Poverty hotspots and the correlates of subnational development

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Abstract
Economic prosperity is unevenly distributed across geography, even within national boundaries. As national incomes converge, many subnational areas within countries show widening disparities. Much of the evidence of subnational growth is hampered by inadequate attention to the spatial clustering of economic development. We seek to explain the determinants of subnational growth by taking into account possible neighborhood and spillover effects whereby growth and development are influenced by growth rates in proximate geographic areas. Using data from around 3,000 first-level, subnational areas across 169 countries, we find that spatial autocorrelation is a critical factor in explaining growth at the subnational level. We also find that certain characteristics of these areas affect growth independently of national economic policy, including soil suitability for agriculture and malaria ecologies. We also show that legacies of conflict exert a consistent, negative effect on subnational growth. Our findings carry implications for identifying and for spatial targeting of poverty hotspots.

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Introduction

Economic activity is unevenly distributed across space. Even as national incomes converge, many areas within countries show widening disparities in per capita incomes. The poorest places in the world are barely growing in terms of average income but are growing quite rapidly in terms of population, despite out-migration. What explains persistent stagnation in some places and rapid development in others? Clearly, national economic growth explains a part of this, but subnational income disparities within countries have often proven to be even more durable than cross-country differences. There is evidence showing that economic activity is spatially concentrated within countries (Gennaioli et al. 2014) and that spatial inequality is increasing in the world's fastest-growing economies (World Bank 2009). Income gaps among regions within countries contribute to global income inequality (Krugman 1991; Milanovic 2005). Understanding these spatial inequalities is key to identifying extreme income poverty hotspots at a more granular level than the nation-state.

The sources of spatial disparities have been heavily studied and debated. One set of determinants has been termed "first-nature" characteristics, namely, the extent to which physical locations are suitable to human habitation, mobility, consumption (especially of food), and productive behavior (Henderson et al. 2018; Gallup, Sachs, and Mellinger 1999; Démurger et al. 2002, Diamond 1998; Rodrik et al. 2004; Acemoglu, Johnson and Robinson 2001; Sachs 2003; Easterly and Levine 2003; Hall and Jones 1999). Others have pointed to agglomeration effects or total factor productivity differences, by which some activities benefit from their concentration in denser spaces while others do not (Ellison and Glaeser 1999; Henderson, Shalizi, and Venables 2001; Quah 2002; Beugelsdijk, Klasing, and Milionis 2018, Zhou, Hubacek, and Roberts 2015).

Most empirical research on spatial economic disparities using subnational data on a global basis has relied on simple regression analysis. These approaches, however, do not take into consideration spatial correlations between variables or the spatial dependence of the outcome. Where there is reason to expect regional clustering, conventional approaches that arbitrarily restrict spatial spillovers to zero, or ignore spatial interdependence or diffusion, can produce estimates that are asymptotically biased (Anselin 1988). Estimates obtained using Ordinary Least Squares (OLS) (e.g., Ebener, Murray, Tandon and Elvidge 2005), for instance, are likely to be biased as they disregard possible spatial lags, where one region's growth is affected by the growth of contiguous regions, or spatial errors, where an omitted variable can cause the unanticipated growth in one region to be correlated with neighbors. Our chief contribution lies in examining correlates of subnational growth correcting for spatial lags. While others have done this in specific geographies (Guevara 2016 for Latin America; Bai, Ma and Pan 2012 for China; Cuaresma, Doppelhofer and Feldkircher 2014 for Europe; Rey and Montouri 1999 for the US), this paper is the first to apply such techniques at the global level.

There are three principal theoretical motivations for dependence between nearby observations. First, the spatial proximity of phenomena can prompt interactions between actors, which are likely to be influenced by the behaviors of their neighbors. Second, neighboring units of observations may share characteristics by virtue of the fact that they are clustered in the same location. Third, factors that influence the behaviors of actors in a location may also influence the behavior of actors in nearby locations. Advances in spatial econometrics have developed techniques for estimating these spatial relationships in regression models (Anselin 1988; LeSage 2008; Elhorst 2010).

Here, we rely on parametric spatial analysis to allow model parameters to be a function of location. We investigate the determinants of regional development using data from 2,894 observations based on subnational administrative units from 169 countries. We examine the effects of several first-order geographic characteristics (including soil and malaria suitability) as well as indicators of physical and human capital, market connectivity, and conflict on subnational development.

Using a global, geo-coded, cross-sectional dataset, we find evidence of a strong spatial dependence in regional development, confirming the conjecture that OLS estimates of subnational development are potentially inconsistent and biased. Controlling for this spatial dependence, we find that there is significant spatial lag across regions, i.e., growth in neighboring regions spills over to their neighbors, even if the latter are in different countries. We also find that geography, climate, human capital, and conflict have significant effects on development. Favorable soil conditions, low suitability for malaria based on mean temperature, higher state exposure, reduced elevation, higher estimated years of schooling, and low levels of conflict have positive effects on growth. Interestingly, while travel time to the nearest major city does not have a significant effect on subnational growth across countries, it significantly hampers growth within countries. We also find evidence of conditional convergence—lower-income subnational areas grow faster than higher-income areas, *ceteris paribus*—in line with previous estimates of conditional growth convergence across U.S. states (Barro and Sala-i-Martin 1992). However, the evidence on absolute convergence is quite mixed. Some poor places remain poor over long periods of time.

These findings suggest public policy interventions may be necessary to make a difference in subnational regional development. First, several indicators of physical infrastructure, such as accessibility to a nearby city or historical exposure to the centers of political power, have a significant impact on growth. Second, an ability to reduce the incidence or impact of shocks, such as conflict-related deaths or droughts, can improve growth. Finally, human capital investments create opportunities for growth in specific regions. In each case, direct growth effects in one area have positive spillover effects on neighboring regions.

We identify places that are being left behind—poverty "hotspots"—as well as interventions that could potentially accelerate their development. We want to emphasize that a finding of a positive impact on the growth of any intervention is not sufficient to recommend the intervention to policymakers. Consideration has to be given to costs as well as benefits, and our approach focuses only on the benefit side of the ledger. Nevertheless, the proper measure of benefits, both direct and indirect, is necessary for informed spatial policymaking.

One consequence of our finding of conditional convergence is that if the principle of "leave no one behind" or of greater social inclusion in growth is to be taken seriously, specific spatial policies will be needed. Simply assuming that internal migration or conditional convergence through catch-up growth will equalize opportunities for all runs counter to existing evidence. Disturbingly, we find that the number of people living in poverty hotspots is rising over time due to natural population growth outstripping out-migration. This is consistent with findings elsewhere (OECD 2018) that high population growth rates in poor areas can undermine stability and developmental prospects, creating a kind of "poverty trap." In such instances, a spatial big push of public and private investments may be needed.

Data and descriptive statistics

We rely on a geo-referenced, cross-sectional dataset in which the units of observation are first-level subnational units based on the Database of Global Administrative Areas (GADM 2018), representing all the subnational units in the world that are one level below the national level. It consists of 3,610 subnational cantons, districts, governorates, prefectures, provinces, and states in all countries in the world.

Subnational GDP levels and growth

For our analysis, we derive subnational growth estimates utilizing the gridded GDP data, in 2011 purchasing power parity (PPP) dollars, offered by Kummu, Taka, and Guillaume (2020). We take their 2000 and 2015 estimates of GDP in 5 arc-minute resolution and sum within each GADM3.6-1 polygon, i.e., subnational unit. We then divide these GDP level estimates by the population count from the Gridded Population of the World Version 4 dataset from CIESIN (2018). This provides our estimates of GDP per capita in 2000 and 2015, from which we calculate the GDP per capita compound annual growth rate for each subnational unit.

