to the capital and the coast correlate negatively with upward IM; this most likely reflects African states' weak capacity to broadcast power far from the main urban hubs and limited public investment in the countryside. Colonial investments in railroads and roads as well as missionary presence correlate positively with upward IM and negatively with downward IM. Though these correlations are robust to controlling for the parental stock of literacy, they do not identify causal effects. However, they are suggestive of how historical contingencies related to colonization and geographic attributes may influence not only initial economic conditions, but also the trajectories of local economies.

The observed differences in regional IM may result from two quite different forces. On the one hand, regions may have a causal impact on mobility, by providing higher quality infrastructure, more schools, and better occupational opportunities. On the other hand, regional disparities could reflect sorting, as families with higher ability and/or valuation of education move to areas with better opportunities.

In the third part, we assess the relative magnitudes of these two factors. As a starting point, we estimate within-household specifications looking at the effect of place-of-birth-IM on the probability that children born to illiterate parents will complete primary education. By comparing siblings born and partly raised in regions with different IM, we account for family characteristics. The within-family analysis reveals that while sorting is sizable, the district a child grows up in matters crucially for whether she will complete primary education. We then employ the neat approach of Chetty and Hendren (2018a) to isolate the one-way effect of regions on educational mobility. The methodology exploits differences in the age at which children of migrant households move across districts to distinguish “*selection*” from “*regional exposure effects*”. Both forces are at play. Selection is far-from-negligible; families' sorting into better (worse) locations correlates strongly with children's educational attainment. This result adds to the recent findings of Young (2013), who uses survey data to document two-way rural-urban migration in developing countries based on differences in human capital. The analysis also uncovers sizable “*regional exposure effects*” both for boys and girls. A child who moves with her uneducated parents to a region with a one-standard-deviation higher IM than her birthplace at the age of 6, has a 7 percentage points higher likelihood of completing primary schooling, compared to her sibling who at the time of the move was already 11 years old.

Related Literature Our work contributes to and blends two strands of literature that have, thus far, moved in parallel. The first is the growing research that studies intergenerational mobility. Solon (1999) and Black and Devereux (2011) review works on

intergenerational mobility in income/wealth and education, respectively.¹ A key challenge has been the matching of children to parental outcomes; as such, most earlier works rely on relatively small samples from surveys. Card et al. (2018) use census data from the entire US population in 1940 to map educational mobility by looking at children residing with at least one parent (as we do). They show rising mobility during the first half of the 20th century, which differs across race and states.² Chetty et al. (2014) provide a mapping of IM in income across US counties and explore its correlates. Chetty and Hendren (2018a) use matched parents-children administrative tax records of moving families to isolate the effect of neighborhood exposure on mobility from sorting. Our work is similar in spirit to the study of Asher et al. (2018), on educational mobility across Indian regions and to the parallel work of the World Bank trying to construct measures of intergenerational mobility in education and income across many countries using survey data (Narayan et al. (2018)). Finally, our paper relates to Becker et al. (2018) who develop a theory of intergenerational mobility where parental investments in education result in persistent differences in economic status even in the absence of capital market imperfections and differences in innate ability.

The second strand is the research on African development (Young (2012), Pinkovskiy and Sala-i-Martin (2014)). The literature has moved from mostly cross-country approaches focusing on national features (e.g., Gunning and Collier (1999), Bates (2015)), to within-country analyses that connect Africa’s contemporary development to its colonial and pre-colonial past. This research provides compelling evidence of historical continuity as well as instances of rupture in the evolution of the economy and polity (Michalopoulos and Papaioannou (2019) provide a review). Nevertheless, this literature has not opened the “black box” of intergenerational linkages. A natural question is whether the correlation between deeply rooted factors and current outcomes reflects the one-time effect of the former on initial (at-independence) conditions or if these identified historical legacies have also changed the transmission of opportunity across generations. By building granular data on IM across African regions and exploring in a systematic manner its correlates we can begin answering such questions.³

Structure In Section 2, we present the census data on educational attainment and detail the construction of the intergenerational educational mobility measures. Section

¹Olivetti and Paserman (2015) and Olivetti et al. (2018) study IM in income in the United States from 1850 till 1940. Charles and Hurst (2004) use PSID data to estimate intergenerational persistence in wealth across US households. Alesina et al. (2018) compare actual social mobility and perceptions across several industrial countries. Early studies on intergenerational mobility in education include Bowles (1972), Blake (1985), and Spady (1967). Hertz et al. (2008) estimate country-level IM coefficients for various cohorts across 42 countries. Hilger (2017) calculates educational IM in the United States since WWII. Azam and Bhatt (2015) and Golley and Kong (2013) estimate mobility in education in India and China, respectively. Long and Ferrie (2013) describe the dynamics of occupational intergenerational mobility in the US and the UK since mid-19th century. They document higher levels of upward mobility in the early decades in the US, which however vanish in the Inter-war period.

²A strand of the mostly US-centered literature looks at racial differences in intergenerational mobility (e.g., Chetty et al. (2018), Davis and Mazumder (2018), Derenoncourt (2018)). These studies relate to our companion work (Alesina et al. (2019)), where we map ethnic and religious differences in social mobility across Africa.

³In an innovative case study, Wantchekon et al. (2015) study the intergenerational impact of colonial schools in Benin. They show that colonial schools not only raised income, education, and well-being of students and their communities, but that the benefits spread to the second and third generation.

3 describes IM across African countries and regions. Section 4 presents the results from the exploration of the geographic, historical and at-independence correlates of educational mobility. In Section 5, we first explore within-household variation on children’s place of birth to isolate selection (migration) from regional features affecting intergenerational mobility. We then exploit differences in ages-at-move among migrants to estimate regional exposure effects on educational mobility. In Section 6, we summarize and discuss avenues for future research.

2 Data and methods

2.1 Why Education?

We focus on education for several reasons. First, income and wealth data are available for a tiny share of the African population and only for a handful of countries. For instance, Alvaredo et al. (2017) report that for Ghana, Kenya, Tanzania, Nigeria, and Uganda, income data encompass less than 1% of the adult population, while for most African countries tax records do not exist, as the share of the underground economy is substantial (Porta and Shleifer (2008), La Porta and Shleifer (2014)) and fiscal capacity very weak (Besley and Persson (2013)). Moreover, consumption data are noisy, cover small samples, and are not spatially disaggregated. In contrast, education data are available since the late 1960s and have a fine temporal and geographic resolution. Second, measurement error in educational attainment is a lesser concern compared to that of reported income, wealth or consumption. Education is also useful in mapping intergenerational mobility, as people tend to complete primary schooling, which is the key educational achievement for most of Africa, by the age of 14. Hence, unlike lifetime earnings or wealth, the analysis can start when adults are relatively early in the life-cycle. Third, education is strongly correlated with income/wealth across countries (e.g., Barro and Lee (2013) and regions (Gennaioli et al. (2014)); a large body of research in labor economics shows that education causally affects lifetime income (Card (1999), Krueger and Lindahl (2001)). Individual (Mincerian) returns to schooling are sizable and possibly larger in low-income countries.⁴ Fourth, as we show in Appendix D with data from the Demographic and Health Surveys (DHS) and the Afrobarometer Surveys, years of schooling correlate positively with various proxies of well-being; living conditions, child mortality and fertility, attitudes toward domestic violence, and proxies of political and civic engagement.

2.2 Sample

Our analysis is based upon individual records, retrieved from 68 national censuses from 26 countries: Benin, Botswana, Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Morocco, Mozambique, Nigeria, Rwanda, Sene-

⁴Young (2012) reports Mincerian returns in the range of 11.3% (OLS) to 13.9% (2SLS) in a sample of 14 Sub-Saharan African countries with data on labour income from the Demographic and Health Surveys. These estimates are higher than in 11 non-SSA low income countries [range between 8.7% (OLS) and 10.4% (2SLS)] and the “consensus” estimate of 6.5% – 8.5% in high income countries. Caselli et al. (2014) report lower returns in Sub-Saharan Africa of 8.5%. In line with the earlier work of Psacharopoulos (1994) they also estimate a negative relationship between Mincerian returns and years of schooling (which is steeper in 1995 as compared to 2005). Montenegro and Patrinos (2014) estimate higher Mincerian returns in SSA (12.5%) compared to the rest of the world (9.7%).

gal, Sierra Leone, South Africa, Sudan, South Sudan, Tanzania, Uganda, Zambia, and Zimbabwe. We retrieve the data from IPUMS (Integrated Public Use Microdata Series) International, hosted at the University of Minnesota Population Centre. IPUMS reports harmonized, representative samples, typically 10%.⁵ As of 2015, the countries in our sample were home to slightly more than 850 million people, representing around 75 percent of Africa’s population and GDP.

Overall, IPUMS records education for around 93 million individuals. We drop those younger than 14 years, so as to allow children to complete primary schooling (changing this cutoff to 12 or 16 does not change the results). This leaves us with around 66 million observations. To assign children to their parents (and estimate IM), we use information for individuals of who co-habitate with an older generation. This brings the sample down to 20.3 million observations. For households with three or more generations, an individual’s education could appear both as the education of an “old” generation (vis a vis one’s children) and as the education of a “young” generation (vis a vis one’s parents). For simplicity, we drop such households, further reducing the sample to 14,149,328 individuals.⁶ Appendix Table A.1 gives details on sample construction: census years, coverage rates, number of individuals.

The final dataset includes information on 14,149,328 “young” individuals, older than 14, who cohabit with at least one member of an “older” generation. Estimating IM of individuals who reside with at least one older person (normally a parent) raises “cohabitation selection” issues. Following Card et al. (2018), we restrict the maximum age of “children” in the sample to either 18 or 25 years (see also Hilger (2017)). Thus we estimate IM on 12.1 million and 7.3 million individuals for the samples in the age brackets 14-25 and 14-18, respectively. IPUMS also reports information on respondents’ current residence, allowing us to assign individuals to “coarse” and “fine” current administrative units. Districts are typically admin-2 and in some countries admin-3 areas (e.g., Sudan or Mali). Provinces are larger, almost always admin-1 areas (e.g., provinces in South Africa or states in Nigeria).⁷ Our sample covers 365 provinces and 2,813 districts across the 26 countries. Appendix table A.2 provides details of the three samples we work with: 14-18, 14-25, and 14+.

For 23 countries, hosting 10.3 million “young” aged 14-25, IPUMS also records place of birth, which allows us to assess migrant status. For a subset of 7.8 million individuals from 15 countries, we additionally have information on the timing of move, if any. Appendix tables A.3 and A.4 again provide details of the three samples: 14-18, 14-25, and 14+.

2.3 Methodology

We construct measures of *absolute* IM that reflect the likelihood that children acquire higher/lower/similar educational attainment than individuals in the same household be-

⁵One exception is Nigeria; data come from household surveys conducted in consecutive years between 2006 and 2010. We aggregate the yearly waves and count them as one census-year.

⁶In an earlier draft, we had included multigenerational households. The results are similar.

⁷For Botswana, Lesotho, and Nigeria, IPUMS reports one administrative unit, “Districts” in Botswana and Lesotho, “States” in Nigeria; we thus use this aggregation both for districts and for provinces. In a few instances (in Ghana after 1984, in Burkina Faso in 1985, in Ethiopia in 1984, in Malawi in 1987, and in South Africa after 1996) the number of districts and regions changes between censuses, as administrative boundaries are sometimes redrawn. For our analysis, we have harmonized administrative boundaries.

longing to the immediately previous generation who cohabitate with them (parents and/or extended family members, such as aunts and uncles⁸).

There are four main educational attainment categories: (i) no schooling and less than completed primary; (ii) completed primary (and some secondary); (iii) completed secondary (and some tertiary); and (iv) completed tertiary and higher. Individuals with incomplete secondary education are assigned to completed primary, individuals with incomplete tertiary education are assigned to completed secondary. For the education of the “old” we take the average attainment of individuals one generation older in the household, rounded to the nearest integer. Our results are almost identical if we use the minimum or maximum.

For an initial look at the data, we construct 4×4 transition matrices covering all four broad educational categories. We impose two criteria to ensure that individuals have truly completed their schooling and are not misclassified: we require individuals to be at least (a) 18 years old, and (b) 9 years older than their years of schooling.⁹ This is the only place in the paper where we impose this restriction. Figure 1 (a) shows the Africa-wide transition matrix using all censuses, while figures 1 (b) and (c) reproduce the transition matrices for Mozambique and Tanzania, respectively. The height of each cell (vertical axis) indicates the probability that the child has the respective educational attainment, conditional on his/her parents having the educational attainment depicted in the horizontal axis. The bars’ width indicates the percentage of parents with each of the four main educational attainment categories. Across Africa (pooling across all country-censuses) roughly 75% of the “old” generation has not completed primary schooling and only 1.2% of the “old” generation has completed tertiary education. 26% of African children whose parents have not completed primary schooling, manage to do so; 12% finish high-school and 2% even get a college degree.

Since three-fourths of “old” Africans have not completed primary school, we focus on the likelihood that children born to parents without any schooling or less than completed primary (that for simplicity we label “illiterate”) manage to complete primary education (we label them “literate”). This is our proxy of upward educational (social) mobility. Our measure of downward mobility is the likelihood that children born to literate parents fail to complete primary schooling themselves.¹⁰

To construct absolute (upward and downward) IM measures at the country, and at the district (admin-2/3) level, we first define the following indicator variables:

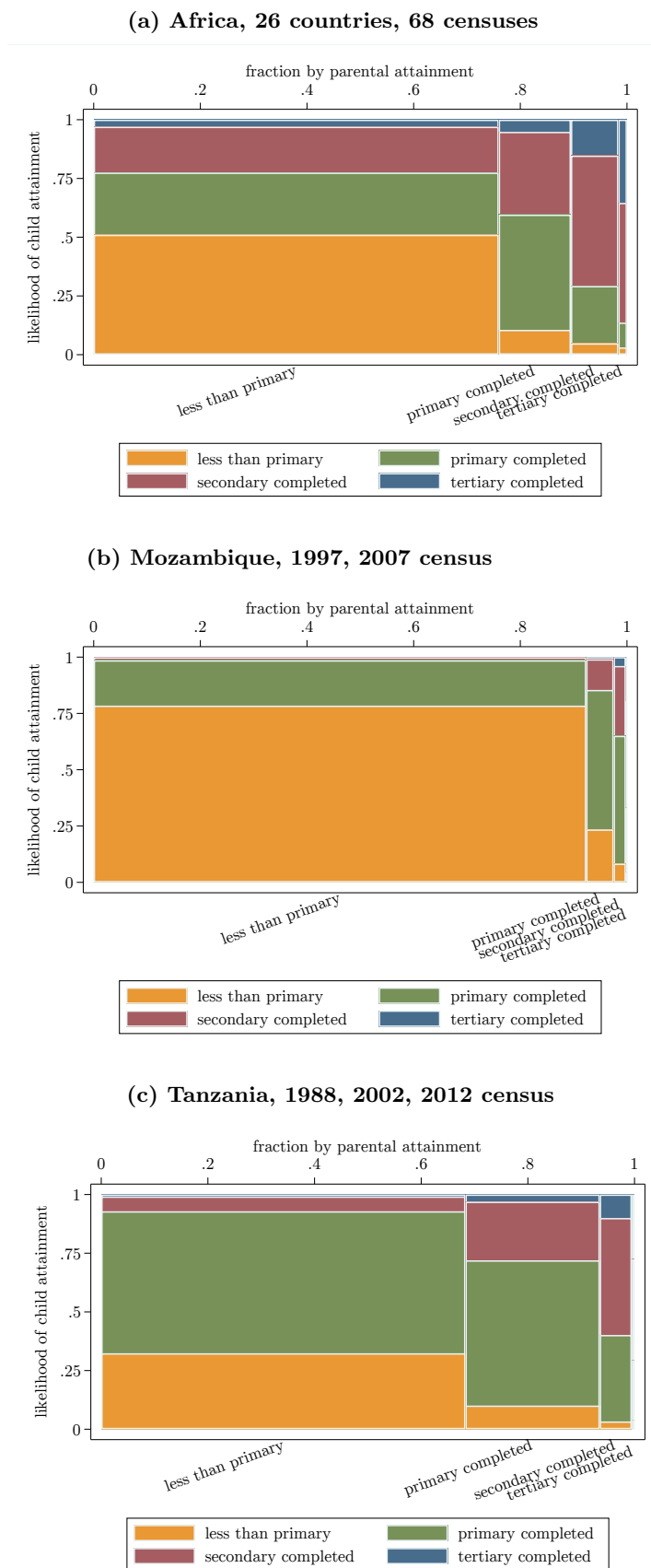
- $\text{lit_par}_{ibct} = 1$ if the parent of individual i born in birth-decade b in country c and observed in census-year t is literate and zero otherwise.
- $\text{IM_up}_{ibct} = 1$ if a child i born to illiterate parents in birth-decade b in country c and observed in census-year t is literate and zero otherwise.

