Econometrica, Vol. 89, No. 1 (January, 2021), 1–35

INTERGENERATIONAL MOBILITY IN AFRICA

ALBERTO ALESINA
Harvard University, IGIER, CEPR, and NBER

SEBASTIAN HOHMANN

STELIOS MICHALOPOULOS
Department of Economics, Brown University, CEPR, and NBER

ELIAS PAPAIOANNOU
Department of Economics, London Business School and CEPR

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 2800 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 regional differences in mobility reflect spatial sorting or their independent role. 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.

Alberto Alesina: https://scholar.harvard.edu/alesina/home
Sebastian Hohmann: sebas.hohmann@gmail.com
Stelios Michalopoulos: smichalo@brown.edu
Elias Papaioannou: eliasp@london.edu

This paper is dedicated to the memory of Alberto Alesina, who passed away after resubmitting the final draft of the paper. We are grateful to three anonymous referees for extremely useful comments. Also, we thank our discussants in various conferences Oriana Bandiera, Sara Lowes, Markus Poschke, and Nathaniel Hendren as well as to Francesco Caselli, Raj Chetty, and Antonio Ciccone for detailed comments. We are thankful for useful discussions and feedback to James Fenske, Larry Katz, Nathan Nunn, David Weil, Elisa Cavatorta, Shaun Hargreaves, Jim Robinson, Sam Asher, Paul Novosad, Charlie Rafkin, and Yining Geng. We also got useful feedback from conference and seminar participants at the University of Zurich, UPF, Monash University, Warwick, Brown, Harvard, King's College, Tufts, Copenhagen, Sheffield, Williams, Stockholm, the NBER Summer Institute, the PSE Conference on Culture, Institutions, and Economic Prosperity, the Workshop on Intergenerational Mobility, Gender and Family Formation in the Long Run, Statistics Norway, the Firms, Markets and Development Workshop in Siracusa, and . We also thank Remi Jedwab, Adam Storeygard, Julia Cagé, Valeria Rueda, and Nathan Nunn for sharing their data. Papaioannou gratefully acknowledges financial support from the European Research Council (Consolidator Grant ORDINARY), LBS Wheeler Institute for Business and Development, and RAMD. All errors and omissions are our responsibility.

1. INTRODUCTION

THERE IS rising optimism about Africa, a continent with 1.2 billion opportunities, as the The Economist (2016) touted not long ago. The formerly "hopeless continent" is gradually becoming the "hopeful" one (The 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.

We take the first step toward mapping, exploring, and explaining intergenerational mobility across the continent. We look at educational attainment using census data covering more than 16 million individuals across 27 African countries and 2846 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? 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 districts 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 new country and regional-level measures of educational opportunity. As recent works on intergenerational mobility in income (e.g., Chetty, Grusky, Hell, Hendren, Manduca, and Narang (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 absolute downward mobility, defined as the likelihood 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 reside with parents or older relatives.

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, though there is a nonnegligible gender gap in the Sahel and North Africa. Spatial disparities in mobility exhibit inertia: 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 generation, but the association is weaker.

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, with 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 forces. On the one hand, regions may exert a causal impact on mobility, for example, providing higher-quality infrastructure, more and better schools. 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.*" Both forces are at play. Selection is present; families' sorting into better (worse) locations correlates strongly with child attainment. 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 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 destination choice. The regional childhood exposure estimates remain significant.

Overall, the analysis 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).[1] Card, Domnisoru, and Taylor (2018) used the US population census of 1940 to map absolute educational mobility looking at children residing with at least one parent. They document rising mobility during the first-half of

[1]Early studies on intergenerational mobility in education include Bowles (1972), Blake (1985), and Spady (1967). Hertz, Jayasundera, Piraino, Selcuk, Smith, and Verashchagina (2008) estimated country-level IM coefficients across 42 countries. Hilger (2017) studied trends in educational IM in the United States over the 20th century, while Chetty et al. (2017) and Davis and Mazumder (2020) studied the dynamics of absolute IM in income in the US.

the 20th century, which differs across race and states.[2] Chetty, Hendren, Kline, and Saez (2014) provided a mapping of IM in income across US counties and explore its correlates. Chetty and Hendren (2018a, 2018b) used 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. 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 main contribution to this research is to compile new statistics and characterize the educational mobility for many African countries and regions, distinguishing also between gender and rural-urban residence. Moreover, 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 the origins of African development that provides compelling evidence of historical continuity as well as instances of rupture in the evolution of the economy and polity (see Michalopoulos and Papaioannou (2020) for a review). An open question is whether the correlation between deeply rooted factors and current outcomes reflects the one-time effect of the former on initial conditions or if historical shocks have altered the transmission of opportunity across generations. By building data on IM across African regions and exploring its correlates, we begin answering such questions. Moreover, by isolating the role of regions on mobility from sorting, we start unbundling the mechanisms linking geography-history to contemporary development.

Structure. 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, Chancel, Piketty, Saez, and Zucman (2017) reported 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 is 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 early in the life cycle. Fourth,

[2]A strand of the US-focused literature looks at racial differences in mobility (e.g., Chetty, Hendren, Jones, and Porter (2020), Davis and Mazumder (2018), Derenoncourt (2018)). These studies relate to our companion work Alesina, Hohmann, Michalopoulos, and Papaioannou (2020b, 2020a), where we explore ethnic and religious differences in educational mobility across Africa.

parental investment in children's education is at the heart of theoretical work in intergenerational linkages (e.g., Becker and Tomes (1979), Loury (1981)). Fifth, a voluminous research in labor economics shows that education causally affects lifetime income (e.g., Card (1999)). Individual returns to schooling are sizable in low-income (African) countries.[3] Sixth, in the Appendix (Section C.2) in the Online Supplemental Material (Alesina, Hohmann, Michalopoulos, and Papaioannou (2021)), using geo-referenced Demographic and Health Surveys (DHS) and 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, attitudes toward domestic violence, political and civic engagement.

2.2. *Sample*

2.2.1. *Countries and Regions*

We use individual records, retrieved from 69[4] 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%.[5] As of 2015, the sample countries were home to about 850 million people, representing around 75% of Africa's population and GDP. IPUMS also reports residence, allowing us to assign individuals to "coarse" and "fine" administrative units. Our sample spans 367 provinces (admin-1) and 2846 districts (admin-2 or 3 units) of a mean (median) size of 5206 (1578) sqm.[6]

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.[7] Figure A.1 in the Appendix portrays the evolution of the pan-African distribution of educational attainment across cohorts. Education rises, mostly reflecting increasing completion of primary schooling. The share of Africans with tertiary education is minuscule

[3]Most 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), Caselli, Ponticelli, and Rossi (2014)). Young (2012) estimated Mincerian returns of about 11.3% (OLS) to 13.9% (2SLS) across 14 Sub-Saharan African countries using DHS data, higher than in 11 non-SSA low income countries [range of 8.7% (OLS)–10.4% (2SLS)]. Montenegro and Patrinos (2014) estimated Mincerian returns of about 12.4% in Africa, compared to 9.7% for the rest of the world. Four of the top five countries are in Africa. Psacharopoulos and Patrinos (2004) document a mean 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.

[4]We start from 74 censuses. We discard Burkina Faso (1985), Kenya (1979), and Liberia (1974), as they lack identifiers to match children to older relatives. We also remove Togo (1960 and 1970), as they do not cover all regions.

[5]In Nigeria, data come from household surveys conducted in consecutive years between 2006 and 2010. As the number of observations is small, we aggregate the survey waves and count them as one census year.

[6]For Botswana, Lesotho, and Nigeria, IPUMS reports one level of administrative units. 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]We validated the IPUMS data across country-cohorts with the Barro and Lee (2013) statistics and at the regional level using DHS; correlations exceed 0.9 (Appendix Section C)

even for the 1980s-born, while secondary education has increased modestly.[8] 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. Table B.I in the Appendix gives details on sample construction.

For a first look at the data, we construct 4×4 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, 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%.

2.3. *Methodology*

We construct measures of *absolute* IM that reflect the likelihood that children complete a strictly higher or lower education level than 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 (results are similar if we take the minimum or maximum).[9] As the relevant dimension for Africa during this period regards the completion of primary schooling, we focus on this aspect.[10]

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

- lit_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.

[8]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 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.

[9]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)).

[10]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)); others work with rank-rank correlation coefficients and intergenerational rank movements (e.g., Asher, Novosad, and Rafkin (2020), Geng (2018), Chetty et al. (2014)). While rank-based measures isolate the relative movement of children in the distribution compared to the older generation from the overall increase, they may be sensitive to measurement error (see Mogstad, Romano, Shaikh, and Wilhelm (2020)). Other studies (e.g., Card, Domnisoru, and Taylor (2018), Davis and Mazumder (2020) and Chetty et al. (2017)) focused, as we do, on absolute transition likelihoods. Gottschalk and Spolaore (2002) provided a theoretical exploration of different mobility measures. The absolute IM measures correlate strongly with the IM coefficient across both countries and regions. The correlation of the absolute IM statistics with the intergenerational correlation is small though.