Figure 1 maps subnational growth around the world. The general pattern is one of rapid growth in East and South Asia, along with selected regions in Africa, Latin America, and Europe. Very slow growing areas are concentrated in Africa, Latin America, and some advanced economies.

In Figure 2, we show the initial income levels in 2000 of regions across the world. The color-coding of the map mimics standard country income classifications in 2000, as defined by the World Bank: low income, lower-middle income, upper-middle income, and high income. These classifications, however, are based on market exchange rates averaged over three years,[3] while our regional data is in PPP dollars. To convert the PPP estimates to GNI per capita Atlas method (current US$), we apply the country-level ratio between these figures, using World Development Indicators (World Bank 2020), to each subnational unit of that country. This is an approximation as it does not properly account for differences in prices within a country, but the differences are likely to be modest compared to cross-country price differences.

Table 1 gives summary statistics of the distribution of per capita income across countries and subnational units. The rows show subnational classification, while the columns show national classification. Thus, looking at the first row, the Table shows 1,203 of the administrative units in our dataset have low per capita income levels. Of these, 882 units (about three-quarters) are in low-income countries, another 223 are

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[3] This is called the Atlas method by the World Bank.

located in lower-middle-income countries, 73 in upper-middle-income countries, and 25 in high-income countries. Looking at the columns, we also see considerable regional inequalities within countries. For example, Column 3 shows that in countries classified as upper-middle income in 2000, there were 73 low income regions, 132 lower-middle income regions, 353 upper-middle income regions, and 96 high income regions.

By 2015 (Figure 2, lower panel), large parts of Asia, including all of China and most of India and the Indian subcontinent, had graduated from the low income classification. The remaining pockets of poverty are more concentrated. The figure shows the continued challenges in Central and Eastern Africa, albeit with some improvements in West Africa. In Asia, there is a cluster of low income localities in North-East India and the Northern foothills of the Himalayas, Myanmar, and Laos, in Afghanistan and surrounding territories, and in the lower Mekong area. In Latin America, North East Brazil and some regions of Central America continue to show low income levels.

Across the world, there are 538 poverty hotspots—administrative units that were classified as low income in both 2000 and 2015—with a population of 1.12 billion in 2015. These are distributed across 77 countries, far more than the 31 countries classified by the World Bank as low income in 2015 (Table 2). Population growth in poverty hotspots is positive and greater than the population growth in non-hotspot areas, indicating that natural population growth in poor localities is outstripping out-migration. This is not surprising as fertility is closely correlated with income levels and mothers' education (Kirk 1996, Lesthaeghe 2010, Martin 1995, McCrary and Royer 2011). Economic growth in hotspots is below economic growth in other areas, suggesting a widening of spatial inequality over time.

Covariates

We control for a number of factors that can affect the growth trajectories of subnational areas. Table 3 lists covariates under 4 categories: (i) geography; (ii) physical connectivity; (iii) human capital; and (iv) governance. Further detail on covariate descriptions and data sources are available in the appendix.

On the presumption that geographic endowments affect long-term development, we include a measure of agricultural soil suitability (Data Basin 2010), along with a measure of elevation to control for differences in physical geography and land arability (AidData Geoquery 2019). We also include a dummy variable to account for the presence of oil or gas deposits within the boundaries of the subnational unit (Pierskalla, Schultz, and Wibbels 2017).

In their seminal report *Reshaping Economic Geography* (2009), the World Bank Group argued that distance—or the time and cost required to get the labor force to economic production hubs and goods to market—is a critically important correlate of growth. The better the infrastructure and connectivity, the greater the mobility of labor. To account for this, we include a measure of average distance to the nearest port (World Port Index

Database 2019) and travel time to major urban centers – the nearest city of 50,000 or more persons (AidData Geoquery 2019).

Human capital, defined as the "productive wealth embodied in labor, skills, and knowledge," is central to accelerating development in lagging places (UN 1997). We include the average expected years of schooling between 1998 and 2002 at the subnational level (Global Data Lab 2020).

Additionally, we control for malaria as a simple proxy for the burden of infectious disease. Malaria ecologies are commonly associated with low growth areas due to effects on the productivity and health of the population. Malaria and other diseases affect the economy directly but also indirectly, through adverse consequences for childhood development and the quality of human capital for decades (Holding and Kitsao-Wekulo 2004). We use malaria "temperature suitability" score rather than the actual prevalence of malaria to avoid endogeneity (Malaria Atlas Project 2020).

Following Pierskalla, Schultz, and Wibbels (2017), we control for local exposure to a state capital over time—essentially a measure of a geography's contact with the institutions of national political power, and to the fiscal, bureaucratic, enforcement, public-goods, and behavioral consequences of proximity to "statehood"—based on the historical and contemporary location of capital cities, and on the assumption that physical distance represents the projection of state authority. We term this "state exposure."

We also control for conflict deaths as a further indicator of governance. Violence is increasing worldwide, and the number of civil conflicts is on the rise (Jackson 2017; Blattman and Miguel 2010). Political violence has spread across more than fifty countries in the past decade and a half (OECD 2016). The measurement of conflict is empirically tricky. We code each subnational unit depending on the presence of war, armed conflict, or political violence relying on indicators taken from the Uppsala Conflict Data Program (AidData Geoquery 2019). All areas that experienced fatalities resulting from conflict between 1989 and 2000 are coded 1, 0 otherwise.

Empirical strategy

Our principal contribution lies in explicitly accounting for spatial autocorrelation in subnational income growth at the global level. Where there is reason to expect economic development to cluster in particular locations, conventional approaches that arbitrarily restrict spatial spillovers to zero or ignore spatial diffusion can produce asymptotically biased estimates. We begin by exploring whether subnational income growth (shown in Figure 1) is randomly distributed among our administrative units or whether spatial dependence is statistically significant.

We use the Moran's *I* statistic to test for the presence of global spatial autocorrelation in per capita income growth and error terms of the initial OLS model. A global Moran's *I* measures the extent to which subnational growth is clustered, dispersed, or randomly distributed across administrative areas by computing the deviation from the mean growth rate for each subnational unit of analysis (Kelejian and Robinson 2004; Kelejian and Prucha 2001). Moran's *I* values range from –1 (perfect dispersion) to +1 (perfect clustering), while zero corresponds to a random spatial pattern (the OLS assumption). As Table 4 and Figure 3 depict, spatial clustering is positive and statistically significant for first- or second-order contiguous subnational areas.

Spatial dependence across subnational units are defined through the symmetric $n \times n$ geographic first- or second-order contiguity weighting matrix **W** of non-negative spatial weights. Each element of the weighting matrix **W**, w_{ij}, represents the spatial influence of subnational area *i* on subnational area *j*, where $w_{ij} = 1$ if area *i* is first- or second-order contiguous with area *j*, 0 otherwise. A queen contiguity matrix was selected as the most appropriate method to represent the spatial relationships in the data due to the irregularity of polygons that comprise subnational area boundaries. A queen matrix considers two geographic units as neighbors if they directly share a border or vertex; we also report results using a rook matrix that only considers regions to be neighbors if they have a common border. Our matrix weighting is normalized such that the $(i,j)^{th}$ element of the matrix becomes w_{ij}/v, where *v* is the largest modulus of the Eigenvalues of **W** (spectral normalization).