⁸See appendix A.2 for details of how we assign individuals to generations.

⁹Imposing (b), gives children a 3-year “buffer” between recorded education and the education they would have completed if they had continuously been at school up to that point. This ensures that recorded years of schooling reflect actual attainment. Since we drop younger individuals to allow Africans in our sample enough time to complete schooling, the reported statistics do not capture the sizable expansion of secondary and tertiary education during the last 20 years.

¹⁰Defining mobility in terms of primary education leaves our estimates less vulnerable to measurement error compared to IM estimates based on zero years of schooling. See appendix A.6 for details.

Figure 1: Educational Transition Likelihoods [Intergenerational Mobility in Education]



This figure shows the transition matrices for four broad educational attainment categories for all of Africa, Mozambique and Tanzania. Unlike in the remainder of the paper, the sample consists of individuals aged 18+ who are at least 9 years older than their years of schooling, co-residing with at least one individual of an older generation.

- $\text{IM_down}_{ibct} = 1$ if a child i born to literate parents in birth-decade b in country c and observed in census-year t is illiterate and zero otherwise.

Then, for the country-specific analysis, we run the following regressions, pooling information from all censuses:

$$\text{lit_par}_{ibct} = \alpha_c^o + [\gamma_b^o + \delta_b^y + \theta_t] + \epsilon_{ict} \quad (1)$$

$$\text{IM_up/down}_{ibct} = \alpha_c^y + [\gamma_b^o + \delta_b^y + \theta_t] + \epsilon_{ict}, \quad (2)$$

where lit_par_{ibct} and IM_up/down_{ibct} are the indicators for parental literacy and child IM, respectively. To account for time trends, we condition on birth-decade fixed effects for the “young” (δ_b^y) and the “old” (γ_b^o) and census-year fixed effects (θ_t).

In estimating parental literacy (equation (1)), we are computing (conditional on cohort and time-effects) simple means among all individuals for whom we observe their parents’ educational attainment. Hence, the estimated country fixed effects ($\hat{\alpha}_c^o$) reflect the shares of literate parents net of census-year and cohort effects. By contrast, when we compute measures of IM, we are computing conditional means. To this end, we estimate equation (2) twice: once for upward IM and once for downward IM. For upward IM, we estimate it only in the sample of children of illiterate parents, which allows us to interpret the country fixed effects ($\hat{\alpha}_y^o$) as the conditional likelihood that children born to illiterate parents become literate. For downward IM, we estimate it in the sample of literate parents and interpret $\hat{\alpha}_y^o$ as the conditional likelihood that children of literate parents become illiterate.

For the within-country analysis, we run similar specifications at the district level, r . We estimate country-by-country:

$$\text{lit_par}_{ibcrt} = \alpha_r^o + [\gamma_b^o + \delta_b^o + \theta_t] + \epsilon_{ibcrt} \quad (3)$$

$$\text{IM_up/down}_{ibcrt} = \alpha_r^y + [\gamma_b^o + \delta_b^o + \theta_t] + \epsilon_{ibcrt}. \quad (4)$$

2.4 Cohabitation Selection

We can only estimate IM of individuals who reside with their parents. This raises concerns of selection, as the intergenerational transmission of education may differ for cohabiting families and kids and parents who live apart. This issue is less pressing when focusing on young children that almost always cohabit with their parents. Coresidence rates of children at the age of 8 and their parents exceed 99%. The problem is, of course, that the younger children are, the greater the risk of misclassifying individuals as “less-than-primary” when in fact they would complete primary education one or two years after we observe them in the census.

We estimate IM for individuals aged 14-18. In this sample of 7,389,448 individuals, the coresidence rate is close to 94% (see appendix table A.6). The country in the sample with the lowest coresidence rate among 14-18 year olds is Guinea, with 82.3%, whereas Egypt and Lesotho have coresidence rates above 98%. While by looking at this sample, we miss tertiary and secondary attainment, in our setting most of the “action” is between no schooling and completed primary. We also work with a larger sample of 12,186,241

individuals aged 14-25. This gives us a bigger sample, including college graduates, while cohabitation is still reasonably high (75%). In appendix A.5, we present simple statistics on the distribution of the *level* of education across countries and cohorts that do not rely on individuals co-residing with their parents.

3 Intergenerational Mobility across African Countries and Regions

This Section gives the main patterns of IM across African countries and regions. First, we present the cross-country statistics. Second, we provide a mapping of the African land of opportunity. Third, we report the cross-country and within-country across regions association between IM and literacy levels. Fourth, we distinguish across gender and rural-urban status.

3.1 IM across African Countries

Table 1 shows simple (unconditional) country-level estimates of intergenerational mobility.

Table 1: Country-level estimates of intergenerational mobility (IM)

	(1)	(2)	(3)	(4)	(5)	(6)
mobility / N	upward	upward	downward	downward	N with ϵ_0 obs.	N with ϵ_0 obs.
age range	14-18	14-25	14-18	14-25	14-18	14-25
South Africa	0.788	0.809	0.059	0.045	608,010	1,071,079
Botswana	0.704	0.713	0.057	0.049	22,558	36,415
Egypt	0.651	0.658	0.060	0.053	1,929,103	3,587,039
Nigeria	0.643	0.690	0.078	0.059	35,624	58,191
Zimbabwe	0.630	0.697	0.142	0.112	27,976	40,769
Tanzania	0.596	0.640	0.170	0.145	576,537	842,474
Ghana	0.578	0.585	0.129	0.108	298,264	483,839
Cameroon	0.522	0.541	0.103	0.093	188,275	295,440
Zambia	0.486	0.506	0.189	0.172	222,481	340,380
Kenya	0.450	0.520	0.205	0.159	469,787	719,194
Lesotho	0.437	0.487	0.253	0.208	24,197	42,910
Morocco	0.432	0.425	0.057	0.063	304,981	578,796
Benin	0.412	0.416	0.166	0.156	120,975	189,761
Uganda	0.365	0.408	0.282	0.238	274,831	401,937
Senegal	0.294	0.309	0.154	0.143	80,565	138,792
Rwanda	0.285	0.341	0.463	0.380	189,357	296,126
Sierra Leone	0.256	0.275	0.310	0.269	23,137	36,632
Guinea	0.229	0.244	0.308	0.285	51,278	81,339
Liberia	0.218	0.293	0.514	0.404	19,302	32,126
Mali	0.209	0.214	0.195	0.183	189,519	299,397
Burkina Faso	0.173	0.187	0.185	0.166	150,467	215,475
Malawi	0.158	0.233	0.445	0.341	195,856	294,976
Ethiopia	0.130	0.158	0.219	0.183	738,516	1,089,002
Sudan	0.112	0.163	0.367	0.249	400,140	651,194
Mozambique	0.101	0.143	0.432	0.341	174,810	245,422
South Sudan	0.040	0.068	0.747	0.631	36,451	58,768
mean / total	0.368	0.400	0.261	0.217	7,389,448	12,186,241

Columns (1) and (2) give upward-IM estimates. They reflect the likelihood that children, aged 14-18 and 14-25, whose parents have not completed primary schooling will manage to complete at least primary education. Columns (3) and (4) give downward-IM estimates. They reflect the likelihood that children, aged 14-18 and 14-25, whose parents have completed primary schooling or higher will not manage to complete primary education. Columns (5) and (6) give the number of observations used to estimate the country-specific IM statistics (children whose parental education is reported in the censuses). Countries are sorted from the highest to the lowest level of upward IM in the 14-18 sample (column (1)). “mean” gives the simple average of the 26 country-estimates.

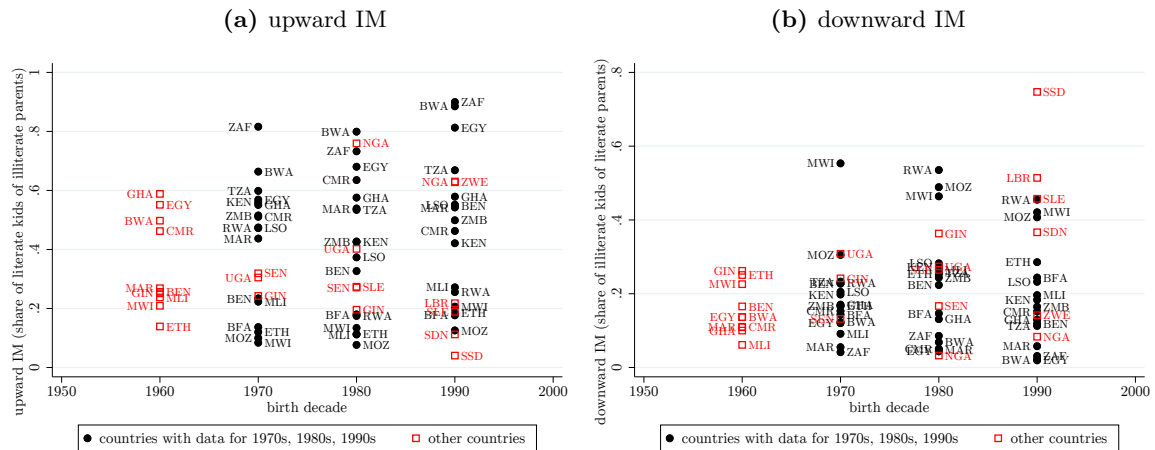
Columns (1) and (2) ((3) and (4)) report upward (downward) IM means. Columns (5) and (6) give the number of children (young) for the 14 – 18 and the 14 – 25 sample. (The two

series are strongly correlated, $\rho > .97$).¹¹ In the average country, less than forty percent of children of illiterate parents have managed to complete primary education. Downward IM is lower, but far from negligible: approximately one out of four children born to literate parents does not complete primary education.

The pan-African mean masks sizable country variation. The likelihood that children of illiterate parents will complete at least primary education ranges from an abysmal 5% in South Sudan and 10% in Mozambique to 80% in South Africa and 70% in Botswana. The lowest upward IM is in the Sahel (Sudan, Burkina Faso and to a lesser extent Mali and Senegal) and the highest in Southern Africa (Botswana, Zambia, Zimbabwe, and South Africa) with Western and Eastern African countries in the middle. Downward mobility is negatively correlated with upward mobility ($\rho = -.76$ and $-.73$ for the two age groups). In South Sudan about 70 per cent of children born to “literate” parents fail to complete primary school, while the corresponding likelihood in Botswana, South Africa, Egypt, and Nigeria is less than 10 percent.

Do the simple cross-sectional averages obscure trends in IM? Figure 2 portrays the evolution of IM across cohorts. Panel (a) plots upward IM, while Panel (b) plots downward IM. It shows country-specific IM for children aged 14-18 and born in the 1960s (that corresponds for most countries to the first post-independence decade), 1970s and the 1980s (when many countries faced civil warfare), and the 1990s (when countries took the first steps towards democratic rule). The figure distinguishes countries with full cohort coverage and those without (Appendix Figure B.1 presents similar statistics for the 14 – 25 age group).

Figure 2: IM at the country-birth-decade level, ages 14-18



The figures report upward (panel A) and downward (panel B) Intragenerational Mobility in educational attainment (IM) across decade birth cohorts for children aged 14-18. Black solid circles indicate countries with data covering the 1970s, the 1980s, and the 1990s. Red hollow squares indicate countries with data covering just some cohorts.

Though not readily apparent because of the wide cross-country variability, there is a positive continental trend in upward-IM. The mean (median) IM goes from .36 (.27) for the 1960s-born, to .41 (.47) and .40 (.42) for children born in the 1970s and 1980s and rises to .48 (.5) for those born in the 1990s. Appendix Tables B.4 and B.5 present the regression analogues; compared to the 1960s-cohort, children born to illiterate parents in the 1990s

¹¹As the census timing differs across countries, Appendix Table B.1 reports the corresponding statistics netting out cohort fixed-effects and census fixed-effects (equation (2)); the patterns are similar.

enjoy a 10 percentage points higher likelihood of completing primary education. There is sizable variation on the dynamics of IM. Upward-IM has increased considerably (by roughly 25 percentage points) in Botswana, Egypt and Benin. But it has remained roughly flat or even fallen in Ethiopia, Mozambique, Cameroon, Zambia, and Kenya. Downward IM increases slightly with an equivalent increase in variability across countries. Downward mobility increased in countries with devastating warfare in the 1980s and 1990s, such as Liberia, South Sudan, Rwanda, and Mozambique and fell in the more stable countries, Botswana, Egypt, and South Africa.

Nevertheless, the correlations between IM in the 70s, 80s, and 90s are strong, exceeding 85% for upward IM and 70% for downward IM, implying strong inertia. We further analyzed the cross-sectional and dynamic variability by regressing country-cohort IM on country fixed effects, then cohort fixed effects, and then country- and cohort fixed effects and comparing the in-sample fit. For the 17 countries with IM statistics covering the 70s, 80s, and 90s, this exercise reveals the following: When we add both sets of fixed effects, the R^2 is high, .924 and .847, for the upward IM and the downward IM specification, respectively. The strong fit reflects almost exclusively country features. The R^2 with just the country constants in the upward (downward) IM regression is .905 (.829). In contrast, the R^2 for the cohort-effects only specification is just .02 for both upward and downward IM. The stability of educational IM across cohorts in Africa echoes the pattern in India (Asher et al. (2018)).

3.2 Mapping the Land of Opportunity in Africa

Many African countries are large and there are evident disparities in geography and well-being. So where is the land of African opportunity? Figure 3 provides a mapping of social mobility across the continent. Panel (a) shows the distribution of upward IM across (mostly admin-2) districts and Panel (b) plots downward IM.