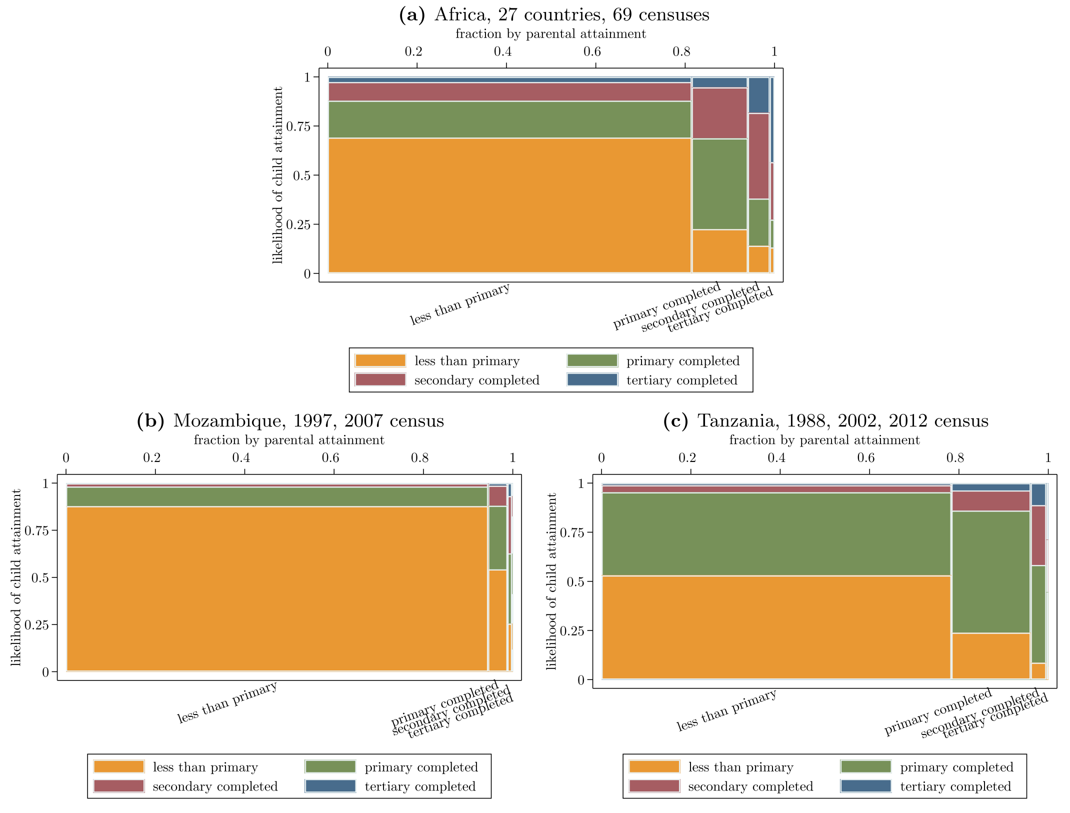

FIGURE 1.—Educational attainment transition matrices. The figure shows the transition matrices for four educational attainment categories for Africa, Mozambique, and Tanzania. The sample consists of individuals aged 25 and older, coresiding with at least one individual of an older generation.

- IM_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.
- IM_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:

$$\text{lit\_par}_{ibct} = \alpha_c^o + \left[\gamma_b^o + \delta_b^y + \theta_t\right] + \epsilon_{ict}, \tag{1}$$

$$\text{IM\_up/down}_{ibct} = \alpha_c^y + \left[\gamma_b^o + \delta_b^y + \theta_t\right] + \epsilon_{ict}, \tag{2}$$

For parental literacy (equation (1)), we compute means among all individuals for whom we observe their parents' (older generation relatives) attainment, netting birth-decade fixed effects for the "young"(δ_b^y) and the "old"(γ_b^o) and census-year fixed effects (θ_t). For upward IM, we estimate equation (2) for children whose parents have not completed primary education; thus the country fixed effects ($\hat{\alpha}_c^y$) reflect the conditional likelihood that children of illiterate parents become literate, netting cohort and census effects. For downward IM, we estimate (2) for children whose parents have completed at least primary; so $\hat{\alpha}_c^y$ 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).

$$\text{lit\_par}_{ibcrt} = \alpha_r^o + \left[\gamma_b^o + \delta_b^o + \theta_t\right] + \epsilon_{ibcrt}, \tag{3}$$

$$\text{IM\_up/down}_{ibcrt} = \alpha_r^y + \left[\gamma_b^o + \delta_b^o + \theta_t\right] + \epsilon_{ibcrt}. \tag{4}$$

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 cohabitate 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 mostly completed and cohabitation rates are still high (see also Hilger (2017)).

We use census information on the "relationship to household head" to recover the "old" generation and take the average of their educational attainment. Section D in the Appendix provides details, discussing also how we deal with heterogeneity in family structure (e.g., nuclear families, presence of young wives). The Appendix 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.[11] 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 the results.]

For individuals aged between 14 and 18 years, the coresidence rate across all censuses with an older generation relative is 84% (see Appendix Table D.II). 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) reported coresidence rates for African Americans and whites in the US 1940 census of about 78% and 89%, respectively.

We also work with individuals aged 14–25, as this increases the sample considerably, including also high school and college graduates, while cohabitation is still reasonably high (around 70%). The Appendix (Section D) gives details and also reports the distribution of district-level cohabitation rates; the mean (median) is 82% (82.5%). Cohabitation rates have slightly risen, though this most likely reflects improvements in census details.

[11]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*." Some censuses distinguish between biological, adopted, and step-children (e.g., Nigeria, South Africa, Zambia), but most do not.

TABLE I

COUNTRY-LEVEL ESTIMATES OF INTERGENERATIONAL MOBILITY (IM)[a]

Mobility/N Age Range	Census Years	(1) Upward 14–18	(2) Upward 14–25	(3) Downward 14–18	(4) Downward 14–25	(5) N With e_0 obs 14–18	(6) N With e_0 obs 14–25
South Africa	1996, 2001, 2007, 2011	0.791	0.814	0.068	0.049	1047,243	1944,362
Botswana	1981, 1991, 2001, 2011	0.704	0.716	0.069	0.058	44,516	76,211
Zimbabwe	2012	0.664	0.738	0.146	0.108	49,855	79,290
Egypt	1986, 1996, 2006	0.637	0.628	0.071	0.066	2128,269	4056,814
Nigeria	2006, 2007, 2008, 2009, 2010	0.63	0.65	0.084	0.074	38,885	63,868
Tanzania	1988, 2002, 2012	0.595	0.636	0.177	0.151	860,096	1,358,638
Ghana	1984, 2000, 2010	0.566	0.556	0.159	0.142	489,957	845,090
Togo	2010	0.51	0.526	0.19	0.179	46,958	83,442
Cameroon	1976, 1987, 2005	0.509	0.506	0.117	0.115	270,300	443,222
Zambia	1990, 2000, 2010	0.486	0.507	0.2	0.182	307,043	484,973
Kenya	1969, 1989, 1999, 2009	0.454	0.523	0.219	0.169	624,501	1,016,810
Lesotho	1996, 2006	0.437	0.496	0.289	0.231	38,310	71,965
Morocco	1982, 1994, 2004	0.414	0.393	0.107	0.122	397,451	785,159
Benin	1979, 1992, 2002, 2013	0.376	0.354	0.232	0.231	192,949	326,478
Uganda	1991, 2002	0.358	0.393	0.311	0.277	345,215	518,395
Rwanda	1991, 2002, 2012	0.292	0.35	0.472	0.383	237,006	388,219
Senegal	1988, 2002	0.255	0.256	0.243	0.234	158,517	283,080
Sierra Leone	2004	0.248	0.245	0.368	0.35	42,905	72,534
Liberia	2008	0.221	0.297	0.538	0.418	31,437	55,981
Mali	1987, 1998, 2009	0.205	0.197	0.262	0.27	267,300	433,470
Guinea	1983, 1996	0.193	0.179	0.402	0.403	84,865	144,991
Burkina Faso	1996, 2006	0.184	0.189	0.267	0.253	201,788	294,456
Malawi	1987, 1998, 2008	0.155	0.225	0.48	0.384	246,463	383,502
Ethiopia	1984, 1994, 2007	0.129	0.152	0.302	0.273	851,496	1,300,687
Sudan	2008	0.119	0.174	0.394	0.274	466,630	799,231
Mozambique	1997, 2007	0.111	0.158	0.512	0.419	267,367	419,569
South Sudan	2008	0.041	0.07	0.767	0.646	48,071	83,835
mean/total		0.381	0.405	0.276	0.239	9,785,393	16,814, 272

[a]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 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 fail to complete primary education. Columns (5) and (6) give the number of observations (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.

3. INTERGENERATIONAL MOBILITY ACROSS COUNTRIES AND REGIONS

3.1. *IM Across African Countries*

3.1.1. *Baseline Measures*

Table I 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 40% 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.

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% in more stable ones like Botswana, South Africa, Egypt, and Nigeria. The uncovered cross-country heterogeneity in absolute IM across Africa is considerably larger than the cross-Indian state and cross-Chinese province variability in relative IM documented by Asher, Novosad, and Rafkin (2020) and Geng (2018), respectively.[12]

Given heterogeneity in family structures across the continent, we estimated different IM statistics for children coresiding 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 coresiding 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. Table E.2 in the Appendix reports the statistics across countries. 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 (Appendix Figure E.2(b)). In Figure 2, we explore the evolution of rural–urban gaps. 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. 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. Table E.II in the Appendix 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. Figure 3 shows the evolution of male–female

[12]Geng (2018) documented a province range in IM rank-rank coefficients of 0.25 to 0.5 in the 2000 Chinese Census. The range across (340) prefactures is between −0.033 to 0.661. Asher, Novosad, and Rafkin (2020) estimated a range of relative educational mobility of 0.17 to 0.72 across 124 Indian districts and 0.26 to 0.60 across 25 states. Yet, as our statistics reflect absolute rather than relative changes of children's position in the educational distribution, the estimates' ranges are not directly comparable. The variability of educational mobility across the US is lower than the pan-African one illustrated here. Fletcher and Han (2018) reported IM schooling coefficients ranging from 0.3 till 0.6 across US states (median 0.45) using survey data in 1982, 1992, and 2004. Hilger (2017) reported a coefficient of variation of around 0.3 for educational mobility across US states.

FIGURE 2.—Upward IM urban-rural gap. The figure plots the difference in upward IM between individuals aged 14–18 residing in urban and rural locations by country and birth decade. The 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 code book does not provide precise information. Rural–urban status is not reported for Morocco.

differences in upward-IM. There is a gender gap for the 1960s cohorts (especially when we exclude Botswana) that disappears for the 1980s and the 1990s cohorts. To be sure, there are countries where boys fare much 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.2(a)).