Following the decision rules recommended by Anselin (2005), Lagrange multiplier tests (see appendix), and the nature of the variables indicated that a spatial autoregressive (SAR) model, including a spatial lag of the dependent variable, is the most appropriate for our spatial regression analyses. Our estimation takes the following standard functional form:

$$y_i = \alpha + \rho \mathbf{W} y_i + \beta_i \mathbf{X} + \varepsilon_i \qquad (1)$$

where y_i is an $n \times 1$ measure of real per capita GDP growth (2011 PPP dollars), between 2000 and 2015, consisting of one observation for every subnational unit in the sample ($i = 1,\dots, n$), **X** denotes a $k \times n$ matrix of exogenous explanatory variables, β_i is a $k \times 1$ vector of parameters, ε_i is an $n \times 1$ vector of independently and identically distributed errors for each given subnational unit. The spatial autoregressive term is ρ, and the spatial lag is obtained by multiplying **W** by the vector of observations for the dependent variable. In an attempt to discern whether spillover effects are purely internal or whether they also cross national borders, we modify our base model to have country fixed effects and compare results with and without.

Results

Local spatial autocorrelation

If the level of spatial dependency varies across space, then the capacity to detect and pinpoint spatial heterogeneity is more desirable. We rely on local Moran's I, as recommended by Anselin (1995), to measure the degree of dependence in GDP per capita in 2015 in subnational unit * relative to the income levels across all other subnational units. Local Moran's I can discern cluster structures of high- or low-value concentration among local observations. Figure 4 identifies the cross-regional variation in local spatial autocorrelation. The map indicates high-high value clusters (high-income regions surrounded by other high-income areas) and low-low clusters (poorly performing areas surrounded by other low-income areas) that ignore national boundaries. It also shows outliers—high-income areas surrounded by low-income areas and vice versa. These local indicators of spatial association show three areas of poverty "clusters"—low-income areas neighbored by low-income regions: the Amazon basin, sub-Saharan Africa, and Central-South Asia.

Benchmark spatial regressions

Spatial analysis recognizes that covariates in the present location will affect growth in neighboring locations, which will, in turn, affect growth in the location under investigation through the spatial dependence parameter ρ given above. Indeed, a change in any covariate will have both a direct effect (i.e., the effect of changes in regressors on growth in the same subnational location) and an indirect effect on the outcome for other subnational areas following the structure of the weighting matrix. These indirect effects, therefore, are global in nature (Anselin 2003). Total effects comprise the sum of direct and indirect effects. The autoregressive effect of growth is positive and significant, indicating that a one percentage change in per-capita growth in neighboring subnational regions with first- or second-order contiguity will increase growth in the region under investigation by 0.65 percent ($p < 0.001$). Regression tables may be found in the appendix.

Figure 5 and Table 5 present the main results from our spatial analysis, decomposing direct effects, indirect or spillover effects, and total effects. Effects of ten covariates are displayed: baseline GDP per capita (in 2000), agricultural suitability of soil, state exposure, temperature suitability for malaria spread, presence of oil or gas deposits, elevation, average distance to the nearest port, travel time to the nearest major city, expected years of schooling, and presence of deadly armed conflicts. Panel (A) shows the full, unrestricted sample. Consistent with previous evidence, the initial level of GDP per capita has a negative effect on growth. We estimate the conditional subnational convergence rate to be 1.1 percent per year. Subnational areas with more arable soil areas experienced faster growth. Meanwhile, tropical temperatures that facilitate the reproduction of *Anopheles* mosquito larva reduce economic growth: a one-unit increase in the *p. falciparum* suitability index decreases growth by 1 percent. Lower elevations are also associated with faster growth. Meanwhile, exposure to state authority shows a small but significant effect on growth, indicating that historical proximity to central political powers does somewhat benefit subnational administrative areas contemporaneously. The presence of oil or gas deposits, the average distance from ports, and travel time to urban areas have no effect. Human capital, as measured by expected years of schooling, by contrast, has a strong positive effect on subnational development. Finally, the presence of a conflict resulting in deaths lowers subnational growth by 0.3 percent.

Disaggregating development by subnational units allows us to examine growth processes that, as local indicators of spatial autocorrelation show, may ignore national boundaries. Nevertheless, the effects of national policies on subnational growth cannot be discounted. National development strategies, as well as country-level characteristics, may exert an influence on subnational growth. Rather than controlling for multiple country-level factors in spatial regression, we add country-level fixed effects. With the inclusion of country dummy variables, the effect of the spatial lag of growth falls from 0.65 to 0.18 ($p < 0.001$), indicating that neighborhood effects are reduced by two-thirds when controlling for national-level factors, but that cross-border spillovers still exist and are significant.

The resulting, within-country relationships are shown in panel (B) of Figure 5 and Table 5. Baseline per capita income, agricultural suitability, and malaria retain their effects; these are the subnational growth factors that operate within-country as well as cross-nationally. The coefficient on one factor that was insignificant in the earlier regression—travel time to major cities—is now moderately negative, suggesting that proximity to a city in another country where a national border has to be crossed is not a significant driver of growth, but higher travel time to a city within the same country adversely affects growth. The expected years of schooling exerts no effect on growth when controlling for all country-level characteristics. State exposure, elevation, and conflict do not show any significant within-country effect on subnational development as well. All other covariates remain insignificant.

Robustness

Instrumenting conflict with drought

It is possible that conflict may be affected by local economic development or that subnational growth and conflict may be driven by common factors in proximate areas. It is possible, for example, that armed insurgent groups may be drawn to poorer areas in order to see more willing recruits. In addition, negative economic shocks may exacerbate endemic tension in multi-ethnic or multi-religious regions, precipitating group conflict. These dynamics make conflict potentially endogenous to growth.

Environmental shocks can precipitate political shocks that result in conflict-related deaths, often in interrelated ways (Smith 2015). Both factors have been associated with persistent underdevelopment and poverty at the national level, with some analyses showing that the two are related—that drought can increase the likelihood of conflict over resources (Miguel, Satyanath, and Sergenti 2004). Climate change poses an increasing risk to the global community: concentrations of CO_2 and other long-lived greenhouse gases continue to increase; biodiversity is declining; tropical reefs and oceanic habitats are facing profound losses, and land degradation covers about 29 percent of the global land area (UNEP 2019). Addressing environmental shocks is central to accelerating development and ensuring that places are not left further behind.

As have others, by instrumenting conflict with an indicator of drought or the standardized evapotranspiration index (SPEI), we attempt to resolve the endogeneity issue (SPEIbase v.2.5. 2017). Environmental factors strongly influence conflict, particularly through drought, and it is unlikely that climatic factors that affect droughts can be directly influenced by growth in the short-term. In sum, SPEI fulfills the standard variability and exclusion requirements for an instrumental variable (IV): it affects the potentially endogenous variable conflict, and it exerts no direct or confounding effect on the outcome of interest, i.e., subnational growth.

Figure 6 and Table 6 show IV results (see appendix for raw regression tables). For IV spatial regressions, we rely on generalized spatial two-stage least squares estimation incorporating all regressors from the main model, with conflict treated as an additional endogenous covariate instrumented by SPEI. The IV results are largely symmetric with the main results. Baseline GDP per capita, soil suitability, state exposure, and expected years of schooling all retain their direction and significance. However, the effects of malaria and elevation are not robust to the IV specification. The negative effect of conflict, controlling for its endogeneity, increases tremendously from 0.3 percent to 2.5 percent. When including country-fixed effects, as with the previous estimation, baseline GDP per capita, soil, malaria, and travel time to urban areas retain their effects. Meanwhile, state exposure, expected years of schooling, and conflict are no longer significant.

Sensitivity to spatial weighting matrix choice

We test the sensitivity of our results to the choice of the spatial weighting matrix. We utilize alternative contiguity and inverse distance matrices to obtain global Moran's *I* statistics. More specifically, we include first-order and rook contiguity matrices, in addition to inverse distance matrices with different distance cutoffs. The results, shown in Table 7, are consistent with the results from the queen-contiguity matrix.