Figure 3: Pan-Africa: District-level estimates of IM, individuals aged 14-18

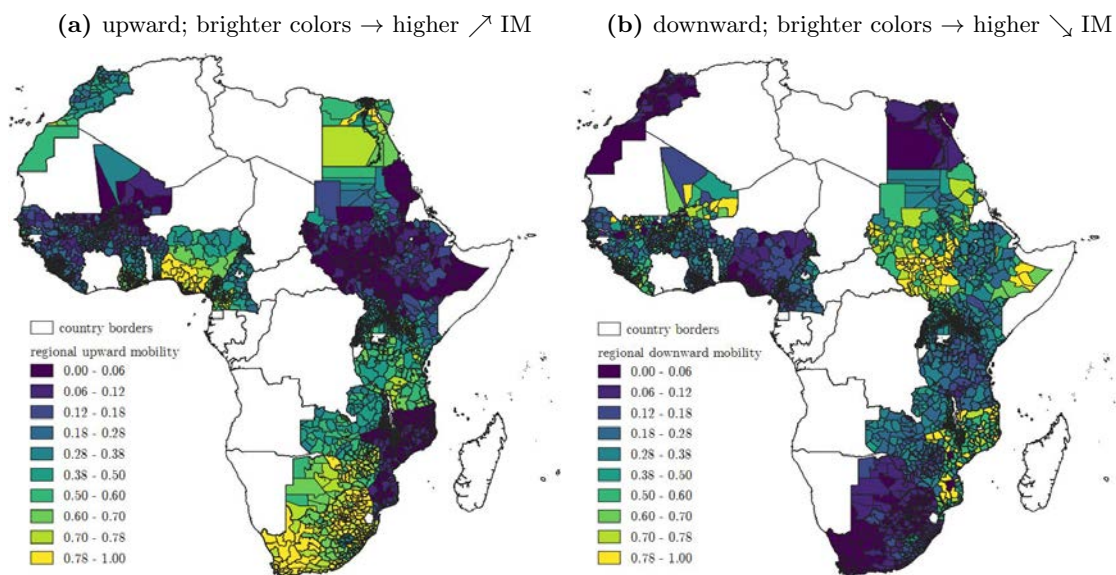
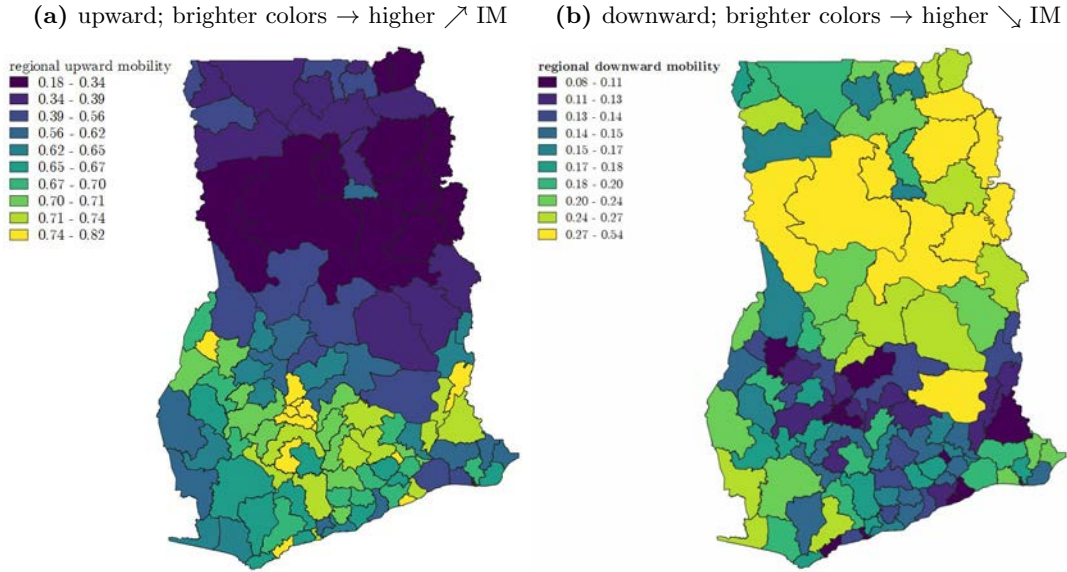


Table 2 gives summary statistics (mean, median, and range) by country. The district-level average and median for upward (downward) IM across the 2,813 regions are 0.40 (0.30)

and 0.38 (0.25), respectively, quite close to the cross-country values. More strikingly perhaps, there is considerable variability in IM across regions in a given country.

Figure 4: Ghana: District-level estimates of IM, individuals aged 14-18



As an example, figures 4 (a) and (b) portray upward and downward IM across 102 regions in Ghana. While average upward IM in Ghana is 0.57, regional IM ranges from 0.18 to 0.82 with rates below 0.4 in the Northern regions and above 0.7 in the South. The mean downward mobility is 0.20, but it varies from 0.08 to 0.50. This north-south gradient mirrors both the country’s religious geography as well as colonial-era missionary activity and transportation investments, a topic we return to below.

Regional variation in IM is high in other countries (Table 2).¹² For example, in Burkina Faso the average upward-IM of 0.132 masks huge variability with regional IM ranging from 0.028 to 0.52. In Uganda the IM range is even wider [0.015 – 0.69]. Overall, spatial differences in IM are wider in countries with lower levels of social mobility. A simple linear regression of the coefficient of variation on mean upward IM yields a highly significant slope (s.e.) of -1.12 (0.18) with an R^2 of 0.63. But, even for countries with relatively high rates of upward IM, like Cameroon where a child born to illiterate parents has 52% probability of completing primary education, where the family resides plays a critical role: In some districts upward mobility is nearly guaranteed whereas in others it is almost impossible (the upward IM range is 0.09 – 0.89).

Figure 5 plots the distribution of upward and downward regional IM for different cohorts. Upward-mobility for Africans born in the 1960s was quite low across the continent. Regional IM increased somewhat in the next two decades (by roughly 5%). The distribution shifts to the right for the 1990s-born children. Appendix Tables B.6 and B.7 report the regression analogues; conditional on district unobserved features, children of illiterate

¹²For some districts and census years downward mobility is 0 and in others is 1. These extreme values reflect the relatively small number of observations in some regions. The mean (median) district estimate is based on 1936 (891) matched-to-parents children ($st.dev = 3, 287$). The estimates are similar if we limit attention to regions with at least 100 observations.

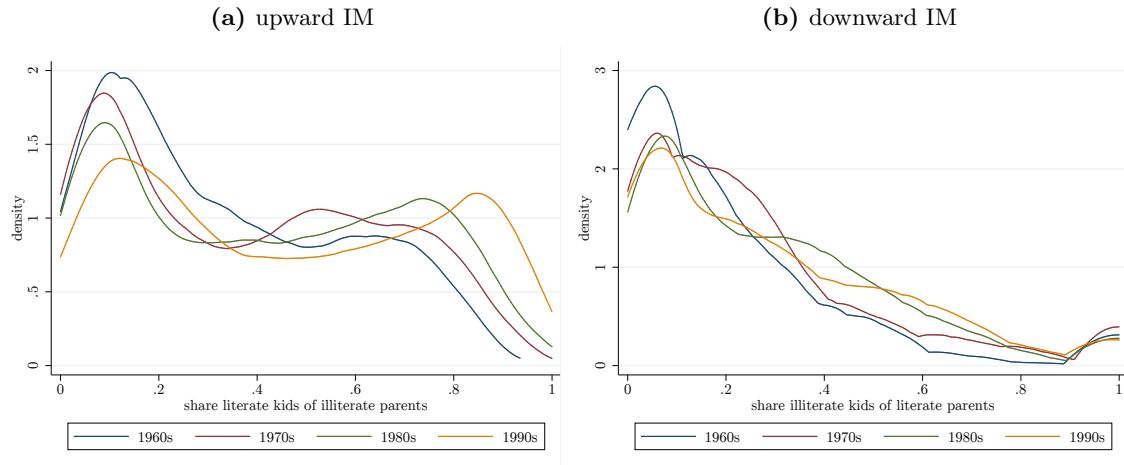
Table 2: Summary statistics: district-level estimates of IM

country	districts	upward					downward				
		mean	median	stdev	min	max	mean	median	stdev	min	max
South Africa	216	0.780	0.800	0.075	0.555	0.896	0.075	0.065	0.040	0.024	0.227
Botswana	23	0.719	0.714	0.079	0.554	0.909	0.069	0.070	0.031	0.000	0.143
Zimbabwe	88	0.715	0.726	0.148	0.400	1.000	0.156	0.157	0.084	0.007	0.402
Nigeria	37	0.708	0.765	0.201	0.330	0.963	0.085	0.070	0.043	0.019	0.166
Egypt	236	0.683	0.694	0.105	0.418	0.914	0.063	0.058	0.033	0.013	0.177
Tanzania	113	0.614	0.611	0.094	0.408	0.854	0.176	0.170	0.068	0.054	0.358
Ghana	110	0.588	0.650	0.158	0.181	0.820	0.183	0.166	0.074	0.077	0.541
Cameroon	230	0.551	0.588	0.203	0.088	0.896	0.210	0.168	0.147	0.000	0.875
Kenya	173	0.498	0.514	0.187	0.048	0.873	0.246	0.252	0.101	0.038	0.548
Zambia	72	0.479	0.467	0.127	0.284	0.785	0.266	0.278	0.097	0.074	0.468
Morocco	59	0.441	0.424	0.145	0.160	0.723	0.070	0.057	0.058	0.000	0.429
Lesotho	10	0.421	0.437	0.060	0.317	0.492	0.297	0.303	0.061	0.204	0.389
Uganda	161	0.383	0.382	0.128	0.015	0.696	0.352	0.353	0.117	0.124	1.000
Benin	77	0.381	0.381	0.132	0.111	0.649	0.218	0.204	0.077	0.083	0.455
Rwanda	30	0.297	0.280	0.063	0.220	0.469	0.494	0.518	0.102	0.226	0.623
Senegal	34	0.275	0.209	0.164	0.078	0.616	0.212	0.194	0.144	0.000	0.857
Sierra Leone	107	0.232	0.185	0.149	0.032	0.694	0.484	0.500	0.208	0.000	1.000
Ethiopia	97	0.208	0.119	0.235	0.000	0.865	0.349	0.311	0.202	0.000	1.000
Malawi	227	0.200	0.163	0.115	0.052	0.643	0.500	0.511	0.129	0.141	0.778
Liberia	47	0.185	0.180	0.081	0.034	0.345	0.569	0.566	0.167	0.000	1.000
Guinea	34	0.182	0.179	0.085	0.063	0.491	0.336	0.325	0.128	0.136	0.619
Sudan	129	0.153	0.097	0.144	0.001	0.551	0.533	0.500	0.200	0.224	1.000
Mali	242	0.144	0.128	0.096	0.013	0.578	0.388	0.333	0.269	0.000	1.000
Burkina Faso	45	0.129	0.123	0.080	0.029	0.526	0.252	0.231	0.118	0.000	0.714
Mozambique	144	0.091	0.064	0.086	0.015	0.707	0.587	0.581	0.202	0.000	1.000
South Sudan	72	0.043	0.024	0.056	0.000	0.319	0.831	0.848	0.158	0.400	1.000
overall	2813	0.405	0.379	0.269	0.000	1.000	0.304	0.247	0.235	0.000	1.000

This table shows summary statistics for district level estimates of IM (estimated without fixed effects). The row “overall” shows the overall summary statistics for all districts in the sample.

parents born in the 1990s face an 11 percentage points higher likelihood to complete primary education, as compared to children born in the 1960s in the same district. The variability of upward-IM has increased over time. Figure 5 (b) plots the evolution of regional downward IM. The mean has increased only slightly, but the variability has increased (st. dev. in 1960s = .20, st. dev. in 1990s = .25).

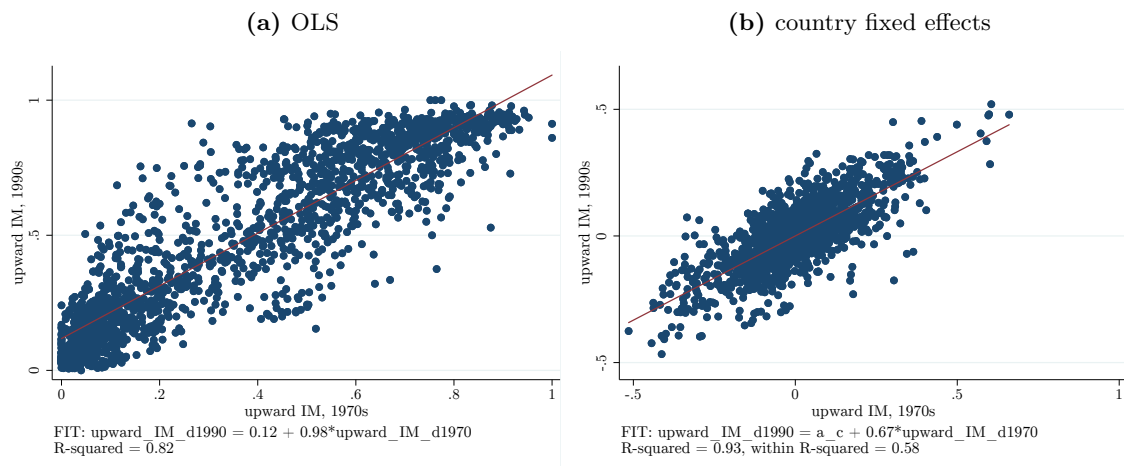
Figure 5: Distribution district \times cohort level IM



These figures plot the distribution of district-level upward (panel (a)) and downward (panel (b)) intergenerational mobility for the four birth-decades from the 1960s to the 1990s.

Similarly to the cross country patterns, IM is persistent at the sub-national level. Regressing upward district-level IM for 1990s-born cohort on the 1970s (1960s) cohort yields a slope of .98 (.87) and an R^2 of .819 (.59). Adding country fixed effects increases the R^2 to .932 (.82), while the slope decreases to .67 (.52). Figure 6 illustrates these patterns [See also Appendix figures B.2-B.3 for further evidence on persistence].

Figure 6: District-level upward IM over time



These figures visualize two regressions that link district-level upward IM in the 90s to district-level upward IM in the 70s. Panel (a) shows the simple linear regression, panel (b) shows the regression with country fixed effects.

