Intergenerational Mobility in Africa∗

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Abstract

We examine intergenerational mobility (IM) in educational attainment in Africa since independence using census data. First, we map IM across 27 countries and more than 2,800 regions, documenting wide cross-country and especially within-country heterogeneity. Inertia looms large as differences in the literacy of the old generation explain about half of the observed spatial disparities in IM. The rural-urban divide is substantial. Though conspicuous in some countries, there is no evidence of systematic gender gaps in IM. Second, we characterize the geography of IM, finding that colonial investments in railroads and Christian missions, as well as proximity to capitals and the coastline are the strongest correlates. Third, we ask whether the differences in mobility across regions reflect spatial sorting or the independent role of the former. To isolate the two, we focus on children whose families moved when they were young. Comparing siblings, looking at moves triggered by displacement shocks, and using historical migrations to predict moving-families’ destinations, we establish that, while selection is considerable, regional exposure effects are at play. An extra year spent in a high-mobility region before the age of 12 (and after 5) significantly raises the likelihood for children of uneducated parents to complete primary school. Overall, the evidence suggests that geographic and historical factors laid the seeds for spatial disparities in IM that are cemented by sorting and the independent impact of regions.

Keywords: Africa, Development, Education, Inequality, Intergenerational Mobility.

JEL Numbers. N00, N9, O10, O43, O55

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1 Introduction

There is rising optimism about Africa, a continent with 1.2 billion opportunities, as the Economist (2016) touted not long ago. 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 even speak of an African “growth miracle” (Young (2012)). However, anecdotal evidence indicates widespread inequalities, uneven progress, and poverty traps, suggesting that the “miracle” may not be for all. 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 16 million individuals across 27 African countries and 2,846 regions. Reconstructing the joint distribution of parental and offspring education since the 1960s, when most of Africa becomes independent, allows us to shed light on a variety of 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 mobility, or do areas with higher mobility attract families more eager to climb the social ladder?

1.1 Results Preview

In the first part of the paper, we compile and present new country and regional-level measures of educational opportunity. As recent works on intergenerational mobility in income (e.g., Chetty et al. (2017)) and education (Card, Domnisoru, and Taylor (2018)), we construct measures of absolute 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 the offspring of parents with completed primary education fail to do so. To account for “selection on cohabitation”, we focus on ages between 14 and 18, as in this age range, children have largely finished primary school and still overwhelmingly reside with parents or older relatives (as Card, Domnisoru, and Taylor (2018)).

We document large cross-country differences in upward and downward mobility. 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, Guinea, and Malawi hovers below 20%. Most importantly, there is substantial within-country variation. In Kenya, a country with a close-to-average upward IM of 50%, the likelihood that children of illiterate parents will complete primary education ranges from 5% (in the Turkana region in the Northwest) to 85% (in Westlands in Nairobi). Upward IM is higher in urban as compared to rural areas. While there is a gender gap in educational levels, intergenerational mobility is, on average, similar for boys and girls across the continent, though in the Sahel and North Africa, there is a non-negligible gender gap. Spatial disparities in mobility exhibit considerable persistence: Upward IM is higher in countries and regions with higher literacy among the old. Variation
in the latter accounts for roughly half of the observed IM variability. Downward mobility is also linked to the literacy of the old, but the association is less strong.

In the second part of the paper, we characterize the geography of IM in Africa by looking at geographical and historical variables that have been linked to regional development. Upward IM is higher and downward IM is lower in regions close to the coast and the capital, those characterized by rugged terrains and low malaria. Among the historical legacies, colonial transportation investments and missionary activity are the strongest correlates of mobility. These correlations are present when we exploit within-province variation and when we estimate LASSO to account for multicollinearity and measurement error. While these associations do not identify causal effects, they suggest how historical contingencies, related to colonization and geography, have influenced not only initial conditions (the literacy of the old generation) but also the trajectories of regional economies.

The observed differences in regional IM may be the result of two distinct forces. On the one hand, regions may exert a causal impact on mobility, for example, providing higher-quality infrastructure, more and better schools, and occupational opportunities. On the other hand, there may be 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 employing the approach of Chetty and Hendren (2018a). The methodology exploits differences in the age at which children of migrant households move to distinguish “selection” from “regional childhood exposure effects.” We find that both forces are at play. Selection is far from negligible: families’ sorting into better (worse) locations correlates strongly with child educational attainment. This result adds to Young (2013), who, using survey data, documents 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. An additional year in the higher mobility region before the age of 12, and especially between 5 – 11, increases the likelihood that children of households without any education manage to complete primary schooling.

To advance on the identification of regional exposure effects, we conduct three exercises, separately and jointly. First, we explore whether the educational attainment of siblings whose family moved is proportional to their age difference interacted with differences in mobility between the permanent residents in origin and destination districts. The regional childhood exposure estimates from the household-fixed-effects specifications are similar to the baseline ones. Second, we look at moves taking place in periods of abnormal outflows, as these instances more likely reflect displacement shocks exogenous to households’. We continue finding considerable regional exposure effects for moving children in the critical-for-primary schooling age (5 – 11) and somewhat smaller before 5. Third, we use historical migration to project -and account for- households’ (endogenous) choices of destination. The regional childhood exposure estimates remain significant.

Overall, the analysis of the newly-compiled statistics of educational IM suggests that the vast spatial differences in mobility reflect both sorting and regional exposure effects. The uncovered inertia, coupled with the strong association between mobility (and old’s literacy) with historical and geographic traits, suggests that these features have shaped regional dynamics post-independence.
1.2 Related Literature

Our work blends two strands of literature that have, thus far, moved in parallel. The first is the growing research studying intergenerational mobility (see Solon (1999) and Black and Devereux (2011) for reviews). As matching children to parental outcomes is challenging, most of the earlier studies relied on relatively small samples from surveys. For example, Fletcher and Han (2018) study educational mobility in the US working with surveys covering around 10,000 individuals. Card, Domnisoru, and Taylor (2018) use the US population census of 1940 to map educational mobility looking at children residing with at least one parent. They document rising mobility during the first half of the 20th century, which differs across race and states. Chetty et al. (2014) provide a mapping of IM in income across US counties and explore its correlates. Chetty and Hendren (2018a; b) use matched parents-children administrative tax records of moving families to isolate the effect of neighborhood exposure on income IM from sorting. Our work relates to Asher, Novosad, and Rafkin (2020) and Geng (2018), who also map and study educational mobility across Indian and Chinese regions, respectively (see also Azam and Bhatt (2015) and Golley and Kong (2013)). In parallel work, the World Bank compiles measures in intergenerational mobility in education and income for many countries using survey data (Narayan et al. (2018)). Our key contribution to this research is to compile new statistics and characterize the educational mobility for many African countries and regions. The richness of the census data further allows us to distinguish between gender and rural-urban residence. Most importantly, we estimate regions’ independent influence on mobility, showing at the same time that bidirectional sorting (from higher to lower opportunity regions and vice versa) is considerable.

The second strand is the research on African development that has moved from cross-country approaches focusing on national features (e.g., Gunning and Collier (1999), Bates (2015)) to within-country analyses. 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 (2020) provide a review). A question that the literature has so far not addressed 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 historical shocks have also altered the transmission of opportunity across generations. By building granular data on IM across African regions and systematically exploring its correlates, we begin answering such questions. Moreover, by isolating the role of regions on mobility from that of sorting, we start unbundling the mechanisms linking geography-history to contemporary development.

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2. A strand of the US-focused literature looks at racial differences in mobility (e.g., Chetty et al. (2018b), Davis and Mazumder (2019), Derenoncourt (2018)). These studies relate to our companion work (Alesina et al. (2019)), where we explore ethnic and religious differences in educational mobility across Africa.
In Section 2, we present the census data on educational attainment and detail the construction of the intergenerational mobility measures. Section 3 describes IM across African countries and regions. Section 4 explores the geographic, historical, and at-independence correlates of educational mobility. In Section 5, we exploit differences in ages-at-move among migrant children to isolate regional childhood exposure effects from sorting. 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 data are available for a tiny share of the African population and 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. Moreover, consumption data are noisy and cover small samples. In contrast, education data are available at a fine geographic resolution. Second, measurement error in educational attainment is a lesser concern compared to that of reported income, wealth, or consumption. Third, education is useful in mapping intergenerational mobility, as people tend to complete primary schooling, which is the key educational achievement across most of Africa, by the age of 12—14. Hence, unlike lifetime earnings, the analysis can start when individuals are relatively early in the life cycle. Fourth, parental investment in children’s education is at the heart of theoretical work in intergenerational linkages (e.g., Becker and Tomes (1979), Bénabou (1994), Loury (1981), Becker et al. (2018)). Fifth, education correlates strongly with income across countries (e.g., Barro and Lee (2013); Gennaioli et al. (2014)); a voluminous 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 appear larger in low-income (African) countries. Sixth, in the Appendix (section C.2), using all geo-referenced Demographic and Health Surveys (DHS) and the Afrobarometer Surveys, we present evidence of a strong correlation between educational attainment and various proxies of well-being in Africa including living conditions, child mortality and fertility, attitudes toward domestic violence, political and civic engagement.

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3Most studies suggest higher returns to education in low-income countries, as compared to the “consensus” estimate of 6.5%—8.5% in high-income countries (e.g., Psacharopoulos (1994), Psacharopoulos and Patrinos (2004), Caselli, Ponticelli, and Rossi (2014)). Young (2012) estimates Mincerian returns of about 11.3% (OLS) to 13.9% (2SLS) across 14 Sub-Saharan African countries using DHS data, much higher than in 11 non-SSA low-income countries [range of 8.7% (OLS) - 10.4% (2SLS)]. Montenegro and Patrinos (2014) estimate Mincerian returns of about 12.4% in Africa, compared to 9.7% for the rest of the world. Four of the top-5 countries are in Africa. Psacharopoulos and Patrinos (2004) further document an average increase in wages for those with completed primary of 37.6% across 15 Sub-Saharan African countries in the 1980s and 1990s, as compared to 26.5% for secondary and 27.8% for tertiary.
2.2 Sample

2.2.1 Countries & Regions

We use individual records, retrieved from 69 national censuses from 27 countries: Benin, Botswana, Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Morocco, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, South Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe. We obtain the data from IPUMS (Integrated Public Use Microdata Series) International, hosted at the University of Minnesota Population Centre, that reports harmonized representative samples, typically 10%. As of 2015, the sample countries were home to about 850 million people, representing around 75 percent of Africa’s population and GDP. IPUMS also reports residence at the time of the census, allowing us to assign individuals to “coarse” and “fine” administrative units. Our sample spans 367 provinces (admin-1) and 2,846 districts (admin-2 or 3 units).

