Spatial and temporal variation in family decision-making:

A diffusion perspective in Sub-Saharan Africa

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Abstract: This paper maps spatial and temporal variation in family decision-making norms and analyzes the spatial relationship between urbanization, education and husband's dominance in decision-making about their wife's health using pooled Demographic and Health Surveys from 28 countries in sub-Saharan Africa. Using adaptive bandwidth kernel density estimates we show considerable spatial heterogeneity in reports of husband's dominance in decision-making about wives' health both between and within countries in an earlier (e.g. 2000s) and later (e.g. 2010s) period. Cells with similar values of male dominance on decision-making tend to be concentrated geographically, indicating processes of social diffusion might be spreading norms about decision-making. Spatial panel fixed effects models suggest that increases in urbanization and women's education are associated with decreases in husband's dominance in decision-making. Furthermore, husband's dominance decreases as women's education in neighboring cells becomes more widespread, which is consistent with a diffusion perspective.

Keywords: Africa, decision-making, families, spatial analysis

Introduction

Family norms about women's status are central to demographic understandings of health and wellbeing of women and their families (Balk, 1994; Defo, 1997; M. Hindin, 2000; Oppenheim Mason, 1987; Upadhyay & Hindin, 2005). However, it is notoriously difficult to measure norms, and further difficult to assess how and why they spread over time and space. This paper uses reports about men's dominance in decision-making on their wife's health in sub-Saharan Africa (SSA) as a measure that captures norms about women's status within the family. We document variation in husband's reported dominance[1] in decision-making over time and space and explore the spatial factors that predict declines in men's reported dominance. In doing so, we draw on a rich demographic literature on the importance of diffusion of new ideas and norms as an important catalyst for demographic change.

SSA makes a particularly insightful case study for this topic because African countries have some of the lowest levels of women's reported participation in family decision-making throughout low-income countries (Pesando & GFC Team, 2018). Nonetheless, there have been declines over time in reported male dominance in household decision-making in SSA even though socioeconomic development remains low in many places. Because industrialization, improved employment or other markers of socioeconomic development have been largely absent in SSA, and thus cannot explain the reported decline in male dominance, diffusion of norms about women's status could represent an important explanation for changes observed at the aggregate level. This could be particularly the case because urbanization and mass education—two of the

[1] The term 'husband's dominance' is used interchangeably with 'men's dominance' and 'male dominance'.

major factors hypothesized to be important for diffusion—have increased in many places in SSA.

We start by providing a descriptive overview of the spatial dimensions of husband's reported dominance in decision-making on wives' health in SSA using pooled Demographic and Health Surveys and Malaria Indicators Surveys from across sub-Saharan Africa. By applying spatial interpolation methods, we estimate husband's reported dominance in decision-making about their wives' health for each observational unit (i.e., 50 km by 50 km area) within each country for populated areas of the country. This facilitates the creation of high-resolution maps that visualize geographical distribution of the proportion of women in the grid cell who report that their husband is the sole decision-maker about their health at two time points (e.g. in the early 2000s and approximately ten years later), thus highlighting heterogeneity in men's reported dominance both within and between countries, and visually depicting changes between the earlier and later time points. This also means we can assess whether there is spatial clustering in reports of male dominance in neighboring geographic units, which would be consistent with a diffusion perspective. We also explore how much of the variation in changes in men's reported dominance are within—as opposed to between—countries, given enormous ethnic and social heterogeneity both between and within African countries.

Next, we analyze the spatial relationships between education, urbanization and reported male dominance in decision-making using panel fixed effects spatial regression methods. Following approaches used by Vitali and Billari (2017) to test for diffusion, we allow for spatial dependence in both the dependent and explanatory variables to estimate how women's education and urbanization impact reported male dominance in health decision-making. Importantly, this allows us to assess both the direct effects of education and urbanization in the respondent's cell and the indirect effects of education and urbanization in neighboring cells on husband's reported dominance in decision-making. The latter provides a test of diffusion, and is particularly relevant because mass education and urbanization are two of the major pathways through which diffusion of norms are hypothesized to occur in the demographic literature (Pierotti, 2013).

