Surveys in Mathematics and its Applications

ISSN 1842-6298 (electronic), 1843-7265 (print)
Volume 10 (2015), 113 – 137

PUBLIC SERVICE ALLOCATION, SOCIAL UTILITY AND SPILLOVER EFFECTS: A REVISED BENEFIT INCIDENCE APPROACH

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Abstract. In many developing countries, public service provision continues to fall short of demand. In the presence of severe infrastructure backlogs and different returns on public investment expenditure, marginal benefit incidence theory envisages that measures aimed at maximizing average access rates have contradictory impacts in the medium term. While relatively uniform expansion of access coverage across target areas can be achieved in some sectors, geographical disparities may persist or worsen in others. This study revises and extends a previous modeling approach by testing for endogenous eligibility, geographically-varying functional relationships, and number of uncompensated losers (*numbers effect*) as an additional social welfare objective. Relative to medium-term changes in access rates in primary schools and healthcare, spatial and geographically weighted regression models are applied to districts in Niger. Results point to an eligibility threshold which exceeds the average coverage rate for primary education, some evidence of *numbers effect* as a target for healthcare, and substantial spatial heterogeneity particularly for primary schools.

1 Introduction

In many developing countries, public service provision continues to fall short of demand. The geographical distribution of public services and infrastructure in a developing country can be assumed to depend on its social utility function. To assess the marginal impact on beneficiaries of public expenditures and related service expansion across regions and/or income quintiles, benefit incidence analysis (BIA)

2010 Mathematics Subject Classification: 91B16; 91B18; 91B72.

Keywords: social welfare function; regional planning and public services; spatial and geographically weighted regressions.

This research was carried out while the author was associate professor at the Dept. of Informatics and Econometrics of UKSW - Card. S. Wyszyński University in Warsaw, following a first analysis undertaken when he worked for UNDP in Niamey, Niger.
The author would like to thank participants at AREUEA International Conference, Hebrew University of Jerusalem, June 2013, for helpful comments.

is usually applied (unlike *expenditure* incidence analysis, which is focused on service providers; Ajwad and Wodon [2]). Social utility is generally assumed to depend on average access to a service, to be maximised subject to a budget constraint and without assuming *a priori* social and regional redistribution targeting. The marginal impact of public expenditure and related service expansion paths will reflect eligibility criteria and spatial effects consistent with this goal, and will vary across sectors. With successive improvements in average access rates, cross-district disparities can be envisaged to increase for sectors with severe backlogs in public access coverage especially in rural areas, and with no adequate targeting of poor groups (for instance, for healthcare, particularly with regard to hospital-based services). Conversely, these disparities can be expected to decline for sectors which have already reached a more uniform distribution of utilities, such as primary schools. In an alternative scenario, the allocation of improved or newly established public services may follow different objective functions, such as redistribution in favour of poorer districts or creation and development of a few 'growth poles' regardless of equity objectives ([18]).

The hypothesis of different marginal benefit paths across public service sectors can be tested on municipalities or districts within a national territory, or within administrative regions in a decentralised system. Econometric estimates from spatial Tobit models (with spatially weighted variables accounting for diffusion effects) applied to primary education and healthcare across districts in Niger, suggest more articulated patterns than the above arguments ([27]): both sectors appear to benefit from 'autonomous' gains for worse-off districts, but hardly any additional gain is found to accrue to these districts in terms of average treatment effects, relative to districts randomly selected after accounting for socio-demographic characteristics (with no selectivity bias based on Tobit estimates). However, econometric results of that previous study rely on two alternative values for (a) the eligibility thresholds (chosen *a priori* based on initial-period average rates of public service coverage across districts and individuals, without testing for looser or stricter selection criteria), and (b) the diffusion cut-off distances, respectively.[1]

This analysis substantially revises and extends this modelling approach in three directions, with a view to testing whether (i) revealed eligibility thresholds over- or understate the average rates of access coverage, thus not closely reflecting BIA assumptions, (ii) the geographical diffusion of service provision is in line with reducing the number of uncompensated losers as an additional social welfare objective (Bentham's *numbers effect*, which in the income distribution literature is equated to numbers below the poverty line, and here to numbers remaining without access to public services), and (iii) marginal improvements in public service delivery are characterised by spatial heterogeneity, thus implying biased and inefficient OLS regressions. With a reapplication to the above BIA case study, the analysis therefore queries an *a priori* use of average accessibility as a universal yardstick (to distinguish worse off from better off target areas), an exclusive focus on distribution and efficiency as social welfare objectives, and unique functional relationships across regions of a country (which imply uniform spatial dependence without local variations). The remainder of this paper proceeds as follows: in section 2, theoretical elements are reassessed and linked to the econometric modelling with global spatial regressions and geographically weighted regressions (GWRs); section 3 reports and discusses the econometric results for primary education and healthcare in Niger, while section 4 draws concluding remarks.

2 Benefit incidence analysis

2.1 Theoretical background

Accessibility and standards of public services can be explained by three types of determinants, which vary across (and within) target areas, as follows: (i) valuation of and willingness to pay (WTP) for services by residents, (ii) distribution weights in the social welfare function (SWF) of central and local governments, and (iii) costs of public service delivery. *Ex post*, the first and third type of determinants can be relied on to measure the value to beneficiaries of government-subsidised services, based on virtual prices reflecting individuals' own valuation of these services and marginal costs of providing the services, respectively ([12]). Conventional BIA studies typically focus on the unit costs of provision, but this may seriously understate the value of the benefits to an individual (e.g. cost of child immunisation campaign compared with lifelong effects), while the scope for using social indicators and non-monetary measures of impact is still scarcely investigated ([35]).

Most households will be reluctant to settle in remote areas due to inadequate access to public utilities. In Tiebout's seminal contribution ([34]) of a local government model in a developed country, consumers are assumed to be fully informed on differences in local public goods and services, and preferences are largely met by individuals' free movement within the country. In many developing countries, internal migration is limited and local communities have only a minor role in design and planning of public services (on the non-engagement of healthcare 'teams' at district level in Niger, see Meuwissen [28]). Therefore, issues related to distribution weights and cost of service provision are likely to be more relevant factors, while the WTP criterion can have an indirect impact with government perceptions of consumer preferences partly reflected by distribution weights attached to gains/losses of different social groups.