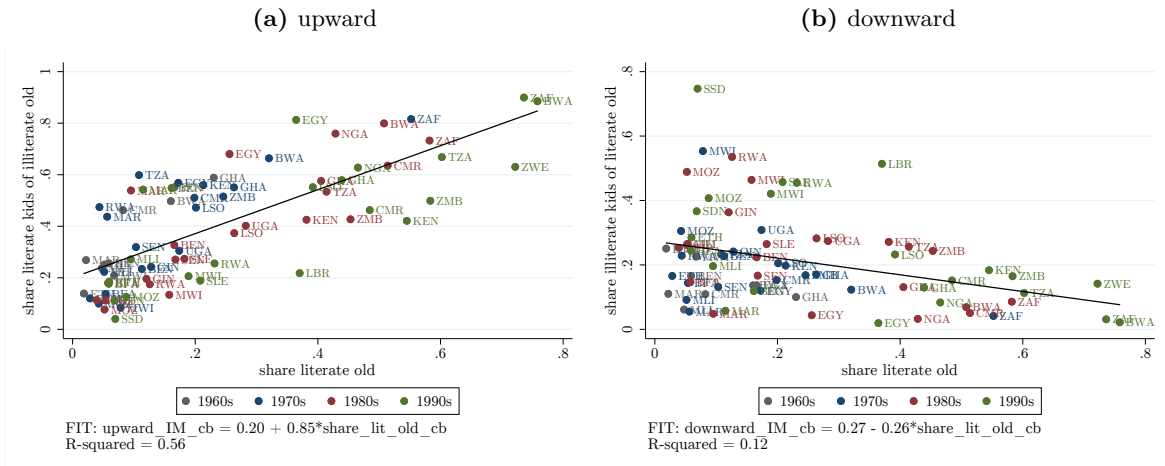
3.3 Literacy and IM

We commence the descriptive analysis correlating the newly-compiled IM measures with the literacy of the old generation. Our exploration is motivated by recent evidence, among others by Chetty and Hendren (2018a) and Chetty et al. (2016), showing that upward mobility is higher in regions with better outcomes (wealth, education, income). While these correlations do not have a causal interpretation, it is interesting to know whether the variability in social mobility varies systematically with the stock of education. [In Section 5 we tackle identification].

3.3.1 Cross-Country Patterns

While our focus rests on understanding the vast regional disparities within countries, we commence our analysis with a brief look at the cross-country picture. Figure 7 plots the relationship between IM (on the vertical axis) and the share of literacy of the old generation of the respective cohort (on the horizontal axis). Panel (a) explores the cross-country-cohort association for upward IM, while Panel (b) plots the corresponding association with downward IM. [Different colors show different cohorts.]

Figure 7: Literacy and IM at the country-birth-decade level



The figures plot upward-IM and downward-IM against across country-birth-cohorts against the share of the “old” generation that has completed primary education. The figures also report the simple OLS regression fit.

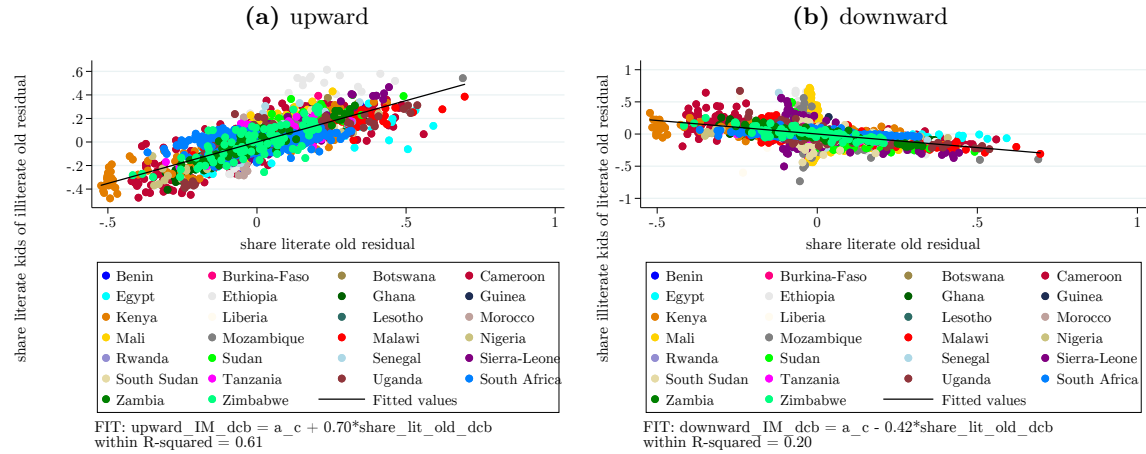
A positive association emerges between the share of completed primary of the “old” generation in the country and the likelihood that children whose parents have not completed primary schooling, manage to complete elementary school. In Ethiopia, Burkina Faso, Mozambique, North and South Sudan, where for all cohorts the share of literacy of the “old” generation is less than 20%, the likelihood that children of illiterate parents will complete primary is below or close to 20%. In contrast, the likelihood that children of illiterate parents will complete primary schooling exceeds 60% in countries-cohorts where the “old” generation is –on average– more educated, as, for example, in South Africa, and Botswana. The simple LS regression of IM on old generation’s literacy pooled across all cohorts, suggests that a one percentage point increase in literacy is associated with a .85 percentage point increase in upward IM; the literacy of the “old” generation explains 56% of the cross-country-cohort variation in upward IM. The literacy of the “old” gen-

eration also correlates with downward IM, albeit more weakly.¹³ A one percentage point increase in the “old” generation’s literacy maps into a 0.26 fall in downward IM and the old generation’s literacy explains 12% of the variation in downward IM.

3.3.2 Regional Patterns

Figures 8 (a) and (b) plot the association between upward and downward IM and mean literacy rates of the “old” generation across 2,813 districts (using different colors for different countries).

Figure 8: Literacy and IM at the district level



To net out trends, we first run regressions (3) and (4) including all cohort and census-year fixed effects and extract coefficients $\hat{\alpha}_r^o$ and $\hat{\alpha}_r^y$. These are estimates of district-specific IM and parental literacy net of census and cohort effects. Second, we regress the “cleaned” measure of IM on the “cleaned” measure of the old generation’s literacy, adding also country fixed-effects, i.e. $\hat{\alpha}_{cr}^y = \alpha_c + \beta \times \hat{\alpha}_{cr}^o + \epsilon_{cr}$. There is an evident positive association between the literacy of the “old” generation and upward IM, a pattern that echoes the cross-country one. Likewise, there is a negative -though less steep- correlation between downward IM and the literacy of the old. While there is considerable heterogeneity across countries, these correlations are not driven by some countries or cohorts.

Table 3 reports the regression estimates. Due to spatial correlation, standard errors are clustered at the province-level. The cross-sectional slope in columns (1) and (2) on the share of the old generation that has completed primary education is 0.77 and -0.486 in the upward-IM and the downward IM specification, respectively. Both estimates are highly significant. In columns (3) and (4) we add country constants. The within-country correlations retain economic and statistical significance. A 10-percentage points increase in the literacy of the “old” in the district is associated with a roughly 7 percentage point increased likelihood that the children of illiterate parents will manage to complete primary schooling and a 4.4% percentage points lower chance that kids of literate parents will not complete primary schooling. In columns (5) and (6) we replace the country constants

¹³This most likely reflects: (i) the smaller variability of downward-IM, as compared to upward-IM; and (ii) outlier observations in downward-IM, mostly coming from cohorts born in countries with sizable conflict (e.g., Sudan, Liberia, Sierra Leone).

with (280) admin-1 fixed-effects¹⁴); while there is nothing causal about these estimates, this accounts for provincial differences in literacy and IM. The estimates retain statistical significance though they drop in absolute value (0.56 and -0.385).

Table 3: Literacy and IM at the district-level

	(1)	(2)	(3)	(4)	(5)	(6)
	IM up	IM down	IM up	IM down	IM up	IM down
share literate old	0.770*** (0.029)	-0.486*** (0.032)	0.703*** (0.040)	-0.422*** (0.030)	0.560*** (0.041)	-0.385*** (0.035)
R2	0.650	0.305	0.885	0.700	0.934	0.755
within-R2			0.611	0.204	0.460	0.113
N	2809	2787	2809	2787	2726	2704
country-FEs	no	no	yes	yes	no	no
province-FEs	no	no	no	no	yes	yes

The dependent variable is the district-level share of literate kids of illiterate parents (estimated net of census year and old and young birth decade fixed effects). The independent variable is the country-level share of literate parents (also estimated net of fixed effects). Standard errors clustered at the admin-1 (province)-level in parentheses. $*p < 0.1$, $**p < 0.5$, $***p < 0.01$.

In regions with relatively low levels of literacy among the old, the young face a lower likelihood of becoming literate. The strong positive (negative) association between the level of literacy of the old generation and upward (downward) IM among the young is suggestive of educational traps and divergence in educational attainment across countries. This finding is similar to the one of Asher et al. (2018), who also find that state’s/region’s mean education is the strongest correlate of upward educational mobility in India.

The estimates, while non-causal, suggest path dependence in human capital accumulation: disadvantaged children (from non-educated families) are more likely to complete primary school in regions with relatively higher initial stocks of literacy. This result is consistent with Jedwab et al. (2017), who document path-dependence stemming from colonial infrastructure investment (an issue we explore in the next section). Path dependence can reflect various mechanisms. First, inertia may stem from poverty trap dynamics that are especially salient in rural Africa, where (subsistence) agriculture is the typical mode of economic activity. Second, as regions with high levels of literacy tend to have better infrastructure (as we show in the next section), path dependence may stem from sunk costs in railroad-road construction. Third, given the limited state capacity of African states and the associated under-provision of public goods, sunk costs may also apply to school construction. Fourth, the results may reflect internal migration and sorting of families to regions with higher/lower educational opportunity (an issue that we examine in Section 5). Fifth, the estimates could at least partly reflect human capital externalities (e.g., Krueger and Lindahl (2001)) and peer effects that may be especially strong in a continent with large spatial differences in development.

¹⁴This is lower than the total number of provinces (365) because for Botswana, Lesotho, and Nigeria we only have province-level information.

3.4 Heterogeneity

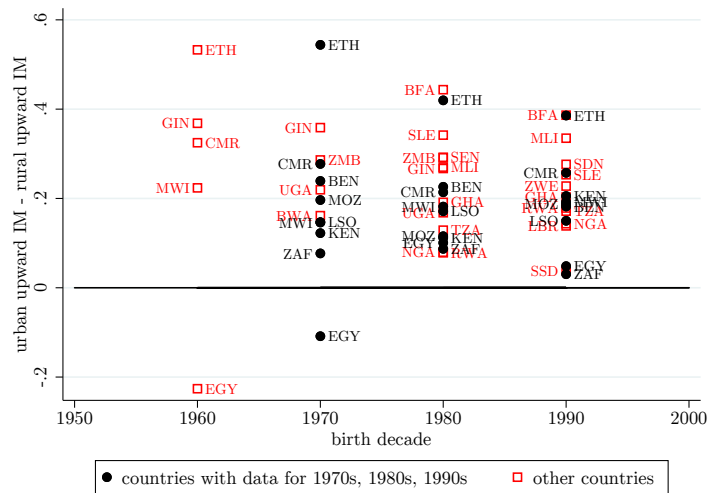
The census data allow us to construct country and regional measures of IM by gender and rural-urban status, enabling a more in-depth analysis of social mobility.

3.4.1 Rural-Urban

Appendix Table B.2 gives country-level IM for rural and urban households, using censuses' classification.¹⁵ The country ordering is not much affected as the various IM measures correlate strongly; the correlation between rural and urban IM is 0.85 for both the upward and downward measures. Setting aside South Sudan, which is an evident outlier, upward IM in urban places ranges from 0.21 in Mozambique to 0.84 in Zimbabwe and South Africa (mean 0.33 and st.dev 0.225). The variability in rural upward IM is wider: on the one end, it hovers around 0.06 in Mozambique, Ethiopia, South and North Sudan, but on the other end it exceeds 0.6 in Nigeria, Egypt, Zimbabwe, Botswana, and South Africa (mean 0.53 and st.dev 0.197).

In Figure 9 we explore the evolution of differences in IM between rural and urban families. The horizontal axis portrays the children's birth-decade and the vertical axis plots the gap between average IM for children residing in urban versus rural areas, born in the same decade. There is a clear rural-urban divide with upward IM being lower for rural households; the average gap is 18% for all cohorts. This pattern applies to all countries, but Egypt. The rural-urban gap is the highest in countries with overall low levels of mobility and literacy. For example, there is a gap of about 40 percentage points between rural and urban places in Ethiopia and Burkina Faso; the rural-urban gap is below 10 percentage points in South Africa and Botswana.

Figure 9: Upward IM urban-rural gaps

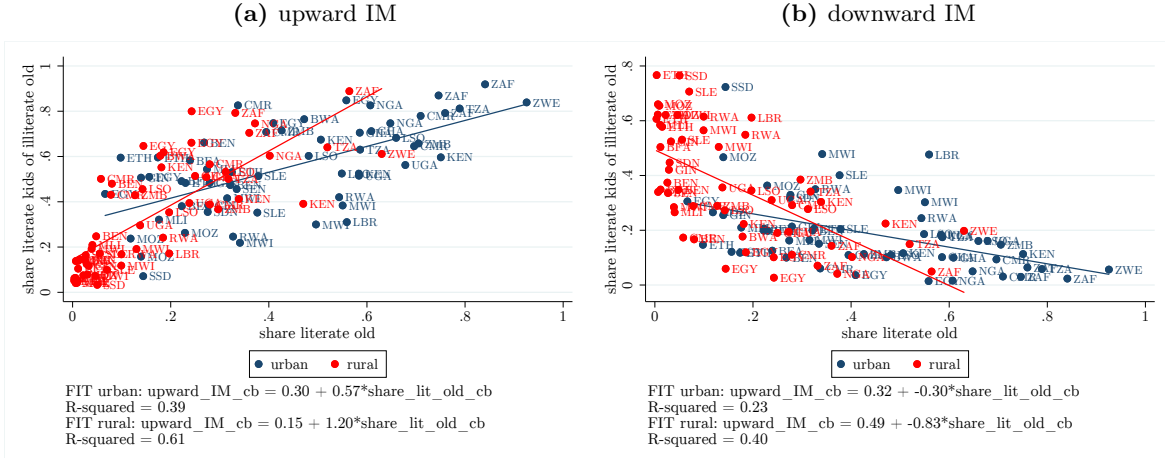


We then explored heterogeneity in the literacy-IM association between urban and rural households. Figure 10 plots the cross-country association between IM and old generation's

¹⁵The criteria for the rural-urban classification vary across countries. In some countries, they are based solely on population cutoffs, while in others they reflect localities' economic activity. In some instances, the statistical codebook does not provide any concrete information on the classification. Rural-urban status is not reported for Morocco. Appendix table A.1 gives details.

literacy separately for urban and rural households. Panel (a) looks at upward IM, while Panel (b) at downward IM.

Figure 10: Literacy and IM at the country-birth-decade level, urban/rural



These figures visualize two regressions that link IM across countries-cohorts to old generation's literacy separately for rural and for urban places, that is, we estimate $\widehat{IM}_{cb}^{\text{urban or rural}} = \alpha + \beta \times \widehat{\text{lit_par}}_{cb}^{\text{urban or rural}} + u_{cb}$. Panel (a) shows the scatter plots and regressions for upward IM and panel (b) those for downward IM.

Three observations emerge. The first regards the intercept. Children residing in rural places have a mere 13% base probability of upward mobility. The corresponding probability is 31% for children in urban areas. Likewise, in rural areas, children born to literate parents have a staggering 49% base probability of falling below their parental educational attainment. The corresponding statistic is 32% in urban areas. Second, the likelihood that kids of illiterate (literate) parents will (not) manage to complete primary education is positively (negatively) related to the mean education of the “old” generation for both urban and rural households. Third, the positive association between upward IM and literacy of the old generation is quite steep for rural households, while for urban households the association is flatter. The literacy of the old explains around 61% of the variation of rural households IM, while the R^2 for urban households is around 39%. In the downward IM plot, the slope is almost 3-times as large in rural as compared to urban households (0.3 versus 0.83); in rural areas with just a few educated old it is much more likely that children of literate parents will not complete primary schooling as compared to cities.