Women's status and family decision-making

In this paper, we focus on women's reports about their husband's dominance in making decisions about their own health as a measure that captures gender norms about women's status within the family. This type of family decision-making question has been widely-used to assess women's abilities to make strategic choices that impact personal and family well-being (M. Hindin, 2000; Peterman, Schwab, Roy, Hidrobo, & Gilligan, 2015; Smith, Ramakrishnan, Ndiaye, Haddad, & Martorell, 2003). Decision-making measures have been validated in studies showing that women's reported participation in family decision-making is associated with higher levels of contraceptive use, improved child health and nutrition, and higher probability of women's rejection of wife beating across diverse contexts in sub-Saharan Africa (Amugsi, Lartey, Kimani-Murage, & Mberu, 2016; M. Hindin, 2000; Smith et al., 2003; Uthman, Lawoko, & Moradi, 2010). Furthermore, alternative measures of women's status—including age, education, assets, and income—are highly predictive of women's participation in family decision-making in sub-Saharan Africa (Behrman, 2017; Kishor & Subaiya, 2008; Kritz

& Makinwa-Adebusoye, 2018), thus suggesting that reports about decision-making adequately capture some latent construct of women's status.

Nonetheless, gender inequality is complex and multi-dimensional and there is no one way to measure women's status (Mason, 1986); the measure we focus on in this paper is one of many ways to approach this issue. Furthermore, it is notoriously difficult to fully understand the "black box" of what actually happens in the family (Haddad, Hoddinott, & Alderman, 1997) and there are many important critiques of what decision-making measures actually capture. For example, husbands and wives sometimes provide different responses to questions about decision-making and property ownership (Behrman & Frye, 2018; Doss, Meinzen-Dick, & Bomuhangi, 2014; Kilic & Moylan, 2016) and variations in wording about women's decision-making leads to differences in estimates of the prevalence of women's decision-making across contexts (Peterman et al., 2015). Some of these discrepancies in reports about decision-making may be due to issues of social desirability bias because women answer questions based on how they think they should answer as opposed to what actually transpires in the family.

Although we acknowledge that our analysis is limited in its ability to assess whether reports of decline's in men's' dominance in decision-making actually correspond with what happens in the family, we nonetheless maintain that this measure provides important information on gender norms about women's status. In sub-Saharan Africa, discourse about women's "empowerment" and "modern" gender relations in the family are often the subject of development policies and programming that are widely dispensed through media, publicity, and NGO workers among others (Thornton, Dorius, & Swindle, 2015; Thornton, Pierotti, Young-DeMarco, & Watkins, 2014). Thus, it is highly plausible that norms about whether it is “acceptable” to report that men dominate decision-making might change more quickly than actual behaviors. Although social desirability bias might play a role in women’s responses, these reports would nonetheless capture important normative change related to the socially desirable role for women to play in family decision-making.

A diffusion perspective on spatial and temporal variation in women’s status and family decision-making

Diffusion of new ideas and norms are central to theories of demographic change. Most notably, a large demographic literature explores how the diffusion of ideas about smaller family sizes and norms about the acceptability of birth control were key to the timing of the fertility transition in Europe (Coale, 1986; Susan Cotts Watkins, 1987). For example, the seminal Princeton Fertility Project pioneered by Coale, Watkins and others showed that fertility decline in Europe occurred first in places with cultural and linguistic similarities, rather than in places that were forerunners of industrialization. This suggests that diffusion of norms among culturally similar groups were essential to eventual behavioral change, a finding that runs counter to modernization theories that predicted industrialization and modernization processes would lead to fertility decline (Goode, 1963).

Diffusion of norms and ideas about fertility and family have also played a role in more recent scholarship about how and why demographic change occurs. The literature on the Second Demographic Transition suggests that ideational change valuing individual autonomy and self-fulfillment were important precursors of the low and lowest low fertility observed in many parts of contemporary Europe (Lesthaeghe, 2014; Van de Kaa, 2001). Drawing on a diffusionist perspective, researchers have increasingly adopted spatial analysis methods and found evidence of diffusion of norms related to fertility, marriage and cohabitation, nonmarital childbearing, and reproductive health in both contemporary high and low income contexts (Mita & Simmons, 2018; Nazio & Blossfeld, 2003; Vitali & Billari, 2015; Vitali, Aassve, & Lappegård, 2015).