We use these alternative matrices to rerun our spatial regression analyses as well. The results, visualized in Figure 7, show that the derived effects from our main model are robust to the choice of the spatial weighting matrix. Almost all variables retain their effects, with the exception of conflict losing its significance when inverse distance matrices are used. A detailed table of the derived effects and regression results can be found in the appendix.

Heterogeneity of treatment effects

For policy purposes, it is important to understand if there is non-random variability in the magnitude of treatment effects across different places. As a check, we run our benchmark spatial regressions separately by income groups using World Bank income classifications for 2000. There is no theoretical reason to believe that growth drivers are the same at all income levels. For example, agricultural soil suitability is probably not important for high-income countries. The results for low- and lower-middle income countries are presented in Table 8. The rest of the results and regression tables can be found in the appendix. The convergence retains its significance for lower-middle-income countries, with low-income countries exhibiting significance only within countries. Malaria stands out as the most important factor that inhibits growth in low- and lower-middle-income countries. On the other hand, we find evidence that agricultural suitability has a positive effect on the income growth for low and lower-middle-income countries. Another interesting finding from this comparison is the effect of conflict. While conflict does not appear to affect income growth in low-income countries, it does affect lower-middle income growth. State exposure, oil or gas deposits, elevation, and expected years of schooling all matter for low-income countries, while they are not significant for lower-middle-income countries. These findings make intuitive sense.

Conclusion

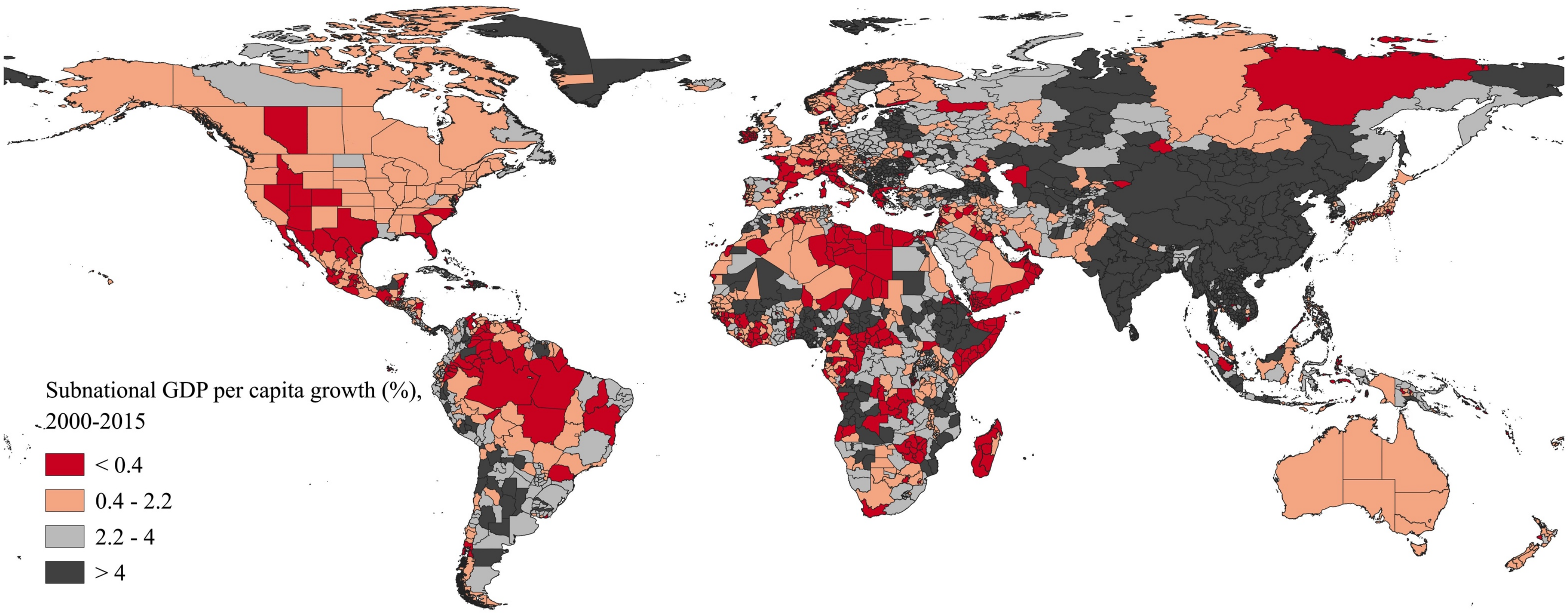
In 2015, over 1 billion people still lived in places where average income levels have been low for a prolonged period of time. As we have shown in this paper, these poverty hotspot regions are located within low-income, middle-income, or even high-income countries. A new toolkit of advanced geospatial technologies now permits an ever-more granular understanding of where the most vulnerable reside, even in places where the national averages are relatively high, and what can be done to get them back on track. Our local spatial autocorrelation analysis has shown that the poverty hotspots that require the most immediate attention in the world are in the Amazon basin, sub-Saharan Africa, and Central-South Asia.

It is a fallacy to argue that natural migration will move people from poor areas to places that offer more opportunity and subsequently provide a solution for the regional inequalities. At least for the time being, higher fertility rates are pushing population growth rates in poorer places, above those in more prosperous places, even within each country. It is also short-sighted to overlook the current political tension around cross-country migration, where the number of forcibly displaced people reached 79.5 million worldwide by the end of 2019 (UNHCR 2020).

Recent advances in geospatial technology provide granular data on many indicators, including income, that can be used for policymaking. In order to leave no one behind, we need to be able to identify lagging regions and explore the factors that prevent these regions from developing.