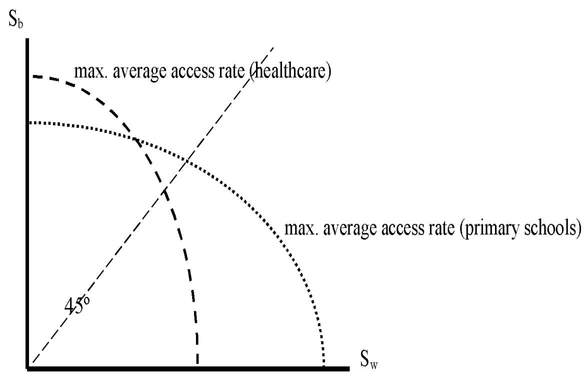
In an aid-dependent low-income economy as Niger, distribution weights and costs of public service delivery will also be influenced by donors' public spending priorities. The extent to which and likely pro-poor direction which foreign aid can exercise as a leverage on public sector and regional planning would deserve an accurate analysis, which could consider the role of sound economic policies and institutions, and effective interaction and collaboration between donor countries and local government. High rehabilitation backlogs in some public infrastructure in Africa appear to be the consequence of past misallocations by both recipient and donor countries: for instance, the earmarking of foreign funds on concessional terms for new road construction has raised the relative cost of maintenance funds for domestic markets, with road maintenance tending to be neglected given its less visible immediate impact and more easily deferred investment ([8]). Even if this topic lies beyond the scope pursued here, one can assume that donors largely share (or at least they should share within transparent and sound institutional environments, especially with the 'new' conditionality of recent years; Mosley *et al.* [30]) the same development goals, namely maximising the shadow-priced net benefits to the recipient country, which account for distribution and other social welfare objectives.[2]

In a developing economy, the public sector allocation will vary according to type of service and infrastructure needs ([3]). Public services which register relatively higher average access rates and are less dependent on a pre-existing infrastructure grid can be envisaged to follow a more balanced diffusion process and be largely pro-poor even in the absence of outright pro-poor policies, except if public authorities pursue anti-egalitarian strategies. This pattern can be illustrated by primary schools, which do not require substantial infrastructure investment in remote districts. When they require instead substantial infrastructure and severely fall short of universal coverage, public utilities expand more easily in and around districts which are already partly endowed with the needed infrastructure (unless equalisation of service provision is striven for as an urgent priority). In the medium term, service improvements may turn out to remain skewed in favour of the non-poor, even though social policies are not openly biased against the poor: maximising local service access is less costly when delivery expansion is close to pre-existing infrastructure, where residents exercise pressure for adequate service coverage and quality. Healthcare is likely to follow this second pattern, with sparsely populated, poor districts often benefiting marginally from public investment. For some public services, costly coping mechanisms (e.g., water from trucks supplementing piped water supply; Walker *et al.* [37]) are often the only option for many residents in areas with poor infrastructural coverage. This typically concerns basic services such as telephone, water and electricity, and is regarded by some authors as evidence against the rationale for low user charges. In this view, rationing of excess demand might restrict subsidised services to richer households, and can be redressed by adopting high user charges coupled with discriminatory pricing (Thobani [33]; among counterarguments in recent years, see Fredriksen [19]).

In terms of marginal incidence within a reference (e.g. 4-year) period, each sector can be assumed as in Ajawad and Wodon ([2], [3]) to face a separate, exogenously set budget, which reflects the types of determinants discussed above and is allocated between districts with relatively better and worse socioeconomic conditions and infrastructure coverage ($E = E_b + E_w$, with b=better off, w=worse-off, E=expenditure). In each district, the average access rate to a public service (S_i, with $i = b, w$) is a function of allocated expenditure, i.e. $S_i = f_i(E_i)$, which is increasing and strictly concave for both district groups, thus being $f_i' > 0$ and $f_i'' < 0$. Prior to reaching optimal delivery with universal access, for any given level of expenditure E_z $(0 < E_z < E_{max})$, worse-off districts will lag behind in access coverage $(f_w(E_z) < f_b(E_z))$.

In the long-term, starting from a non-uniform spatial distribution of assets, people in better off districts are largely net contributors to social infrastructure projects, while people in poorer districts are mostly receivers of net transfers ([26]). However, in the medium term and assuming budget-constrained maximisation of average access rates, marginal improvements in access rates $(f_i'(E_i))$ will reflect the above patterns, i.e. $f_w'(E_w) < f_b'(E_b)$ for healthcare as long as no sufficient infrastructure network is in place, and $f_w'(E_w) > f_b'(E_b)$ for primary schools. With the marginal impact of spending in poorer districts being relatively lower for healthcare, and higher for schools, public authorities will target points on the production possibility frontiers (Fig. 1) to the left of the 45° line (where $S_w = S_b$) in the former sector, and to the right in the latter (transformation curves are elongated in the direction of respective returns on investment).

Figure 1: Public service production possibility frontiers



Primary education (dotted line) vs. healthcare and basic infrastructure services (dashed line)

2.2 Accounting for uncompensated losers

A programme of expansion of social services will be selected if its shadow-priced net benefits are higher than any alternative competing project. Net benefits are measured as the difference between the benefits received by the private sector and the costs incurred by the public sector, subject to the minimal approval condition that $B(Q) - C(Q) > 0$. As in Orr ([31]) and Brent ([6]), the social utility function of taxpayers as a group can be assumed to positively depend not only on own income, but also on transfers in favour of poorer residents (i.e. 'commodity [or service] interdependence'), with psychic and possibly indirect economic benefits from supporting welfare programmes in the form of in-kind transfers.[3] However, particularly in a least developed country such as Niger, the scope for interdependence in social group utility functions of taxpayers in better off districts is bound to mainly concern recipients in the same districts: positive externalities from the provision of basic healthcare and education for the poor are likely be felt within districts or, more broadly, regions, but more hardly so across regions.