Table 4 explores heterogeneity in the within-country association between old generation's literacy and IM for children growing up in rural and urban places. In line with the cross-country patterns, the old's literacy - upward-IM correlation is considerably stronger in rural areas, 0.70 (in (1)) versus 0.48 (in (2)). A Chow test strongly rejects the null hypothesis of coefficient equality. In columns (5)-(6) we add province fixed-effects to partly account for broad geographic variation. The estimate in the urban sample is 0.375, while in the rural sample it is 0.55, a considerable and significant difference. The specifications in (3)-(4), (7)-(8) yield similar thought attenuated patterns. The correlation between the old's education in the district and downward IM is steeper (negatively) for rural, as compared to urban, households. The difference of the two slopes is around 10 percentage points in the province fixed-effects specifications. To the extent that those leaving villages and small towns to urban centers have higher aspirations and latent ability, the ramifica-

tions for rural Africa are dire, as the decline in the stock of education in the rural areas will lower upward and increase downward IM. We return to this issue in Section 5.

Table 4: Literacy and IM at the district-level, urban/rural

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IM up	IM up	IM down	IM down	IM up	IM up	IM down	IM down
share literate old	0.481*** (0.039)	0.698*** (0.055)	-0.259*** (0.023)	-0.436*** (0.044)	0.375*** (0.043)	0.546*** (0.067)	-0.225*** (0.034)	-0.318*** (0.039)
R-squared	0.744	0.850	0.617	0.671	0.823	0.909	0.710	0.748
N	1930	2575	1842	2459	1930	2575	1842	2459
sub-sample	urban	rural	urban	rural	urban	rural	urban	rural
country FEs	yes	yes	yes	yes	no	no	no	no
province FEs	no	no	no	no	yes	yes	yes	yes
p: coeff-equal	0.0000		0.0000		0.0049		0.0217	

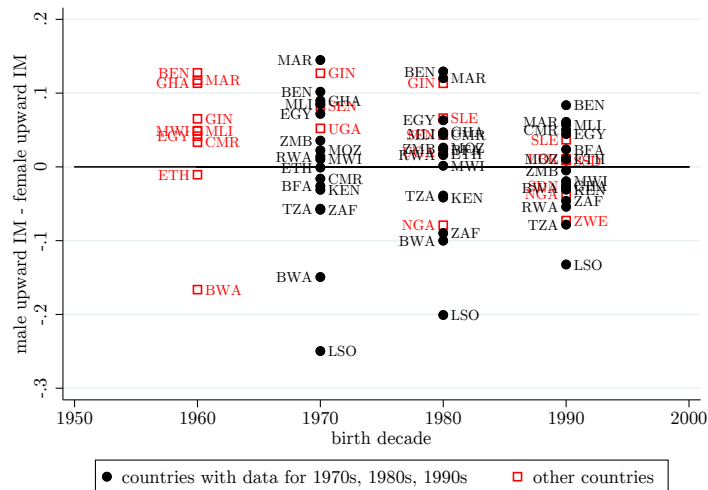
The dependent variable is the district-level share of literate kids of illiterate parents (estimated net of census year and old and young birth decade fixed effects). The independent variable is the district-level share of literate parents (also estimated net of fixed effects). Standard errors clustered at the admin-1 (province)-level in parentheses. $*p < 0.1$, $**p < 0.5$, $***p < 0.01$. p -values for coefficient equality in the urban/rural sub-samples are from a Chow-test ($\sim \chi^2$ under H_0).

3.4.2 Gender Heterogeneity

To shed light on gender differences, (see Jayachandran (2015), Ashraf et al. (forthcoming), Bandiera et al. (2017), among others) we estimate IM for boys and girls. Appendix Table B.3 gives the country means. The correlation of the IM measures for boys and girls are very high (around .95) and as such the cross-country rankings are quite similar to the aggregate measures in Table 1.

Figure 11 shows the evolution of the male-female differences in IM. We do not observe major differences in the likelihood that girls whose parents have not completed primary schooling will manage to complete primary education, as compared to boys.

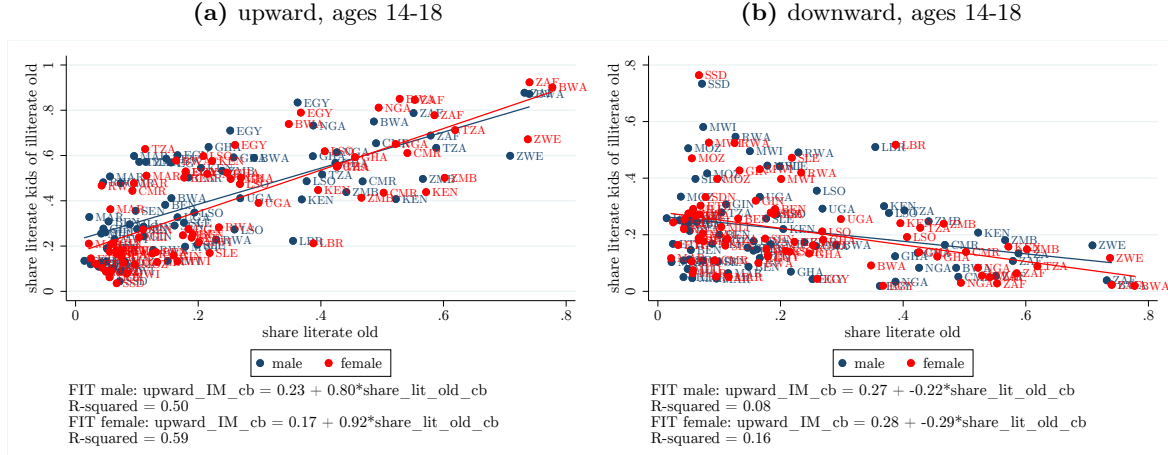
Figure 11: Upward IM male-female gaps, individuals aged 14-18



There is a small gender gap for the 1960s cohorts (especially when we exclude Botswana) that disappears in the 1980s and the 1990s cohorts. To be sure there are countries where boys are disproportionately favored compared to girls, including Benin, Mali, Egypt, Guinea, and Morocco, but girls in Lesotho, Botswana, Tanzania and South Africa, in fact, enjoy an edge over boys born to illiterate parents (see Appendix Table B.3).

We then explored heterogeneity in the association between literacy and IM across gender both at the country and the regional level. Figure 12 (a)-(b) plots the linear regression association between country-cohort level IM with country-cohort level parental literacy, estimated separately for girls and boys. Upward (downward) mobility is marginally higher (lower) for males compared to females. The positive (negative) association between the likelihood of (not) completing primary schooling for children born to illiterate (literate) parents and the share of literate old is equally strong for both boys and girls.

Figure 12: Literacy and IM at the country-birth-decade level, male/female



These figures visualize two regressions that link IM across countries-cohorts to old generation's literacy separately for male and for female places, that is, we estimate $\widehat{IM}_{cb}^{\text{male or female}} = \alpha + \beta \times \widehat{\text{lit_par}}_{cb}^{\text{male or female}} + u_{cb}$. Panel (a) shows the scatter plots and regressions for upward IM and panel (b) those for downward IM.

Table 5: Literacy and IM at the district-level, male/female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IM up	IM up	IM down	IM down	IM up	IM up	IM down	IM down
share literate old	0.648*** (0.039)	0.760*** (0.044)	-0.380*** (0.028)	-0.460*** (0.037)	0.506*** (0.043)	0.598*** (0.048)	-0.364*** (0.036)	-0.395*** (0.040)
R-squared	0.864	0.869	0.660	0.629	0.921	0.925	0.718	0.706
N	2804	2805	2716	2742	2804	2805	2716	2742
sub-sample	male	female	male	female	male	female	male	female
country FEs	yes	yes	yes	yes	no	no	no	no
province FEs	no	no	no	no	yes	yes	yes	yes
p: coeff-equal	0.0000		0.0054		0.0000		0.1606	

The dependent variable is the district-level share of literate kids of illiterate parents (estimated net of census year and old and young birth decade fixed effects). The independent variable is the district-level share of literate parents (also estimated net of fixed effects). Standard errors clustered at the admin-1 (province)-level in parentheses. * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$. p -values for coefficient equality in the male/female sub-samples are from a Chow-test ($\sim \chi^2$ under H_0).

Table 5 associates the regional IM estimates with old generation's literacy separately for boys (odd-numbered columns) and for girls (even-numbered columns). Let us start with the upward-IM analysis in columns (1)-(2) and (5)-(6). The country (province) fixed-effects coefficient in the sample of boys is 0.65 (0.51), while in the girls sample it is larger, 0.76 (0.60); a Chow test of coefficient equality suggests that the difference is statistically different than zero. The environment, as captured in regional literacy, seems to matter more for girls as compared to boys. In regions with very low education level, girls from families without much schooling have a much lower chance than boys to complete primary education. The downward IM estimates in columns (3)-(4) and (7)-(8) yield similar results,

as the coefficients in the girls sample are always more negative, as compared to boys. In Section 5.2, when we re-examine gender asymmetries, we also find that regional exposure effects in the years relevant for primary education are stronger for girls.

3.5 Summary

The mapping of educational mobility across Africa reveals new regularities in the spatial distribution of opportunity across the continent. First, there are wide differences in IM across countries. Second, regional disparities in IM are even larger and appear especially wide in countries with low levels of education and mobility. Third, pan-African upward IM has somewhat increased since independence, though in many countries there have been no major changes. Fourth, upward IM is strongly linked to the average parental education in the country/region. Likewise, downward IM is inversely correlated to the literacy of the old generation, though this association is less strong. These patterns are consistent with poverty traps (or low convergence), since improvements in educational attainment are larger in regions with relatively higher human capital levels. Fifth, the correlation between the old generation’s literacy and IM is especially strong for rural, as compared to urban households, a pattern that may partly be behind the recent rise in African urbanization. Sixth, the regional analysis reveals that the old’s literacy IM correlations are somewhat stronger for girls, as compared to boys, suggesting that a favorable (unfavorable) environment may be particularly beneficial (detrimental) for girls.

4 The Geography of Intergenerational Mobility

In this Section, we examine the correlates of regional IM without any pretense of identifying causal effects. Our objective is to uncover a set of stylized facts that characterize the geography of educational IM. As Chetty et al. (2014), we run univariate specifications linking the proxies of intergenerational mobility with geographical, historical, and at-independence regional characteristics. As the literacy of the old generation is a strong correlate of IM, we also report specifications conditioning on it. The regression analysis, albeit simple, is useful in addressing the following question: Do the geographic or historical factors under consideration influence contemporary development through their linkages with initial conditions, that still matter due to strong inertia? Or are these factors also associated with the rate at which initial conditions are transmitted intergenerationally?

4.1 Specification

The empirical specification reads:

$$IM_{r,c} = \theta_c + G_{r,c}\Phi + H_{r,c}\Gamma + Z_{r,c}\Psi \ [+ \ \lambda L_{r,c}^o \] + \zeta_{r,c}.$$

$G_{r,c}$ are geographic features of district r in country c ; $H_{r,c}$ denotes historical, colonial and pre-colonial regional characteristics, and $Z_{r,c}$ are at independence economic features. Given the vast country heterogeneity we add country fixed effects (θ_c), though in the appendix we also report results without. In some permutations, we condition on the share of the old generation with completed primary schooling or higher, $L_{r,c}^o$. Appendix C.1 provides definitions and sources for all variables and also gives the summary statistics. Table

6 reports the estimates. Panel *A* looks at geographic features. Panel *B* looks at colonial and pre-colonial features, while Panel *C* looks at at-independence economic structure correlates of mobility. Column (1) reports the correlation between the variable specified on the left column with the share of literacy among the “old” generation; this allows benchmarking the IM estimates. Column (2) reports the correlation between the variable of interest and the likelihood that children born to illiterate parents complete primary education (upward IM); column (3) gives the correlation with upward IM, conditional on the share of the “old” generation with completed primary. Column (4) reports the number of regions. Columns (5)-(7) report analogous estimates looking at downward mobility. To make the estimates comparable, the table reports standardized “beta” coefficients that measure how many standard deviations the dependent variable changes in response to a one standard deviation change of the explanatory variable. Standard errors clustered at the province-level are reported below the estimates.

In the appendix, we report various permutations that we comment on below: (*i*) in the 14 – 25 age sample (table C.2); (*ii*) looking at the 1990s cohort that has the widest coverage (table C.5); (*iii*) replacing the country constants with province fixed-effects, so as to account for local unobservable features (table C.3); (*iv*) without the country constants (table C.4); and (*v*) jointly inserting geographic, historical, and at-independence factors on the RHS (tables C.6 and C.7).

4.2 Geography

Geography features prominently in explaining Africa’s underdevelopment (e.g., Sachs (2006)). And given the strong inertia documented in the previous section, it is natural to examine the correlation of IM with geographic, and ecological features.

Distance to the Capital Much evidence documents the limited ability of African states to exercise control far from the capitals (e.g., Michalopoulos and Papaioannou (2014a) and Campante et al. (2019)). Even during colonization, the limited public goods were confined to the capital and a few urban hubs (Herbst (2000)). In line with this, column (1) shows that the literacy of the “old” is systematically higher in districts closer to the capitals. Column (2) reveals a significant association between proximity to capital and upward mobility. The standardized coefficient drops considerably, once we condition on the literacy of the “old” generation in column (3), from -0.29 to -0.094 , though it remains precisely estimated. The picture is similar when we look at downward mobility: the likelihood that children of parents with completed primary education will not finish primary school is significantly higher in districts further from the capital. The association between IM and distance to the capital is robust to various perturbations, retaining significance when we run province fixed-effects specifications.

Distance to the Border African borders appear unruly and conflict prone.¹⁶ The association between distance to the border and literacy of the “old” is weak (0.04) and

¹⁶See Alesina et al. (2011) and Michalopoulos and Papaioannou (2016) for evidence linking border artificiality and ethnic partitioning to underdevelopment and conflict.