3.2. *Mapping the African Land of Opportunity*

3.2.1. *Cross-Sectional Patterns*

Figure 4 illustrates social mobility across the continent, mapping Africa's land of opportunity. Panel (a) shows the distribution of absolute upward IM across (mostly admin-2) districts and Panel (b) plots absolute downward IM.

Table II reports summary statistics by country. The district-level (unweighted) average and median for upward (downward) IM across the 2846 regions are 0.40 (0.34) and 0.375 (0.294), respectively, close to the cross-country values.[13] As an example of the large within country variation, 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

[13] As in some countries, like Nigeria, districts are large, the map misses within-region spatial variation in IM that is likely nonnegligible.

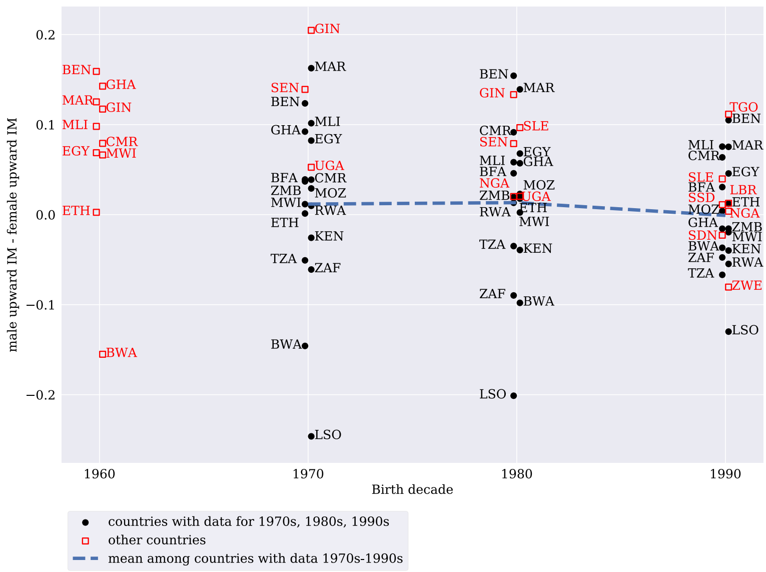

FIGURE 3.—Upward IM male-female gap. The figure plots the difference (gap) in upward IM between male and female young individuals aged 14–18 by country and birth decade.

downward mobility is 0.20, but it varies from 0.08 to 0.50. This north–south gradient mirrors both the country's religious geography as well as colonial-era missionary activity and transportation investments; topics we return to below.

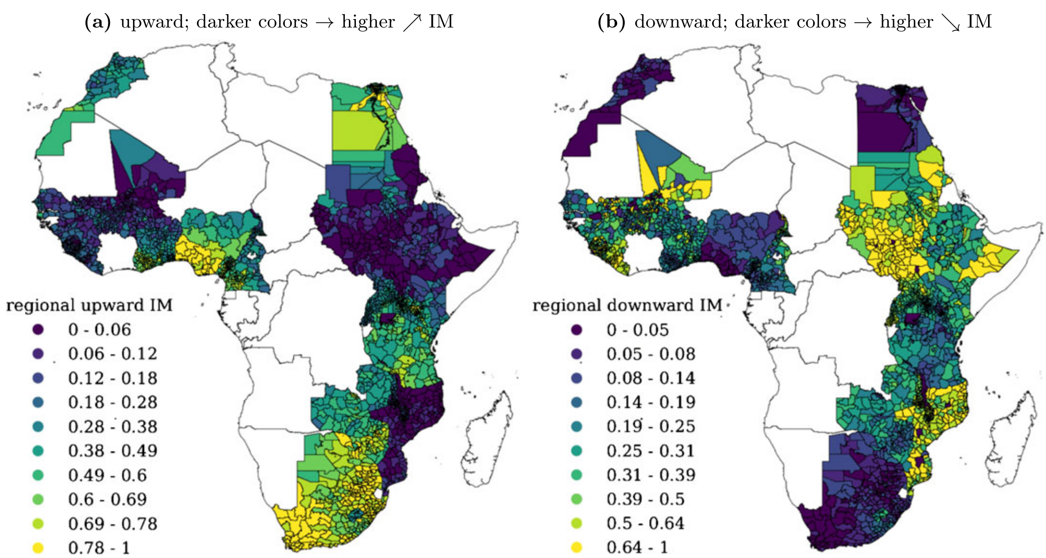

FIGURE 4.—District-level upward and downward IM.

TABLE II

SUMMARY STATISTICS: DISTRICT-LEVEL ESTIMATES OF IM[a]

		Upward					Downward				
Country	Districts	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max
South Africa	216	0.788	0.802	0.07	0.565	0.897	0.081	0.073	0.038	0.018	0.217
Zimbabwe	88	0.734	0.746	0.136	0.428	1.0	0.161	0.161	0.086	0.02	0.462
Botswana	23	0.71	0.717	0.083	0.5	0.826	0.076	0.077	0.027	0.0	0.133
Nigeria	37	0.7	0.772	0.21	0.301	0.957	0.094	0.083	0.051	0.02	0.189
Egypt	236	0.673	0.683	0.108	0.392	0.914	0.076	0.068	0.039	0.013	0.242
Tanzania	113	0.615	0.619	0.096	0.391	0.836	0.182	0.181	0.068	0.056	0.369
Ghana	110	0.577	0.637	0.157	0.176	0.803	0.214	0.198	0.077	0.101	0.557
Cameroon	230	0.539	0.58	0.208	0.083	0.895	0.228	0.182	0.144	0.035	0.812
Kenya	173	0.504	0.523	0.189	0.054	0.872	0.261	0.269	0.108	0.041	0.586
Togo	37	0.493	0.506	0.13	0.235	0.687	0.252	0.242	0.093	0.092	0.543
Zambia	72	0.48	0.472	0.123	0.282	0.771	0.275	0.28	0.096	0.084	0.483
Morocco	59	0.429	0.422	0.14	0.158	0.702	0.144	0.13	0.066	0.062	0.375
Lesotho	10	0.421	0.423	0.057	0.318	0.497	0.328	0.337	0.06	0.235	0.419
Uganda	161	0.373	0.374	0.124	0.019	0.659	0.382	0.38	0.118	0.152	0.933
Benin	77	0.36	0.369	0.126	0.105	0.597	0.274	0.264	0.079	0.123	0.594
Rwanda	30	0.302	0.283	0.061	0.228	0.468	0.501	0.53	0.095	0.255	0.623
Senegal	34	0.253	0.183	0.151	0.078	0.592	0.316	0.282	0.132	0.149	0.793
Sierra Leone	107	0.219	0.17	0.143	0.032	0.667	0.563	0.581	0.189	0.142	1.0
Ethiopia	94	0.207	0.123	0.223	0.008	0.81	0.427	0.412	0.195	0.0	1.0
Malawi	227	0.195	0.16	0.111	0.049	0.562	0.533	0.551	0.122	0.179	0.8
Liberia	47	0.187	0.194	0.079	0.032	0.348	0.613	0.594	0.115	0.397	1.0
Guinea	34	0.156	0.151	0.072	0.06	0.432	0.441	0.44	0.098	0.25	0.68
Sudan	129	0.155	0.104	0.142	0.001	0.556	0.549	0.545	0.177	0.27	1.0
Burkina Faso	45	0.144	0.138	0.077	0.03	0.501	0.328	0.328	0.1	0.0	0.609
Mali	241	0.142	0.126	0.093	0.014	0.538	0.455	0.406	0.223	0.0	1.0
Mozambique	144	0.094	0.066	0.084	0.017	0.67	0.641	0.625	0.158	0.141	1.0
South Sudan	72	0.043	0.021	0.055	0.0	0.31	0.849	0.864	0.138	0.5	1.0
total	2846	0.403	0.375	0.267	0.0	1.0	0.337	0.294	0.235	0.0	1.0

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

IM varies greatly across regions in many countries.[14] In Burkina Faso, for example, the average upward-IM of 0.132 masks a regional range from 0.03 to 0.50. In Uganda, the upward-IM range is wider [0.015–0.69]. Spatial differences in IM are wider in countries with lower levels of mobility, a pattern that adds to the literature showing that underdevelopment moves in tandem with regional inequalities (see Kanbur and Venables (2005) for review).

[14]For some districts, mobility is either zero or one. These extremes reflect the small number of observations. The mean (median) district estimate is based on 1936 (891) children (st.dev = 3287). The patterns are similar if we restrict to regions with many observations.

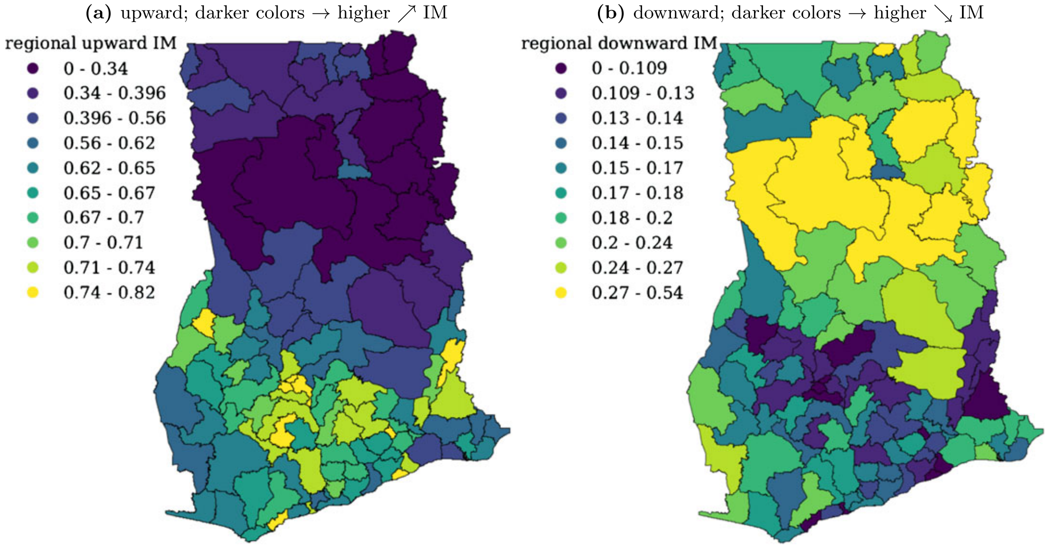

FIGURE 5.—Ghana: District-level upward and downward IM.