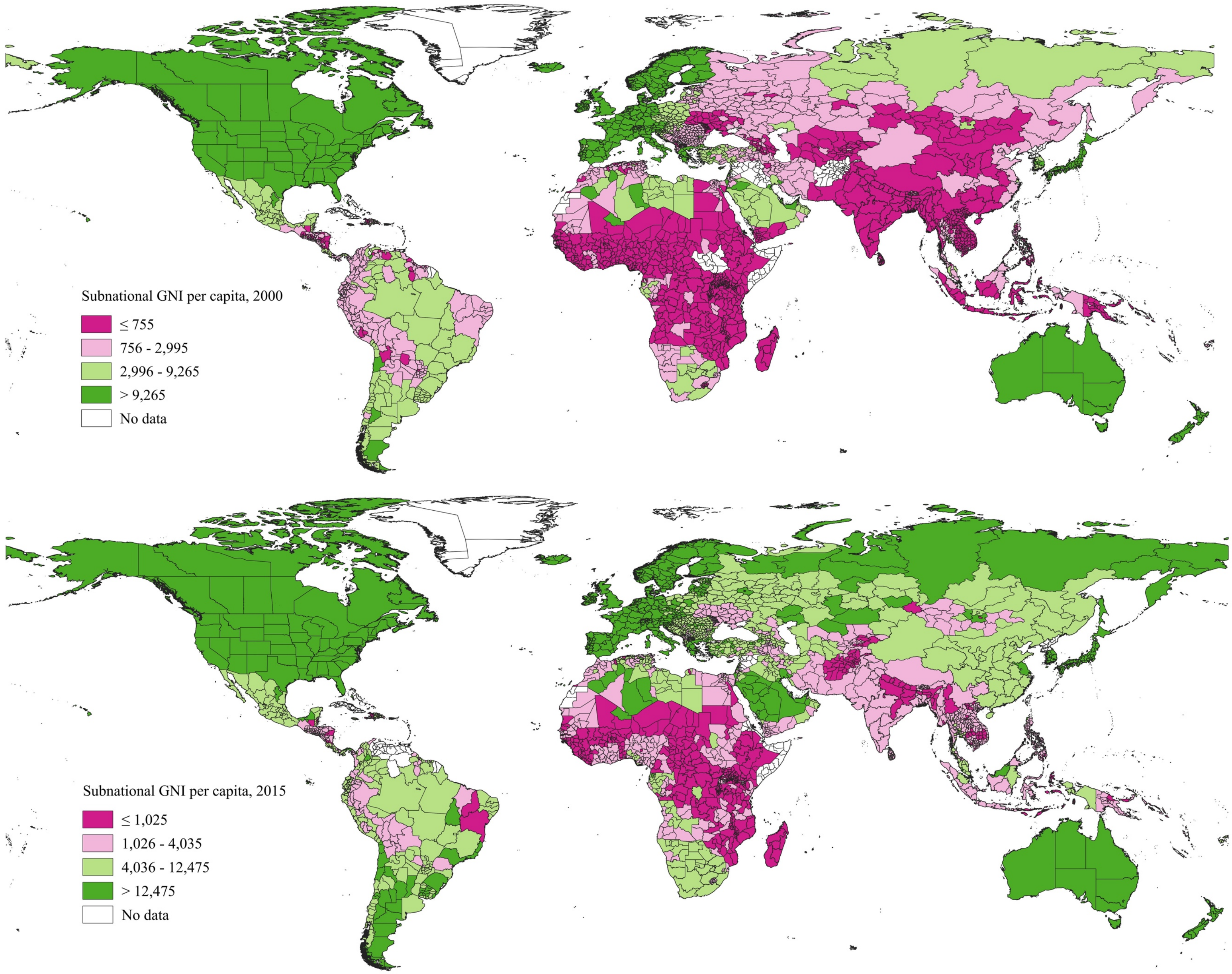
Using the data that is currently available, we find strong empirical evidence that while certain places indisputably face geographic constraints—such as extreme temperatures, inhospitable soil, and proximity to the national border—other variables within the purview of policymaking also hold significant explanatory power. Human capital, infrastructure, and connectivity, shock-readiness, and governance all impact the extent to which a region develops or lags, suggesting that public officials have at their disposal a powerful antidote to poverty: inclusive local policies and institutions. We hope that as additional location-specific data becomes available, it can be used to (i) highlight underserved areas, (ii) encourage public officials to allocate resources to areas identified and underserved, and (iii) provide citizens with domestic accountability mechanisms that help ensure that resource allocation is more responsive to local needs (BenYishay and Parks 2019).

Figure 1: Subnational GDP per capita growth, 2000-2015



Source: Authors' calculations based on Kummu, Taka, and Guillaume (2020), CIESIN (2018), and World Bank income classifications for 2000.

Figure 2: Subnational GNI per capita, Atlas method (current US$), 2000 and 2015



Source: Authors' calculations based on Kummu, Taka, and Guillaume (2020), CIESIN (2018), and World Bank income classifications for 2000 and 2015.