2.2.2 Education

IPUMS records education for around 93 million individuals. Dropping those younger than 14 to allow for primary school completion leaves about 66.8 million observations. We validated the IPUMS data across country-cohorts with the widely-used Barro and Lee (2013) statistics and at the regional level using DHS, finding correlations exceeding 0.9 (see Appendix Section C). Appendix Table A.1 reports country averages of education per country-census, while Appendix Figure A.1 portrays the evolution of the pan-African distribution of educational attainment across cohorts. Education rises, though this mostly reflects increasing completion of primary schooling. The share of Africans with tertiary education is minuscule even for the 1980s-born, while secondary education has increased only modestly.

For our analysis, we need to observe education for children and at least one individual of the immediately older generation. This requirement brings the sample to 25.8 million. Appendix table B.1 gives details on the sample construction.

For a first look at the data, we construct $4 \times 4$ attainment transition matrices for individuals older than 25 years. Figure 1(a) shows the Africa-wide transition matrix using all censuses, while figures 1(b) and (c) zoom in Mozambique and Tanzania, respectively. The vertical axis indicates the likelihood that the child has the respective education.

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4 Starting from the set of 74 censuses available from IPUMS, we discard Burkina Faso 1985, Kenya 1979, and Liberia, 1974 as these lack identifiers needed to match children to older relatives. We also remove Togolese Censuses of 1960 and 1970, as they are small and do not cover all regions.

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

6 For Botswana, Lesotho, and Nigeria, IPUMS reports one administrative unit. In in Ghana after 1984, Burkina Faso in 1985, Ethiopia in 1984, Malawi in 1987, and South Africa after 1996, districts change, as administrative boundaries are redrawn. We have harmonized these countries’ boundaries.

7 There are four 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). We use attainment, rather than years of schooling, for many reasons. First, the attainment data have much wider coverage than years of schooling. In the raw IPUMS data, there are about 25.5 million records with attainment but without years of schooling. The latter is missing altogether for four countries and several censuses. Second, there is likely less noise on completion data as compared to schooling years, which are often inferred from the former. Third, looking at children, whose parents have not completed primary schooling, allows for a common across countries, simple to grasp baseline.
conditional on the older generation attainment, depicted on the horizontal axis. 81.5% of the “old” generation across the continent has not completed primary schooling. 19% of African children, whose parents have not completed primary schooling, manage to do; 9.5% finish high-school, and 2.5% get a college degree. The figure also illustrates the sharp differences between the two Eastern African countries. In Tanzania, 47% of children whose parents have not finished primary school manages to do so; in Mozambique, the corresponding share is 12%.

**Figure 1:** Educational Attainment Transition Matrices

(a) Africa, 27 countries, 69 censuses

(b) Mozambique, 1997, 2007 census

(c) Tanzania, 1988, 2002, 2012 census

The figure shows the transition matrices for four educational attainment categories for all of Africa, Mozambique and Tanzania. The sample consists of individuals aged 25 and older, co-residing with at least one individual of an older generation.

### 2.3 Methodology

We construct measures of *absolute* IM that reflect the likelihood that children complete a strictly higher or lower education level than the members of the immediately previous generation in the household (parents and/or extended family members, such as aunts and uncles). For the education of the “old”, we take the average attainment of individuals one generation older in the household, rounded to the nearest integer. The results are almost
identical if we use the minimum or maximum. As the relevant dimension for Africa during this period regards the completion of primary schooling, we focus on this aspect.

To construct absolute IM measures, we first define the following indicator variables:

- \( \text{lit}_{\text{par}}_{ibct} \) equals 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. We label “illiterate” those who have not completed primary education and “literate” those who have.

- \( \text{IM}_{\text{up}}_{ibct} \) equals 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.

- \( \text{IM}_{\text{down}}_{ibct} \) equals 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, we estimate the following specifications, pooling observations across all censuses and countries:

\[
\text{lit}_{\text{par}}_{ibct} = \alpha_c + [\gamma_b + \delta_y^b + \theta_t] + \epsilon_{ict} \tag{1}
\]

\[
\text{IM}_{\text{up}}/\text{down}_{ibct} = \alpha_y + [\gamma_b + \delta_y^b + \theta_t] + \epsilon_{ict}, \tag{2}
\]

For parental literacy (equation (1)), we compute means among all individuals for whom we observe their parents’ attainment, netting birth-decade fixed effects for the “young” (\( \delta_y^b \)) and the “old” (\( \gamma_b \)) and census-year fixed effects (\( \theta_t \)). For upward IM, we estimate equation (2) for children whose parents have not completed primary education; thus the country fixed effects (\( \hat{\alpha}_c \)) reflect the conditional likelihood that children of illiterate parents become literate, netting cohort and census effects. For downward IM, we estimate (2) in the sample of children whose parents have completed at least primary; so \( \hat{\alpha}_c \) measure the conditional likelihood that children of literate parents do not complete primary schooling netting census-year and cohort effects.

For the regional analysis, we run similar specifications at the district level, country-by-country, and extract the demeaned literacy of the old generation, upward-IM, and downward-IM (conditioning on cohort and census fixed-effects).

\[
\text{lit}_{\text{par}}_{ibcrt} = \alpha_r + [\gamma_b + \delta_y^b + \theta_t] + \epsilon_{ibcrt} \tag{3}
\]

\[
\text{IM}_{\text{up}}/\text{down}_{ibcrt} = \alpha_y + [\gamma_b + \delta_y^b + \theta_t] + \epsilon_{ibcrt}, \tag{4}
\]

\footnote{Some studies use data that match children to either mothers or fathers (e.g., Asher, Novosad, and Rafkin 2020). Others, like we do, take the average (e.g., Hilger 2017), while some take the highest value (e.g., Geng 2018). Taking the mean, maximizes coverage; see also Davis and Mazumder (2020) who use data from surveys where children are matched to either mothers or fathers to maximize coverage.}

\footnote{The intergenerational mobility literature has employed various measures (see Black and Devereux 2011). Many studies focus on (one minus) the intergenerational coefficient obtained from a regression of children on parental schooling (e.g., Hertz et al. 2008); other studies work with rank-rank correlation coefficients and intergenerational rank movements (e.g., Asher, Novosad, and Rafkin 2020, Geng 2018). Other studies (e.g., Card, Domnisoru, and Taylor 2018, Davis and Mazumder 2020) and Chetty et al. (2017) focus, as we do, on absolute transition likelihoods. Gottschalk and Spolaore 2002 provide a theoretical exploration of different mobility measures.}
2.4 Cohabitation Selection

Estimating the IM of individuals who reside with at least one older family member (usually a biological parent) raises cohabitation-selection concerns, as the transmission of education may differ between children living with older family member(s) and those that do not. This issue is less pressing for young children, as almost all of them cohabit with their parents. The younger the child, however, the higher the risk of misclassifying her attainment as “less-than-primary” when in fact she would complete primary education a few years after we observe her in the census. Hence, following Card, Domnisoru, and Taylor (2018), we focus on “children” aged 14 – 18 years, as by then primary education is completed and cohabitation rates are still quite high (see also Hilger (2017)).

We use census information on the “relationship to household head” to recover the “old” generation for 14 – 18 year olds and then take the average of the educational attainment of the “old” members. Appendix Section D provides details, discussing, among others, how we deal with heterogeneity in family structure (e.g., nuclear families, presence of young wives). The Appendix also reports statistics for each census, as their detail differ. On average, cohabitation with any relatives for children aged 14 – 18 is around 94.5%. However, the “relationship to household head” variable is coarsely documented in some censuses. To maximize coverage and avoid misclassifying coresidence with older family member(s) due to census coarseness, we assign “other relatives (not elsewhere classified)” to the “old” generation if they are at least 15 and less than 40 years older than the child. [This imputation affects about 10% of the sample and does not affect any of the results.]

For individuals aged between 14 and 18 years, the average coresidence rate across all censuses is around 84% (see appendix table D.2). Cohabitation rates with an older family member exceed 90% in 11 censuses; it is between 85% – 90% for 15 and between 80% – 85% for 17. The lowest coresidence rate is recorded in Kenya in 1969 (63.3%), in Malawi in 1987 (68.9%), and in Botswana in 1991 and 2011 (around 70%). As a reference point, Card, Domnisoru and Taylor (2018) report coresidence rates for African Americans and whites in the US 1940 census of about 78% and 89%, respectively.

We also focus on individuals aged 14-25. Doing so increases the sample size considerably, including also high-school (and even college) graduates, while cohabitation is still reasonably high (around 70%) 11 The Appendix (Section D) gives details. As we mostly work with regional data, the Appendix also reports the distribution of district-level cohabitation rates; the mean (median) is 82% (82.5%), close to the country statistics. There is some weak evidence that cohabitation rates have risen between the earlier and the later cohorts, though this most likely reflects improvements in censuses.

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10 An extreme example is the Togo 2010 census, which classified 92.9% of individuals 14 – 18 years as cohabitating with some relative. Due to the census’ sparse categorization of the relationship to family head, about half of the children are classified as residing with “other relatives.” Similarly, some censuses distinguish between biological, adopted, and step-children (e.g., Nigeria, South Africa, Zambia, Benin in 2013), but others do not (e.g., Rwanda, Ghana).

11 As we show below the correlation of upward and downward IM across the two age brackets (14 – 18 and 14 – 25) exceeds 0.95. Hence, the patterns reported are not driven by the age bracket chosen.

12 We show in the following sections that results remain unchanged if we restrict our analysis to regions where cohabitation exceeds 80%.
3 Intergenerational Mobility across Countries and Regions

3.1 IM across African Countries

3.1.1 Baseline Measures

Table 1 shows simple (unconditional) country-level estimates of intergenerational mobility (columns (1)-(4)) alongside the number of children (young) for the 14−18 and the 14−25 sample. (The series are strongly correlated, $\rho > .97$). On average, less than forty percent of children of illiterate parents have managed to complete primary education. Downward IM is considerable, as approximately one out of four children born to literate parents does not complete primary education.