In benefit incidence theory applied to public services, the SWF of central and local government depends on an efficiency objective, represented by average service access coverage, and possibly a distribution objective, with socioeconomic group-specific distribution weights. In the simple dual framework of sub-section 2.1, these weights can be defined as v_b and v_w, for better off versus worse off individuals (and the respective districts), with fairness in distribution implying $v_w > v_b$. If budget-constrained maximisation of average access rates is pursued in the presence of severe cross-district imbalances in infrastructure coverage, efficiency is likely to be targeted as first priority, with a clearer trade-off relative to distribution.

Define an index s of public service access as a random variable with density $f(s)$, with an eligibility access threshold s^* separating better off from worse off individuals. The access variable s can be based on an inverse scale of physical distance of each household's residence from the nearest public service utility (with $s \cong 0$ no access, and $s \to \infty$ prompt access). Following the additive decomposition property of integration, the SWF can be formulated as a weighted average of mean access of the population below and above the threshold, respectively (as given by the first and second terms of equation (2.1). This reflects an efficiency objective, i.e. maximising the average access, and a distribution objective, captured by the weights v_w and v_b. As in Brent ([7]) relative to a multi-objective SWF accounting for economic efficiency, income distribution and *numbers effect*, the number of uncompensated losers (N) is added here as a third objective in the SWF (a parameter α_N measures a social negative weight on N, and its subscript denotes that this weight also depends on social valuations of individuals in N).

$$W = v_w \int_0^{s^*} sf(s)ds + v_b \int_{s^*}^{\infty} sf(s)ds + \alpha_N N \tag{2.1}$$

Mean access μ can be expressed as $\int_0^{\infty} sf(s)ds$. The mean access (weighted by the respective headcount ratio) of residents below the threshold is given by:

$$\mu^* = \int_0^{s^*} sf(s)ds / \int_0^{s^*} f(s)ds = \mu[F_w(s)/F(s)] \tag{2.2}$$

where $F_w(s)$ is the share of total service access by residents below the threshold $(= [\mu^* F(s)]/\mu))$, and $F(s)$ the headcount ratio (i.e. ratio of residents below the threshold to total country residents). Hence, (2.1) can be rewritten as:

$$W = v_w \mu F_w(s) + v_b[\mu - \mu F_w(s)] + \alpha_N N = (v_w - v_b)\mu^* F(s) + v_b \mu + \alpha_N N \quad (2.3)$$

With no inclusion of *numbers effect* as a separate objective ($N = 0$ or $\alpha_N = 0$), a two-objective SWF violates an equity-related axiom: a marginal increase in the share of residents below the threshold brings about a decline in social welfare only if the inequality between distribution weights is reversed, that is: $\partial W/\partial F(s) < 0 \leftrightarrow v_b > v_w$. If each individual receives the same weight in society (after controlling for v_w and v_b)[4], the *numbers effect* can be re-expressed as $\alpha_N N = \alpha(N/P) \leq \alpha F(s)$ (with P population size). In this case, the inclusion of a separate additive term accounting for the uncompensated losers avoids the above violation as long as the parameter α complies with the restriction:

$$\alpha < -(v_w - v_b)\mu^* < 0 \quad (2.4)$$

In a dynamic framework of public access improvements across districts, an operational functional form corresponding to (2.3) can be expressed as:

$$\Delta lnS_i = v_b \mu + \beta X_i + [(v_w - v_b)\mu] r_i + \gamma N_i + \epsilon_i = \theta + \beta X_i + \delta r_i + \gamma N_i + \epsilon_i \quad (2.5)$$

where the rate of change of service access by district (hence with S_i in logarithmic form, with $i = b, w$)[5] is modelled linearly in terms of a constant, a component of observable characteristics expressed in a vector of variables X_i, an eligibility binary variable r_i based on an access threshold ($r_i = 0$ for $S_i > S^*, r_i = 1$ for $S_i \leq S$), a proxy N_i for the *numbers effect*, and a component of unobservable factors (given by the zero-mean error term ϵ_i). If the distribution objective matters, the gain in mean access for worse off districts is measured by the parameter δ, while γ is an *ex post* parameter associated with N in (2.3) ($\gamma = 0 - \alpha_N = -\alpha_N = -\alpha/P_i$, with 0 corresponding to an ideal outcome without uncompensated losers). Eq. (2.5) can be seen as a restricted version of a switching regression model ([36]: 262), given two regimes, that is in this case public access improvement vs. lack thereof. Alternatively, if spatial heterogeneity is present with no well-defined threshold, this would justify GWR with no use of dummies, and r_i in (2.5) would be replaced with a proxy for initial access conditions, which would also capture geographically varying spatial diffusion (Table 1: *lnhca*, *lnsch*).

3 Econometric results

3.1 Data sources

Statistical sources of the variables, based on official census and survey information, are reported in Table 1, along with related descriptions and summary statistics. Previous econometric results on the same data for Niger found that district population and average household size are relevant control variables in regressions explaining medium-term expansion of service access in primary education and healthcare, respectively ([27]). Therefore, these variables have been retained for this analysis. Similarly, spatial spillovers across the national territory are proxied by two spatially lagged variables used in that study, with spatial weight matrices based on the minimum distance threshold of 239 km (so defined since each observation has at least one neighbor) or, alternatively, a threshold of 420 km. The latter is closer to an average cross-district connectivity level in the country, as it amounts to 2/5 of the range between minimum and maximum feasible distances.[6]

Indicators of *numbers effect* are based on the number of residents in primary school age who are not enrolled to school (Table 1: *Nsch*), and residents living more than 5 km from a healthcare centre (*Nhca*). Due to this choice of proxies for the *numbers effect* (in the absence of more detailed disaggregate information), in this case $N/P = F(s)$ in sub-section 2.2. To account for three agro-climatic zones in Niger, isohyets-delimited zone dummies have been used: Sahelo-Saharan (/Saharan) areas represent the implicit category, as distinct from Sahelian and Sahelo-Sudanian (/Sudanian) areas which correspond to central and southern isohyets, respectively (defined in Table 1, with regions and districts listed underneath).[7] To partly redress rightward-skewed patterns in data distributions, indicators of access coverage and population are transformed in natural logarithms. As the dependent variables are log-differenced, this allows direct estimation of elasticity parameters. Across global spatial regressions and with other variables unaltered, 5% shifts in eligibility thresholds (Table 1: dummy r) around the ranges used in Mainardi ([27]: *a priori* thresholds were 40% and 50% for healthcare, and 50% and 60% for primary education) allow testing the relevance of average access rates as a yardstick for targeting 'worse off' districts. For space reasons, Table 2 reports a number of selected grid-search estimation results, based on statistical significance of the eligibility dummy parameter.