3.3. *Trends*

In Table III, we examine how average IM evolves for Africans born in the 1960s, 1970s, 1980s and 1990s.[15] The within-country and within-district estimates show a mild increase in upward IM in the 1970s and 1980s. Upward IM is about 12 percentage points higher for the 1990s-born as compared to those born in the 1960s. Downward IM is falling over time, though at a weaker and more heterogeneous pace.[16]

Figure 6 illustrates the correlation of regional upward-IM for the 1990s and the 1970s cohorts. There is an almost one to one link with a strong fit. The slope decreases to .67 in the country fixed-effects specification.

3.4. *Literacy of the Old and IM*

Motivated by evidence from the recent research agenda on intergenerational mobility (e.g., Chetty, Friedman, Hendren, Jones, and Porter (2020)) 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, Willem, 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.

[15]Appendix E.3 portrays the distribution of regional IM 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.

[16]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 for the 1930s, 1940s, and 1950s born cohorts, but started falling after. The increase was acute for African Americans, though the decline applied to both whites and blacks.

TABLE III

EVOLUTION OF IM ACROSS COHORTS[a]

	(1) IM Up	(2) IM Down	(3) IM Up	(4) IM Down
1970s cohort	0.0549	−0.00812	0.0171	−0.00536
	(0.034)	(0.030)	(0.028)	(0.049)
1980s cohort	0.0572	0.00713	0.0567	−0.0271
	(0.040)	(0.029)	(0.047)	(0.049)
1990s cohort	0.117	−0.0295	0.124	−0.0752
	(0.042)	(0.028)	(0.041)	(0.043)
R2	0.908	0.855	0.919	0.710
within R2	0.221	0.064	0.228	0.038
N	71	71	7551	7147
level	country	country	district	district

[a]The table reports OLS estimates associating cohort-level upward IM (in columns (1) and (3)) and downward IM (in (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 in parentheses.

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 school 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

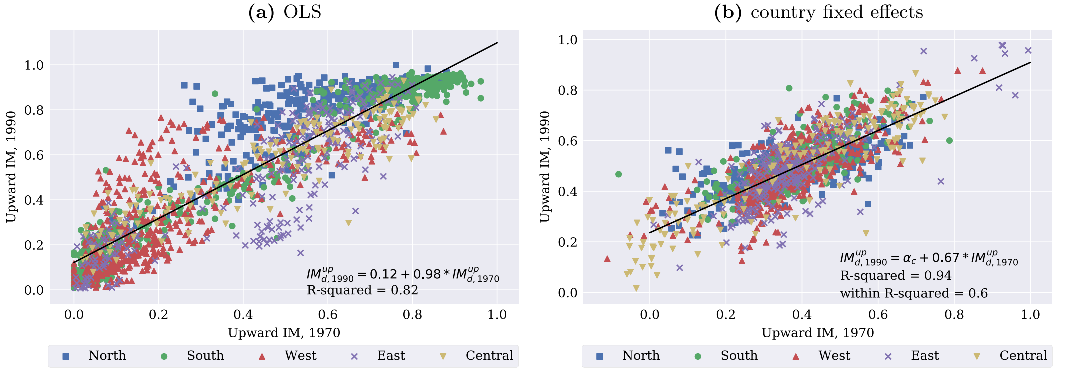

FIGURE 6.—District-level upward IM over time. The figures visualize the link between district-level upward IM for the 1990s to the 1970s cohorts. Panel (a) shows the simple linear regression fit; panel (b) shows the regression with country fixed effects fit. Dots are color-coded by African region following the classification of Nunn and Puga (2012).

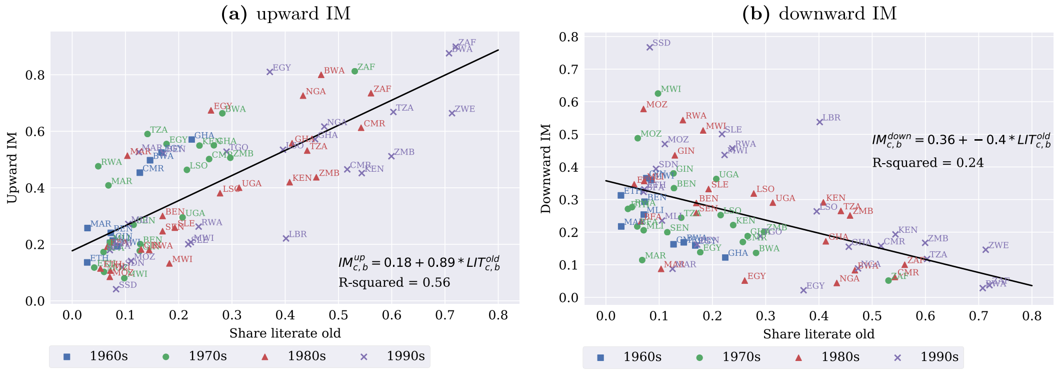

FIGURE 7.—Literacy of the old generation and intergenerational mobility across countries. The figures plot upward-IM and downward-IM across country-birth-cohorts against the share of the "old" generation that has completed primary education. The figures also report the unweighted OLS regression fit.

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. Compared to upward IM, downward IM appears more sensitive to cohort-specific civil conflict (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. 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 relatively local features. This pattern is similar to Asher, Novosad, and Rafkin (2020) that a state's/region's mean education is the strongest correlate of upward educational mobility in India. Similarly, Güell, Pellizzari, Pica, and Rodríguez Mora (2018) documented a significantly positive correlation between IM in well-being and education across Italian regions.

Hence, disadvantaged (from noneducated) families children are more likely to complete primary school in regions with relatively higher literacy. Path dependence can reflect various mechanisms. First, poverty trap dynamics that are especially salient in subsistence agriculture rural Africa. Second, sunk costs in large-scale investments and infrastructure. Third, persistent spatial disparities in schools may be a contributing factor. Fourth, inertia may result from internal migration and spatial sorting. Fifth, the estimates may partly reflect human capital externalities (as Wantchekon (2019) shows 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.4, reveals two noteworthy patterns. First, the association between IM and the share of literate old applies to both genders though it is somewhat stronger for girls.

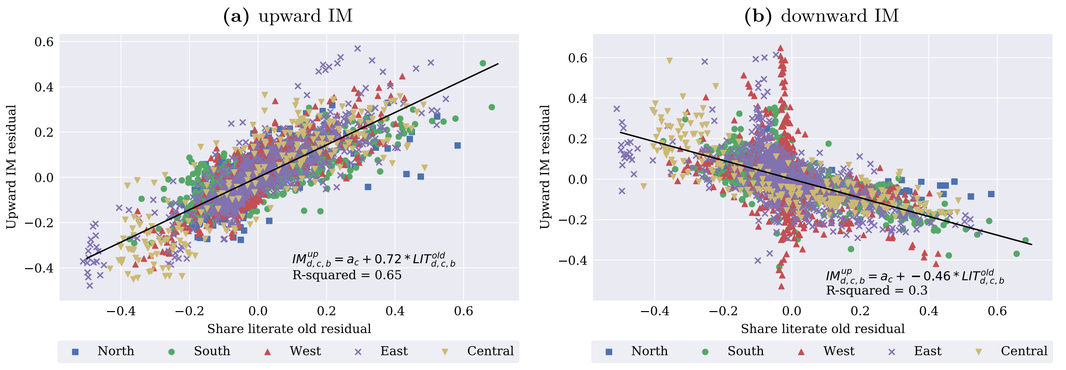

FIGURE 8.—Literacy of the old generation and IM at the district level. The figures plot district-level upward IM (left panel) and downward IM (right panel)against the share of the "old" generation with completed primary education ($\hat{\alpha}^o_{cr}$) net of census and cohort effects. The figures also show the unweighted linear regression line fit, net of country fixed effects; $\hat{\alpha}^y_{cr} = \alpha_c + \beta \times \hat{\alpha}^o_{cr} + \epsilon_{cr}$. Dots are color-coded by African region.

Second, while inertia is present for both rural and urban households, the educational fate of the young generation appears more sensitive to the old's heritage in rural places.

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, within-country regional disparities in IM are 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 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 slow convergence, [17] 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.

4. CORRELATES OF INTERGENERATIONAL MOBILITY

In this section, we explore the correlates of regional IM, aiming to characterize its geography. We run univariate specifications linking IM to geographical, historical, and at-independence variables, discussed in the research on the origins of African development and studies on mobility outside Africa. [Appendix F provides variable definitions and sources.] 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)

[17]In Alesina et al. (2020b), we show that terms typically estimated in education-growth-convergence regressions have a natural connection to absolute upward and downward IM. Our approach therefore connects to studies on educational convergence.