There are myriad explanations for the processes throughout which diffusion of norms occurs. At the micro-level, social interaction plays an important role in spreading new ideas and conceptions about what behavior is admissible (Bongaarts & Watkins, 1996). Technological changes—such as the spread of cellphones and internet—may also play an important role in the diffusion of new ideas and norms among individuals (Billari, Rotondi, & Trinitapoli 2017). In low income countries, the spread of new ideas can occur through development programming which often centers around an idealized set of norms and values set by external international actors (Pierotti, 2013; Thornton et al., 2014; 2015). The rise of global media and entertainment may also contribute to the diffusion of norms, for example exposure to radio and television programming that included family planning messaging has been shown to have an impact on fertility and family planning usage in Africa and Asia (Dewi, Suryadarma, & Suryahadi, 2013).

Most studies that take a diffusionist perspective on demographic behavior focus on diffusion of norms related to fertility and marriage (Reed, Briere, & Casterline, 1999). To the best of our knowledge few studies apply a diffusionist perspective to measures—such as family decision-making—that more directly capture norms about women's status. One exception documents a large decline in the acceptability of wife-beating throughout a range low and middle-income countries at the start of the twenty first century (Pierotti, 2013). Pierotti shows that urbanization and education are both associated with rejection of wife beating, which would be consistent with a diffusionist perspective since both schools and urban areas are spaces where people may come into contact with new ideas about gender norms via exposure to new media, exposure to new people from other backgrounds, regions or countries and exposure to women in new roles (e.g. teachers, medical professionals etc.) (Caldwell, 1980). Both schools and urban areas are also sites where individuals have the opportunities to interact with others in new ways and to perform new gender roles for the first time.

Data and Measures

Our analysis uses Demographic and Health Surveys (DHS) data, which is collected by ICF international in collaboration with host-country country governments. Since the 1980s the DHS Program has collected standardized nationally representative cross-sectional surveys on reproductive health, women's status, and demographic wellbeing across low- and middle-income countries. The DHS uses a two-stage sampling procedure that first identifies primary sampling units (PSUs) (also known as clusters), and then randomly selects households within those clusters for interviews. All women in the household aged 15-49 are interviewed, and sampling weights can be applied so that the sample is nationally representative of women of reproductive age. Starting in the 1990s, but most systematically from the early 2000s onwards, GPS coordinates of the clusters were also collected, which allows us to link interviewed women to their geographic location at time of survey. To maintain respondent confidentiality, DHS randomly displaces the latitude/longitude position of clusters up to 2 km for urban clusters and up to 5 km for rural clusters. This displacement may cause some clusters to lie outside the country boundaries. We change the coordinates of the clusters outside of national boundaries to be the nearest point on the country's border. In order to do this, we use administrative boundary shapefiles obtained from the freely available Database of Global Administrative Areas (GADM) and projected using the World Geodetic System 1984 projection.

For this analysis, we pool micro-level DHS data from 28 sub-Sahara African countries using 15 DHS surveys collected in the period 2001–2005 and 32 DHS surveys collected in the period 2010–2014. We use all DHS survey waves for SSA which include GPS data, providing us with a total of 360,931 women living in 21,795 clusters (see Figure 1 for spatial distribution of clusters). Table 1 presents additional information about the characteristics of the samples (all data are weighted using the DHS sampling weights).

[Table 1 here]

The main outcomes of interest is constructed based on a question where the female respondent is asked who in the family is the main decision-maker about her own health. This is a commonly used measure of women's status that has been used and validated throughout the demographic literature (Pesando & GFC Team, 2018), although as we discussed in the literature review there are limitations to this measure such as reporting bias. We construct a variable for the share of households in a given grid cell in which the women's partner/husband is the sole decision maker on the women's health, where a grid cell is a 50 km by 50 km area referenced by a single coordinate pair which represents its center. In our analytical strategy section (below), we provide further detail on the construction of cell-level indicator.

We adopt cutting-edge techniques from spatial analysis that have recently been applied to mortality and adolescent pregnancy in sub-Saharan Africa (Burke, Heft-Neal, & Bendavid, 2016a; Neal, Ruktanonchai, Chandra-Mouli, Matthews, & Tatem, 2016) to generate our measures of decision-making at high spatial resolution (discussed below). To the best of our knowledge, this is the first-time spatial methods such as these have been applied to assess the spatial distribution and geographic diffusion of a measure that captures intra-familial gender norms such as decision-making as opposed to morbidity or reproductive health. One methodological advantage of focusing on decision-making measures is that we are confident women's responses about decision-making correspond with their current geographic location. On the other hand, women's retrospective reports about child mortality or pregnancy capture their geographic location at survey, and not their geographic location when these events actually occurred.