Table 6: District-level correlates of IM

variable	upward IM				downward IM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	share literate old	IM	IM controlling for share literate old	N	IM	IM controlling for share literate old	N
Panel A: geography							
ln(distance to capital)	-0.297*** (0.038)	-0.295*** (0.039)	-0.097*** (0.026)	2809	0.218*** (0.029)	0.092*** (0.023)	2787
ln(distance to border)	0.051 (0.036)	0.014 (0.032)	-0.024* (0.012)	2809	-0.028 (0.025)	-0.003 (0.015)	2787
ln(distance to coast)	-0.195*** (0.057)	-0.242*** (0.051)	-0.105*** (0.018)	2809	0.154*** (0.036)	0.062*** (0.016)	2787
ln(1+malaria stability)	-0.242*** (0.049)	-0.242*** (0.052)	-0.071*** (0.026)	2798	0.168*** (0.044)	0.055 (0.035)	2776
ln(1+agricultural suitability)	-0.034 (0.056)	0.013 (0.049)	0.038** (0.019)	2768	-0.018 (0.036)	-0.035 (0.027)	2746
ln(terrain ruggedness)	0.104** (0.048)	0.113*** (0.040)	0.037* (0.019)	2799	-0.087*** (0.033)	-0.038* (0.020)	2777
oil field dummy	0.014 (0.026)	0.010 (0.025)	-0.000 (0.010)	2784	-0.003 (0.020)	0.004 (0.016)	2762
diamond mine dummy	-0.013 (0.012)	-0.015* (0.009)	-0.005 (0.007)	2784	0.029** (0.013)	0.022* (0.012)	2762
Panel B: history							
ln(distance to railroad)	-0.315*** (0.042)	-0.329*** (0.039)	-0.094*** (0.020)	2299	0.247*** (0.025)	0.083*** (0.019)	2277
ln(distance to road)	-0.264*** (0.028)	-0.244*** (0.028)	-0.049*** (0.016)	2515	0.212*** (0.021)	0.082*** (0.020)	2493
ln(distance to cath. mission)	-0.362*** (0.060)	-0.342*** (0.057)	-0.087*** (0.024)	2809	0.235*** (0.039)	0.066** (0.027)	2787
ln(distance to prot. mission)	-0.354*** (0.046)	-0.329*** (0.038)	-0.086*** (0.019)	2809	0.237*** (0.029)	0.081*** (0.022)	2787
ln(distance to precolon. empire)	0.023 (0.040)	-0.017 (0.029)	-0.034 (0.026)	2809	0.014 (0.032)	0.026 (0.031)	2787
ln(distance to precolon. state)	-0.037 (0.039)	-0.059* (0.033)	-0.031* (0.017)	2809	0.041* (0.024)	0.022 (0.017)	2787
Panel C: contemporary							
ln(population density 1950)	0.226*** (0.041)	0.237*** (0.039)	0.081*** (0.021)	2797	-0.146*** (0.025)	-0.041** (0.017)	2775
urban share (born < 1960)	0.378*** (0.021)	0.246*** (0.029)	-0.021 (0.022)	2531	-0.234*** (0.021)	-0.094*** (0.018)	2513
agri. empl. share (born < 1960)	-0.597*** (0.029)	-0.439*** (0.025)	-0.088** (0.038)	2430	0.319*** (0.024)	0.100*** (0.024)	2412
manuf. empl. share (born < 1960)	0.234*** (0.041)	0.156*** (0.033)	0.004 (0.017)	2430	-0.105*** (0.027)	0.001 (0.017)	2412
serv. empl. share (born < 1960)	0.579*** (0.031)	0.434*** (0.026)	0.097** (0.039)	2430	-0.319*** (0.022)	-0.110*** (0.022)	2412

This is not a normal regression table. In the column entitled “share literate old” the dependent variable is the district share of parents with at least primary schooling (estimated net of country-year and country-birth-decade fixed effects for young and old). In the columns entitled “IM” it is the district-level share of children of parents with less than primary who complete at least primary (for upward IM, columns (2)-(4)) or the share of children of parents with at least primary who complete less than primary (for downward IM, columns (5)-(7)) (estimated net of country-year and country-birth-decade fixed effects for young and old), which is also the LHS in the columns entitled “IM controlling for share literate old”. Each row shows the results of regressions of these variables on the LHS on one RHS variable (indicated in the rows) at a time. The regressions in the two columns “IM controlling for share literate old” additionally control for the share of parents with at least primary schooling (estimated net of country-year and country-birth-decade fixed effects for young and old), – that is they include the LHS variable of the columns “share literate old” on the RHS. All specifications include country fixed effects (not reported). Coefficients are standardized. Standard errors clustered at the province-level in parentheses. * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$. ■ ■ lines indicate that variables remain significantly correlated with IM when we control for the share of literate parents.

the estimate does not pass standard significance thresholds. The correlation between (upward and downward) IM and distance to the border is likewise small; in most specifications the coefficient is statistically indistinguishable from zero. Neither IM nor education correlates strongly with distance to the border.

Distance to the Coast A cursory look on a satellite image of nighttime light density shows that African development is concentrated along the coastline. Proximity to the coast, among others, is linked to the presence of Europeans and associated investments during the colonial era. Distance to the coast correlates significantly with the “old” generation’s literacy (column (1)). The specifications in column (2) ((5)) show that upward (downward) educational mobility is significantly higher (lower) in regions proximate to the coast. The coefficient retains significance when we condition on the literacy of the old (in (3) and (6)) though the estimate declines. The correlations retain economic and statistical significance, when we replace the country constants with province fixed effects.

Malaria Malaria has been invariably linked to Africa’s underdevelopment (e.g., Gallup and Sachs (2001), Cervellati et al. (2016), Depetris-Chauvin and Weil (2018)). We associate the two proxies of intergenerational mobility (and the literacy of the “old”) with an index reflecting a district’s malaria ecology (from Kiszewski et al. (2004)). In line with earlier works, education is lower in regions ecologically friendly to malaria. Column (2) (column (5)) shows that upward (downward) educational IM is significantly lower (higher) in regions with an environment favorable for the transmission of malaria. Specifications (3) and (6) reveal that the negative (positive) association between malaria ecology and upward (downward) IM operates above and beyond initial differences in literacy. This – to the best of our knowledge – novel result suggests that malaria-prone regions are on a divergent trajectory. Initial educational conditions have been worse; but upward mobility is lower and downward mobility is higher in districts with malaria, even when we condition on the “level” effect.

Land Quality for Agriculture We then link IM to the quality of land (soil suitability) for agriculture, as the latter has been linked to economic outcomes both in the pre-industrial and contemporary era (Michalopoulos et al. (2019)). There is some weak positive association between soil quality and the stock of literacy; however the correlation between land suitability and IM never passes standard statistical significance thresholds.

Ruggedness We then examined the association between IM and ruggedness that correlates positively with cross-country economic performance in Africa. Different explanations have been proposed to rationalize this pattern that is unique to Africa. Nunn and Puga (2012) argue that regions with rugged terrain were shielded from Africa’s slave trades that have been detrimental to Africa’s long-run development (Nunn (2008)). Moreover, malaria stability is more pervasive in the lowlands compared to the highlands, protecting populations in the latter from the adverse effects of the disease. Setting the origins of this relationship aside, there is a positive and significant association between terrain ruggedness and the literacy of the “old” generation (column (1)), a result that adds to

the cross-country patterns of Nunn and Puga (2012). Columns (2)-(3) uncover that upward educational mobility is significantly higher in rugged regions, while columns (5)-(6) show that in regions with rugged terrain downward mobility is lower. However, when we replace the country constants with province fixed effects the association between IM and ruggedness breaks down.

Natural Resources A large literature on the “natural-resource curse” links conflict and other aspects of underdevelopment to the presence of oil, diamonds, and precious minerals. [See, among others, Ross (2004), Berman et al. (2017), Guidolin and La Ferrara (2007).] But, Hohmann (2018) shows that across African regions natural resource shocks are associated with higher education and structural transformation. We associated IM with indicator variables for the presence of diamond mines or oil fields. Natural resources are somewhat related to literacy, but the association with IM is weak at best. This most likely reflects opposing influences; conflict/animosity on the one hand and employment/development on the other. We also examined whether IM is related to proximity to other mineral sites (like silver or platinum mines), without detecting any correlation.

4.3 History

Drawing on the research agenda that links contemporary proxies of economic, social, and political development to colonial and precolonial features (see Michalopoulos and Papaioannou (2019) for an overview), in table 6 - Panel *B* we report specifications associating IM with historical features.

Colonial Road and Railroad Infrastructure Colonial investments in railroads and roads have played a crucial role in African countries’ post-independence development and seem to explain path-dependence (e.g., Jedwab et al. (2017), Jedwab and Moradi (2016), Okoye et al. (2017), Huillery (2009)). We regress IM on the log distance to colonial railroads and colonial roads (data come from Jedwab and Storeygard (2017) and cover all Sub-Saharan African countries, but South Africa). There is a positive association between proximity to railroads-roads and literacy among the “old”. Log distance to colonial railroads is significantly positively related to upward IM and negatively to downward IM. These patterns hold when we control for the share of literacy of the old; the standardized coefficients are quite similar in the upward and downward IM specifications with both railroads and roads (around 0.08). Colonial railroads are not only associated with development at independence (as reflected in the education of the “old”), but also seem to boost intergenerational transmission.

Colonial Missions A considerable body of research uncovers sizable local effects of Christian, especially Protestant, missionary activity on education (Nunn (2014), Cage and Rueda (2017), Wantchekon et al. (2015), Okoye and Pongou (2014)). We thus examined the correlation between IM and proximity to colonial missions using digitized data from Nunn (2010) and Cagé and Rueda (2016). There are 1,321 (361 Catholic, 933 Protestant, 27 British and Foreign Bible Society) and 723 (Protestant only) missions in these

datasets. The specifications in column (1) reveal a strong within-country positive correlation between proximity to Christian missions and literacy rates of the “old”. There is a significantly positive (negative) correlation between proximity to missions with upward (downward) IM. When we condition on the literacy of the “old” generation, the coefficient on log distance declines, but remains statistically significant (beta around 0.09 for upward IM and 0.07 for downward IM). While data on Christian missions are incomplete and there may be systematic biases (Jedwab et al. (2018)), the analysis shows that pre-independence schooling investments of Christian missions may have lasting effects, both by shaping initial literacy which in turn increase educational mobility and also by affecting mobility directly.

Pre-colonial Political Centralization and Early Statehood We also explored the correlation between IM and pre-colonial political centralization that recent works link to contemporary development (e.g., Michalopoulos and Papaioannou (2013), Michalopoulos and Papaioannou (2014b), Gennaioli and Rainer (2007), Alsan (2015), and Depetris-Chauvin (2016)). We correlate IM with the distance to the centroid of the nearest large kingdom or empire using data from Brecke (1999), as geocoded by Besley and Reynal-Querol (2014) and log distance to pre-colonial states using Murdock’s data (Murdock (1959), Murdock (1967)) though data are missing for some parts of the continent. There is no systematic link between distance to pre-colonial states and upward or downward IM with the Brecke (1999) data. The standardized coefficient is significant at the 90% level with the incomplete Murdock map. But the correlation loses significance when we control for province fixed effects in either sample.

4.4 At-Independence Correlates

In Panel *C* of table 6 we correlate IM with at-independence economic factors. For most variables, we use census data for individuals born before 1960. To net out migration effects (discussed in the next Section), we use information only from individuals who reside in their birth-district (the results are similar if we use all individuals). As we lack migration information for Lesotho, Nigeria, and Zimbabwe, the sample now spans 23 countries (see Appendix Table A.3).

At-Independence Development We look at how IM relates to (the log of) population density in 1950, which for most countries corresponds to the period just before independence, using data from Klein Goldewijk et al. (2010). Population density serves as a good proxy of local development in Africa that at the time was characterized by Malthusian dynamics. There is a significantly positive association between log population density in 1950 and the literacy of the “old” generation. Population density correlates positively and significantly with upward IM (column (2)) and negatively with downward IM (column (5)). The coefficients drop once we account for the share of the “old” generation with completed primary school, but the estimates are significant at the 99% level. Population density matters relatively more for upward -as compared to downward- IM (“beta” coefficients of 0.08 and -0.04).

Industrial Specialization Motivated by the literature on structural transformation in Africa (e.g., McMillan et al. (2014), Diao et al. (2017), Hohmann (2018)) and the evidence on persistence, we explored the correlation between IM with the share of employment in agriculture, manufacturing, and services at independence. The specifications in (1) show that initial human capital is considerably higher in regions with a relatively higher employment share in the “modern” sectors (services-manufacturing) as compared to the traditional sector (agriculture). The share of agriculture is significantly negatively correlated with upward mobility and positively correlated with downward mobility; these patterns also hold when we condition on the literacy of the “old” generation in the district. The standardized coefficients imply considerable magnitudes. A one standard deviation increase in the share of agricultural employment ($\sigma = .30$) is associated with a 0.44 standard deviation fall in upward mobility ($\sigma^{IM_up} = .249$) and a 0.32 standard deviation increase in downward IM ($\sigma^{IM_down} = .243$). The regressions with the share of services in the RHS yield a “mirror” image. Upward IM is significantly higher and downward IM is significantly lower in regions that had a higher share of employment in services. These patterns are also present in the 14–25 age sample, when we just focus on the 1990s cohort and when we condition on admin-1 fixed-effects (see appendix C.2). Our results square well with the analysis of Asher et al. (2018) across Indian districts, who also document a strong positive association between manufacturing employment and educational mobility.

Rural-Urban Literacy is significantly higher in more urbanized regions. At the same time, upward mobility is higher and downward mobility is lower in relatively more urbanized regions. Once we condition on the share of literacy of the “old” generation, the correlation between upward IM and the share of urban households weakens and turns insignificant, while the correlation with downward IM retains its economic and statistical significance. Conditional on the education of the previous generation, in urban places the likelihood that kids of parents without schooling manage to complete primary schooling is not that different from more rural places; but, the likelihood that children of literate parents will not complete elementary schooling is considerably lower.

4.5 Summary

The correlation analysis that aims to characterize the spatial distribution of Africa’s educational mobility shows that geographic and colonial-era features are related to IM. Proximity to the coast and the capital is related to higher (lower) upward (downward) mobility, even when one conditions on the initial “level” of literacy. Intergenerational mobility is also linked to terrain ruggedness (positive) and malaria (negative). In contrast, the correlation between educational mobility and natural resources is weak and statistically insignificant. Proximity to colonial railroads and Christian missions, that provided education and basic health, are also linked to higher levels of social mobility. Pre-colonial statehood correlates neither with educational mobility nor with education. At-independence development, reflected in regional population density, urbanization, and “structural transformation” proxies correlate strongly with education as well as intergenerational mobility, conditional on the education stock. This implies considerable inertia.

5 Regional Exposure Effects

Setting aside the origins of spatial differences in education and IM, to what extent do districts exert a causal effect on mobility? To answer this question, we look at migrant families and exploit within-household variation in children’s exposure to regions with different degrees of intergenerational mobility. To the extent that a district’s IM is a sufficient statistic of the economic and social environment that shapes educational decisions, within-household variation can help us in identifying the causal effects of regions on individual outcomes. We employ two approaches. First, we apply a straightforward household fixed-effects strategy looking at multi-children families, who have moved over time, thereby subjecting siblings to different environments. Second, we follow the approach of Chetty and Hendren (2018a) that exploit differences in the exact timing of children’s moves across districts to capture regional exposure effects at different ages.¹⁷

5.1 Approach 1. Within-Family Estimates

5.1.1 Specification

We estimate the following regression in the sample of young individuals from households with at least two children born in different districts:

$$\begin{aligned} \text{IM_up/down}_{ihbct} &= \psi_h + \gamma_b^{\text{parents}} + \delta_b^{\text{child}} + \theta_{ct} + \lambda \times \text{gender}_{ihbct} \\ &+ \beta \times \widehat{\text{IM}}_{bcr}^{\text{up/down nm}} + \epsilon_{ihbct}. \end{aligned} \quad (5)$$

The dependent variable is an individual-level intergenerational mobility indicator. IM_up equals one if child i born in birth-decade b , region r and country c , to illiterate parents in household h is literate in census-year t . IM_down takes the value of one if a child of parents who have completed primary schooling is illiterate and zero otherwise. As with the purely observational estimates above, we look only at children of illiterate parents when we estimate the equation for upward IM and we only look on children of literate parents when we estimate the regression for downward IM. $\gamma_b^{\text{parents}}$ and δ_b^{child} are birth-decade fixed-effects for parents and children, respectively, gender indicates boys/girls, and θ_{ct} denotes country-census-year fixed effects. $\widehat{\text{IM}}_{bcr}^{\text{up/down nm}}$ is a country-district-birth-decade-of-the-child average IM, computed among non-movers (individuals born in the same place as the one that they reside at the time of the census), i.e.,

$$\widehat{\text{IM}}_{bcr}^{\text{up nm}} = \frac{\sum_i \text{IM_up}_{ihbct}^{\text{nm}}}{\sum_i \mathbb{I}(\text{illiterate parents}_{ihbct}^{\text{nm}})} \quad (6)$$

$$\widehat{\text{IM}}_{bcr}^{\text{down nm}} = \frac{\sum_i \text{IM_down}_{ihbct}^{\text{nm}}}{\sum_i \mathbb{I}(\text{literate parents}_{ihbct}^{\text{nm}})}. \quad (7)$$

¹⁷For all countries, except Lesotho, Nigeria, and Zimbabwe, IPUMS records an individual’s birth place. For many countries, birth-place identifiers are not at the same level as residence. In some cases, birth places are at admin-1 level, whereas the residence is recorded at admin-2 level. In other cases, region of residence and birth place are at the same level. To assess migration status, we harmonized region of residence and region of birth, choosing the finest possible level of aggregation. We end up with 1,341 “birth/current residence regions”.