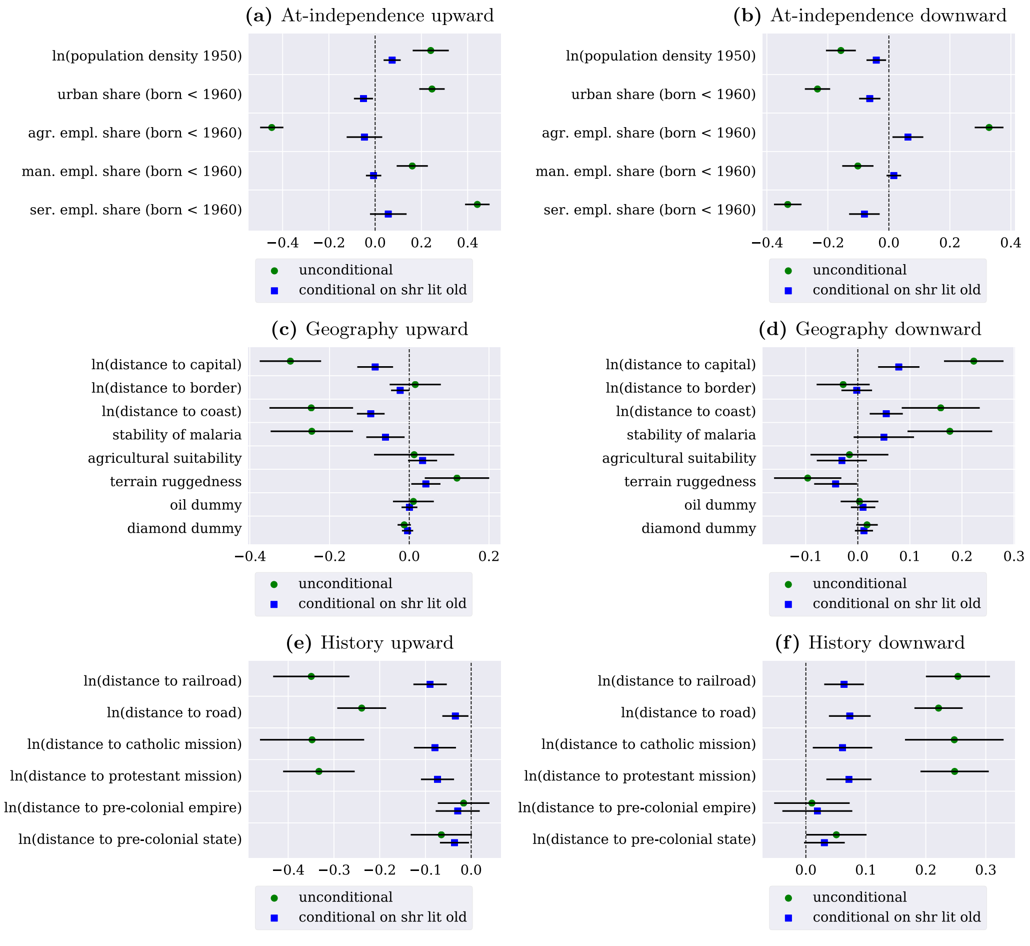

FIGURE 9.—Within-country correlates of regional IM.

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. Figures 9 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: (*i*) adding province constants to condition on more localized, time-invariant features. (*ii*) dropping North African countries, as their historical development differs from Sub-Saharan Africa; (*iii*) excluding regions with cohabitation below 80%.

4.1. *Development at Independence*

We commence examining the association between IM and proxies of economic development in the 1950s–1960s when most African countries turn independent. Figures 9(a)–(b) plot the correlations. We first explore how IM relates to (the log of) population density in 1950, that we take as a proxy for local development. 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. 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)), we explore the correlation between IM and the employment shares across broad economic sectors.[18] 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." The specifications using the labor share in services or manufacturing on the RHS yield a "mirror" image.[19]

4.2. *History*

Figures 9(c)–(d) plot the correlations between IM and historical variables.

Colonial Roads and Railroads. Colonial railroads and roads have played an important role in African countries' post-independence development (e.g., Jedwab and Moradi (2016)). Log distance to colonial railroads is significantly related to both upward and downward IM, even conditional on the old's literacy. 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 uncover positive effects of Christian missionary activity on education (e.g., Wantchekon, Klašnja, and Novta (2015)). We examine the correlation between IM and proximity to colonial missions using data from Nunn (2010) and Cagé and Rueda (2016). There are 1321 (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). 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 0.07). While data on missions are coarse (Jedwab, Meier zu Selhausen, and Moradi (2018)), the analysis suggests that 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 precolonial political centralization that correlates with regional contemporary development (Michalopoulos and Papaioannou (2013)). We associate IM with log distance to the centroid of the nearest precolonial kingdom/empire using data from Brecke (1999) and to precolonial states using Murdock (1967) (though data are missing for parts of the continent). Distance to precolonial states is not a robust correlate of IM.

[18]We use data for individuals born before 1960. To abstract from migration, 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 with the concurrent analysis of Asher, Novosad, and Rafkin (2020), who document higher relative upward educational mobility rates in urban-manufacturing, service-oriented Indian districts as compared to those specializing in agriculture.

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)). During colonization, the limited public goods were confined to the capital and a few urban hubs. The literacy of the "old" is much higher in the capital than the hinterlands; similarly upward IM also declines further from the capital city. The standardized coefficient drops, once we condition on the literacy of the "old," 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). Nevertheless, there is no systematic association between IM and distance to the border.

Distance to the Coast. Economic activity in Africa is concentrated along the coastline. Thus, 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.

Malaria. We associate IM with an index reflecting a district's malaria ecology that has been linked to Africa's underdevelopment (e.g., Gallup and Sachs (2001)). Malaria correlates strongly with IM; the association 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 that correlates positively with cross-country economic performance in Africa, as rugged terrain shielded regions from slave raids (Nunn (2008)).[20] Moreover, as malaria is pervasive in the lowlands, populations in mountainous terrains are less affected. 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 Nunn and Puga (2012) that across African countries ruggedness correlates positively with output.

Natural Resources. The "natural resource curse" literature links conflict and underdevelopment to oil, diamonds, and precious minerals (e.g., Berman, Couttenier, Rohner, and Thoenig (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 mechanisns, as natural resource wealth also spurs human capital accumulation and structural transformation in Africa (Hohmann (2018b)).

[20]We also run specifications using regional proxies of slave trade intensity using data from Nunn (2008)). The data are, however, not well suited for our analysis. First, the data are at the ethnicity rather than 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 Ethiopia, North, and South Sudan, Mali, Kenya, Nigeria, and Senegal.

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.2—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 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 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 drop roughly by two-thirds. These patterns suggest that geography and history mostly matter by shaping at-independence development (education of the "old"), which appears quite persistent across most African countries.[21]

5. REGIONAL CHILDHOOD EXPOSURE EFFECTS

Does the environment "cause" mobility? To answer this question, we follow the approach of Chetty and Hendren (2018a) 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.

We first describe the semiparametric 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 displacement shocks in the origin and use past migration destinations to "instrument" for the location of moving families to advance on causation.

[21]Two caveats apply here. First, 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.

5.1. *Baseline Semiparametric 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:

$$\text{IM\_up}_{ihbmcod} = [\psi_h +]\alpha_{ob} + \alpha_m + \sum_{m=1}^{18} \beta_m \times \mathbb{I}(m_i = m) \times \Delta_{odb} + \sum_{b=b_0}^{B} \kappa_b \times \mathbb{I}(b_i = b) \times \Delta_{odb} + \epsilon_{ihbmcod}, \tag{5}$$

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, Δ_{odb}, denotes the difference between upward educational mobility of permanent residents in the destination minus origin for children born in cohort b:

$$\Delta_{odb} = \widehat{\text{IM}}\_\text{up}^{\text{nm}}_{bd} - \widehat{\text{IM}}\_\text{up}^{\text{nm}}_{bo}.$$

Average region-cohort upward IM, computed among nonmovers (individuals residing in their place of birth at the time of census), is a sufficient statistic summarizing the economic and social environment that shapes educational decisions. We estimate a different slope, β_m, for each age of move (years 1 to 18) controlling for any direct effect via age of move constants, α_m; these capture disruption effects and any other age-specific unobserved feature that affects the education trajectory. Origin-region $\times$ birth-decade fixed effects, α_{ob}, account for unobserved factors of the child's birthplace at the time of birth. We add interactions of destination-origin differences in cohort-specific IM with cohort effects, to partly 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 (3231) origin-cohort fixed effects, variation comes from children born in the same place in the same decade, who move to regions with different mobility.[22] Modeling exposure effects in proportion to years spent in destination follows Chetty and Hendren (2018a), who derive a similar parsimonious relationship from a generic setting of exposure effects.

The age-specific slopes, β_m, are identified even in the presence of sorting; that is, 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, parents more likely to invest in their children's education can 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 ψ_h. In these models, the age-specific slopes, β_m, reflect the

[22] The only difference, namely Chetty and Hendren (2018a) is that we are not interacting the origin-cohort effects α_{ob} with age-at-move m. Doing so would require adding more than 100, 000 fixed-effects, 1084 (regions) $\times$ 5 (cohorts) $\times$ 18 (age at move).

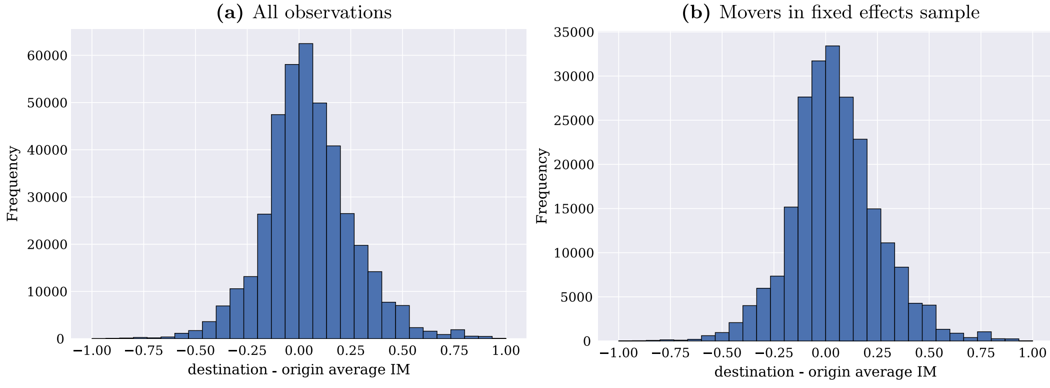

FIGURE 10.—Differences in intergenerational mobility between destination and origin. The figures plot the distribution of Δ^{nm}_{odb}—the destination minus origin differences in cohort-region average non-migrant IM. Panel (a) plots the distribution for all migrant children, aged 14–25. $\mu = 0.049$, $p_{50} = 0.034$, $\sigma = 0.214$. 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. $\mu = 0.048$, $p_{50} = 0.034$, $\sigma = 0.214$.