<table>
<thead>
<tr>
<th>Country</th>
<th>Census Years</th>
<th>Mobility / N</th>
<th>Age Range</th>
<th>Upward</th>
<th>Downward</th>
<th>N with $e_0$ obs</th>
<th>N with $e_0$ obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>South Africa</td>
<td>1996, 2001, 2007, 2011</td>
<td>0.791</td>
<td>14-18</td>
<td>0.814</td>
<td>0.068</td>
<td>1,047,243</td>
<td>1,944,362</td>
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<tr>
<td>Botswana</td>
<td>1981, 1991, 2001, 2011</td>
<td>0.704</td>
<td>14-18</td>
<td>0.716</td>
<td>0.069</td>
<td>44,516</td>
<td>76,211</td>
</tr>
<tr>
<td>Zimbabwe</td>
<td>2012</td>
<td>0.664</td>
<td>14-18</td>
<td>0.738</td>
<td>0.146</td>
<td>49,855</td>
<td>79,290</td>
</tr>
<tr>
<td>Egypt</td>
<td>1986, 1996, 2006</td>
<td>0.637</td>
<td>14-18</td>
<td>0.628</td>
<td>0.071</td>
<td>2,128,269</td>
<td>4,056,814</td>
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<td>Nigeria</td>
<td>2006, 2007, 2008, 2009, 2010</td>
<td>0.63</td>
<td>14-18</td>
<td>0.65</td>
<td>0.084</td>
<td>38,885</td>
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<td>Tanzania</td>
<td>1988, 2002, 2012</td>
<td>0.595</td>
<td>14-18</td>
<td>0.636</td>
<td>0.177</td>
<td>860,996</td>
<td>1,358,638</td>
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<td>Ghana</td>
<td>1984, 2000, 2010</td>
<td>0.566</td>
<td>14-18</td>
<td>0.556</td>
<td>0.159</td>
<td>489,517</td>
<td>843,090</td>
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<td>Togo</td>
<td>2010</td>
<td>0.51</td>
<td>14-18</td>
<td>0.526</td>
<td>0.19</td>
<td>46,958</td>
<td>83,442</td>
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<td>Cameroon</td>
<td>1976, 1987, 2005</td>
<td>0.569</td>
<td>14-18</td>
<td>0.506</td>
<td>0.117</td>
<td>270,300</td>
<td>443,222</td>
</tr>
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<td>Zambia</td>
<td>1990, 2000, 2010</td>
<td>0.486</td>
<td>14-18</td>
<td>0.507</td>
<td>0.12</td>
<td>307,043</td>
<td>484,973</td>
</tr>
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<td>Kenya</td>
<td>1969, 1989, 1999, 2009</td>
<td>0.454</td>
<td>14-18</td>
<td>0.523</td>
<td>0.219</td>
<td>624,501</td>
<td>1,016,830</td>
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<td>Lesotho</td>
<td>1996, 2006</td>
<td>0.437</td>
<td>14-18</td>
<td>0.496</td>
<td>0.289</td>
<td>38,310</td>
<td>71,965</td>
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<td>Morocco</td>
<td>1982, 1994, 2004</td>
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<td>14-18</td>
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<td>0.107</td>
<td>397,451</td>
<td>785,159</td>
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<tr>
<td>Benin</td>
<td>1979, 1992, 2002, 2013</td>
<td>0.376</td>
<td>14-18</td>
<td>0.354</td>
<td>0.232</td>
<td>192,949</td>
<td>326,478</td>
</tr>
<tr>
<td>Uganda</td>
<td>1991, 2002</td>
<td>0.358</td>
<td>14-18</td>
<td>0.393</td>
<td>0.311</td>
<td>345,215</td>
<td>518,395</td>
</tr>
<tr>
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<td>0.292</td>
<td>14-18</td>
<td>0.35</td>
<td>0.472</td>
<td>237,006</td>
<td>388,219</td>
</tr>
<tr>
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<td>0.256</td>
<td>0.243</td>
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</tr>
<tr>
<td>Sierra Leone</td>
<td>2004</td>
<td>0.248</td>
<td>14-18</td>
<td>0.245</td>
<td>0.268</td>
<td>42,905</td>
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<tr>
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<td>0.297</td>
<td>0.538</td>
<td>31,417</td>
<td>55,981</td>
</tr>
<tr>
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<td>14-18</td>
<td>0.197</td>
<td>0.262</td>
<td>267,300</td>
<td>433,470</td>
</tr>
<tr>
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<td>0.402</td>
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<td>144,991</td>
</tr>
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<td>14-18</td>
<td>0.189</td>
<td>0.267</td>
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<td>0.302</td>
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<td>0.394</td>
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<tr>
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</tr>
<tr>
<td>Mean / Total</td>
<td></td>
<td>0.384</td>
<td>14-18</td>
<td>0.405</td>
<td>0.276</td>
<td>9,785,393</td>
<td>16,814,272</td>
</tr>
</tbody>
</table>

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 unweighted average of the 27 country-estimates.

The pan-African mean masks sizable variation. The likelihood that children of illiterate parents will complete at least primary education ranges from an abysmal 4% in South Sudan and 11% 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. Downward IM is the highest in countries plagued by long-lasting conflicts, such as Rwanda (0.47), Liberia (0.54), Mozambique (0.51), and South Sudan (0.77). Downward IM is below 10 percent in more stable ones like Botswana,
South Africa, Egypt, and Nigeria. The uncovered cross-country heterogeneity in absolute IM across Africa is considerably larger (about twice as large) than the cross-Indian state and cross-Chinese province variability in relative IM documented by Asher, Novosad, and Rafkin (2020) and Geng (2018), respectively.13

Given heterogeneity in family structures across the continent, we exploit the richness of the census data and estimated different IM statistics for children co-residing with biological parents, other older generation relatives, and both. Appendix E.1 reports the cross-country measures. Upward IM is somewhat higher and downward IM lower for children co-residing with biological parents. However, the various measures are strongly correlated (0.95) and the country rankings not much affected by family structure.

3.1.2 Rural-Urban Residence

We compiled IM separately for rural and urban households both at the country and district levels. Appendix Table E.2 reports the statistics across countries14. The correlation between rural and urban IM is 0.85 for both the upward and downward measures. Setting aside South Sudan, an outlier, upward IM in urban places ranges from 0.21 in Mozambique to around 0.85 in Zimbabwe and South Africa (mean 0.53 and st. dev. 0.2). The variability in rural upward IM relative to the mean is wider (mean 0.33 and st. dev. 0.22), hovering around 0.06 in Mozambique, Ethiopia, South and North Sudan but exceeding 0.6 in Nigeria, Egypt, Zimbabwe, Botswana, and South Africa. Overall, the rural-urban gap in mobility is the highest in poor countries (see Appendix Figure E.2).

In Figure 2 we explore the evolution of rural-urban gaps in IM across cohorts. Upward IM is on average 18% higher for urban, as compared to rural households, for all cohorts and countries, but Egypt in the 1960s and 1970s. The rural-urban gap is the highest in countries with low levels of mobility and literacy (and income). 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.

3.1.3 Gender

We also estimate IM separately for boys and girls, as gender disparities are considerable (e.g., Jayachandran (2015), [Ashraf et al.] (2020), [Bandiera et al.] (2017))). Appendix Table E.3 gives the country means. The correlation of the IM measures for boys and girls exceed .90 and, as such, the cross-country ranking is similar to the benchmark (Table 1).

Figure 3 shows the evolution of male-female differences in upward-IM. There is a gender gap for the 1960s cohorts (especially when we exclude Botswana) that disappears for the

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13Geng (2018) documents a province range in intergenerational mobility rank-rank coefficients of 0.25 to 0.5 in the 2000 Chinese Census. The variability across (340) prefectures is larger, range of −0.033 to 0.661. Asher, Novosad, and Rafkin (2020) estimate a range of educational mobility of 0.17 to 0.72 across 124 Indian districts and 0.26 to 0.60 across 25 states.

The variability of educational mobility across the US is much lower than the pan-African one illustrated here. Fletcher and Han (2018) report IM schooling coefficients ranging from 0.3 till 0.6 across US states (median of about 0.45) using survey data in 1982, 1992, and 2004. Hilger (2017) reports a coefficient of variation of around 0.3 for educational mobility across US states. Likewise, the (coefficient of) variation in income IM across US, documented by Chetty et al. (2014) is considerably smaller than our estimates.

14The criteria for the rural-urban classification vary. In some countries, statistical agencies rely solely on population cutoffs, while others use localities’ economic activity. In a few instances, the statistical codebook does not provide precise information. Rural-urban status is not reported for Morocco.
1980s and the 1990s cohorts. To be sure, there are countries where boys fare considerably better than girls: the gender gap is salient in North Africa (Morocco and Egypt) and the Sahel (Senegal, Togo, Mali, and Ethiopia). However, girls born to illiterate parents in many Southern and Eastern African countries, like Lesotho, Botswana, Tanzania, and South Africa, enjoy a small edge in completing primary schooling over boys. Gender differences in mobility are not related to GDP per capita (Appendix Figure E.3).

3.2 Mapping the African Land of Opportunity

3.2.1 Cross-Sectional Patterns

Figure 2 provides an illustration of social mobility across the continent, mapping Africa’s land of opportunity. Panel (a) shows the distribution of upward IM across (mostly admin-2) districts and Panel (b) plots downward IM.

Table 2 reports summary statistics by country. The district-level (unweighted) average and median for upward (downward) IM across the 2,846 regions are 0.40 (0.34) and 0.375 (0.294), respectively, close to the cross-country values. There is considerable spatial variability in IM in a given country.

As an example, Figures 5 (a) and (b) portray upward and downward IM across 110 regions in Ghana. While average upward IM is 0.58, 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 its colonial-era missionary activity.
Figure 3: Upward IM Male-Female Gaps, individuals aged 14-18

The figure plots the gap (male minus female) in upward IM between male and female young individuals aged 14-18 (children) by country and birth decade.

Figure 4: District-level Upward and Downward IM, individuals aged 14-18

(a) upward; brighter colors → higher \( \uparrow \) IM  
(b) downward; brighter colors → higher \( \downarrow \) IM

and transportation investments, topics we return to below.

Regional variation in IM is substantial in many countries (Table 2). In Burkina Faso, for example, the average upward-IM of 0.132 masks a regional range from 0.03 to 0.50.