In our main analysis, we assess whether there is evidence of diffusion of norms about decision-making across time and space (discussed in detail below). As part of this, we are particularly interested in two important social trends that we hypothesize play a key role in diffusion: (1) the spread of women's education; and (2) urbanization. We measure women's education by creating a variable for the percentage of women in the cell who have at least some education at the time of survey using DHS data (e.g. have ever been to school). We measure urbanization by creating a variable for nighttime light intensity in the cell, i.e. lights from cities, towns, and other sites with persistent lighting, including gas flares. Nighttime light intensity is a commonly used measure of urban growth (Schneider, Friedl, & Potere, 2010) and economic activity (Ghosh et al., 2010), and is preferred to the DHS measure of urbanization, which cannot be used in this analysis because it is dichotomous and not continuous (because our maps are prevalence maps, we need a continuous measure of urbanization). Data on nighttime light intensity are taken from the freely available dataset of Global DMSP-OLS Nighttime Lights of the National Geophysical Data Center within the U.S. National Oceanic and Atmospheric Administration and are available for each year 1992 to 2013 at a spatial resolution of 30 arc-second grids (about 1 km by 1 km at the equator). For our analysis, we download data for the years 2003 and 2012, i.e. the median years of surveys included, and aggregate them at a 0.50 x 0.50-degree resolution by taking the mean across all 30 arc-second grid cells.

Methods

Spatial interpolation

The first step of our analysis is to explore spatial and temporal heterogeneity in household participation processes in SSA. To this end, we apply spatial interpolation methods to estimate the decision-making indicator for each observational unit, i.e. 0.50 x 0.50-degree grid cell (about 50 km by 50 km at the equator), across time. Spatial interpolation is the process of using points (e.g., DHS clusters, Figure 1) with known values to estimate values for all cells on the map and thus obtain gridded data. We adopt kernel density estimation (KDE) which is a non-parametric method for estimating density that uses all the data points to create an estimate of how the density of events varies over a given area. It produces a smooth map in which the density at every location reflects the number of points in the surrounding area. This can then be used to create prevalence surfaces, or heat maps, by generating a ratio of case data to control data. Further details of the methodology used are described at length in the literature (Joseph, Vallo, Seydou, Msellati, & Meda, 2017).

Using these methods, we create high-resolution maps of family decision-making that allow us to visually assess how men's dominance in family decision-making varies geographically. We explore how decision-making varies temporarily by creating maps for both the earlier (e.g. early 2000s) and later (e.g. 2010s) rounds of the DHS, and also creating a map of change in decision-making between the earlier and later rounds. The latter is done only for the 15 countries that have *both* an earlier and a later round of the DHS. In order to understand corresponding changes in education—which we think might be important for diffusion of norms about decision-making—we create comparable maps for the education variable. We cannot create a map of change for the light intensity variable (our proxy for urbanization) because in some cells light intensity is zero and has remained stable over time; however, changes can still be detected by visually comparing the maps between the earlier and later rounds. Finally, to validate the results of our gridded data, we aggregate the cell-level estimates at the country level by taking the mean across all cells and using the country boundary shapefile in order to obtain a measure of family decision-making and education at the country level. We then check for consistency by comparing their distribution with the country-level estimates obtained from the micro data.

Source of variation in family decision-making

For the second part of our analysis, we quantify the importance of within-country versus between-country variation in women's participation in family decision making in each time period. This is important, because many national boundaries in SSA were artificially imposed during the colonial period, thus nationally boundaries frequently cut across ethno-linguistic groups and encompass highly heterogenous groups of people. Given enormous within country ethnic and social heterogeneity, it is plausible that there might be as much variation in norms about decision-making within countries as between countries. To empirically asses the importance of between versus within country variance we regress our main variable of interest—male dominance in decision making on women's health—on a set of country indicators using ordinary least-squares (OLS) regression (Burke, Heft-Neal, & Bendavid, 2016a). The R-squared of this regression represents the proportion of total variation in family decision-making explained by differences across countries.