3.2 Spatial regression estimates

Results of spatial regressions show a good explanatory power in terms of adjusted R^2, particularly for primary schools, with failed rejection of the hypotheses of residual non-normality and serial correlation (Table 2; residual autocorrelation might arise due to the cross-district sample design, given geographically contiguous observations). Neither the district population (results not shown), nor its location in terms of agro-climatic zone appear to substantially matter for changes in access to public healthcare, while they do for the respective changes in access to primary education. Unlike results of previous (Tobit: see note 1) model estimates, household size does not turn out to have a significant explanatory role for healthcare.

Relative to spatial diffusion effects, shorter-range diffusion seems to predominate for primary schools (Table 2: *lnsch(sp-min)* vs. *lnsch(sp)*). Relative to healthcare

Figure 2: Regions of Niger

instead, the cut-off distance near an average connectivity level yields spatial parameter estimates with relatively higher statistical significance (*lnhca(sp)* vs. *lnhca(sp-min)*). Regardless of values of the eligibility dummy, worse off districts are found to register additional gains in access over the medium term, with results being nearly equivalent for the two sectors. By contrast, the *numbers effect* turns out to be either irrelevant, as a criterion for primary schools (with a negative parameter sign for the variable *Nsch*), or not to play a definite relevant role, as highlighted by mixed evidence in terms of statistical significance of the positive parameters associated with the variable *Nhca* (Table 2).[8]

If regression results based on a 45% threshold are relied on, the respective healthcare regression specification (Table 2: H3) yields estimates suited to test the parameter inequality restriction for equation (2.3) (sub-section 2.2). Based on the median value of the cross-district population in 2003 (P_i) and the average healthcare coverage rates in the initial period of 2000-01 of (i) districts under or equal to the 45% threshold and (ii) the whole district sample, and assuming that the ratio of these rates approximately corresponds to the ratio of the respective latent mean access indices (μ^*/μ), the result would be compatible with restriction conditions (2.4), i.e., with reverse signs: $-\alpha_N(P_i)(= -\alpha) = 0.0009(306.08) = 0.275 > \delta(\mu^*/\mu)(= (v_w - v_b)\mu^*) = 0.17(0.31/0.37) = 0.142 > 0$. However, the grid search on eligibility dummies, also based on the alternative cut-off distances in spatial weight matrices, suggests thresholds of 40% for healthcare (for which the parameter associated with the *numbers* effect is statistically insignificant), and 55-60% for primary schools (Table 2: H2 and S2-S3). The former percentage figure is close to the cross-district average access rate for healthcare, which was nearly 38% in 2002-03, while the latter tends to overstate the respective figure for primary education (51.5% in 2004-05).

3.3 GWR estimates

A general specification of a GWR model can be expressed as follows:

$$y_i = \beta_{0i}(u) + \beta_{1i}(u)x_{1i} + \beta_{2i}(u)x_{2i} + ... + \beta_{ki}(u)x_{ki} + \epsilon_i \tag{3.1}$$

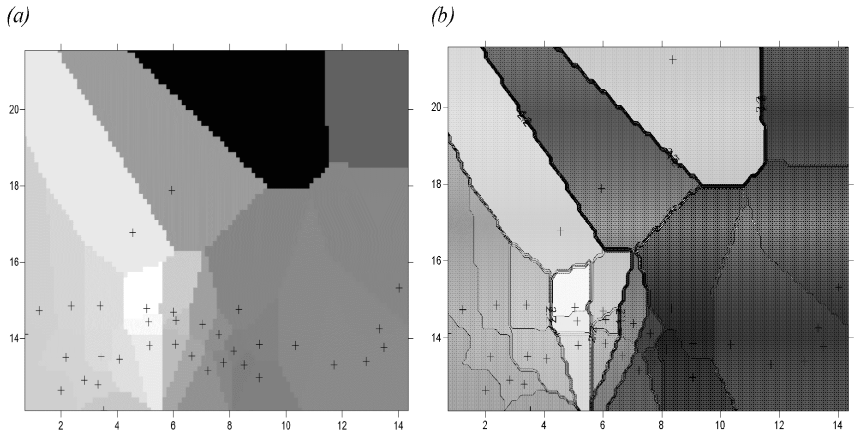
$$\beta(u) = \left(X'W(u)X\right)^{-1} X'W(u)y \tag{3.2}$$

$$w_i(u) = [1 - (d_i(u)/\delta_i)^v]^v \qquad\qquad (d_i(u) < \delta_i) \tag{3.3}$$

The regression parameters $\beta_{zi}(z = 0, 1, ...k)$ in (3.1) are realisations of continuous functions $\beta(u)$ at location point $i(u)$ (with u a vector of geographical coordinates), and ϵ_i is an independently normally distributed random error term ([9]). If $\beta(u)$ is constant across spatially independent sample observations, (3.1) can be estimated with OLS. If $\beta(u)$ varies following a decay function which reflects the geographical principle of distance-decay, (3.1) can be estimated by GWR, which is a weighted least squares estimator with weights conditioned on location u (eq. (3.2)). As an adaptive decay weighting scheme, which varies according to the density in the neighbourhood of each focal point (with less steep weight functions for e.g. regions with more sparse districts), a bi-square (near-Gaussian) kernel is nested in (3.3) (for $v = 2$; $w_i(u) = 0$ if $d_i(u) \geq \delta_i$). For samples with irregularly distributed locations and area sizes such as the case of districts in Niger, adaptive kernels are more suitable than fixed kernels ([25]). The bandwidth parameter δ_i delimits the maximum distance of local spatial dependence around a location, and the related optimal number of kernel points (Table 3: n) can be chosen based on minimum cross-validation regression error sum-of-squares (omitting the i^{th} observation) and/or lowest Akaike Information Criterion ($\mathrm{AIC_c}$, corrected for small sample bias and tendency to undersmooth in kernel estimation; [14]: 8; [22]). In this analysis, both criteria have led to selection of bi-square kernels with the same number of points.