\footnote{For some districts and census years, downward mobility is 0 and 1. These extremes reflect the relatively small number of observations. The mean (median) district estimate is based on 1,936 (891) matched-to-parents children (\( \text{st.dev} = 3,287 \)). The patterns are similar if we limit attention to regions with at least 100 observations.}
Table 2: Summary Statistics: District-Level Estimates of IM

<table>
<thead>
<tr>
<th>country</th>
<th>districts</th>
<th>mean</th>
<th>median</th>
<th>stdev</th>
<th>min</th>
<th>max</th>
<th>mean</th>
<th>median</th>
<th>stdev</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>South Africa</td>
<td>216</td>
<td>0.788</td>
<td>0.802</td>
<td>0.07</td>
<td>0.565</td>
<td>0.897</td>
<td>0.081</td>
<td>0.073</td>
<td>0.038</td>
<td>0.018</td>
<td>0.217</td>
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<td>Zimbabwe</td>
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<td>0.746</td>
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<td>0.428</td>
<td>1.03</td>
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<td>0.161</td>
<td>0.086</td>
<td>0.02</td>
<td>0.462</td>
</tr>
<tr>
<td>Botswana</td>
<td>21</td>
<td>0.71</td>
<td>0.717</td>
<td>0.083</td>
<td>0.5</td>
<td>0.826</td>
<td>0.076</td>
<td>0.077</td>
<td>0.027</td>
<td>0.0</td>
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<td>Nigeria</td>
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<td>0.7</td>
<td>0.772</td>
<td>0.21</td>
<td>0.301</td>
<td>0.957</td>
<td>0.094</td>
<td>0.083</td>
<td>0.051</td>
<td>0.02</td>
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<td>0.108</td>
<td>0.392</td>
<td>0.914</td>
<td>0.076</td>
<td>0.068</td>
<td>0.039</td>
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<td>Tanzania</td>
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<td>0.096</td>
<td>0.391</td>
<td>0.836</td>
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<td>0.181</td>
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<td>0.895</td>
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<td>0.041</td>
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<td>0.328</td>
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</tr>
<tr>
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<td>0.625</td>
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<td>total</td>
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<td>1.0</td>
<td>0.337</td>
<td>0.294</td>
<td>0.235</td>
<td>0.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

This table shows summary statistics for district level estimates of IM. “Total” shows the unweighted summary statistics across all districts.

Figure 5: Ghana: District-level Upward and Downward IM, individuals aged 14-18

(a) upward; brighter colors → higher \( \uparrow \) IM

(b) downward; brighter colors → higher \( \downarrow \) IM

In Uganda, the upward-IM range is even wider \([0.015 \text{ – } 0.69]\). Overall, spatial differences in IM are wider in countries with lower levels of social mobility, a pattern that adds to the literature showing that underdevelopment moves in tandem with regional inequalities (see Williamson (1965) for an early contribution, Kanbur and Venables (2005) for review, Alesina, Michalopoulos, and Papaioannou (2016) for recent evidence, and Figueiredo Walter (2020) for the role of misallocation of schooling resources).
3.3 Trends and Persistence

In Table 3 we examine how average IM evolves for Africans born in the 1960’s, 1970’s, 1980’s and 1990’s. The within-country and within-district estimates show a mild (and statistically insignificant) increase in upward IM in the 1970s and 1980s. Upward IM is about 12 percentage points higher and statistically significantly so for the 1990s-born as compared to those born in the 1960s. Downward IM is falling over time, though at a much weaker and more heterogeneous pace.

Table 3: Evolution of IM across cohorts

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<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>IM up</td>
<td>IM down</td>
<td>IM up</td>
<td>IM down</td>
</tr>
<tr>
<td>1970s cohort</td>
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<td>-0.00812</td>
<td>0.0171</td>
<td>-0.00536</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.030)</td>
<td>(0.028)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>1980s cohort</td>
<td>0.0572</td>
<td>0.00713</td>
<td>0.0567</td>
<td>-0.0271</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.029)</td>
<td>(0.047)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>1990s cohort</td>
<td>0.117∗∗∗</td>
<td>-0.0295</td>
<td>0.124∗∗∗</td>
<td>-0.0752∗</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.028)</td>
<td>(0.041)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>R2</td>
<td>0.908</td>
<td>0.855</td>
<td>0.919</td>
<td>0.710</td>
</tr>
<tr>
<td>within R2</td>
<td>0.221</td>
<td>0.064</td>
<td>0.228</td>
<td>0.038</td>
</tr>
<tr>
<td>N</td>
<td>71</td>
<td>71</td>
<td>7551</td>
<td>7147</td>
</tr>
<tr>
<td>level</td>
<td>country</td>
<td>country</td>
<td>district</td>
<td>district</td>
</tr>
</tbody>
</table>

The table reports OLS regression estimates associating cohort-level upward IM (in columns (1) and (3)) and downward IM (in columns (2) and (4)) across countries (in (1)-(2)) and across regions (in (3)-(4)) with cohort indicators; the 1960s cohort serves as the omitted category. Specification (2) includes country constants (not reported) and specification (4) includes region constants (not reported). Standard errors clustered at the country-level are reported below the estimates in parentheses. ∗p < 0.1, ∗∗p < 0.5, ∗∗∗p < 0.01.

Figure 6 illustrates the correlation of regional upward-IM for the 1990s and the 1970s cohorts (where coverage is considerably higher as compared to the 1960s or the 1950s). There is an almost one to one link with a strong fit; the $R^2$ is .82. The slope decreases to .67 in the country-fixed-effects specification, implying somewhat lower inertia within, as compared to, across countries.

3.4 Literacy of the Old and IM

Motivated by evidence both from the recent research agenda on intergenerational mobility (e.g., [Chetty and Hendren (2018a) and Chetty, Hendren, and Katz (2016)]) showing that upward mobility is higher in regions with better outcomes (wealth, education, income) and research on African growth stressing poverty traps and slow convergence (e.g., Gunning and Collier (1999)), we examine the association between IM and literacy rates of the “old generation”. While these correlations do not have a causal interpretation, they allow us to explore inertia. [In Section 5 we tackle identification].

16 Appendix E.4 portrays the evolution of the regional distribution of upward and downward IM over time across cohorts. The standard deviation of upward IM is roughly constant though the distribution becomes less skewed over time. The standard deviation of downward IM falls slightly over time.

17 There is some relation of these patterns with the ones that Hilger (2017) presents for the US. He finds that the share of children with strictly higher educational attainment than their parents increased in the US for 1930, 1940, 1950s born cohorts, but started falling for the 1970s. The increase was acute for the African-American population, though the decline applied to both whites and blacks.
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. Dots are color-coded by African region following the classification of Nunn and Puga (2012).

### 3.4.1 Cross-Country Patterns

Figure 7, panel (a), plots the relationship between country-level IM across cohorts and the literacy rate of the old generation of the respective cohort. A strong positive association emerges. In Ethiopia, Burkina Faso, Mozambique, North, and South Sudan, where for all cohorts the share of literate “old” is less than 20%, the likelihood that children from illiterate parents will complete primary is below or close to 20%. The analogous statistic for Botswana and South Africa, where the old-cohorts’ literacy rate exceeds 50%, hovers around 70%. A one-percentage-point increase in the literacy of the old is associated with a .89 percentage points increase in upward IM; and variation in the former explains 56% of the cross-country-cohort variation in upward IM. Figure 7 Panel (b) uncovers a similar though attenuated relationship between the literacy of the “old” generation and downward IM. A one percentage point increase in the “old” generation’s literacy maps into a 0.4 decline in downward IM; the old generation’s literacy explains about a fourth of the variation in downward IM. It appears that, compared to upward IM, downward IM is more sensitive to cohort-specific civil conflict episodes (e.g., Sudan, Liberia, Sierra Leone).

### 3.4.2 Regional Patterns

Figures 8 (a) and (b) plot the district-level association between upward and downward IM and mean literacy of the “old” generation, netting country-cohort and census effects. We observe a strong association between the literacy of the “old” and upward IM across African regions. Likewise, there is a negative -but less steep- correlation between downward IM and the literacy of the old. Specific countries or cohorts do not drive these correlations. A 10 percentage points increase in the literacy of the “old” is associated with a roughly 7 percentage points increase in the likelihood that children of illiterate parents will complete primary and a 4.5 percentage points lower chance that kids of literate parents will fall below parental literacy. The estimates retain statistical significance and decline modestly.
when we replace the country constants with admin-1 fixed effects to account for local features. This pattern is similar to [Asher, Novosad, and Rafkin (2020)](https://example.com), who also find that a state’s/region’s mean education is the strongest correlate of upward educational mobility in India. Similarly, [ Güell et al. (2018)](https://example.com) document a significantly positive correlation between IM in well-being and education across Italian regions.

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

(a) upward IM

(b) downward IM

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 unweighted OLS regression fit.

These correlations 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 literacy. 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 main mode of economic activity.
Second, as regions with high levels of literacy tend to have the better infrastructure (as we show in the next Section), path dependence may stem from sunk costs in large-scale investments, such as railroads and roads. Third, persistent spatial disparities in schools may be a contributing factor. Fourth, inertia may be due to internal migration and spatial sorting (an issue that we examine in Section 5). Fifth, the estimates may (partly) reflect human capital externalities (as Wantchekon (2019) and Wantchekon, Klašnja, and Novta (2015) show in Benin).

3.4.3 Heterogeneity

We explored heterogeneity in the old’s literacy-IM association in terms of the child’s gender and the rural-urban household residence. The analysis, reported for brevity in Appendix E.5, reveals two noteworthy patterns. First, the positive (negative) association between upward (downward) IM and the share of literate old applies to both boys and girls; the correlation is somewhat stronger for girls. Second, while inertia is present for both rural and urban households, the old’s literacy - IM correlation is steeper in rural areas. The educational fate of the young generation appears more sensitive to the old’s educational heritage in rural as opposed to urban locations. To the extent that those leaving the villages and small towns, to settle in urban centers, have higher aspirations and latent ability, the ramifications for rural Africa are dire, as the educational decline in rural areas will lower upward and increase downward IM. We return to this issue in Section 5.

3.5 Summary

The mapping of the spatial distribution of educational opportunity across Africa reveals new regularities. First, there are wide differences in IM across countries. Second, and most importantly, the within-country regional disparities in IM are also quite large, especially in low education/income countries. Third, upward mobility is higher and downward IM lower for urban households. Fourth, gender disparities are, on average, small, but in many countries in the Sahel and North Africa, it is harder for girls of uneducated parents to complete primary schooling. Fifth, upward IM is strongly linked to the average parental education in the region. Likewise, downward IM is negatively correlated to the literacy of the old generation, though this association is less strong. Sixth, inertia is more substantial for rural, as compared to urban households. These patterns suggest poverty traps or slow convergence, dynamics, as improvements in educational attainment among illiterate households are larger in regions with relatively higher human capital levels. Persistence may stem either from regions’ independent impact on educational mobility or from spatial sorting. We return to this question in section 5 after characterizing the correlates of spatial variation in mobility.