Figure 3: Moran scatterplot of subnational GDP per capita growth

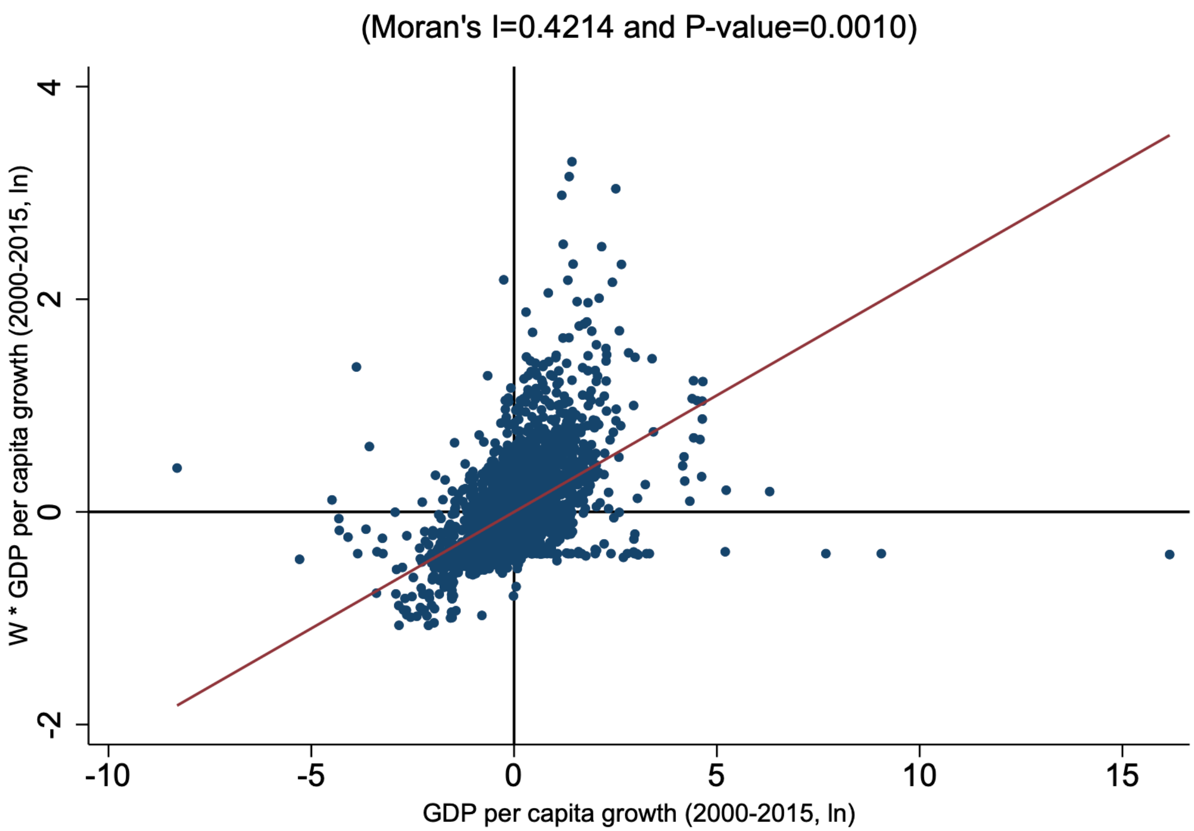


Figure 4: Local spatial autocorrelation

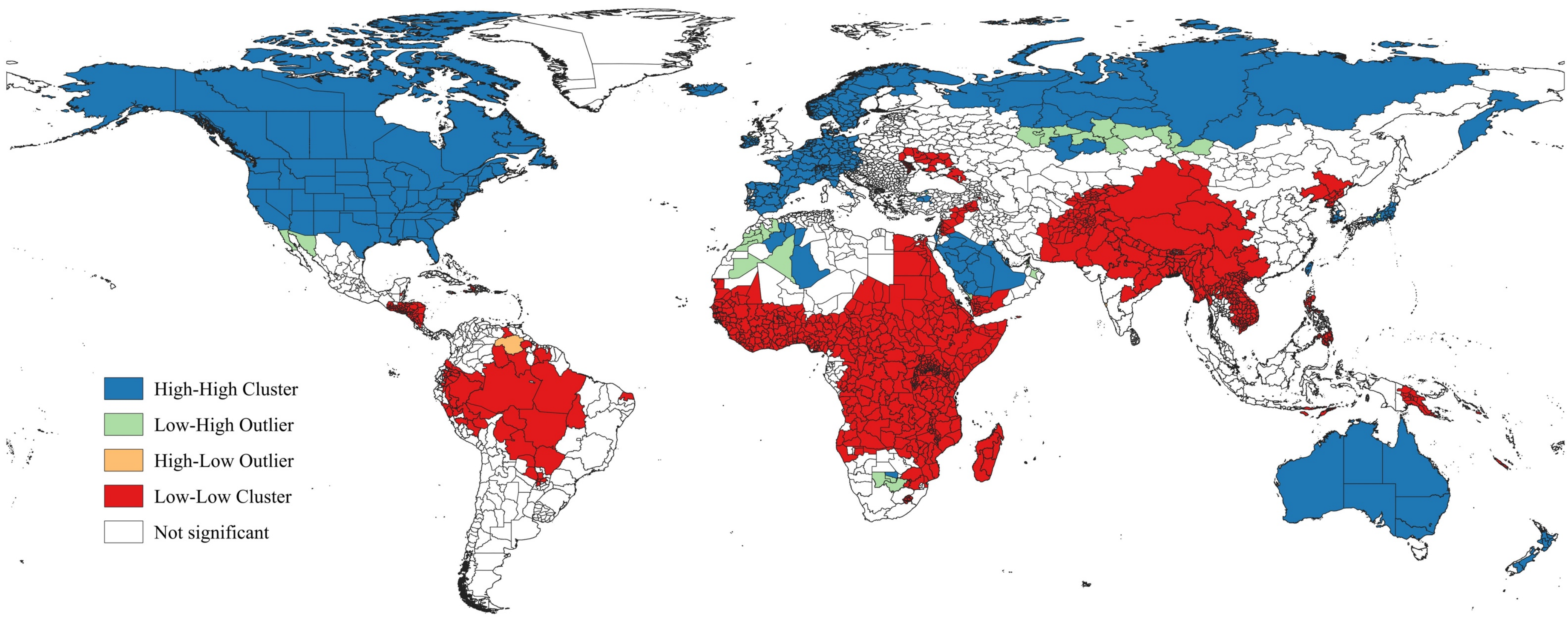
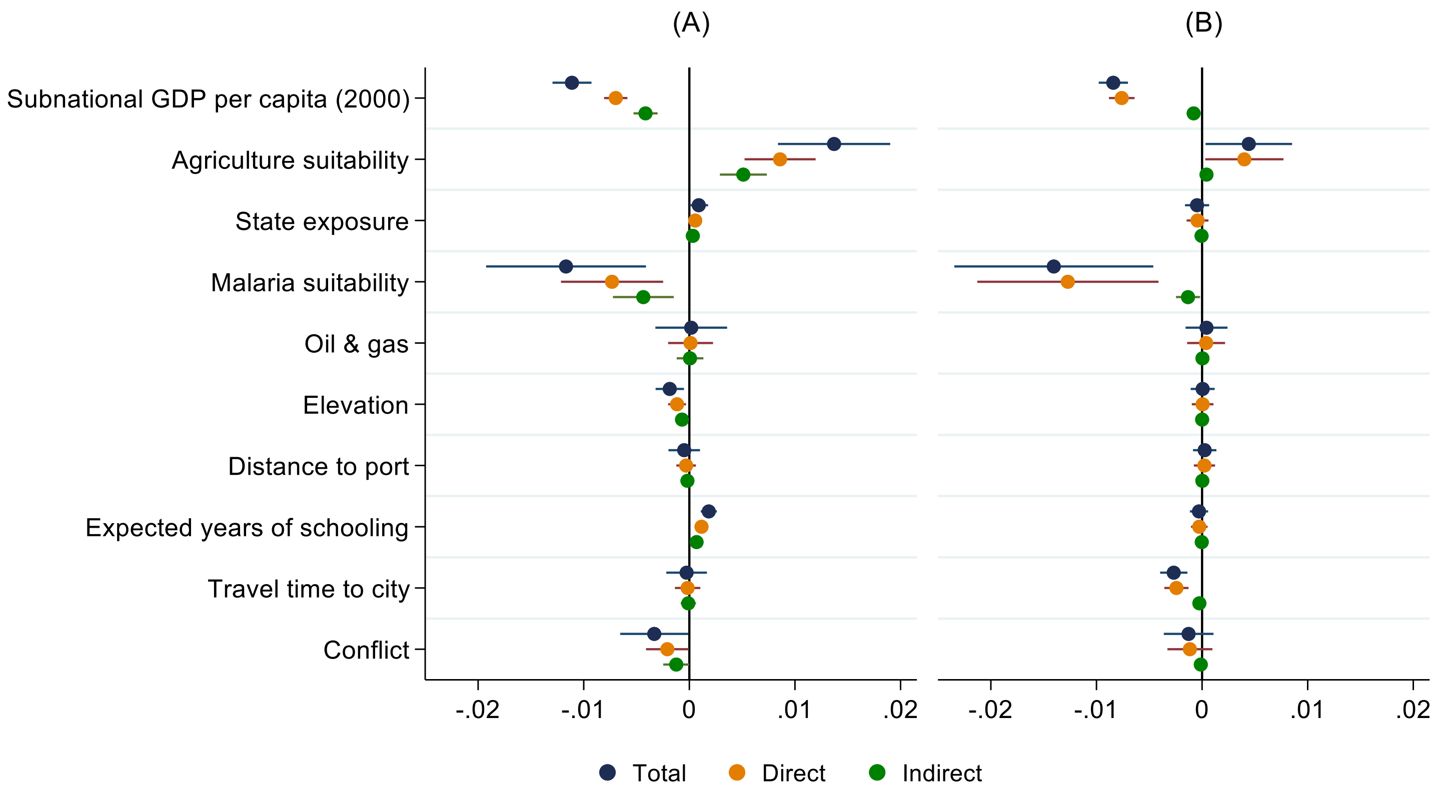
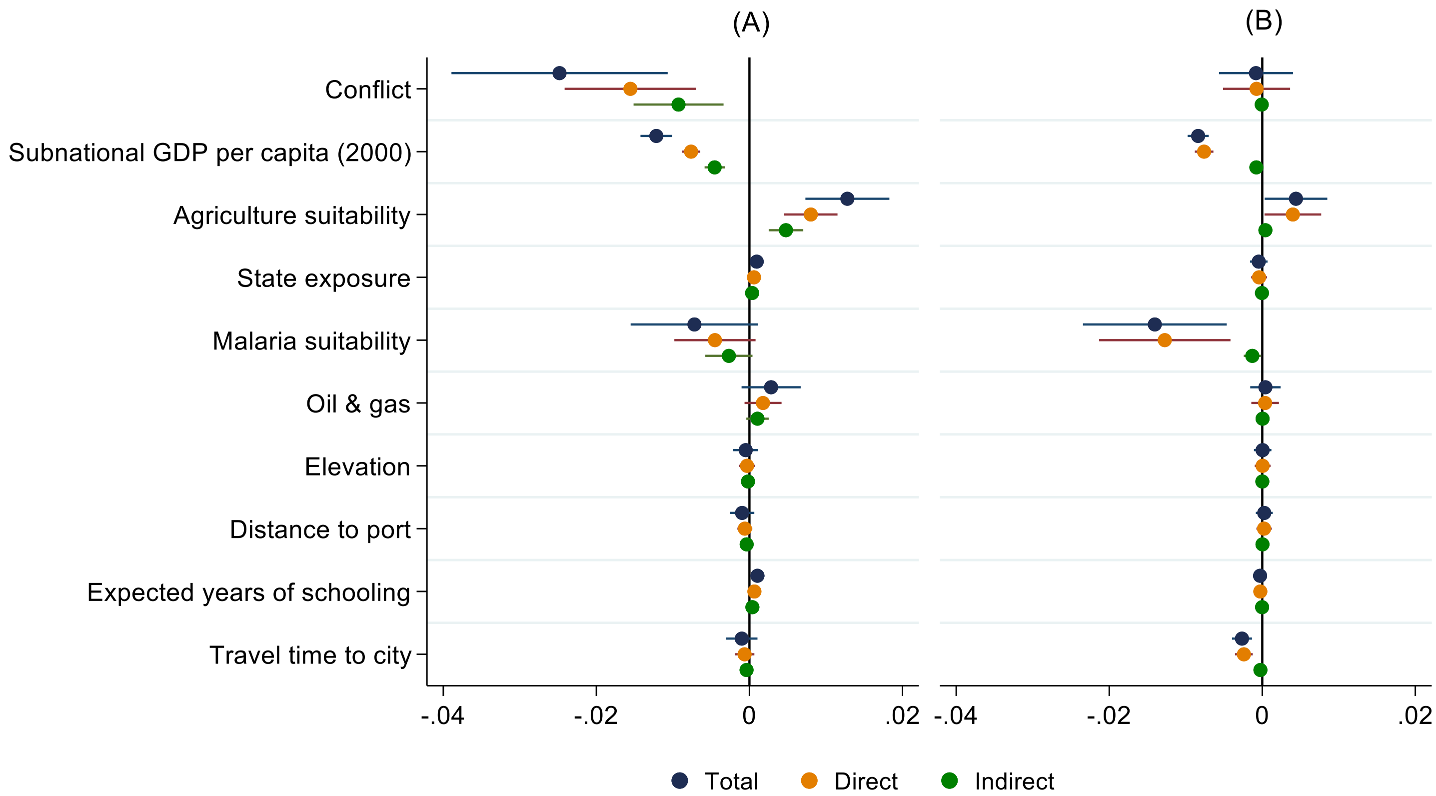