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 some of their children. We return to this issue below.

5.1.2. *Sample and Descriptive Statistics*

In this section, we work with a sample of 16 countries (11, 169, 357 matched-to-parents children, aged 14–25, whose household moved before 18) where IPUMS records the current and birth region, and years in the current residence.[23] Overall, the average (median) migrant outflow share [number of migrants leaving a region divided by total residents] during census years (where we 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) used IPUMS 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 US states 2005–2016.[24]

Figure 10 plots the histogram of Δ^{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

[23]The countries (number of observations) [number of regions] are Benin (28,076) [76], Cameroon (38,415) [230], Egypt (81,525) [27], Ethiopia (16,340) [87], Ghana (20,259) [10], Guinea (8718) [34], Kenya (21,177) [177], Morocco (27461) [58], Mali (22,256) [47], Malawi (10,986) [30], Rwanda (11,687) [103], Sudan (24,276) [25], Togo (7616) [36], Uganda (28,764) [56], South Africa (13,483) [9], and Zambia (45,136) [72]. 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 and end up with 1084 "*birth/current residence regions.*"

[24]The literacy rate of the old generation for households moving to regions with higher mobility exceeds that of the nonmoving households by 21 percentage points. Moving households in destinations with lower than the origin IM also have an old-generation literacy edge over nonmoving households of 0.07. As our analysis focuses on children of households where the old generation has not completed primary education, we effectively condition on such differences.

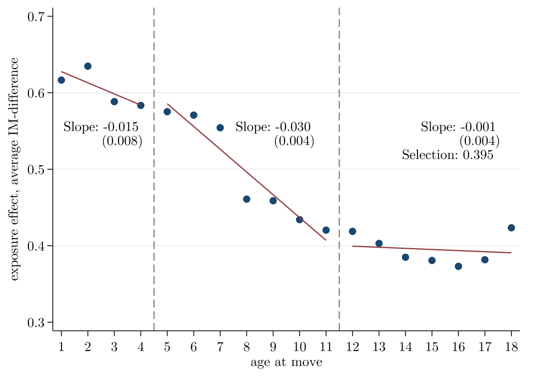

FIGURE 11.—Semiparametric childhood exposure effects on primary education, Observational estimates.

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% move to regions with higher upward IM. These statistics complement Young (2013) who documents substantial bidirectional urban–rural migration flows across African regions with survey data.

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*. Households moving to regions with higher (lower) IM have unobservable characteristics translating into a higher (lower) propensity that children complete primary school. 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 $IM = 0.6$, standard deviation $= 0.49$). 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) defined 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, we obtain an estimate of about -0.03. That is, for every additional

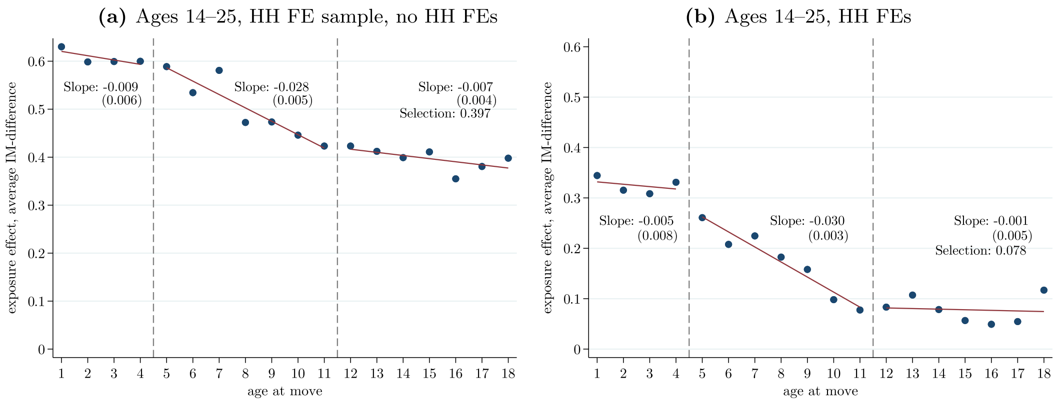

FIGURE 12.—Semiparametric childhood exposure effects on primary education, observational and within–family estimates.

year spent in this age bracket, a child of illiterate parents sees her chances for completing primary increase by roughly 3 percentage points. If instead we run a regression pooling across ages 1–11, we obtain a slope of -0.022 (0.002).

5.1.4. *Household Fixed-Effects Estimates*

We then add to regression equation (5) family-specific constants, ψ_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, 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 unobserved family 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 (Δ^{nm}_{odb}) 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, $\hat{\beta}^{fe}_m$, fall for children moving when they are between ages 5 and 12. The estimate of the exposure effects for ages 5–11 is $\gamma^{fe}_m = \hat{\beta}^{fe}_{m+1} - \hat{\beta}^{fe}_m = -0.03$.

The comparison of the cross-sectional to the within-household specifications reveals that sorting is considerable; around two-thirds of the total magnitude. The marginal impact of moving to areas with higher (lower) mobility 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 where families choose to move does not vary with children's age.[25]

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):

$$\begin{aligned}
\text{IM_up}_{ihbmcod} = [\psi_h +] \sum_{b=b_0}^{B} \mathbb{I}(b_i = b) \times \big(\alpha_b^1 + \alpha_b^2 \times \widehat{\text{IM}}\text{_up}_{ob}^{\text{nm}}\big) \\
+ \sum_{m=1}^{18} \zeta_m \times \mathbb{I}(m_i = m) + \sum_{b=b_0}^{B} \kappa_b \times \mathbb{I}(b_i = b) \times \Delta_{odb} \\
+ \mathbb{I}(m_i < 5) \times \big(\beta_0 + (18 - m_i) \times \beta_1\big) \times \Delta_{odb} \\
+ \mathbb{I}(5 \le m_i \le 11) \times \big(\gamma_0 + (18 - m_i) \times \gamma_1\big) \times \Delta_{odb} \\
+ \mathbb{I}(m_i \ge 12) \times \big(\delta_0 + (18 - m_i) \times \delta_1\big) \times \Delta_{odb} + \epsilon_{ihbmcod}. \qquad (6)
\end{aligned}$$

Instead of origin-cohort fixed effects, α_{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 preschool years (ages 1–4), the ages relevant for primary school (5–11), and post-primary education years (12–18).

5.2.2. *Results*

Table IV 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 ages critical for primary school, 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 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 slope is 0.0305, tightly estimated for children moving between 5 and 11.

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

[25]We 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 most permutations.

TABLE IV

PARAMETRIC ESTIMATES OF REGIONAL CHILDHOOD EXPOSURE EFFECTS[a]

	(1) IM	(2) IM	(3) IM
β: 1–4	0.0189	0.0128	0.00643
	(0.011)	(0.017)	(0.016)
γ: 5–11	0.0309	0.0292	0.0305
	(0.005)	(0.005)	(0.006)
δ: 12–18	−0.000462	0.00159	0.00198
	(0.006)	(0.006)	(0.004)
R-squared	0.142	0.119	0.679
N	406175	226739	226739
age at mig FE	yes	yes	yes
birth decade FE	yes	yes	yes
hh FE	no	no, hhfe sample	yes
age range	14–25	14–25	14–25

[a]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 nonmovers) term, age-at-move indicator variables, birth-decade × destination indicators interacted with destination-minus-origin differences in upward IM, all of which are not reported, and three linear terms for destination-minus-origin differences in the relevant-birth-cohort-nonmover 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.

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 Supplemental Material in the Appendix, Table G.I.

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 educational losses for children moving to worse regions before the age of 12 are roughly equal to the gains of children moving to regions with higher IM.

Regional exposure effects for both boys and girls moving before the age of 5 and after the age of 12 are unstable. 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 Δ_{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 (Appendix Table G.II). These include: (*i*) dropping multigenerational households; (*ii*) looking only at children matched to biological parents; (*iii*) dropping North Africa.

Measurement Error. We considered the possibility of measurement error in Δ_{odb}^{nm} that is not unlikely. First, we miss multiple moves, as censuses just report birth and current region. We also lack information on temporary migration. Second, as districts are large and there is likely within-district variation, IM captures imperfectly the relevant environments at birth and current residence. Third, as Chetty et al. (2020) argue, the "noise to signal ratio is likely amplified since it is identified purely from residual variation in Δ_{odb}^{nm}, controlling for origin quality" (with the origin-cohort constants). To account for classical measurement error in differences in regional IM, we employed a 2SLS estimator based on a sample split (see Appendix Figure G.2). The estimates increase by about 10%. In line with error-in-variables, we obtain somewhat larger estimates when we drop regions with few observations.

Household Income Shocks. 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. Table G.III in the Appendix 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 predict 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 first construct an origin-district-year migration panel for each country that 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 from highest to 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 are similar when we use all data and omit the household constants). 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. 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 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 2 to 5 years with the highest outflows. This is because for most countries, we have outflow data for roughly 40 years.