4 Correlates of IM

In this Section, we explore the correlates of regional IM, aiming to uncover a set of stylized facts that characterize its geography. We run univariate specifications linking IM to geographical, historical, and at-independence variables, frequently discussed in the research on the origins of African development as well in studies on mobility outside Africa. As
the literacy of the old generation correlates strongly with IM, we also report specifications conditioning on it. The correlational analysis, albeit simple, is useful to illustrate whether the geographic and historical factors are associated with contemporary IM only through their correlation with initial conditions (education of the old) that still matter due to inertia, or whether they correlate with the rate at which educational endowments are transmitted intergenerationally above and beyond their association with the initial conditions. Figure 9 summarizes the results.

Appendix F provides variable definitions and sources. The Figures plot the (unweighted) within-country standardized correlation (beta) coefficients between upward and downward IM with the various features. Standard errors are clustered at the country level. The Appendix reports permutations that we discuss below: (i) adding province constants to condition on more localized, time-invariant features. (ii) dropping North African countries, as their historical development differs markedly from those in Sub-Saharan Africa; (iii) excluding regions with cohabitation rates below 80%.

Figure 9: Within-Country Correlates of Regional IM

(a) At-independence upward

(b) At-independence downward

(c) Geography upward

(d) Geography downward

(e) History upward

(f) History downward
4.1 Development At Independence

We begin by examining the association between IM and proxies of economic development in the 1950s-1960s when most African countries turn independent. Figures (a)-(b) plot the correlations. We first explore how IM relates to (the log of) population density in 1950, that we take as a reasonable proxy of local development in Africa. Population density correlates positively and significantly with upward IM and negatively with downward IM. This result may not be surprising, as population density and the literacy of the “old” generation are strongly correlated. Hence, coefficients decline once we account for the latter, though they retain significance. Population density correlates more strongly with upward -as compared to downward- IM (“beta” coefficients of 0.074 and −0.04). A similar pattern obtains when we look at urbanization.

Motivated by the literature on structural transformation in Africa (e.g., McMillan, Rodrik, and Verduzco-Gallo (2014), Diao, Hartgen, and McMillan (2017), Holmanna (2018b)), we explore the correlation between IM with the share of employment in agriculture, manufacturing, and services. Agricultural employment is negatively correlated with upward mobility and positively correlated with downward mobility; these patterns hold when we condition on the literacy of the “old” generation. The specifications using the labor share in services or manufacturing on the RHS yield a “mirror” image.

4.2 History

Figures (c)-(d) plot the correlations between IM and historical variables.

Colonial Road and Railroad Infrastructure Colonial railroads and roads have played an important role in African countries’ post-independence development (e.g., Jedwab, Kerby, and Moradi (2017), Jedwab and Moradi (2016), Huillery (2009)). Log distance to colonial railroads is significantly positively related to upward IM and negatively to downward IM. Proximity to roads is also systematically linked to IM, even conditional on the old’s education, though magnitudes are much smaller. Districts that are one standard deviation closer to colonial railroads have, on average, 0.08 standard deviation higher levels of upward and lower levels of downward mobility. The estimates are virtually unchanged when we explore within-province variation.

Colonial Missions Earlier studies, in Africa and elsewhere, uncover positive effects of Christian missionary activity on education (e.g., Nunn (2014), Wantchekon, Klašnja, and Novta (2015), Okoye and Pongou (2014)). We examine the correlation between IM and proximity to colonial missions using 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, respectively. Proximity to Christian missions correlates significantly with “old’s” literacy rates (results not shown).

---

18 We use data for individuals born before 1960. To abstract from migration (discussed in the next Section), we focus on individuals residing in their birth district (the results are similar if we use all individuals). As we lack migration data for Lesotho, Nigeria, and Zimbabwe, the sample spans 24 countries.

19 These results square well with the concurrent analysis of Asher, Novosad, and Rafkin (2020), who also document higher upward educational mobility rates in urban -manufacturing-service-oriented Indian districts as compared to those specializing in agriculture.
The Figures illustrate a significantly positive (negative) association between proximity to missions with upward (downward) IM. When we condition on the literacy of the “old” the distance coefficient declines in absolute value but retains significance (beta of 0.07). While data on missions are coarse (Jedwab, zu Selhausen, and Moradi (2018)), the analysis suggests that pre-independence schooling investments by Christian missions have lasting consequences, both by shaping initial literacy which in turn increases educational mobility and by directly influencing mobility.

**Precolonial Political Centralization** We then explored the correlation between IM and pre-colonial political centralization that recent works connect to contemporary development (e.g., Gennaioli and Rainer (2007) and Michalopoulos and Papaioannou (2013)). We associate IM with log distance to the centroid of the nearest pre-colonial kingdom/empire using data from Brecke (1999) and to pre-colonial states using Murdock (1959, 1967) (though data are missing for parts of the continent). Distance to pre-colonial states is not a robust correlate of IM.

### 4.3 Geography

Figures 9 (e)-(f) plot the within-country correlations between IM and geographic, location, and ecological features.

**Distance to the Capital** Much evidence documents the limited ability of African states to broadcast power outside the capitals (e.g., Michalopoulos and Papaioannou (2014) and Campanale, Do, and Guimaraes (2019)). During colonization, the limited public goods were confined to the capital and a few urban hubs (Herbst (2000)). The literacy of the “old” is much higher in the capital than the hinterlands; similarly upward IM also declines further from the capital city. Not surprisingly, the standardized coefficient drops, once we condition on the literacy of the “old” generation, from $-0.29$ to $-0.094$, though it remains precisely estimated. The patterns are similar with downward mobility.

**Distance to the Border** African borders appear unruly and conflict prone, as they often partition ethnic groups (e.g., Alesina, Easterly, and Matuszeski (2011) and Michalopoulos and Papaioannou (2016)). Nevertheless, there is no systematic association between IM and distance to the border.

**Distance to the Coast** A cursory look at a satellite image of nighttime light density reveals that economic activity in Africa is concentrated along the coastline. In line with this, literacy falls once one moves inland (results not shown). Proximity to the coast relates to the presence of Europeans and associated investments during colonization, but also to the intensity of slave raids. Upward (downward) educational mobility is significantly higher (lower) in coastal areas. The coefficient retains significance when we condition on the literacy of the old; the “beta” is around $-0.095$ with upward IM and $0.055$ with downward IM.
Malaria  We associate IM with an index reflecting a district’s malaria ecology (from Kiszewski et al. (2004)) that has been invariably linked to Africa’s underdevelopment, (see Gallup and Sachs (2001), Cervellati et al. (2016) and Depetris-Chauvin and Weil (2018)). Upward (downward) IM is significantly lower (higher) in regions with an environment favorable to the transmission of malaria. The negative (positive) association between malaria ecology and upward (downward) IM operates above and beyond initial differences in literacy (that correlate with malaria).

Land Quality for Agriculture  Upward IM is somewhat higher and downward IM is lower in regions with high-quality land, but the correlations do not pass standard statistical significance thresholds.

Ruggedness  We then examined the association between IM and ruggedness. The latter correlates positively with cross-country economic performance in Africa. Nunn and Puga (2012) argue that rugged terrain shielded regions from slave raids that negatively affected development (Nunn (2008)). Moreover, as malaria is pervasive in the lowlands, mountainous terrains protect populations from the adverse effects of the disease. There is a positive and significant association between terrain ruggedness and the literacy of the “old” generation. Upward IM is significantly higher and downward IM is lower in rugged regions. The correlations remain significant when we control for the old generation’s literacy, which is higher in regions with rugged topography. These results add to the cross-country patterns of Nunn and Puga (2012) that in Africa ruggedness correlates positively with contemporary well-being.

Natural Resources  The “natural resource curse” literature links conflict and underdevelopment to oil, diamonds, and precious minerals (e.g., Ross (2004), Berman et al. (2017)). The association between IM and the presence of oil fields or diamond mines is weak and never passes significance thresholds. This most likely reflects opposing mechanisms, as natural resource wealth also spurs human capital accumulation and structural transformation in Africa (Hohmann (2018b)).

4.4 LASSO Estimates

We also employed LASSO (Least Absolute Shrinkage and Selection Operator), a simple machine learning method that is useful in detecting robust predictors in the presence of multi-collinearity and measurement error. The LASSO analysis -reported in Appendix F.3- reveals some interesting patterns that complement the univariate correlations. First, distance to colonial railroads and distance to the capital are the most important features predicting upward and downward IM; this result suggests that colonial transportation investments, though overall small and mostly connecting ports with mineral rich interior areas, had lasting consequences. Second, proximity to natural resource and precolonial

\footnote{We also run specifications using regional proxies of slave trade intensity using data from Nunn (2008) and Nunn and Wantchekon (2011). The data are, however, not well-suited for our analysis. First, the data are at the ethnicity rather than at the region level. Assigning them to contemporary regions overlapping historical homelands using ethnographic maps introduces error. Second, the ethnicity data do not cover the Trans-Saharan and the Red Sea slave trades that are relevant for seven countries (mostly Ethiopia, North, and South Sudan, Mali, and Kenya, but also Nigeria and Senegal).}
states have minimal power predicting IM. Third, terrain ruggedness, distance to the coast, and malaria ecology lie in-between, carrying some modest power predicting regional IM. Fourth, proximity to Protestant missions is a robust predictor of IM, while proximity to Catholic missions drops out of the empirical model once regularization increases.

### 4.5 Summary

Colonial railroads, proximity to the capital, and to (Protestant) missions correlate strongly with mobility. Geographic aspects, terrain ruggedness and malaria ecology are also relevant in characterizing educational mobility. In contrast, natural resources, proximity to borders and precolonial statehood do not seem to play a role. As these variables also correlate with the old generation’s literacy, which is the most influential covariate of mobility, when we condition on it, the coefficients retain statistical significance but drop roughly by two-thirds. Hence, these patterns suggest that geography and history mostly matter by shaping at-independence development (education of the “old” generation), which appears quite persistent across most African countries.