In terms of adjusted R^2 and $\mathrm{AIC_c}$, GWR models are found here to outperform classical OLS regressions with the same independent variables (e.g., an OLS regression with the same regressors as H7 -in Table 3- yields an $\mathrm{AIC_c} = 9.33$).[9] This indication is also supported by statistically significant joint-parameter spatial non-stationarity F-tests, especially for primary schools (Table 3, BFC-F: S6-S7; [10]). Similarly, Monte Carlo significance tests on individual local parameter estimates partly reject the hypothesis of no spatial variability, particularly for the primary education sector ([9]). Moreover, the standard errors of parameters turn out to be underestimated by OLS in some cases, as ranges corresponding to 68% confidence bands (i.e. $\beta_{(OLS)} \pm \sigma_\beta$) do not exceed inter-quartile ranges of the respective GWR parameters, which make up 50% of these estimates (Table 3: (IQR)*). Upper and lower extreme values of local parameters also show in some cases sign reversal relative to global regression and median-level GWR parameters, relative to district population (with some negative local parameters in GWRs) and the proxies for *numbers effect* (*Nhca*, *Nsch*).

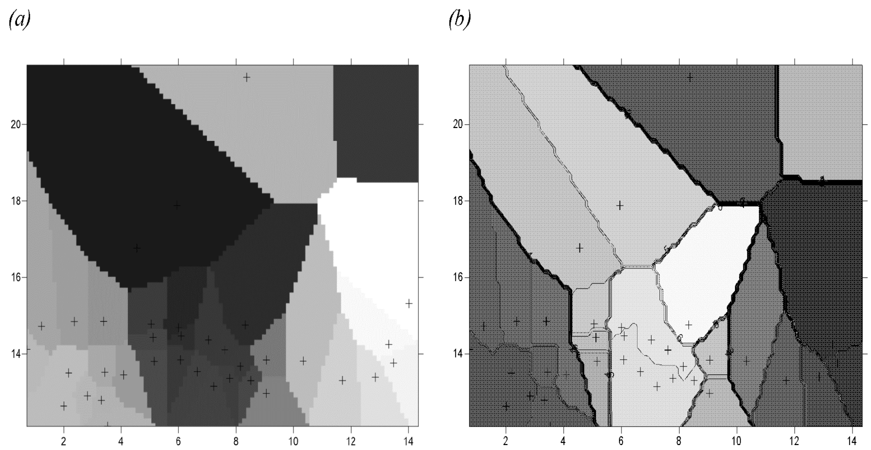
Figure 3: Local impact on healthcare: GWR parameters and t-statistics for the *numbers effect*



Variable: *Nhca* (model [H6]). Lighter shading for nearest neighbour grid nodes with (a) higher parameter estimates, (b) higher t-statistics in absolute values (mean: t=1.35 [min. 0.2, max. 2.81]). Geographical location coordinates indicated in the surface map.

Regression diagnostics of goodness-of-fit, a residual normality test (based on a small sample correction to the Jarque-Bera test; see Hendry and Doornik [21]), and relatively less collinear local parameter estimates ($\rho(\beta_{zi})$) give preference to models H6 and S7 among alternative GWR specifications and different initial reference periods, for healthcare and primary schools respectively (see Table 3). Based on econometric results of these models, improvements in public healthcare access have been relatively less responsive on average to initial coverage rates, but more consistent in terms of *numbers effect* and less spatially unstable, compared with the primary education sector. To better understand GWR results, nearest-neighbour grids of local parameters and related t-statistics for the *numbers effect* can be visualised in Figures 3 and 4, for H6 and S7 respectively. The maps highlight heterogeneous local impacts on public service access in terms of numbers of uncompensated losers: *ceteris paribus*, while for healthcare some central-western districts (Illela and Tahoua, among a few others) turn out to have 'benefited' most, for primary education the *numbers effect* appears to have been relatively better targeted in the south-east (in districts such as Diffa and Nguigmi). [10] Relative to the education sector, local population size turns out to be especially relevant as a factor associated with improved access coverage for districts in the south-central regions of Maradi and Zinder, such as Tessaoua and Tanout (Fig. 5).

Figure 4: Local impact on primary education: GWR parameters and t statistics for the numbers effect

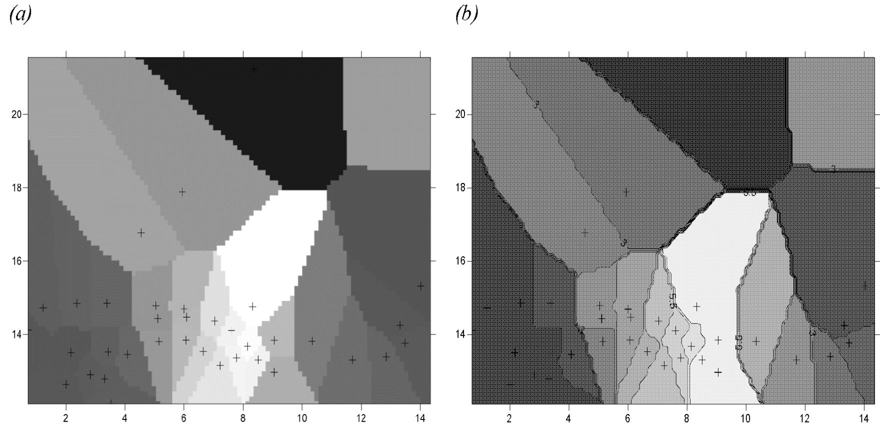


Variable: *Nsch* (model [S7]). Lighter shading for nearest neighbour grid nodes with (a) higher parameter estimates, (b) higher t-statistics in absolute values (mean: t=3.42 [min. 0.8, max. 6.93]). Geographical location coordinates indicated in the surface map.