Crucially, ψ_h is a household constant that accounts for family features, related, among others, to ethnicity, religion, background, aspirations, etc. Hence, the coefficient of interest, β , is identified from within-family variation in children’s birth place. Such variation arises because a family started out in one location, had one or more children there, and then moved to a different region, where other children were born.

Before reporting the results a caveat is in order. Estimation contains (non-negligible) measurement error, as we are not using information on the exact timing of children’s move. As such, the cohort-regional place-of-birth IM variables may not reflect very well the environment that children experienced. We address this issue in the next subsection, where we exploit information in the exact timing of move. We view the simple within-family estimates as an introductory step towards the more elaborate estimates that follow.

Compared to the purely observational estimates, there are three major amendments in the sample. First, we run the above regression equation across individuals of families that have both migrant and non-migrant children. Second, since children of the same family that differ by just a couple of years will be subject to similar environments, even if born in different places, we require that they are born at least 5-years apart. Imposing this (ad hoc) restriction increases the chances that the children were not only born but also grew up in different regions. Imposing the 5-year gap means that we cannot estimate the specification in the sample of individuals 14 – 18. We thus focus on the 14 – 25 sample, but we also report results in the sample of individuals aged 14 and older. Third, to make the estimation of IM as clean as possible, we focus on children for whom we observe their mothers and fathers (whereas in the observational part we included extended family members in the estimation of previous generation’s attainment).¹⁸

5.1.2 Results

Table 7 presents the results. Even-numbered specifications report the baseline household fixed effects estimates. Odd-numbered columns report otherwise identical regressions, but without the household constants. The comparison of the two sets of estimates allows us to gauge the role of selection.

Panel *A* looks at upward IM. The cross-sectional estimates in (1) and (3) show that the likelihood that children whose parents have not completed primary schooling will manage to finish primary school is significantly higher when born in regions with relatively high upward IM. In (2) and (4) we add household fixed effects to exploit within-family variation from migrant families with siblings born in different regions. The coefficients are positive and highly significant; the estimate in (2) implies that illiterate parents’ children born in regions with a ten percentage points higher upward mobility have a 2.65 percentage points higher likelihood to complete primary schooling, as compared to their brothers and sisters. The within-family estimate is considerably smaller than the cross-sectional one, suggesting that family characteristics correlate strongly with mobility.

¹⁸The results are similar if we also include extended family members. We refrain from doing so to better isolate the influence of the “environment” from that of the “family”.

Table 7: Household fixed effects estimates

Panel A: RHS = upward IM				
	(1)	(2)	(3)	(4)
	upward IM	upward IM	upward IM	upward IM
non-migrant upward IM	0.670*** (0.022)	0.265*** (0.024)	0.680*** (0.020)	0.341*** (0.018)
R-squared	0.143	0.649	0.162	0.617
within R-squared	0.047	0.008	0.054	0.021
N	164258	164258	280055	280055
households	62960	62960	92933	92933
number of birth regions	1301	1301	1339	1339
Panel B: RHS = downward IM				
	(1)	(2)	(3)	(4)
	downward IM	downward IM	downward IM	downward IM
non-migrant downward IM	0.472*** (0.025)	0.333*** (0.035)	0.399*** (0.022)	0.269*** (0.024)
R-squared	0.068	0.535	0.056	0.501
within R-squared	0.019	0.009	0.016	0.008
N	76529	76529	119030	119030
households	31207	31207	43699	43699
number of birth regions	1151	1151	1190	1190
country-year FEs	Yes	Yes	Yes	Yes
y+o cohort FEs	Yes	Yes	Yes	Yes
household FEs	No	Yes	No	Yes
age-range	14-25	14-25	14+	14+
minimum age gap	5	5	5	5

The dependent variable in panel A is an indicator equal to one if a child of parents without primary education completes at least primary and zero otherwise. In panel B it is an indicator equal to one if a child of parents with at least primary education does not complete primary education and zero otherwise. In panel A, the RHS variable of interest is average upward IM of non-migrant individuals born in the same region and birth-decade as individual i . In panel B, it is average downward IM of non-migrant individuals born in the same region and birth-decade as individual i . Standard errors clustered at the birth-region-level in parentheses. $*p < 0.1$, $**p < 0.5$, $***p < 0.01$.

Panel *B* looks at downward IM. The significantly positive cross-sectional estimates in (1) and (3) suggest that the likelihood that children of parents with completed primary schooling will not manage to finish elementary schooling is significantly higher for children born in regions with low intergenerational mobility. In columns (2) and (4) we add household constants, to compare siblings born in different regions. The implied effects of regional IM fall, though the estimates are significant at the 99% confidence level. Places with higher average downward mobility do worse in keeping children of literate parents from slipping into illiteracy. Literate parents' children born in regions with a one percentage point higher downward educational mobility in their cohort face a 0.333 percent lower likelihood to complete primary schooling, as compared to their brothers and sisters.

5.2 Approach 2. Age-at-Move and Exposure Effects

Our second and preferred identification strategy to approximate regions' effects on mobility follows Chetty and Hendren (2018a) and exploits variation in the timing of move between origins and destinations to identify regional "exposure-effects". This approach focuses exclusively on migrant children; it compares the educational attainment of children who

moved to a better/worse region in terms of average mobility at different ages to identify the rate at which their education converges to those of permanent residents. The identification idea is that if regions have a causal effect on individual mobility, this effect should be stronger, the longer the exposure to the environment lasts¹⁹. We first describe the semi-parametric econometric specification and report the baseline estimates. Second, we present parametric estimates of regional exposure effects and explore asymmetries across gender and the direction of movement (from better to worse and regions and vice versa).

5.2.1 Econometric Specification

The starting point of the Chetty and Hendren (2018a) methodology is a generic specification that links children’s outcomes to those of permanent residents in the destination. For children who moved from place of birth o to destination region d at age m , their education can be expressed with the following regression:

$$\begin{aligned} \text{IM_up}_{ibmcod} = & [\psi_h +] \alpha_{ob} + \alpha_m + \sum_{m=1}^{18} \beta_m \times \mathbb{I}(m_i = m) \times \Delta_{odb} \\ & + \sum_{b=b_0}^B \kappa_b \times \mathbb{I}(b_i = b) \times \Delta_{odb} + \epsilon_{i,ibmcod}, \end{aligned} \quad (8)$$

The dependent variable equals one if the child of illiterate parents manages to complete primary education (or higher) and zero otherwise (upward mobility). α_{ob} denote origin-region \times birth-decade fixed effects. These account for unobserved factors at the level of where and when a child was born. The variable of interest, Δ_{odb} , is the difference in upward educational mobility of permanent residents (non-movers) in the destination versus origin for all children born in birth cohort b :

$$\Delta_{odb} = \widehat{\text{IM_up}}_{bd}^{\text{nm}} - \widehat{\text{IM_up}}_{bo}^{\text{nm}},$$

where mean region-cohort upward mobility is defined in equation (6). We estimate a different slope, β_m , for each age of move (years 1 to 18), controlling for any direct effect via age-of-move constants, α_m ; these capture disruption effects and any other age-specific unobserved feature that affects the education trajectory. Following Chetty and Hendren (2018a), we augment the specification with interactions of destination-origin differences in cohort-specific IM with cohort fixed effects, to account for potential differential measurement error across cohorts (this has no effect on our estimates).

The idea behind equation (8) is that if children move from places with worse to places with better educational opportunities ($\Delta_{odb} > 0$), and exposure matters for educational outcomes, the earlier the move occurs, the greater the effect on the outcome (Chetty and Hendren (2018a)). Since we include (thousands of) origin-cohort fixed effects (2,916 in the 14 – 25 sample and 4,175 in the 14+ sample), variation comes from children born in the same place in the same time, who, however, move to regions with different social mobility.²⁰

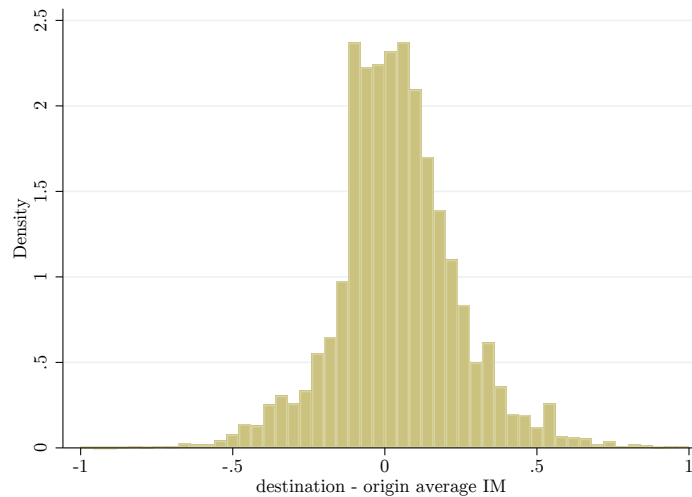
¹⁹See Chetty and Hendren (2018a) for references on the vast literature in sociology and economics of moving to better neighborhoods.

²⁰The only difference vis a vis Chetty and Hendren (2018a) is that we are not interacting the origin-cohort effects α_{ob} with age-at-move m . Doing so would require adding more than 100,000 fixed-effects, 1300 (regions) \times 5 (cohorts) \times 18 (age at move).

The age-specific slopes, β_m in equation (8), are identified even in presence of sorting; i.e., illiterate parents with higher latent propensity to educate their children are more likely to move to higher opportunity environments. The identifying assumption is that the timing of the move is not correlated with the latent ability of their (younger) children. In other words, parents who were more likely to invest in their children’s education are allowed to move from worse to better environments on average compared to parents who were not going to do so, but the more ambitious parents should not move earlier rather than later. As this is not a weak assumption, we relax it estimating a household fixed-effects variant of equation (8). In this permutation (with ψ_h), the identifying assumption is that parents who move to better places do not do so to favor specifically some of their children.

Distribution of Δ_{odb}^{nm} Before reporting the results, it is useful to visualize the cohort-specific regional differences in IM (of non-movers) between origin and destination. $\Delta_{odb}^{nm} \leq 0$, as families may move to places with better or worse IM. Figure 13 plots the histogram of Δ_{odb}^{nm} for children aged 14 to 25. The mean and median are positive, .04 and .03; on average, families move to regions with higher levels of upward mobility. However, migration flows both ways. Roughly 157,000 children move to a region with higher IM (57%) and around 116,000 (43%) move to regions with lower IM. These statistics complement the findings of Young (2013) who documents substantial bidirectional urban-rural migration flows across African regions with survey data. There is non-negligible variation; the standard deviation is 0.20.

Figure 13: Destination-origin differences in IM



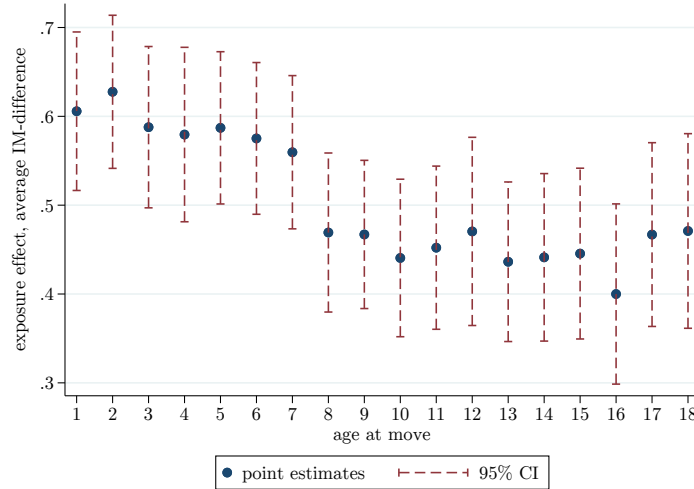
This figure plots the distribution of Δ_{odb}^{nm} – the destination minus origin differences in cohort-region average non-migrant IM – for all migrants children aged 14-25.

5.2.2 Baseline Semi-parametric Estimates

Figure 14 plots the estimated age-specific exposure effects, $\hat{\beta}_m$, against the child’s age when their parents move. The figure uncovers two regularities: “*regional exposure effects*” that are particularly strong for children aged 6 – 11 and “*selection effects*”. The figure

also shows 95% confidence bands based on standard errors clustered at both origin and destination region levels.

Figure 14: Semi-parametric estimates of exposure effects



This figure plots observational (without household fixed effects) semi-parametric estimates of regional exposure effects $\hat{\beta}_m$ from equation (8) against the ages at which children move. 95% confidence bands based on double-clustered standard errors (origin and destination levels) are also shown.

First, the slopes are significantly positive for children moving at all ages. This applies even for children who move at the age of 14–18 ($\hat{\beta}_m \approx 0.45$).²¹ As, almost by definition, moving at the age of 14–18 cannot have a causal effect on primary educational attainment that is often completed by 12–13 years, these estimates provide direct evidence of *selection effects*. Families (with parents who have not completed primary schooling) moving to regions with higher (lower) IM have better (lower) unobservable characteristics translating into a higher likelihood that the children will finish primary school. The figure further shows that the degree of selection does not vary much with the age of children’s move after the age of 14–15.