Spatial panel data modelling

After establishing descriptively spatial and temporal trend's in male dominance in health decision-making, the next step of our analysis is to assess whether there is evidence of diffusion in decision-making norms, which we do using spatial panel data modeling methods (described in detail below). The key novelty of our spatial panel modeling scheme is that it allows for spatial autocorrelation in both the dependent (e.g. decision-making) and the explanatory variables (e.g. education and urbanization). Spatial autocorrelation in the dependent variable establishes the extent to which male dominance in health decision-making in any given cell depends on male dominance in health decision-making in other neighboring cells. In other words, it measures the degree to which men's dominance in decision-making about women's health in neighboring cells is related to men's dominance in decision-making about women's health in the reference cell. It consequently identifies whether the decrease in male dominance in health decision-making is characterized by a process of diffusion, that is when new norms and behaviors about family decision-making introduced by the "forerunners" spread across cells. Assuming that significant spatial autocorrelation exists in the dependent variable, the autocorrelation on the explanatory variables enables us to disentangle the extent to which decreases in male dominance in health decision-making are driven directly from the cell's own characteristics as well as indirectly from the characteristics of neighboring cells. In what follows, we go into further detail in the models used to explore these issues.

We start by reviewing a panel data fixed effects model, which can be described as follows:

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it}$$

–where our dependent variable y_{it} is the proportion of women reporting that their husband/partner is the sole decision maker about the women's health in cell i and year t, $\boldsymbol{x}_{it}$ is the vector of independent variables (in our case, proportion of women with at least some education and urbanization as measured by the nighttime lights), $\boldsymbol{\beta}$ is the matching vector of coefficients, and μ_i denotes cell-specific fixed effects, assumed to be constant over time and independent of the error term ε_{it}.

The panel data fixed effects model produces unbiased parameter estimates provided that our observations (in our case, the cells) are independent. The assumption of independence does not hold if, instead, observations are spatially dependent. In this case, models including spatial effects are more suitable. Spatial effects are generally introduced into the model using a spatial weighting matrix, W_i, a positive matrix where the rows and columns correspond to the cross-sectional observations, which measures the neighboring structure across cells. Neighbors are here defined on the basis of a contiguity criterion, according to which two cells are neighbors if they share a common edge or a common vertex. An element of the matrix, w_{ij}, equals $1/\pi_i$ if $j \in N(i)$ and 0 otherwise, where $N(i)$ defines the set of all neighbors of i, and π_i is the number of neighbors of i, and expresses the existence of a neighbor relation between i and j.

If spatial dependence exists, the simple panel data fixed effects model can be extended to include spatially lagged variables or spatial error autocorrelation. In this paper, we consider three types of spatial panel specifications: the spatial lag (SAR) panel model, the spatial error (SEM) panel model, and the spatial Durbin (SDM) panel model. The SAR panel model can be expressed as follows:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it}$$

–where λ is the coefficient of the spatially lagged dependent variable and referred to as the spatial autocorrelation coefficient in the dependent variable. This set-up allows the proportion of women reporting that their husband/partner is the sole decision maker about the women's health in cell i and year t, y_{jt}, to depend on the percentage observed in neighboring cell j and year t, y_{jt}. A positive estimate of λ indicates that decreases in male dominance in health decision-making in neighboring cells are associated with decreases in male dominance in health decision-making in the reference cell. It informs us about the existence of a diffusion mechanism, according to which reductions in male dominance in health decision-making spread across cells, after controlling for observed characteristics and unobserved time-invariant characteristics. Unlike the cross-sectional spatial models, where λ represents a spatial pattern reflecting a diffusion process, the introduction of the time dimension in spatial panel models reinforces the interpretation of λ as reflecting diffusion.

The SER panel model can be described as follows:

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + u_{it}, \qquad u_{it} = \rho \sum_{j=1}^{N} w_{ij}u_{jt} + \varepsilon_{it}$$

–where u_{it} is the spatially autocorrelated error term.

To determine whether the panel SAR model or the panel SEM model best describes the data than a model without any spatial interaction effects, one may use the Lagrange Multiplier (LM) tests for a spatially lagged dependent variable and for spatial error autocorrelation. The robust LM tests (Anselin, Bera, Florax, & Yoon, 1996) may then be used to identify which spatial effects (λ and/or ρ) is relevant and the existence of one type of spatial dependence conditional on the other (Elhorst, 2014). These tests test the hypothesis that the panel spatial model specifications improve the fit and are based on the residuals of the panel data fixed effects model, each following a chi-square distribution with one degree of freedom. If all hypothesis are rejected, i.e. the panel data fixed effects model is dismissed in favor of the panel SAR model or the panel SEM model, one should be careful to select one of these two models. We explain why below.