### 5 Regional Childhood Exposure Effects

Does the environment “cause” mobility? To answer this question, we follow the approach of [Chetty and Hendren (2018a)](Chetty_Hendren_2018) and exploit differences in the timing of children’s moves across districts to isolate regional childhood exposure effects from sorting. This approach compares the educational attainment of children whose families moved to a better/worse region -in terms of average mobility- at different ages to identify the rate at which their attainment converges to that of permanent residents. If regions affect individual mobility, this effect should be stronger, the longer the exposure to the new environment.

In this Section, we first describe the semi-parametric specification, discuss the identifying assumptions, and report the results. Second, we present parametric estimates, explore heterogeneity, and summarize the sensitivity checks. Third, we isolate moves due to abnormal displacement shocks in the origin and use past migration destinations to “instrument” for the location of moving families to advance on causation.

#### 5.1 Baseline Semi-Parametric Estimates

##### 5.1.1 Specification

For children who moved from place of birth $o$ to destination region $d$ at age $m$, their attainment can be expressed as follows:

Two caveats apply here. First, due to lack of random assignment, these correlations do not imply causal effects. Second, the correlations may reflect differential measurement error across the various regressors and the education of the old generation.
\[
\text{IM}_{\text{up}, \text{ihbmcod}} = \left[ \psi_h + \right] \alpha_{ob} + \alpha_m + \sum_{m=1}^{18} \beta_m \times I(m_i = m) \times \Delta_{odb} + \\
\sum_{b=bo}^{B} \kappa_b \times I(b_i = b) \times \Delta_{odb} + \epsilon_{ihbmcod},
\]

(5)

The dependent variable equals one if child, \(i\), born in cohort \(b\) in country \(c\) to illiterate household \(h\), completes primary education (or higher) and zero otherwise (upward IM). The variable of interest, \(\Delta_{odb}\), denotes the difference between upward educational mobility of permanent residents in the destination versus origin for children born in birth cohort \(b\):

\[
\Delta_{odb} = \hat{\text{IM}}_{\text{up}b} \hat{\text{nm}} - \hat{\text{IM}}_{\text{up}bo} \hat{\text{nm}}.
\]

Average region-cohort upward IM is computed among non-movers (individuals residing in their place of birth at the time of census). \(\hat{\text{IM}}_{\text{up}b} \hat{\text{nm}}\) is a sufficient statistic summarizing the economic and social environment that shapes educational decisions in origin and destination. We estimate a different slope, \(\beta_m\), for each age of move (years 1 to 18) controlling for any direct effect via age of move constants, \(\alpha_m\); these capture disruption effects and any other age-specific unobserved feature that affects the education trajectory. Origin-region \(\times\) birth-decade fixed effects, \(\alpha_{ob}\), account for unobserved factors of the child’s birthplace at the time of birth. Following Chetty and Hendren (2018a), we add interactions of destination-origin differences in cohort-specific IM with cohort effects, to account for potential differential measurement error across cohorts and other trends (this has no effect). The intuition of the above specification is that if children move from regions with worse to places with better educational opportunities (\(\Delta_{odb} > 0\)), and exposure matters, the earlier the move, the greater the effect of the region. Since the specification includes (3,231) origin-cohort fixed effects, the variation comes from children born in the same place in the same decade, who move to regions with different levels of mobility.\(^{22}\)

The age-specific slopes, \(\beta_m\), are identified even in the presence of sorting; i.e., parents without primary schooling, but with a higher propensity to educate their children, are more likely to move to regions with better opportunities. The identifying assumption is that the timing of the move is uncorrelated with latent children’s ability. In other words, more likely to invest in their children’s education parents are allowed to move from worse to better environments, on average; but the more “ambitious” parents should not move earlier. Since this is a restrictive assumption, we relax it estimating a household fixed-effects variant of equation (5), with \(\psi_h\). In these models, the age-specific slopes, \(\beta_m\), reflect the extent to which educational attainment differences between siblings relate to the regional gap at the age of move, interacted with differences in the mobility of permanent residents between origin and destination, \((m1 - m2)\Delta_{odb}\). The identifying assumption is that households who move to places with higher (lower) upward mobility do not do so to favor (discriminate against) some of their children. We return to this issue below.

\(^{22}\)The only difference vis a vis Chetty and Hendren (2018a) is that we are not interacting the origin-cohort effects \(\alpha_{ob}\) with age-at-move \(m\). Doing so would require adding more than 100,000 fixed-effects, 1,084 (regions) \(\times\) 5 (cohorts) \(\times\) 18 (age at move).
5.1.2 Sample and Descriptive Statistics

In this section, we work with a sample of 16 countries (11,169,357 observations in the age group 14 – 25) where IPUMS records the current and birth region, and years in the current residence. Overall, the average (median) migrant outflow share [number of migrants leaving a region divided by total number of residents] during census years (where we also observe total population) is 0.081 (0.038), while the corresponding mean (median) inflow share is 0.058 (0.038). These statistics are broadly in line with the survey evidence in FAO (2017) and United Nations Conference on Trade and Development (2018). Hohmann (2018a) uses (the same) IPUMS census data to estimate migration gravity equations within African countries. He documents distance elasticities of about 1, quite close to the estimates of migration flows across U.S. states 2005-2016.

Figure 10 plots the histogram of $\Delta nm/odb$. Panel (a) looks across the entire sample of moving children (406,175); panel (b) looks at children of moving families that we consider in the within-household specifications (226,739). The mean and median are positive, .05 and .034, respectively; on average, families move to regions with higher levels of upward mobility, though migration flows both ways. Roughly 58% of children move to regions with higher upward mobility and 42% to regions with lower. The standard deviation is 0.21. These statistics complement the findings of Young (2013) who documents substantial bidirectional urban-rural migration flows across African regions with survey data.

Figure 10: Differences in Intergenerational Mobility (IM) among Permanent Residents between Destination and Origin

(a) All observations
(b) Movers in fixed effects sample

The figures plot the distribution of $\Delta nm/odb$ – the destination minus origin differences in cohort-region average non-migrant IM. Panel (a) plots the distribution for all migrant children, aged 14-25. $\mu = 0.049$, $p_{50} = 0.034$, $\sigma = 0.214$. Panel (b) plots the distribution for migrant children, aged 14-25, residing in a household with at least two children of different ages at the time of the move. $\mu = 0.048$, $p_{50} = 0.034$, $\sigma = 0.214$.

---

23 The countries are Benin, Cameroon, Egypt, Ethiopia, Ghana, Guinea, Kenya, Morocco, Mali, Malawi, Rwanda, Sudan, Togo, Uganda, South Africa, and Zambia. For some countries, birth is at admin-1 level, whereas residence is at admin-2 level. In other countries, region of residence and birth are at the same level. We harmonized residence and birth region at the finest level. We end up with 1,084 “birth/current residence regions”.

24 We explored whether moving and non-moving households differ. The literacy rate of the old generation for households moving to regions with higher mobility (than the origin district) is higher by 0.21 than that of non-moving households. Moving households in destinations with lower than the origin mobility also have an old-generation literacy edge over non-moving households, but it is only 0.07. As our analysis focuses on children of households where the old generation has not completed primary education, we effectively condition on any such differences.
5.1.3 Results

Figure 11 plots the age-specific exposure effects, $\hat{\beta}_m$, against the child’s age at the time of the move. The figure uncovers two regularities: “regional exposure effects” that are particularly strong for children aged 5 – 11 and “selection effects.” First, the slopes are significantly positive for children moving at all ages. This applies even for children who move at the age of 13 – 18 ($\hat{\beta}_m \approx 0.40$). Since the destination is rather unlikely to have a causal effect on primary school completion for children moving after the age of 14, the estimates reflect selection effects. Households moving to regions with higher (lower) IM have unobservable characteristics translating into a higher (lower) propensity that children complete primary school. For example, households may move to regions with better opportunities so that their children, who have completed primary schooling, benefit the most. The degree of selection does not vary with children’s age after the age of 13 – 14. Children who move to regions where permanent residents have one percentage point higher upward IM have a 0.4 higher likelihood to complete primary education purely due to spatial sorting.

Second, the estimates reveal regional exposure effects, since moving to a better (worse) district early in life, roughly before the age of 12, translates into a higher (lower) likelihood of upward educational mobility. The estimates are around 0.65 for children whose family moved before they turn 5 years old; the likelihood to complete primary schooling is 30 percentage points higher if parents move to regions with 0.5 higher levels of IM (mean $IM = .6$, standard deviation = .49). As the pure selection effect is around 0.4, regional exposure effects total around 0.25 for children moving shortly after their birth. The relationship between age at move and exposure effects is negative, but not very steep for children moving before 5 – 6; moving to regions with higher mobility yields almost equally large benefits (likelihood to complete primary schooling) for children who are between 1 and 4 years old. The age at move estimates for children moving between ages 5 – 12
decline approximately linearly, revealing that the differential impact of moves in high mobility regions is especially large for younger kids. Chetty and Hendren (2018a) define the regional exposure effect as \( \gamma_m = \hat{\beta}_{m+1} - \hat{\beta}_m \). Regressing the slopes on the age at move for ages 5 to 11 (that are relevant for primary schooling), we obtain an estimate of about \(-0.03\). That is, for every additional year spent in this age bracket, a child of illiterate parents sees her chances for completing primary increase by roughly 3 percentage points.

5.1.4 Household Fixed-Effects Estimates

We then add to regression equation 5) family-specific constants, \( \psi_h \), to exploit variation among children belonging to the same household, who moved at different ages. Doing so, we relax the assumption that latent family characteristics are orthogonal to the move.

Figure 12: Semi-parametric Childhood Exposure Effects on Primary Education, Observational and Within-family Estimates

Figure 12 panel (b) plots the age-specific exposure effects, \( \hat{\beta}_m \), obtained when comparing siblings that moved at different ages; panel (a) omits them to allow comparability of the cross-sectional and the within-household estimates in the same sample (226,739 children from 90,022 households with more than one child in-between 14 – 25). First, the selection/sorting effect, captured by the slopes after age 12, drops significantly, once we account for family unobserved features, from 0.40 (panel (a)) to 0.078 (panel (b)). The 90% confidence intervals (not shown) include 0 for all age-of-move slopes after 12. Family constants account almost fully for selection/sorting.