Second, the non-parametric estimates reveal *regional exposure effects*, as moving to a better (worse) district earlier in life before ages 12–14 generates a higher (lower) likelihood of upward mobility. The estimates are around 0.61 for children whose family moved before they turn 6 years old; the likelihood to complete primary schooling is 30 percentage points higher if their parents move to regions with 0.5 higher levels of IM (mean $IM = .6$, standard deviation = .49). The relationship between age of move and exposure effects is relatively flat for children moving before 6; moving to regions with higher mobility yields equally large benefits in the likelihood to complete primary schooling for children who are 1 or 4 years old. This is not surprising as primary education starts approximately at the age of 6. There is an evident declining pattern of the estimates for children moving between ages 6–12. This suggests that a child moving at the age of 9 has a lower likelihood to complete primary education as compared to a child moving to the same region at the age of 8, 7, or 6. Following Chetty and Hendren (2018a), we define the exposure effect

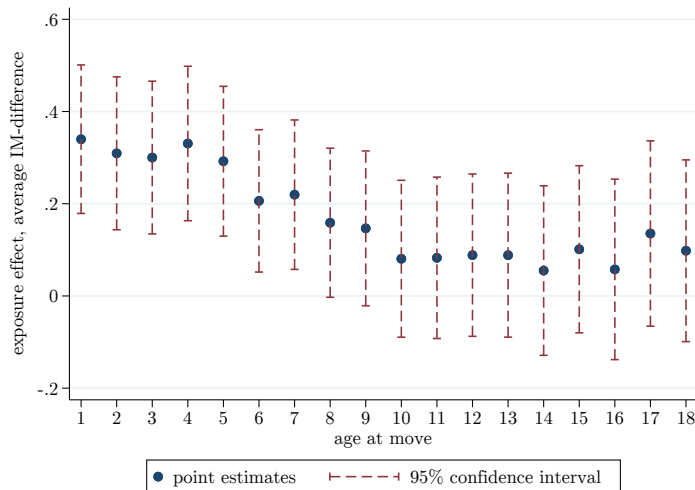
²¹We obtain similar in magnitude positive estimates for ages 19–25.

as $\gamma_m = \hat{\beta}_{m+1} - \hat{\beta}_m$. Regressing the slopes on the age of move for ages 6 to 12 (that are relevant for primary schooling), we obtain an estimate of the average annual exposure effect of $-.019$.

5.2.3 Family Fixed-Effects Semi-parametric Estimates

We re-estimated the semi-parametric specification (equation 8) adding a vector of family constants. This is important, as family characteristics appear to be significant drivers of a child’s probability of completing primary schooling. These estimates exploit variation from migrant-only children of the same family who moved at different ages. By exploiting within-family variation, we also relax the identifying assumption that required latent family features being orthogonal to the timing of move (see Chetty and Hendren (2018a)).

Figure 15: Semi-parametric estimates of exposure effects, household fixed effects



This figure plots household fixed effects semi-parametric estimates of regional exposure effects $\hat{\beta}_m$ from equation (8) against the ages at which children move. 95% confidence bands based on double-clustered standard errors (origin and destination levels) are also shown.

Figure 15 plots the age-specific exposure effects, $\hat{\beta}_m$, obtained by comparing siblings that moved at different ages. Estimation is carried out across 162, 415 children and 65, 579 multi-kid households. Two interesting patterns emerge. First, the selection effect captured in the slopes after age 11 drops significantly once we account for family unobserved features, from 0.45 to 0.07. 95% confidence intervals include 0 for all $\hat{\beta}_m$ after 10 – 11. Family-specific constants account (almost) fully for selection, i.e., purge the estimation from the fact that families more (less) likely to educate their children move to regions with better (worse) educational opportunities. Second, the family-fixed-effects specifications also yield significant regional exposure effects. The slopes for children moving during ages 1 – 5 are around 0.35; two siblings moving to a region with higher IM when they are 1 and 4 have, on average, the same increase in the likelihood to complete primary schooling. If the difference between destination and origin (Δ_{odb}^{nm}) is close to one standard deviation (0.5) the increase in upward-IM is around 18 percentage points for both siblings. The age-of-move slopes, $\hat{\beta}_m^{fe}$, fall for children moving when they are between ages 6 and 12,

suggesting that when a family moves to a higher IM region, the 6-year-old sibling benefits considerably more than her ten-year older sister. The estimate of the exposure effects for the critical-for-primary-schooling ages (6 – 12) is $\gamma_m^{fe} = \hat{\beta}_{m+1}^{fe} - \hat{\beta}_m^{fe} = -.025$. This is similar to the cross-sectional estimate.

5.2.4 Baseline Parametric Estimates

Regression equation (8) is restrictive, as it includes thousands of origin-cohort fixed-effects; this issue becomes more challenging when we add family fixed-effects. Following Chetty and Hendren (2018a) we therefore estimate a parametric variant of specification (8).

$$\begin{aligned}
\text{IM_up}_{ibmcod} = & \sum_{b=b_0}^B \mathbb{I}(b_i = b) \times \left(\alpha_b^1 + \alpha_b^2 \times \widehat{\text{IM_up}}_{ob}^{\text{nm}} \right) + \\
& \sum_{m=1}^{18} \zeta_m \times \mathbb{I}(m_i = m) + \sum_{b=b_0}^B \kappa_b \times \mathbb{I}(b_i = b) \times \Delta_{odb} + \\
& \mathbb{I}(m_i \leq 5) \times (\beta_0 + (18 - m_i) \times \beta_1) \times \Delta_{odb} + \\
& \mathbb{I}(6 \leq m_i \leq 12) \times (\gamma_0 + (18 - m_i) \times \gamma_1) \times \Delta_{odb} + \\
& \mathbb{I}(m_i \geq 13) \times (\delta_0 + (18 - m_i) \times \delta_1) \times \Delta_{odb}. \tag{9}
\end{aligned}$$

Instead of origin-cohort fixed effects, equation (9) includes birth-cohort effects interacted with a linear-in-origin-IM term (the first sum-term). The regression still includes age-at-move dummies to account for disruption effects and interactions between birth-cohorts and destination-origin differences to control for measurement error across cohorts. We no longer estimate separate age-of-move exposure effect slopes, but impose a piecewise linear structure, allowing the regional exposure effects to differ for pre-school years (ages 1 – 5), the ages relevant for primary school (6 – 12), and post-primary education years (13 – 18).

Table 8 presents the parametric estimates in the 14-25 age sample (odd-numbered columns) and in the 14+ sample (even-numbered columns). Let us start with the cross-sectional estimates in columns (1) and (2). The exposure effect for children whose families moved after they were 13 is zero and statistically insignificant. In line with the non-parametric estimates, there is not much benefit for kids in completing primary school, when they move after that age. The estimated exposure effect for children moving between ages 1 and 5 is also small (0.015) and in general insignificant. The likelihood of completing primary school for children whose families move is positive but not much different for children who are very young at the time. In contrast, the exposure effect is significantly positive for children whose parents move when they are in the critical for primary school ages, 6 to 12. The estimate is 0.019 – 0.021, similar to the semi-parametric estimates. The results are similar in the (smaller) sample of individuals that are included in the family fixed-effects specifications that for comparability we report in columns (3) and (4).

Columns (5) and (6) give household fixed-effects estimates. The regional exposure slopes are small and statistically insignificant for children whose families moved when they were older than 13 or younger than 6. The regional exposure slope is significantly positive for children moving between the age of 6 and 12. The coefficient is 0.023 and

tightly estimated. It suggests that if a family with two children moves when the old one is 11 years old and the young one is 6, from a location of zero IM to a location with an IM of one, the likelihood that the younger child would complete primary education is around 14 percentage points higher than the likelihood of her older sibling.

Table 8: Parametric exposure effects estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	IM	IM	IM	IM	IM	IM
β : 1-5	0.0139 (0.012)	0.0172* (0.010)	-0.0000773 (0.014)	0.00510 (0.011)	0.000401 (0.018)	0.00693 (0.013)
γ : 6-12	0.0205*** (0.006)	0.0191*** (0.006)	0.0171** (0.007)	0.0144** (0.007)	0.0227*** (0.008)	0.0190*** (0.007)
δ : 13-18	-0.00515 (0.007)	0.000527 (0.006)	-0.00222 (0.008)	0.00400 (0.007)	-0.00508 (0.007)	0.00159 (0.006)
R-squared	0.099	0.104	0.084	0.087	0.692	0.685
N	273537	335013	162708	199105	162708	199105
households	176523	214431	65694	78523	65694	78523
age at mig FE	yes	yes	yes	yes	yes	yes
birth decade FE	yes	yes	yes	yes	yes	yes
hh FE	no	no	no, hhfe sample	no, hhfe sample	yes	yes
age range	14-25	14+	14-25	14+	14-25	14+

The dependent variable in all regression is a dummy = 1 if the child has completed at least primary, and zero otherwise (i.e. a dummy for IM). The independent variables comprise a linear origin-average-IM (calculated for the birth-cohort relevant to the individual among non-movers) term, age-at-move dummies, birth-decade \times destination dummies interacted with destination-minus-origin opportunity differences (to capture differences in measurement error across locations and cohorts), all of which not reported, as well as three linear terms for destination-minus-origin differences in relevant-birth-cohort-non-mover average IM for move-ages 1-5, 6-12, and 13-18. Standard errors clustered at origin- and destination-levels in parentheses. * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$.

5.2.5 Further Evidence. Heterogeneity

Table 9 reports parametric family fixed-effects specifications that explore heterogeneity across gender and across children that moved to regions with higher (lower) IM than their place of birth.

Gender Columns (1) and (2) examine heterogeneity across gender, estimating a variant of equation (9) where we interact the linear-in-age-at-move regional exposure effects with an indicator for girls. The slopes that capture exposure effects for boys moving before the age of 6 and after the age of 13 are unstable and insignificant. The interactions of Δ_{odb} with the female indicator that captures the additional effect for girls are also statistically indistinguishable from zero. These results are in line with the baseline estimates. The regional exposure effect for primary school age that reflects the impact for boys is significantly positive (0.013); the estimate, however, is smaller than the baseline estimate of 0.023. This is because the regional exposure effect when moving at ages 6 – 12 is especially strong for girls. This is shown by the significantly positive coefficient on the interaction of Δ_{odb} with the female indicator that quantifies the extra benefit (loss) that girls get when they move to regions with higher (lower) mobility during that age. The coefficient on the interaction term is 0.027 in the 14 – 25 sample and 0.0165 in the 14+ sample, suggesting that girls benefit twice as much when moving to regions with better opportunities compared to boys.

Moving to Better-Worse Regions Columns (3) and (4) explore asymmetries between children moving to regions with higher or lower mobility than the origin. We do so by interacting the three linear-in-age-at-move regional exposure effects with a dummy variable that identifies moves to regions with lower than origin IM ($\Delta_{odb} < 0$). The estimates for ages 1 – 5 and 13 – 18 are small and statistically indistinguishable from zero. In contrast, the slope for children moving in the ages 6 – 12 is positive and significant. The estimate is 0.03 in the 14 – 25 sample and 0.019 in the 14+ sample. Moving to better places is associated with significant regional exposure effects for children of primary-school age. The interaction with moving to a region with worse mobility for the 6 – 12 aged children is statistically indistinguishable from zero. This suggests that there is not much of an asymmetry between moves to better or worse conditions.

Table 9: Parametric exposure effects estimates, heterogeneity

male/female			better/worse		
	(1) IM	(2) IM	(3) IM	(4) IM	
β : 1-5, Δ_{odb}^m	-0.0169 (0.024)	0.00249 (0.018)	β : 1-5, Δ_{odb}^+	0.00298 (0.029)	0.0133 (0.021)
γ : 6-12, Δ_{odb}^m	0.0137* (0.008)	0.0126* (0.007)	γ : 6-12, Δ_{odb}^+	0.0296** (0.012)	0.0187* (0.011)
δ : 13-18, Δ_{odb}^m	-0.00739 (0.009)	0.00162 (0.008)	δ : 13-18, Δ_{odb}^+	-0.0148 (0.011)	-0.00186 (0.009)
β : 1-5, $\Delta\Delta_{odb}^f$	0.0384 (0.026)	0.00810 (0.020)	β : 1-5, $\Delta\Delta_{odb}^-$	-0.00712 (0.047)	-0.0179 (0.038)
γ : 6-12, $\Delta\Delta_{odb}^f$	0.0227*** (0.008)	0.0165** (0.008)	γ : 6-12, $\Delta\Delta_{odb}^-$	-0.0179 (0.017)	0.000170 (0.016)
δ : 13-18, $\Delta\Delta_{odb}^f$	0.00601 (0.013)	-0.000328 (0.012)	δ : 13-18, $\Delta\Delta_{odb}^-$	0.0235 (0.020)	0.00813 (0.018)
R-squared	0.694	0.688	R-squared	0.692	0.685
N	162708	199105	N	162708	199105
age at mig FE	yes	yes	age at mig FE	yes	yes
birth decade FE	yes	yes	birth decade FE	yes	yes
hh FE	yes	yes	hh FE	yes	yes
age range	14-25	14+	age range	14-25	14+

The dependent variable in all regression is a dummy = 1 if the child has completed at least primary, and zero otherwise (i.e. a dummy for IM). The independent variables comprise a linear origin-average-IM (calculated for the birth-cohort relevant to the individual among non-movers) term, age-at-move dummies, birth-decade \times destination dummies interacted with destination-minus-origin opportunity differences (to capture differences in measurement error across locations and cohorts), all of which not reported, as well as three linear terms for destination-minus-origin differences in relevant-birth-cohort-non-mover average IM for move-ages 1-5, 6-12, and 13-18. In columns (1) and (2), Coefficient estimates Δ_{odb}^m show the estimates for the reference group (male children). $\Delta\Delta_{odb}^f$ show estimates of differential effects for female children. In columns (3) and (4), coefficient estimates Δ_{odb}^+ show the estimates for the reference group (movers to better places). $\Delta\Delta_{odb}^-$ show estimates of differential effects for movers to worse places. Standard errors clustered at origin- and destination-levels in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusion

In this study we conduct the first systematic exploration of intergenerational mobility in education across African countries and districts since independence.

We structure our analysis into three parts. In the first part, we construct estimates of intergenerational mobility in educational attainment across African countries and re-

gions, distinguishing by gender and rural-urban status. By mapping the African land of opportunity, we uncover sizable regional variation both across and within countries. The strongest correlate of IM is the literacy of the “old” generation. Persistence is stronger for rural, as compared to urban, households and present for both boys and girls. In the second part, we explore the geographic, historical, and economic correlates of intergenerational mobility across 2,809 regions. The goal is to characterize the wide regional variation in educational mobility and guide future research. Upward mobility is higher and downward IM is lower in regions with colonial investments in railroads and roads and areas with Christian missions. Geographical and location-specific features, including distance to the coast and the capital and an ecology favorable to malaria correlate negatively (positively) with upward (downward) IM. At-independence economic factors also relate to mobility. Upward mobility is significantly higher in initially more developed regions, with higher urbanization and employment in services and manufacturing. In the third part, we identify the causal effects of regions on educational mobility by exploiting within-family variation from children whose families moved when children were of primary school age. We document that sorting is sizable. At the same time there are significant regional exposure effects. Boys and (especially) girls whose families move from regions with lower to those with higher upward mobility have a much higher likelihood to complete primary schooling, when the move takes place before the age of 12, as compared to their older siblings.

Our analysis here -as well as in our companion paper Alesina et al. (2019) where we study ethnic and religious differences in educational mobility- call for future research. A first avenue is to examine the causal effects of historical factors on educational mobility, blending the newly compiled IM statistics – that exhibit country, region, cohort, gender, and rural-urban differences – with quasi-natural-experimental variation, exploring the economic mechanisms underlying path dependence, including colonial era and post-independence investments. A second possibility is to examine the role of nationwide educational policies and trade reforms on IM, a largely unexplored area in the context of Africa. A final avenue is to construct measures of each region’s impact on IM – applying the approach of Chetty and Hendren (2018b) – and explore their determinants.

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