4 Conclusion

Interventions designed to improve access to public services are influenced by socio-economic, demographic and location characteristics of demand in different sectors. Partly associated with these characteristics, supply-side political factors and complementarities between public utilities, such as healthcare versus public transport, are also relevant determinants ([17]; [32]). While relatively uniform expansion of access coverage across target areas can be achieved in some sectors, geographical disparities may persist or worsen in others. In sectors with lagging infrastructural development and/or relatively lower average rate of access, residents of better off districts tend to live closer to pre-existing infrastructural networks and efforts are needed to ensure increased marginal benefits to residents of worse off districts. However, as long as there is no adequate coverage and subsidised services are concentrated on facilities in richer areas, public services will more easily expand in better off districts ([2]). This can typically be the case of healthcare in the presence of a weak health insurance market. In sectors with more widespread public coverage, more evenly subsidised

Figure 5: Local impact on primary education: GWR parameters and t statistics for population



Variable: *lnpop* (model [S7]). Lighter shading for nearest neighbour grid nodes with (a) higher parameter estimates, (b) higher t-statistics in absolute values (mean: t=3.14 [min. 0.09, max. 6.06]). Geographical location coordinates indicated in the surface map.

services, and no large investment requirements, benefit incidence theory predicts the opposite case as more likely to occur.[11]

Based on a grid search of access rate thresholds, the *ex post* threshold revealed by spatial regressions turns out to exceed the average cross-district access rate for primary schools in Niger, thus suggesting looser selection criteria for public investment in this sector. As a second issue focused on here, to avoid violating an SWF equity-related axiom, the number of uncompensated losers should be treated as a separate social objective, distinct from efficiency and distribution. For public healthcare, the *numbers effect* proxy has the expected positive sign. However, relative to this effect, econometric estimates for both sectors are to some extent sensitive to shifts in the eligibility dummy, use of population as a control variable, and spatial heterogeneity.

Results of global spatial regressions and regressions with spatially varying bandwidths cannot be easily compared. Relative to primary education, spatial regressions yield statistically significant parameters associated with agro-climatic dummies, thus implying that in this case spatial heterogeneity can partly be accounted for by spatial regimes. However, spatial weight matrices are based on two *a priori* cut-off distances, which are assumed to represent possible spillover effects with relatively shorter and longer ranges: if long-T panel data were available, a more accurate procedure would be to directly estimate the spatial weight matrix ([5]). On the other hand, highly collinear GWR local coefficients can be associated with model instability: this is found relatively often in GWR applications ([38]), and may partly concern some GWR results of this analysis (Table 3: $\rho(\beta_{zi})$). Similarly to limitations of OLS in terms of degrees of freedom for estimation, with small sample sizes an increased risk of spurious correlations between local coefficients can lead to failure of GWR to more thoroughly detect spatial heterogeneity, relative to results achievable with larger datasets ([16]). Rather than regarding them as rival modelling approaches and notwithstanding limitations in data availability in developing countries such as Niger, both spatial regression and GWR can help shed light on factors influencing changes in the geographical allocation of public service delivery in a low-income economy. To gain further insights, the analysis would also benefit from spatially disaggregated time series information when it becomes available (so as to cross-check results based on more refined spatial scales), and from applications to other developing countries.

Notes

[1] A rationale for Tobit modelling lies in a presumed greater degree of inaccuracy of annual surveys in correctly capturing access reversals in Niger. Over the reference periods, negative changes concern four and sixteen observations for primary education and healthcare, respectively. Due to sample size constraints and for better comparability with GWR regressions, this analysis relies on full sample information, including negative changes.

[2] Although aid conditionality exercises policy leverage on local governments, ultimately it is largely up to the latter to decide which expansion paths to follow. For instance, Niger has lagged behind all other low-income countries in Africa in terms of sanitation facilities in rural areas (with only 20% of schools having improved latrines), and this is attributed to low priority for government and local authorities ([40]).

[3] Taking this to an extreme, Jenkins at al. ([24]) argue that transfer programmes, such as provision of free primary education, typically target welfare, not utility of the recipients, with the recipients' welfare being defined by taxpayers. This sub-section partly draws on Brent ([7]) for theory, and Wooldridge ([39]) for regression specifications geared to assess the welfare impact of public programmes. As efficiency objective, mean income is replaced here with mean accessibility to a public service.

[4] This assumption contradicts the WTP criterion, which is a basic underpinning of cost-benefit analysis. As observed by Yitzhaki ([41]), this contradiction is avoided only if this criterion is more than offset by a declining social evaluation of the marginal utility of income (/access to public services) with increasing levels of income (/access).

[5] Assuming a linear relationship of W with righthand variables in (2.5) and given a medium-term time interval ($t = 0, 1$), this implies that $exp(W_{it}) = (S_{i1}/S_{i0})$ and $W_{it} = dlnS_{it}$. This complies with a diminishing marginal utility (concavity) assumption on the SWF (unlike a constant marginal utility assumption if absolute changes ΔS_{it} are taken instead).

[6] The weighting criterion used to construct the spatially lagged variables was based on geographical arc-distances d_{ij} between UN-SALB admin 2-level (=district) centroids of unprojected spherical maps. These distances were estimated with the software GeoDa ([4]). GWR model estimation and related surface maps are based on GWR 3 and Surfer 9, respectively ([15]; [20]).

[7] Administratively, Niger consists of seven regions (plus the capital Niamey, which forms a separate administrative unit; Fig. 2), subdivided into 36 districts (*départements*).

[8]The role of the numbers effects for primary schools turns out to remain irrelevant even if, due to some degree of multicollinearity, population is removed from the regression specification or it is replaced with household size as a control variable: in either case, parameter estimates associated with the variable *Nsch* are statistically insignificant (and the same applies to *hsize*).