Figure 5: Benchmark spatial regression results



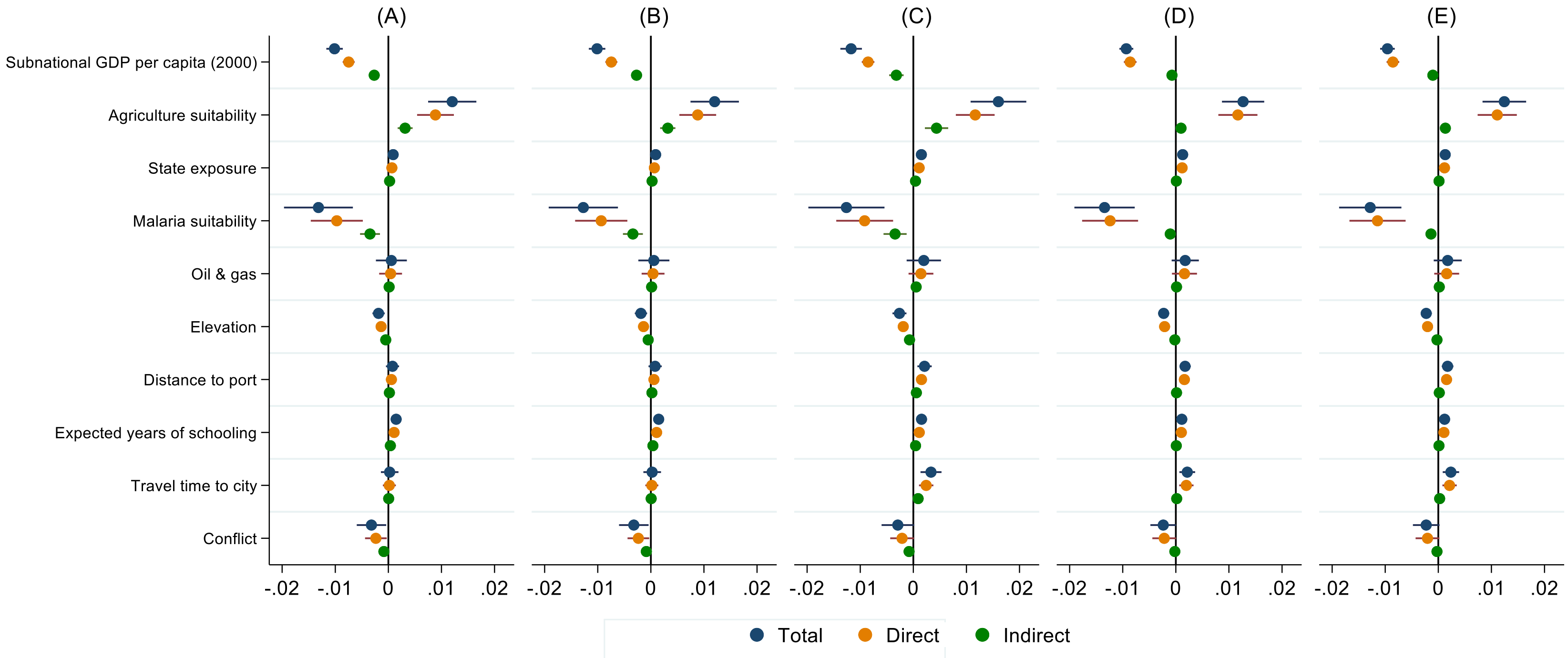
Notes: Graphs show direct, indirect, and total effects based on coefficients from spatial autoregressive regressions, with 95% confidence intervals. The dependent variable is real per capita GDP growth by subnational area, 2000-2015. Figure (B) shows the within-country effects.

Figure 6: IV spatial regression results



Notes: Graphs show direct, indirect, and total effects based on coefficients from generalized spatial two-stage least squares regressions, with 95% confidence intervals. The dependent variable is real per capita GDP growth by subnational area, 2000-2015. Conflict is instrumented by the standardized evapotranspiration index (SPEI). Figure (B) shows the within-country effects.

Figure 7: Benchmark regression results using alternative spatial weighting matrices



Notes: Graphs show direct, indirect, and total effects based on coefficients from spatial autoregressive regressions, with 95% confidence intervals. The dependent variable is real per capita GDP growth by subnational area, 2000-2015. Figures (A) to (E) show results using the following spatial weighting matrices respectively: first-order contiguity, rook contiguity, inverse distance, inverse distance truncated at 500 km, and inverse distance truncated at 1000 km. Tables presenting within-country effects can be found in the appendix.

Table 1: National versus subnational income classifications for 2000

Subnational \ National	Low	Lower-middle	Upper-middle	High	World
Low	882	223	73	25	1,203
Lower-middle	99	683	132	4	918
Upper-middle	5	90	353	38	486
High	2	9	96	448	555
World	988	1,005	654	515	3,162

Source: Authors' calculations based on Kummu, Taka, and Guillaume (2020), CIESIN (2018), and World Bank income classifications for 2000.

Notes: The subnational income classification cutoffs are as follows: Low income (≤755); lower-middle income (755-2,995), upper-middle income (2,995-9,265), high income (>9,265).

Table 2: Income and population trends of poverty hotspots

	Poverty hotspots	Rest of the world
Annual average rate of per capita GDP growth, 2000-2015	1.97%	2.80%
Average GDP per capita (2011 PPP), 2000	926	17,688
Average GDP per capita, (Atlas method current US$), 2000	206	7,771
Average GDP per capita (2011 PPP), 2015	1,263	22,899
Average GDP per capita (Atlas method current US$), 2000	539	15,978
Annual average rate of population growth, 2000-2015	2.61%	0.94%
Population count, 2000	0.79	5.10
Population count, 2015	1.12	5.93

Source: Authors' calculations based on Kummu, Taka, and Guillaume (2020), CIESIN (2018), and World Bank income classifications for 2000 and 2015.