The SDM panel model extends the SAR panel model by adding spatially lagged independent variables and is expressed as follows:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij}y_{jt} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij}\boldsymbol{x}_{ijt}\boldsymbol{\gamma} + \mu_i + \varepsilon_{it}$$

–where $\boldsymbol{x}_{ijt}$ is the vector of independent variables measured in cell j and year t, and $\boldsymbol{\gamma}$ is the matching vector of coefficients. The advantage of this model is that it allows men's dominance in decision-making about women's health in each cell i to depend on a set of characteristics measured in the same cell and on an average of the same characteristics measured in neighboring cells. Therefore, $\boldsymbol{\gamma}$ expresses the extent to which male dominance in health decision-making in cell i is affected by women's education and urbanization averaged over its neighboring cells.

The panel SDM model can be then used to test whether the model can be simplified to a panel SAR model or to a panel SEM model since they are nested within the panel SDM model (Elhorst, 2013; LeSage & Pace, 2009). In particular, this model can be used to test the hypotheses $H_0: \gamma = 0$ and $H_0: \gamma + \lambda\beta = 0$. Both tests follow a chi-square distribution with K degrees of freedom, where K are the number of explanatory variables. If both hypotheses are rejected, then the panel SDM model best describes the data. On the contrary, if the first hypothesis cannot be rejected, the panel SDM model can be simplified to the panel SAR model (Burridge, 1981),provided that the (robust) LM tests also pointed to the panel SAR model. Likewise, if the second hypothesis cannot be rejected, the panel SDM model can be simplified to the panel SEM model (Burridge, 1981), provided that the (robust) LM tests also pointed to the panel SEM model. Elhorst argues that if the (robust) LM tests point instead to another model than the Wald tests, then the panel SDM model should be adopted. This is because the panel SDM model is a more general spatial model.

Finally, after estimating the models and conducting the diagnostic tests (LM and Wald) to select the model that best describes our data, we advance the analysis by studying the spillover effects. Earlier studies may have used only the estimated parameters on the spatially lagged terms to test the existence of spatial spillover effects. However, this may have resulted in incomplete conclusions (LeSage & Pace, 2009). Unlike the fixed-effects model, the coefficient estimates in spatial panel models cannot be interpreted as the marginal effect of a variation in the explanatory variable on the dependent variable. According to LeSage and Pace (2009), a change in a single observation (in our case, cell) associated with any given explanatory variable will influence the cell itself (direct impact) and potentially influence all the other cells indirectly (indirect impact). The total impacts are thus the combination of the direct and indirect impacts. The authors argue that estimated impacts are different from the parameter estimates – and may even have different signs – since estimated impacts include some feedback effects. In particular, for the direct effect, a change in one explanatory variable in cell i has an influence on the dependent variable in cell i also through an effect of from cell i to neighboring cell j, and then back to cell i, via the spatial autocorrelation on the dependent variable. This occurs because each cell is its neighbor's neighbor. For the indirect effect, instead, a change in one explanatory variable in cell i has an influence on the dependent variable in cell j. Therefore, a correct interpretation of the results can be obtained by analyzing the impact estimates. Nevertheless, to offer a richer interpretation of spatial spillovers, we report both the point estimates and the impacts.

Results

Descriptive findings

In this section, we present prevalence maps of husband's dominance in decision-making about women's health and women's education at the national and local levels. The former are choropleth maps in which countries are shaded proportional to the measurement of the variable displayed. The latter are generated using an adaptive bandwidth technique encompassing an optimal number of persons surveyed through the DHS. The optimal N parameter, N_{opt}, is different for each survey since it is a function of survey-specific parameters[2] (see Table 1). In order to have reliable maps, we remove unpopulated cells, e.g. cells where there are lakes, rivers, deserts (data from the freely available Database of Gridded Population of the World, Version 4 of the Center for International Earth Science Information Network).