Second, the household-fixed-effects specifications also yield significant regional exposure effects. The slopes for children moving during ages 1 – 4 are around 0.35; two siblings moving to a region with higher IM when they are 1 and 4, respectively, have, on average, the same increase in the likelihood of completing primary schooling. If the difference between the destination and the origin (\( \Delta_{nm}^{obs} \)) 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 5 and 12. The estimate of the exposure effects for the critical-for-primary-schooling ages (5 – 11) is \( \gamma_m^{fe} = \hat{\beta}_{m+1}^{fe} - \hat{\beta}_m^{fe} = -0.03 \).

The comparison of the cross-sectional to the within-household specifications reveals
that sorting is considerable; around two-thirds of the total magnitude. Nevertheless, the marginal impact of moving to areas with higher (lower) mobility at the critical for primary schooling ages is the same when we look across all moving children and when we compare children of the same family. The fact that the household constants reduce the magnitude of the age at move coefficients, but do not affect their slope suggests that (while selection effects are present) where families choose to move does not vary with children’s ages when they move (see Chetty and Hendren (2018a)). We also run pairwise tests of coefficient equality (see Greene (2011), section 5.4) for all ages-at-move (see Appendix Figure G.1). The difference between the coefficients of ages $1-4$ and $12-18$ is significantly different from zero across all permutations, further revealing regions’ role in educational mobility.

5.2 Parametric Estimates

5.2.1 Specification

Regression equation [5] is demanding, as it includes thousands of origin-cohort fixed effects; this issue becomes more challenging when we add household constants. Following Chetty and Hendren (2018a) we estimate a parametric variant of specification (5).

\[
\text{IM}_{\text{up}hbm\text{cod}} = [\psi_h + \sum_{b=b_0}^B \mathbb{1}(b_i = b) \times (\alpha_b^1 + \alpha_b^2 \times \text{IM}_{\text{up}ob}^m)] + \sum_{m=1}^{18} \zeta_m \times \mathbb{1}(m_i = m) + \sum_{b=b_0}^B \kappa_b \times \mathbb{1}(b_i = b) \times \Delta_{odb} + \mathbb{1}(m_i < 5) \times (\beta_0 + (18 - m_i) \times \beta_1) \times \Delta_{odb} + \mathbb{1}(5 \leq m_i \leq 11) \times (\gamma_0 + (18 - m_i) \times \gamma_1) \times \Delta_{odb} + \mathbb{1}(m_i \geq 12) \times (\delta_0 + (18 - m_i) \times \delta_1) \times \Delta_{odb} + \epsilon_{ihbm\text{cod}}. \tag{6}
\]

Instead of origin-cohort fixed effects, $\alpha_{ob}$, equation (6) includes birth-cohort constants interacted with a linear-in-origin-IM term. The equation also imposes a piecewise linear structure, allowing the regional exposure effects to differ for pre-school years (ages $1-4$), the ages relevant for primary school ($5-11$), and post-primary education years ($12-18$).

5.2.2 Results

Table 4 reports the results. Column (1) shows that the marginal exposure effect for children whose families moved when the children were more than 12 years old is zero and statistically insignificant. The marginal exposure effect for children moving before 5 is 0.019 and weakly significant. Exposure to areas with higher mobility is especially strong for children whose (illiterate) parents move when they are in the critical for primary school ages, roughly between 5 and 11. Reassuringly, the estimate (0.031) is similar to the semi-parametric estimates (obtained in two steps). Column (2) shows that the coefficients for the three age-of-move brackets are similar in the (smaller) sample of individuals that included in the household-fixed-effects specifications, reported in column (3). The marginal exposure for children whose families moved when they were older than 12 is zero. The slope
for moves before 5 years is 0.006, statistically indistinguishable from zero. The regional exposure slope is significantly positive for children moving between 5 and 11. The slope is 0.0305, tightly estimated.

Table 4: Parametric Estimates of Regional Childhood Exposure Effects

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<td></td>
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<tr>
<td>γ: 5-11</td>
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<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>δ: 12-18</td>
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</tr>
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<td></td>
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<td>(0.006)</td>
<td>(0.004)</td>
</tr>
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</tr>
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<tr>
<td>birth decade FE</td>
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<td>hh FE</td>
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<tr>
<td>age range</td>
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</tr>
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</table>

The dependent variable in all specifications is an indicator variable that takes the value of one for children of parents without completed primary education who have completed at least primary education and zero otherwise (upward 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 indicator variables, birth-decade × destination indicators interacted with destination-minus-origin differences in upward IM (to capture differences in measurement error across locations and cohorts), all of which are not reported, and three linear terms for destination-minus-origin differences in the relevant-birth-cohort-non-mover average IM for moves taking place when the child moves, ages 1-4, 5-11, and 12-18. Double clustered at the origin and at the destination district standard errors are reported in parentheses below the coefficients. ∗ p < 0.1, ∗ ∗ p < 0.5, ∗ ∗ ∗ p < 0.01.

5.2.3 Heterogeneity

We examined heterogeneity across children moving to regions with higher (lower) IM than their place of birth and heterogeneity across gender, augmenting equation (6) with interactions between the linear-in-age-at-move regional exposure effects for the three age-of-move brackets with the respective indicator variables. For brevity we report these results in the Online Appendix Table G.1.

There is not much heterogeneity on regional exposure effects between moves to higher and lower IM regions. The estimates are small and statistically insignificant for moves after 12 or during ages 1 – 4 for both sets of children. Regional exposure effects are around 0.03 for moves to either worse or higher IM regions. The loses in completing primary schooling for children moving to worse than their place of birth regions before the age of 12 are roughly equal to the gains of children moving to regions with higher IM.

Regional exposure effects for boys moving before the age of 5 and after the age of 12 are unstable and insignificant. The interactions of ∆odb with the female indicator that captures the additional effect for girls are positive, hinting at somewhat larger effects, but also statistically indistinguishable from zero. The regional exposure effect for primary school age for boys is around 0.023, somewhat smaller than the baseline of 0.03. The interaction of ∆odb with the female indicator for ages 5 – 11 is 0.01, suggesting that girls benefit (lose) somewhat more when moving to higher (lower) mobility regions.
5.2.4 Sensitivity Analysis

The uncovered regional exposure effects and sorting are robust to various permutations (reported in Appendix Table G.2). These include: (i) dropping multi-generational households; (ii) looking only at children matched to biological parents; (iii) dropping North Africa; (iv) accounting for classical measurement error in differences in regional IM with a 2SLS estimator based on a sample split (like Chetty et al. (2018a), see Appendix Figure G.2).

We also looked solely across rural households, where the old generation works in agriculture to assuage concerns that the uncovered regularities reflect income shocks triggering the move and, at the same disproportionately, affecting younger children. While we cannot control for household income at the timing of the move, as we do not observe it, such income effects are likely to be at best moderate for rural African households often engaged in subsistence farming. Appendix Table G.3 shows that an extra year in regions with higher than the origin IM increases the likelihood that children of rural/agriculture households will complete primary schooling in the 5 – 11 age bracket; the marginal effect of moving after 12 is tiny, as is for moves before 5.

5.3 Endogeneity

While the inclusion of household constants accounts for time-invariant family features that affect investments in education, time-varying factors may jointly drive household moves and children’s educational investments in proportion to exposure to the region with higher mobility. We address this -and related- concerns exploiting “push shocks” and using historical migration to project the destination of moving households.

5.3.1 Displacement (Push) Shocks

As a starting point, we look at moves that are more likely to reflect (push/displacement) shocks exogenous to household decisions. To pinpoint anomalous periods of outflows from the origin, we proceed as follows. First, we construct an origin-district-year migration panel for each country (the panel covers roughly the period from 1965 until the last census year). Second, for each district, we regress outflows on a constant and a linear time trend and obtain residuals. Third, we sort the (standardized) residuals for each district from the highest to the lowest. High (positive) residuals indicate years of abnormally large out-migration from a given district, while low (negative) residuals denote below trend outflows. The latter are more likely to reflect a household’s choice to move, while the former capture irregular district out-migration shocks that are more likely to be exogenous from the household’s viewpoint.

Figures 13 (a)-(c) plot the parametric regional exposure effects for the three age groups (1 – 4; 5 – 11; 12 – 18). Conservatively, we report the within-household specifications (results similar when we use all data and omit the household constants).25 As we move from left to right, we successively drop observations focusing more narrowly on children whose families move in abnormal years. The left-most observation for each panel reports

\[25\] In the within-household estimates, looking at moves in years of unusually large outflows mitigates concerns that the timing-of-move is chosen to favor some of the siblings during a particular time.
the benchmark estimates. The 50th percentile looks at moves that took place in years when flows have been above the historical district-specific median. The estimates of the 90th percentile look at moves that occurred during the two to five years with the highest outflows. This is because for most countries, we have outflow data for roughly 40 years.

**Figure 13:** Outflow (Displacement) Anomalies, Household Fixed-Effects Estimates

The figure shows parametric regression estimates of childhood regional childhood exposure effects concentrating, successively, on district-years that experienced increasingly larger migration outflows. Each point reports the marginal effect of one additional year of exposure in the relevant age-at-move range (with $\Delta x = 1$). Panel (a) shows the marginal effect for ages-at-move between 1−4, panel (b) for 5−11, and panel (c) for 12−18, respectively. The left-most point for each graph shows the baseline estimates, where no observations are dropped. The next observation uses observations from district-years with studentized outflow residuals above the 10th percentile, etc. All regressions include household fixed effects. 90% confidence bands are constructed from double clustered standard errors at the origin and destination district.

The marginal effect for moves after 12 (panel (c)) is zero and statistically insignificant. For moves before 5, an additional year in the high (low) IM region does increase (decrease) the likelihood to complete primary schooling. However, the estimate is small (around 0.01) and does not pass standard significance thresholds. The marginal exposure effect is significantly positive for moves when kids are between 5 and 11. The $\gamma$ estimate retains economic and statistical significance when we look at moves that most likely reflect origin-specific displacement shocks, even when we drop 90% of the sample. These results suggest that the baseline estimates reflect regions’ independent impact on children’s educational attainment rather than unobserved time-varying household factors. Moreover, the estimates hint that the effects of moving are similar for families who decide to move for idiosyncratic reasons and displaced households (Chetty and Hendren (2018a) present similar patterns in the US).