Table 3: Descriptive statistics

	n	Mean	Std. Dev.	Min	Max
GDP per capita growth, 2000-2015	2,894	0.027	0.030	-0.221	0.264
GDP per capita, 2000	2,894	14,117	88,881	0	3,606,361
GDP per capita, 2015	2,894	18,831	111,867	1	4,610,848
Geography					
Agricultural suitability	2,894	0.450	0.290	0	0.998
Elevation	2,894	620	653	-14	4,881
SPEI	2,894	-0.546	0.537	-1.821	1.166
Oil or gas	2,894	0.256	0.437	0	1
Physical capital					
Distance to port	2,894	330,495	397,248	1,361	2,436,503
Travel time to city	2,894	320	444	3	10,446
Human capital					
Expected years of schooling	2,894	10.998	3.116	1.863	21.306
Malaria suitability	2,894	0.275	0.252	0	0.783
Governance					
Conflict deaths	2,894	0.347	0.476	0	1
State exposure	2,894	0.050	0.066	0	0.971

Table 4: Global Moran's *I* Statistic

	Normal approximation	Randomization
Moran's *I*	0.4214	0.4214
Mean	-0.0003	-0.0003
Std. dev	0.0064	0.0064
Z-score	65.5685	65.8333
P-value	0.0000	0.0000

Table 5: Benchmark regression results

	(A)			(B)		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Subnational GDP per capita (2000, Ln)	-0.007***	-0.004***	-0.011***	-0.008***	-0.001**	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Agriculture suitability	0.009***	0.005***	0.014***	0.004*	0.000	0.004*
	(0.002)	(0.001)	(0.003)	(0.002)	(0.000)	(0.002)
State exposure (Ln)	0.001*	0.000*	0.001*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Malaria	-0.007**	-0.004**	-0.012**	-0.013**	-0.001*	-0.014**
	(0.002)	(0.001)	(0.004)	(0.004)	(0.001)	(0.005)
Oil & gas deposits	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Elevation (meters, Ln)	-0.001**	-0.001**	-0.002**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Distance to the nearest port (meters, Ln)	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Expected years of schooling (1998-2002, Ln)	0.001***	0.001***	0.002***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel time to the nearest city (mins.)	-0.000	-0.000	-0.000	-0.002***	-0.000*	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Conflict	-0.002*	-0.001*	-0.003*	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
W * Change in subnational GDP per capita (2000 – 2015)		0.6539***			0.1779***	
		(0.0482)			(0.0495)	
Country-fixed effects		No			Yes	
Observations		2,894			2,894	

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

Notes: Tables show direct, indirect, and total effects based on spatial autoregressive regressions. The dependent variable is real per capita GDP growth by subnational area, 2000-2015. Figure (B) shows the within-country effects.

Table 6: IV regression results

	(A)			(B)		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Subnational GDP per capita (2000, Ln)	-0.008***	-0.005***	-0.012***	-0.008***	-0.001**	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Agriculture suitability	0.008***	0.005***	0.013***	0.004*	0.000	0.004*
	(0.002)	(0.001)	(0.003)	(0.002)	(0.000)	(0.002)
State exposure (Ln)	0.001*	0.000*	0.001*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Malaria	-0.005	-0.003	-0.007	-0.013**	-0.001*	-0.014**
	(0.003)	(0.002)	(0.004)	(0.004)	(0.001)	(0.005)
Oil & gas deposits	0.002	0.001	0.003	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Elevation (meters, Ln)	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Distance to the nearest port (meters, Ln)	-0.001	-0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Expected years of schooling (1998-2002, Ln)	0.001*	0.000*	0.001*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Travel time to the nearest city (mins.)	-0.001	-0.000	-0.001	-0.002***	-0.000*	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Conflict	-0.016***	-0.009**	-0.025***	-0.001	-0.000	-0.001
	(0.004)	(0.003)	(0.007)	(0.002)	(0.000)	(0.002)
W * Change in subnational GDP per capita (2000 – 2015)		0.6541***			0.1740***	
		(0.0506)			(0.0496)	
Country-fixed effects		No			Yes	
Observations		2,894			2,894	

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

Notes: Tables show direct, indirect, and total effects based on generalized spatial two-stage least squares regressions. The dependent variable is real per-capita GDP growth by subnational area, 2000-2015. Conflict is instrumented by the standardized evapotranspiration index (SPEI). Figure (B) shows the within-country effects.

Table 7: Global Moran's *I* statistics and test results with alternative spatial weighting matrices

Spatial weighting matrix	First- or second-order contiguity	First-order contiguity	Rook contiguity	Inverse distance	Inverse distance truncated at 500 km	Inverse distance truncated at 1000 km
Moran's *I*	0.4214	0.4934	0.4934	0.4900	0.1701	0.3643
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 8: Benchmark regression results by income groups

	Low income					
	(A)			(B)		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Subnational GDP per capita (2000, Ln)	-0.001	-0.001	-0.002	-0.008***	0.000	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Agriculture suitability	0.010**	0.006*	0.016**	0.007*	0.000	0.007*
	(0.004)	(0.002)	(0.006)	(0.003)	(0.000)	(0.003)
State exposure (Ln)	0.002**	0.001**	0.003**	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Malaria	-0.011*	-0.006*	-0.018*	-0.013*	0.000	-0.013*
	(0.005)	(0.003)	(0.008)	(0.007)	(0.001)	(0.007)
Oil & gas deposits	0.005*	0.003*	0.008*	-0.002	0.000	-0.002
	(0.002)	(0.001)	(0.004)	(0.002)	(0.000)	(0.002)
Elevation (meters, Ln)	-0.004***	-0.002***	-0.007***	-0.002**	0.000	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Distance to the nearest port (meters, Ln)	0.001	0.001	0.002	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Expected years of schooling (1998-2002, Ln)	0.002***	0.001***	0.004***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Travel time to the nearest city (mins.)	0.004**	0.002**	0.006***	-0.002*	0.000	-0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Conflict	-0.001	0.000	-0.001	-0.003	0.000	-0.003
	(0.002)	(0.001)	(0.003)	(0.002)	(0.000)	(0.002)
W * Change in subnational GDP per capita (2000 – 2015)		0.5694***			0.0431	
		(0.0616)			(0.0620)	
Country-fixed effects		No			Yes	
Observations			1,053			

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

Notes: Tables show direct, indirect, and total effects based on spatial autoregressive regressions by income groups. The dependent variable is real per capita GDP growth by subnational area, 2000-2015. Figure (B) shows the within-country effects.

	Lower-middle income					
	(A)			(B)		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Subnational GDP per capita (2000, Ln)	-0.011***	-0.002*	-0.013***	-0.009***	-0.001*	-0.010***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Agriculture suitability	0.009**	0.001*	0.010**	0.004	0.001	0.004
	(0.003)	(0.001)	(0.003)	(0.003)	(0.000)	(0.003)
State exposure (Ln)	-0.001	0.000	-0.001	-0.001	0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Malaria	-0.024***	-0.004**	-0.028***	-0.024**	-0.003	-0.027**
	(0.004)	(0.001)	(0.004)	(0.008)	(0.002)	(0.009)
Oil & gas deposits	0.000	0.000	0.000	0.001	0.000	0.001
	(0.002)	(0.000)	(0.002)	(0.001)	(0.000)	(0.002)
Elevation (meters, Ln)	-0.001	0.000	-0.002	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Distance to the nearest port (meters, Ln)	-0.001	0.000	-0.001	-0.002*	0.000	-0.002
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Expected years of schooling (1998-2002, Ln)	0.001	0.000	0.001	0.001	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Travel time to the nearest city (mins.)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Conflict	-0.003*	-0.001	-0.004*	-0.002	0.000	-0.003
	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)
W * Change in subnational GDP per capita (2000 – 2015)		0.2384***			0.2000***	
		(0.0789)			(0.0734)	
Country-fixed effects		No			Yes	
Observations			873			

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

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