The marginal effects for moves before the age of 5 (panel (a)) and after 12 (panel (c)) are small and statistically insignificant. The marginal exposure effect is significantly positive for moves when kids are between 5 and 11. γ retains economic and statistical significance when we look at moves that most likely reflect origin-specific shocks, even when

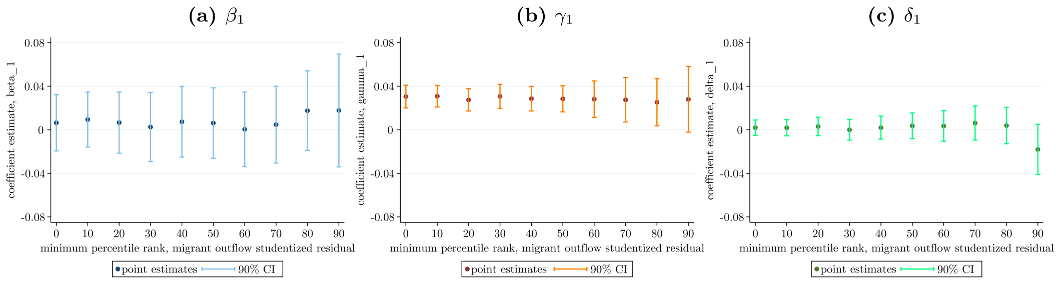

FIGURE 13.—Outflow (displacement) anomalies, household fixed-effects estimates. The figure shows parametric regression estimates of childhood regional childhood exposure effects concentrating, successively, on district-years that experienced increasingly larger migration outflows. Each point reports the marginal effect of an additional year of exposure in the relevant age-at-move range (with $\Delta_{odb} = 1$). Panel (a) shows the marginal effect for ages-at-move between 1–4, panel (b) for 5–11, and panel (c) for 12–18. 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.

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 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 biased. While the household fixed effects partially account for such concerns, the choice of destination may still be correlated with unobserved child features. We use past migration destinations from each origin to predict where moving households will settle with a "shift-share" design. The idea behind this approach is that migrants tend to settle in regions where earlier migrants from their community have moved to (e.g., Derenoncourt (2018)).[26]

Figure 14 shows a binned scatterplot of actual and historical-predicted migration. The elasticity is one and precisely estimated. We then estimated the parametric specification, replacing actual Δ_{odb} with the historical-predicted difference $\hat{\Delta}_{ob}$. Table V, 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

[26]For any migration year y, we compute the destination-d share from origin o as $\sigma_{ody} = \frac{\sum_{x=T_0}^{y-w} \text{migrants}_{odx}}{\sum_{d=1}^{D} \sum_{x=T_0}^{y-w} \text{migrants}_{odx}}$ 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" $\hat{\Delta}_{od}$ as the historic share-weighted analog, $\hat{\Delta}_{ob} = \sum_{d=1}^{D} \Delta_{odb} \times \sigma_{ody}$. Δ_{odb} depends on the average IM of nonmigrants in the migrating children's birth decade in origin and destination. σ_{ody} depends on the number of people who moved from o to d up to w years prior to year y.

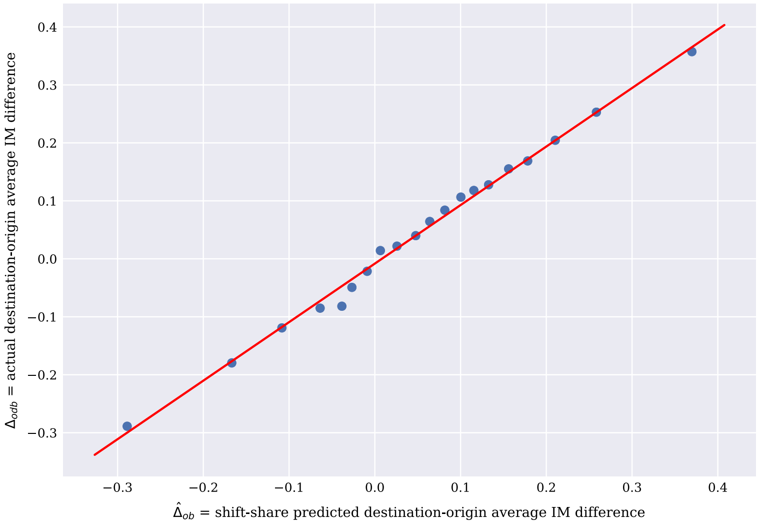

FIGURE 14.—Predicted and actual migration. Binned scatterplot: Δ_{odb} on $\hat{\Delta}_{ob}$. Binned scatterplot of actual destination-minus-origin differences in nonmigrant IM (Δ_{odb}) on the vertical axis and the historical-migration-destination-share weighted-average at the origin $\hat{\Delta}_{ob}$ on the horizontal axis. A regression yields: $\Delta_{odb} = -0.01$ $(s.e. = 0.01) + 1.01$ $(s.e. = 0.046)\hat{\Delta}_{ob}$, R^2: 0.53.

TABLE V

PARAMETRIC ESTIMATES OF REGIONAL CHILDHOOD EXPOSURE EFFECTS: SHIFT-SHARE INSTRUMENT FOR ORIGIN-DESTINATION DIFFERENCES, REDUCED FORM AND IV ESTIMATES[a]

	(1) IM	(2) IM	(3) IM	(4) IM	(5) IM	(6) IM
beta: 1–4	0.0189	−0.00393	−0.00478	0.0185	−0.00362	−0.00579
	(0.013)	(0.019)	(0.020)	(0.013)	(0.018)	(0.020)
gamma: 5–11	0.0413	0.0470	0.0534	0.0407	0.0466	0.0547
	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)	(0.011)
delta: 12–18	0.0145	0.0113	0.00515	0.0132	0.0112	0.00447
	(0.008)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)
R-squared	0.124	0.103	0.679	0.132	0.110	0.007
N	391372	219210	219210	391372	219210	219210
age at mig FE	yes	yes	yes	yes	yes	yes
birth decade FE	yes	yes	yes	yes	yes	yes
hh FE	*no*	no, hhfe sample	yes	no	no, hhfe sample	yes
age range	14–25	14–25	14–25	14–25	14–25	14–25
estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS

[a]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 nonmovers) term, age-at-move indicator variables, birth-decade × destination indicators interacted with destination-minus-origin differences in upward IM, all of which are not reported, and three linear terms for destination-minus-origin differences in the relevant-birth-cohort-nonmover 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.

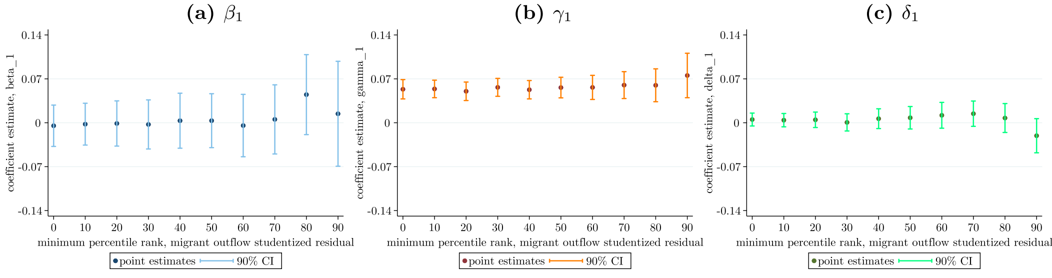

FIGURE 15.—Regional exposure effects from displacement shocks. Household fixed-effects reduced-form estimates. This figure shows parametric regression estimates of regional exposure effects looking, successively, on district-years that experienced increasing larger migration outflows and using predicted by historical migration differences between origin and destination, $\hat{\Delta}_{ob}$. Each point gives the marginal effect of an additional year of exposure with $\hat{\Delta}_{ob} = 1$. Panel (a) shows the coefficients for ages-at-move 1–4, panel (b) for 5–11, and panel (c) those for 12–18. 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.

where we compare siblings, respectively. Columns (3) and (6) report household fixed-effects estimates. 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, most likely because instrumentation reduces classical measurement error (see Section 5.2.4). The corresponding to column (4) OLS estimate (in the sample of 391,371 obs)) with actual, rather than projected, $\hat{\Delta}_{ob}$ is 0.035, about 15% lower than the IV.[27] The 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 (Δ_{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 for the marginal exposure effects from the parametric specification (6) 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 5 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 2–5 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.

[27]In these specifications, Guinea and Egypt (1986) drop, because the residence tenure variable has a maximum of 10 years and we cannot therefore construct the historical migrant share.

Sensitivity Analysis. Section G.3 in the Appendix 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 define "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. The estimates for moves before the age of 5 are positive, but statistically insignificant. The regional exposure estimate for kids moving in-between 5 and 12 hovers around 0.045.

5.4. *Summary*

This section reveals two results: First, sorting is considerable. 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. Regional childhood exposure effects are present, 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 relative (rather than absolute) intergenerational income (rather than education) mobility of Chetty and Hendren (2018a), sorting in Africa appears higher. However, regional exposure effects are similar. We also explored differences across relatively rich and poor African countries, finding similar in both groups selection and regional exposure effects (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 papers Alesina et al. (2020a, 2020b) 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 (like Walter (2020)) 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 to examine 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. Sixth, using finer resolution data on income, consumption, and education one could examine their interrelations and isolate the relative change in children's position in the distribution from the general increase that most African countries have experienced (using, e.g., the bounds approach of Asher, Novosad, and Rafkin (2020)). 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

ALESINA, A., W. EASTERLY, AND J. MATUSZESKI (2011): "Artificial States," *Journal of the European Economic Association*, 9 (2), 246–277. [20]

ALESINA, A., S. HOHMANN, S. MICHALOPOULOS, AND E. PAPAIOANNOU (2020a): "Ethnicity and Social Mobility in Africa," Report. [4,33]

——— (2020b): "Religion and Social Mobility in Africa," Report. [4,17,33]

——— (2021): "Supplement to 'Intergenerational Mobility in Africa'," *Econometrica Supplemental Material*, 89, https://doi.org/10.3982/ECTA17018. [5]

ALVAREDO, F., L. CHANCEL, T. PIKETTY, E. SAEZ, AND G. ZUCMAN (2017): "Global Inequality Dynamics: New Findings From WID.World," *American Economic Review*, 107 (5), 404–409. [4]

ASHER, S., P. NOVOSAD, AND C. RAFKIN (2020): *Intergenerational Mobility in India: Estimates From New Methods and Administrative Data*. [4,6,10,16,19,33]