### 5.3.2 Expected Destination of Moving Households

Moving households, however, even when they relocate due to exogenous reasons, decide where to settle. If a household’s endogenous choice of destination also relates to differential investments into some children, then the estimates may be be biased. While the household fixed effects partially account for such concerns, the choice of destination may still be correlated with unobserved child features. To account for this, we use past migration destinations from each origin to predict where moving households will settle with a “shift-share” approach.\(^\text{26}\)

\(^\text{26}\)The idea behind this well-known approach is that migrants tend to settle in regions where earlier migrants from their community have already settled. Altonji and Card (1991), Card (2001, 2009), Derenoncourt (2018)). For any migration year $y$, we compute the destination-$d$ share from origin $o$ as...
Figure 14: Predicted and Actual Migration. Binned Scatterplot: $\Delta_{odb}$ on $\hat{\Delta}_{ob}$

Binned scatterplot of actual destination-minus-origin differences in non-migrant IM ($\Delta_{odb}$) on the vertical axis and the historical-migration-destination-share weighted-average at the origin $\hat{\Delta}_{ob}$ on the horizontal axis.

Figure 14 shows a binned scatterplot of actual and historical-predicted migration. The elasticity is close to one and precisely estimated. We then re-estimated the parametric specification, replacing actual $\Delta_{odb}$ with the historical-predicted difference $\hat{\Delta}_{ob}$. Table 5, columns (1)-(3), report the “reduced-form” estimates, while columns (4)-(6) report 2SLS that combine the “reduced-form” estimates with the “first stage”. Columns (1)-(4) and (2)-(5) report cross-sectional estimates in the full sample of moving children and in the sample where we compare siblings, respectively. Columns (3) and (6) report household fixed-effects estimates that minimize selection from time-invariant family features. As the first-stage slope is approximately one, the reduced form and 2SLS estimates are similar. The marginal impact of an additional year in the region with higher (lower) mobility in the critical for primary schooling age is significantly positive; the estimate is somewhat larger than the OLS ($0.04 - 0.05$), most likely because instrumentation reduced classical measurement error that is not unlikely (see Chetty and Hendren (2018a)). The regional childhood exposure effect is small and statistically indistinguishable from zero for moves after the age of 12 and before 5.

5.3.3 Blending “Push” Shocks with Expected Destination

In a demanding test that blends the two approaches, we replace (or instrument) actual differences in IM between origin and destination ($\Delta_{odb}$), with those predicted from historical migration ($E[\Delta_{odb}|t-10]$) and sequentially keep observations of moves taking place in anomalous origin-district years. Figures 15 (a)-(c) plot the “reduced-form” estimates

$$\sigma_{ody} = \frac{\sum_{d=1}^{D} \text{migrants}_{od} \times \Delta_{odb}}{\sum_{d=1}^{D} \text{migrants}_{od}}$$

where $D$ is the total number of districts in the country, $T_0$ is the first year for which we observe a migrant and $w$ is a time window; we set $w = 10$ to avoid migration flows reflecting the delayed response to past shocks). For individuals who migrate in year $y$ from $o$ to $d$, we compute “predicted” $\Delta_{od}$ as the historic share-weighted analog, $\Delta_{ob} = \sum_{d=1}^{D} \Delta_{odb} \times \sigma_{ody}$. $\Delta_{odb}$ depends on the average IM of non-migrants in the migrating children’s birth decade in origin and destination. $\sigma_{ody}$ depends on the number of people who moved from $o$ to $d$ up to $w$ years prior to year $y$. 

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Table 5: Parametric Estimates of Regional Childhood Exposure Effects: Shift-share Instrument for Origin-Destination Differences, Reduced Form and IV Estimates

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<td>hh FE</td>
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<td>OLS</td>
<td>2SLS</td>
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</tr>
</tbody>
</table>

The dependent variable in all specifications is an indicator that takes the value of one if the child of parents who have not finished primary education has completed at least primary schooling and zero otherwise (upward 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 indicator variables, birth-decade × destination indicators interacted with destination-minus-origin differences in upward IM (to capture differences in measurement error across locations and cohorts), all of which are not reported, and three linear terms for destination-minus-origin differences in the relevant-birth-cohort-non-mover average IM for moves taking place when the child moves, ages 1-4, 5-11, and 12-18. Columns (1)-(3) report “reduced-form” estimates, using differences in upward mobility between origin and destination district projected by past migration. Columns (4)-(6) report 2SLS (two-stage-least-squares) estimates, where actual differences in upward IM between origin and destination district for moving children is “instrumented” with differences in upward IM projected based on historical migration. Standard errors double clustered at the origin and at the destination district level are reported in parentheses below the coefficients. ∗ p < 0.1, ∗ ∗ p < 0.5, ∗ ∗ ∗ p < 0.01.

The marginal exposure effects from the parametric specification for the three age brackets. The regional exposure effect for moving children after the age of 12 is zero and tightly estimated. The estimate for moves before the age of five is also centered around zero, although the standard error bands are wide. The regional exposure estimate for kids moving in-between 5 and 12 is positive, around 0.045. The coefficient retains significance even when we drop 90% of the observations, effectively looking at children whose families moved in the two-five most abnormal years of out-migration from their place of birth. These estimates – that jointly account for the endogeneity of the move from district o, by looking at years of abnormal outflows, and households’ choices of destination d, by using historical (lagged by 10 years) migration – advance the causal interpretation of regional childhood exposure effects.

**Sensitivity Analysis** Appendix, Section G.3 reports additional results and sensitivity checks focusing on the more demanding approach that focuses on moves in years of displacement shocks and projects households’ choices of destination with historical migration. First, the 2SLS estimates are similar to the reduced-form ones, as the first-stage is approximately 1. Second, we obtain similar results when we omit the household constants and focus on the larger sample that covers children from all moving households. Third, we estimate 2SLS and “reduced-form” specifications, defining “large outflows” at the country-rather than at the region-level. The regional exposure effects for moving children after the age of 12 is zero and quite tightly estimated. The estimates for moves before the age of 12-18 are positive, around 0.045. The coefficient retains significance even when we drop 90% of the observations, effectively looking at children whose families moved in the two-five most abnormal years of out-migration from their place of birth.
This figure shows parametric regression estimates of regional exposure effects looking, successively, on district-years that experienced increasing larger migration outflows and using predicted by historical migration differences between origin and destination, $\Delta_{ob}$. Each point gives the marginal effect of an additional year of exposure with $\Delta_{ob}=1$. Panel (a) shows the coefficients for ages-at-move 1-4, panel (b) for 5-11, and panel (c) those for 12-18, respectively. The left-most point for each graph shows the baseline estimates, where no observations are dropped. The next point uses observations from district-years with studentized outflow residuals ranked above the 10th percentile, etc. All regressions include household fixed effects. 90% confidence bands are constructed from double clustered standard errors at the origin and destination district.

five are positive but small and statistically insignificant. The regional exposure estimate for kids moving in-between 5 and 12 is positive, around 0.045.

5.4 Summing up

The analysis in this Section reveals two results: First, sorting is considerable: children of households who move to regions with higher (lower) mobility have an increased (lower) likelihood to complete primary schooling, even when they move after the age of $12-13$. Nevertheless, sorting does not relate to the age of the move. Second, regions matter. Children who move earlier in life to regions where residents have higher intergenerational mobility are more likely to complete primary schooling. This pattern also applies when we compare siblings. The marginal effect of an extra year of exposure to the high mobility region is roughly equal for the critical-for-primary-education years, around 3–4 percent; for moves before five, the marginal effect of an additional year is positive (around 1 percent), hinting at some gains additional to schooling. Regional childhood exposure effects are considerable, even when we look at moves triggered by displacement shocks at the origin and when we account for the potentially endogenous destination using past migration.

Compared to the US evidence on region’s impact on intergenerational income mobility of Chetty and Hendren (2018a), our analysis shows that sorting-selection is considerably higher in Africa. However, the regional exposure effects do not differ much. We also explored differences across relatively rich and poor countries. The selection effect and the regional exposure effects are of similar magnitude in both groups (Appendix Figure G.3).

6 Conclusion

We conduct a systematic exploration of intergenerational mobility in education across African countries and districts since independence.

In the first part, we compile new estimates of absolute intergenerational mobility in
educational attainment across African countries and regions, distinguishing by gender and rural-urban residence. Opportunities for upward mobility vary substantially across the continent and regions in the same country. The literacy of the “old” generation is a strong predictor of both upward and downward mobility, pointing to inertia and slow convergence. Persistence is more substantial for rural than urban places. Second, we explored the geographic and historical correlates of regional mobility. Upward mobility is higher and downward IM is lower in regions with colonial investments in railroads and those close to Christian, mainly Protestant missions. Distance to the coast and the capital and an ecology favorable to malaria correlate negatively with upward IM and positively with downward IM. Upward mobility is higher in regions that were more developed at independence, with higher urbanization and employment in services-manufacturing. In the third part, we distinguish between spatial sorting and regions’ independent influence on educational mobility. We find that both sorting and regional childhood exposure effects are at play. Boys and girls whose families move to regions with higher (lower) upward mobility have a significantly higher (smaller) likelihood to complete primary schooling when the move takes place before the age of 12 (and after 5). This pattern also applies when we compare siblings, look at moves triggered by regional displacement shocks, and use historical migration patterns to predict moving households’ destination regions. Thus, regions matter crucially for education in Africa, both because households with a latent propensity to invest in their children’s future move to high mobility (high literacy) places and because the environment exerts an independent impact on educational mobility. Regional disparities are wide and unlikely to disappear unless policies specifically target them.

Our analysis here -as well as in our companion paper Alesina et al. (2019) where we study ethnic and religious differences in educational mobility- opens several avenues for future research. A first avenue is to examine the causal effects of historical factors on educational mobility. Such work could combine the newly compiled IM statistics with quasi-experimental variation, to explore the economic mechanisms underlying path dependence, including colonial-era investments. A second avenue is to examine the role of nationwide educational policies (like laws on compulsory primary education) and school construction programs for social mobility, topics largely unexplored in the context of Africa. A third avenue is to construct measures of each region’s impact on IM following the approach of Chetty and Hendren (2018b) and explore regional heterogeneity. Fourth, future work should investigate how the diverse set of family structures across Africa mediate the transmission of education from one generation to the next. It is also important examining differences in the transmission of human capital from mothers, fathers, and other relatives, distinguishing between boys and girls. Fifth, as data on income start to become available, future work could study interconnections between education and income mobility. Finally, one could link the regional statistics to political variables (e.g., electoral competition and participation) and leaders’ characteristics, to study jointly regional, ethnic, and religious favoritism and discrimination.
References


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FAO. 2017. “Evidence on Internal and International Migration Patterns in Selected African Countries.”