[9]The use of $\mathrm{AIC_c}$ instead of AIC is recommended when $N/k < 40$ for the largest-k model ([11]). For models based on the same sample and number of parameters, $\mathrm{AIC_c}$ (and AIC) is analogous to adjusted R^2 in terms of model selection, but the two criteria may differ for different numbers of explanatory variables (hence, $\mathrm{AIC_c}$ estimates in Table 2 are provided for comparisons with regression models in Table 3; Charemza and Deadman [13]).

[10]One should notice that also in terms of dependent variables (*dlnhca* versus *dlnsch*) there is no similarity in cross-district patterns of medium-term access changes, with low linear correlation between these variables ($\rho = 0.2$).

[11]As a matter of fact even at national average levels across countries, according to a wider range of social welfare criteria for the impact of public spending (including BIA applied to income groups), primary education and housing expenditures are found to be consistently pro-poor, while healthcare is not, and as such it is excluded from a composite weighted index of 'pro-poor public expenditure' (including agriculture, water and sanitation, and social security, besides education and housing; Mosley et al. [30]).

Table 1: List of variables and descriptive statistics

Variable	Definition	Sources	Mean	Min.	Max.	Standard dev.	Skewness	Kurtosis
Dependent (censored) variables								
dlnhca	marginal benefit (/cost) in access to healthcare (logarithm of ratio of healthcare access rates: 2007 vs. 2000-01)	MSP/LCE [29] and Niger-Info	0.07	-0.49	0.68	0.28	0.04	2.31
dlnsch	marginal benefit (/cost) in access to primary education (logarithm of ratio of gross primary enrolment rates: 2008-09 vs. 2004-05)	Niger-Info (www.ins.ne)	0.25	-0.24	1.13	0.26	0.77	4.71
Demographic indicators (2004-05)								
hsize	average number of persons per household	INS ([23])	6.72	4.75	9.72	1.23	0.47	2.43
lnpop	population (thousands, natural logarithm)	INS ([23])	5.52	2.94	7.03	0.9	-1.36	4.47
Healthcare								
lnhca	% population residing within 5 km from a healthcare centre (1=100%, natural logarithm; 2002-03 [*2001-02 in italics*])	MSP/LCE [29]]	*-1.07* -1.002	*-1.83* -1.83	*-0.24* -0.2	*0.39* 0.39	*-0.12* -0.18	*2.26* 2.53
Nhca	'numbers effect' in healthcare (number of people residing more than 5 km from a healthcare centre; thousands, 2003)	INS [23] and MSP/LCE [29]	197.1	3.4	451.4	108.7	0.13	2.75

Primary education								
lnsch	gross primary school enrolment rate (1=100%, natural logarithm; 2004-05)	Niger-Info	-0.68	-1.36	0.17	0.28	0.62	4.16
Nsch	'numbers effect' in primary education (number of residents in primary school age who are not enrolled in a primary school; thousands, 2006)	Niger-Info and UNESCO (www.childinfo.org)	23.9	0.19	58.84	13.46	0.34	3.09
Dummies								
isohsahel	Sahelian isohyetal zones (1 if district mostly or entirely lies between northern limit of cropping and 350 mm. rainfall p.a., 0 otherwise; Abdoulaye and Sanders [1])							
isohsudan	Sahelo-Sudanian and Sudanian isohyetal zones (1 if district lies between 350 and 800 mm. rainfall p.a., 0 otherwise; Abdoulaye and Sanders [1])							
r	eligibility for incremental expansion of public service coverage (1 if access to healthcare (/primary schooling)$\leq$ minimum threshold level in initial year; 0 otherwise)							

Table 1: List of variables and descriptive statistics

Districts (region in parentheses) according to isohyets zone (Abdoulaye and Sanders [1]): *Sahelo-Saharan* and *Saharan*: Arlit, Bilma, Tchirozérine (Agadez); Nguigmi, Nguigmi urban (Diffa); Tchintabaraden (Tahoua); *Sahelian*: Diffa, Diffa urban, Maïné-Soroa (Diffa); Dakoro, Mayahi (Maradi); Bouza, Illéla, Keita, Tahoua (Tahoua); Fillingué, Ouallam, Téra, Tillabery (Tillabéri); Gouré, Tanout (Zinder); *Sahelo-Sudanian* and *Sudanian*: Boboye, Dogon-Doutchi, Dosso, Gaya, Loga (Dosso); Aguié, Guidan-Roumdji, Madarounfa, Tessaoua (Maradi); Birni-Konni, Madaoua (Tahoua); Kollo, Say (Tillabéri); Magaria, Matameye, Mirriah (Zinder).

Table 2: Access to healthcare and primary education: spatial regression estimates

Model	[H1]	[H2]	[H3]	[H4]	[S1]	[S2]	[S3]	[S4]
r (grid search)	*35%*	*40%*	*45%*	*50%*	*50%*	*55%*	*60%*	*65%*
Dep. variable		*Dlnhca*				*Dlnsch*		
constant	1.04	0.53	0.72	0.82	0.54	0.54	0.75	1.21
	(2.01)”	(1.12)	(1.24)	(1.34)	(0.51)	(0.57)	(0.8)	(1.21)
lnpop					0.29	0.25	0.23	0.21
					(4.56)*	(4.24)*	(3.92)*	(3.24)*
hsize	0.06	0.05	0.06	0.06				
	(1.64)	(1.53)	(1.69)”	(1.48)				
Nhca	0.0007	0.0004	0.0009	0.0008				
	(1.56)	(0.99)	(2.08)’	(1.76)’				
Nsch					-0.01	-0.009	-0.007	-0.006
					(-2.6)’	(-2.54)’	(-2.05)’	(-1.51)
lnhca*(sp)*	1.42	0.92	1.17	1.24				
[dmax=420.4 km]	(3.25)*	(2.25)’	(2.41)’	(2.46)’				
lnhca*(sp-min)*		*0.59*		*2.42*				
[d_{max}=239.1 km]		*(0.38)*		*(1.33)*				
lnsch*(sp)*					*-0.1*		*0.59*	
[d_{max}=420.4 km]					*(-0.1)*		*(0.7)*	
lnsch*(sp-min)*					2.13	1.93	2.15	2.66
[d_{max}=239.1 km]					(1.62)	(1.6)	(1.8)”	(2.08)’
isohsahel	-0.025	-0.038	-0.11	-0.075	-0.36	-0.38	-0.42	-0.41
	(-0.19)	(-0.32)	(-0.75)	(-0.48)	(-3.62)*	(-4.09)*	(-4.43)*	(-3.98)*
isohsudan	-0.047	-0.038	-0.09	-0.059	-0.37	-0.33	-0.36	-0.41
	(-0.32)	(-0.29)	(-0.57)	(-0.35)	(-3.29)*	(-3.14)*	(-3.4)*	(-3.57)*
r	0.21	0.31	0.17	0.15	0.26	0.33	0.34	0.31
	(2.7)*	(4.16)*	(1.8)”	(1.12)	(3.64)*	(4.44)*	(4.41)*	(3.42)*