BARRO, R. J., AND J. W. LEE (2013): "A New Data Set of Educational Attainment in the World, 1950–2010," *Journal of Development Economics*, 104 (C), 184–198. [5]

BECKER, G. S., AND N. TOMES (1979): "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, 87 (6), 1153–1189. [5]

BERMAN, N., M. COUTTENIER, D. ROHNER, AND M. THOENIG (2017): "This Mine Is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, 107 (6), 1564–1610. [20]

BLACK, S. E., AND P. J. DEVEREUX (2011): "Recent Developments in Intergenerational Mobility," in *Handbook of Labor Economics*, Vol. 4B. Elsevier, 1487–1541. [3,6]

BLAKE, J. (1985): "Number of Siblings and Educational Mobility," *American Sociological Review*, 50 (1), 84–94. [3]

BOWLES, S. (1972): "Schooling and Inequality From Generation to Generation," *Journal of Political Economy*, 80 (3), S219–S251. [3]

BRECKE, P. (1999): "Violent Conflicts 1400 AD to the Present in Different Regions of the World," in *1999 Meeting of the Peace Science Society*, Unpublished Manusrcipt. [19]

CAGÉ, J., AND V. RUEDA (2016): "The Long-Term Effects of the Printing Press in Sub-Saharan Africa," *American Economic Journal: Applied Economics*, 8 (3), 69–99. [19]

CARD, D. (1999): "The Causal Effect of Education on Earnings," in *Handbook of Labor Economics*, Vol. 3, Part A. Elsevier, 1801–1863. [5]

CARD, D., C. DOMNISORU, AND L. TAYLOR (2018): "The Intergenerational Transmission of Human Capital: Evidencefrom the Golden Age of Upward Mobility," 102. [2,3,6,8]

CASELLI, F., J. PONTICELLI, AND F. ROSSI (2014): "A New Dataset on Mincerian Returns," Unpublished Manuscript. [5]

CHETTY, R., AND N. HENDREN (2018a): "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects," *The Quarterly Journal of Economics*, 133 (3), 1107–1162. [3,4,21,22,24,26,29, 32]

——— (2018b): "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates," *The Quarterly Journal of Economics*, 133 (3), 1163–1228. [4,33]

CHETTY, R., J. N. FRIEDMAN, N. HENDREN, M. R. JONES, AND S. R. PORTER (2020): "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility," NBER Working Papers 25147. [14,27]

CHETTY, R., D. GRUSKY, M. HELL, N. HENDREN, R. MANDUCA, AND J. NARANG (2017): "The Fading American Dream: Trends in Absolute Income Mobility Since 1940," *Science*, 356 (6336), 398–406. [2,3, 6]

CHETTY, R., N. HENDREN, M. R. JONES, AND S. PORTER (2020): "Race and Economic Opportunity in the United States: An Intergenerational Perspective," *The Quarterly Journal of Economics*, 135 (2), 711–783. [4]

CHETTY, R., N. HENDREN, P. KLINE, AND E. SAEZ (2014): "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States," *The Quarterly Journal of Economics*, 129 (4), 1553–1623. [4,6]

DAVIS, J., AND B. MAZUMDER (2018): "Racial and Ethnic Differences in the Geography of Intergenerational Mobility," SSRN 3138979. [4]

——— (2020): *The Decline in Intergenerational Mobility After 1980*. [3,6]

DERENONCOURT, E. (2018): "Can You Move to Opportunity? Evidence From the Great Migration," Report, Harvard University. [4,29]

FAO (2017): "Evidence on Internal and International Migration Patterns in Selected African Countries." [23]

FLETCHER, J., AND J. HAN (2018): "Intergenerational Mobility in Education: Variation in Geography and Time," Working Paper 25324, National Bureau of Economic Research. [10]

GALLUP, J. L., AND J. D. SACHS (2001): *The Economic Burden of Malaria*. American Society of Tropical Medicine and Hygiene. [20]

GENG, Y. (2018): "Intergenerational Mobility in China Across Space and Time. Universitat Pompeu Fabra," Report. [4,6,10]

GOTTSCHALK, P., AND E. SPOLAORE (2002): "On the Evaluation of Economic Mobility," *The Review of Economic Studies*, 69 (1), 191–208. [6]

GREENE, W. H. (2011): *Econometric Analysis* (Seven Ed.). Boston: Pearson. [26]

GÜELL, M., M. PELLIZZARI, G. PICA, AND J. V. RODRÍGUEZ MORA (2018): "Correlating Social Mobility and Economic Outcomes," *The Economic Journal*, 128 (611), F353–F403. [16]

GUNNING, J. WILLEM, AND P. COLLIER (1999): "Explaining African Economic Performance," *Journal of Economic Literature*, 37 (1), 64–111. [14]

HERTZ, T., T. JAYASUNDERA, P. PIRAINO, S. SELCUK, N. SMITH, AND A. VERASHCHAGINA (2008): "The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends," *The B.E. Journal of Economic Analysis & Policy*, 7 (2). [3,6]

HILGER, N. (2017): "The Great Escape: Intergenerational Mobility in the United States, 1930–2010," Unpulished Manuscript. [3,6,8,10,14]

HOHMANN, S. (2018a): "Internal Migration in Africa: Evidence From Census Data," Report. [23]

——— (2018b): "Natural Resources, Trade, and Structural Transformation in Africa," Unpublished Manuscript. [20]

JEDWAB, R., AND A. MORADI (2016): "The Permanent Effects of Transportation Revolutions in Poor Countries: Evidence From Africa," *The Review of Economics and Statistics*, 98 (2), 268–284. [19]

JEDWAB, R., F. MEIER ZU SELHAUSEN, AND A. MORADI (2018): "The Economics of Missionary Expansion: Evidence From Africa and Implications for Development," Tech. Rep. 2018-07, Centre for the Study of African Economies, University of Oxford. [19]

KANBUR, R., AND A. J. VENABLES (2005): "Spatial Inequality and Development: Overview of UNU-WIDER Project". Cornell University, Department of Applied Economics and Management Working Papers 127127. [13]

LOURY, G. C. (1981): "Intergenerational Transfers and the Distribution of Earnings," *Econometrica*, 49 (4), 843–867. [5]

McMillan, M., D. Rodrik, and I. Verduzco-Gallo (2014): "Globalization, Structural Change, and Productivity Growth, With an Update on Africa," *World Development*, 63 (C), 11–32. [19]
Michalopoulos, S., and E. Papaioannou (2013): *Pre-Colonial Ethnic Institutions and Contemporary African Development. Econometrica*, 81 (1), 113–152. [19]
——— (2014): "National Institutions and Subnational Development in Africa," *The Quarterly Journal of Economics*, 129 (1), 151–213. [20]
——— (2020): "Historical Legacies and African Development," *Journal of Economic Literature*, 58 (1), 53–128. [4]
Mogstad, M., J. P. Romano, A. Shaikh, and D. Wilhelm (2020): "Inference for Ranks With Applications to Mobility Across Neighborhoods and Academic Achievement Across Countries," NBER Working Papers 26883. [6]
Montenegro, C. E., and H. A. Patrinos (2014): "Comparable Estimates of Returns to Schooling Around the World," Tech. Rep. WPS7020, The World Bank. [5]
Murdock, G. P. (1967): "Ethnographic Atlas: A Summary," *Ethnology*, 6 (2), 109–236. [19]
Narayan, A., R. Van der Weide, A. Cojocaru, S. Redaelli, C. Lakner, D. G. Mahler, R. Ramasubbaiah, and S. Thewissen (2018): *Fair Progress?: Economic Mobility Across Generations Around the World*. World Bank. [4]
Nunn, N. (2008): "The Long-Term Effects of Africa's Slave Trades," *The Quarterly Journal of Economics*, 123 (1), 139–176. [20]
——— (2010): "Religious Conversion in Colonial Africa," *American Economic Review*, 100 (2), 147–152. [19]
Nunn, N., and D. Puga (2012): "Ruggedness: The Blessing of Bad Geography in Africa," *The Review of Economics and Statistics*, 94 (1), 20–36. [15,20]
Psacharopoulos, G. (1994): "Returns to Investment in Education: A Global Update," *World Development*, 22 (9), 1325–1343. [5]
Psacharopoulos, G., and H. A. Patrinos (2004): "Returns to Investment in Education: A Further Update," *Education Economics*, 12 (2), 111–134. [5]
Solon, G. (1999): "Intergenerational Mobility in the Labor Market," in *Handbook of Labor Economics*, Vol. 3. Part A. Elsevier, 1761–1800. [3]
Spady, W. G. (1967): "Educational Mobility and Access: Growth and Paradoxes," *American Journal of Sociology*, 73 (3), 273–286. [3]
The Economist (2000): "Hopless Africa," The Economist. [2]
The Economist (2011): "Africa Rising. The Hopeful Continent," The Economist. [2]
——— (2016): *1.2 Billion Opportunities,* The Economist. [2]
United Nations Conference on Trade and Development (2018): *Economic Development in Africa Report 2018. Migration for Structural Transformation*. United Nations. [23]
Walter, T. F. (2020): "Misallocation of State Capacity? Evidence From Two Million Primary Schools," Report. [33]
Wantchekon, L. (2019): "The Strength of Weak Ties: Educational Externalities and Intergenerational Mobility in Benin," Report, Princeton University. [16]
Wantchekon, L., M. Klašnja, and N. Novta (2015): "Education and Human Capital Externalities: Evidence From Colonial Benin," *The Quarterly Journal of Economics*, 130 (2), 703–757. [19]
Young, A. (2012): "The African Growth Miracle," *Journal of Political Economy*, 120 (4), 696–739. [2,5]
——— (2013): "Inequality, the Urban-Rural Gap, and Migration," *The Quarterly Journal of Economics*, 128 (4), 1727–1785. [24]

Co-editor Fabrizio Zilibotti handled this manuscript.

Manuscript received 28 January, 2019; final version accepted 13 August, 2020; available online 10 September, 2020.