DW	2.13	2.2	2.04	1.97	2.01	2.33	2.39	2.34
Norm. $\chi^2(2)$	2.91	0.74	2.1	1.14	0.64	1.37	0.65	1.87
AIC_c	4.33	-4.45	8.57	10.86	-14.7	-19.85	-19.64	13.35
adj. R^2	0.42	0.54	0.35	0.3	0.6	0.65	0.65	0.59
		(0.46)		*(0.21)*	*(0.57)*		*(0.58)*	

Table 2: Access to healthcare and primary education: spatial regression estimates

In parentheses: t statistics (*p≤0.01,'p≤0.05,"p≤0.10). In italics: parameter estimates and adjusted R^2 of alternative spatial regressions (with replacement of spatial lag variable), based on (a) for healthcare (H2, H4), minimum cut-off distance, and (b) for primary schools (S1, S3), cut-off distance of 2/5 of the range between minimum and maximum feasible distances. DW: Durbin-Watson test. Norm. $\chi^2(2)$: Doornik-Hansen (residual) normality test. AIC_c Hurvich-Simonoff-Tsai corrected Akaike Information Criterion. N: 37 districts.

Table 3: GWR estimates

Model	[H5] OLS	[H6] GWR	[H7] GWR	[H8] GWR	[S5] OLS	[S6] GWR	[S7] GWR
Dep. variable			*Dlnhca*			*Dlnsch*	
intercept	-0.6	-0.69 (0.069)	-1.68* (0.9)*	-1.96* (1.18)*	-0.78	-1.78* (1.54)*	-1.57* (1.87)*
(*min.*, *max.*)	(-2.6)'	(-1.03, -0.33)	(-2.36, 1.08)	(-2.48, 0.56)	(3.42)*	(-4.19, 0.43)	(-3.89, 0.39)
lnpop			0.19* (0.17)	0.24* (0.22)*	0.14	0.22* (0.29)*	0.25* (0.31)*
(*min.*, *max.*)			(-0.28, 0.31)	(-0.18, 0.33)	(2.62)'	(-0.14, 0.71)	(-0.09, 0.7)
hsize	0.05	0.04 (0.006)	0.04 (0.009)	0.035 (0.01)			-0.04 (0.06)*
(*min.*, *max.*)	(1.27)	(0.02, 0.21)	(0.03, 0.08)	(0.026, 0.078)			(-0.12, -0.02)
Nhca	0.0002	0.0006'	-0.0006	-0.0009			
(*min.*, *max.*)	(0.57)	(0.001)* (-0.002, 0.002)	(0.0004) (-0.001, 0.0015)	(0.0006) (-0.0012, 0.0009)			
Nsch					-0.0086	-0.012" (0.012)*	-0.012" (0.012)*
(*min.*, *max.*)					(-2.42)'	(-0.023,0.003)	(-0.021, 0.0004)
lnhca	-0.31	-0.28" (0.19)	-0.43 (0.04)	-0.48 (0.04)			
(*min.*, *max.*)	(-2.71)'	(-0.54, -0.05)	(-0.49, -0.04)	(-0.53,-0.16)			
lnsch					-0.71	-0.95 (0.37)*	-0.79 (0.26)*
(*min.*, *max.*)					(-6.9)*	(-1.18, -0.28)	(-1.11, -0.27)
$\rho(\beta_{zi})$		0.57 (0.03, 0.68)	0.83 (0.06, 0.99)	0.71 (0.05, 0.99)		0.76 (0.69,0.99)	0.67 (0.16,0.98)
Norm.$\chi^2(2)$	4.29	1.18	2.87	5.38"	2.26	4.54"	2.4
BFC-F		3.54'	3.49'	3.28'		8.85*	8.08*
AIC$_c$	6.95	6.14	7.83	5.02	-21.7	-40.17	-33.71
adj. R^2	0.25	0.48	0.38	0.44	0.6	0.876	0.884

N (n)	37	37 (29)	37 (36)	37 (35)	37	37 (23)	37 (24)

Table 3: GWR estimates

˜GWR estimates with proxy for public healthcare access (*lnhca*) measured on 2000-01 (instead of 2002-03). Median estimates of parameters for GWR (individual local parameter spatial variability: *p≤0.01, 'p≤0.05, "p≤0.10; bi-square adaptive kernel). In parentheses: *(a)* for OLS, t statistics, *(b)* for GWR (next to median estimates), inter-quartile range ($*IQR > 2\sigma_\beta$ of 'global' OLS models) and minimum/maximum parameter estimates. $\rho(\beta_{zi})$ correlation coefficients between local parameter estimates (median absolute value, with extreme absolute values in parentheses). Norm.$\chi^2(2)$: Doornik-Hansen (residual) normality test. BFC-F: Brunsdon-Fotheringham-Charlton F-test of (joint-parameter) spatial variability. $\mathrm{AIC_c}$ Hurvich-Simonoff-Tsai corrected Akaike Information Criterion. N sample size (n = local kernel sample size).

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