Figure 2 presents maps of male dominance in health decision-making about women's health in the 2000s and 2010s both at the national and local levels. All four maps show marked heterogeneity across countries. The measure ranges from 17% of households where the husband/partner is the sole decision-maker in Zimbabwe to 74.9% in Burkina Faso in the period 2000–2004, while for the period 2011–2015 it varies from 9% in Lesotho to 83.6% in Mali. Unlike the national-level ones (left), the local-level maps (right) further show heterogeneity within countries and thus allow to identify areas that lag behind. In particular, from these maps we can infer that in the 2000s, the southern areas of Ghana, Guinea, and Nigeria presented low proportions of men's dominance in decision making on women's health. On the contrary, in Eastern and Southern Africa,

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[2] The optimal N parameter (Larmarange et al. 2011) is formally described as follows:

$$N_{opt} = 14{,}172 * n^{0.419} * p^{-0.361} * g^{0.037} - 91.011$$

–where p is the sample prevalence, n is the number of persons surveyed in the sample, and g specifies the number of sample clusters.

instead, East Ethiopia and Kenya and Malawi were lagging behind. Similarly, in the 2010s, there were very high proportions of men's dominance in decision making on women's health in the northern areas of Burkina Faso, Chad, Nigeria, and Mali and in Central Congo.

[Figure 2 here]

The maps in Figure 2 visually reveal that there are neighboring cells that share high values of men's dominance in decision-making about women's health and neighboring cells that share low values of men's dominance in decision-making about women's health, which may be indicative of spatial autocorrelation in this indicator. Formally, the presence of global spatial autocorrelation is tested using the Moran's *I* index, a cross-product statistic between a variable and its spatial lag that tests whether the value of a variable observed in a given location is independent of the value observed in a neighboring location. In other words, it is the slope of a linear regression of the spatially lagged variable (a weighted average of the value of the variable in the neighboring cells) on the original variable (in standardized form). It thus examines whether the spatial pattern is clustered, dispersed, or random. Moran's *I* index is expressed as follows:

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (y_i - \bar{y})^2}$$

–where $\bar{y}$ is the sample mean. The significance of this spatial correlation can be assessed by means of a permutation approach. In our data, the Moran's *I* index equals .89 (p-value < 0.001) in the 2000s and 0.93 (p-value < 0.001) in the 2010s. This indicates a strong and positive spatial interdependence in our indicator, suggesting that cells with similar values of male's dominance in health decision-making tend to be concentrated geographically.

We next turn to the Local Moran statistic, also called Local Indicator of Spatial Autocorrelation (LISA). The LISA allows to identify local clusters and local spatial outliers (Anselin 1995) by indicating if neighboring cells have high or low values. In particular, cells can be deemed as to be not significant or a cluster of 'high-high', 'low-low', 'high-low', and 'low-high' values relative to neighboring cells at a probability level $p \leq 0.05$ (significance values based on permutation). In Figure 3 we show a scatterplot map of the LISA for 2000–2004 and 2011–2015. Cells in the West are defined as 'high-high' areas, that is areas where the proportion of women reporting that their husband/partner is the sole decision maker about the women's health is persistently high across neighboring cells (or also, where male dominance in decision making on women's health is persistently high across neighboring cells). On the contrary, cells in the East are 'low-low' areas, that is areas in which male dominance in decision making on women's health is persistently low across neighboring cells. The map also identifies very few local outliers, defined as 'low-high' and 'high-low' areas, that is cells that have low values of men's dominance in decision making on women's health and neighbors with high values of men's dominance in decision making on women's health, and vice versa.

[Figure 3 here]

We also quantify the importance of within-country versus between-country variation by calculating the R-squared of a regression of our indicator on a set of country dummies. Between-country variation accounts for 58.6% and 68.5% of the total variation in male's dominance in health decision-making in 2000–2004 and 2011–2015, respectively. Similarly, between-country variation accounts for 14.2% of the total variation in changes in male's dominance in health decision-making between 2000–2004 and 2011–2015. Therefore, around 85.8% of the variation in changes in male's dominance in health decision-making is attributed to factors that vary over space and time within countries. This finding suggests that large heterogeneity exists within countries and that changes in gender norms might be explained by local factors within countries than by differences between countries.

In Figures 4 and 5 we present maps of the independent variables that we use in our empirical model, i.e. women's education and urbanization. For the variable women's education, we perform the same analysis as in Figure 2. On the contrary, given that the nighttime light data are disaggregated at the cell level, we can only present the spatial distribution of this variable. Figure 4 shows substantial cross-country variation in women's education in both periods. At the national level, the proportion of women with at least some education ranges from 10.5% in Mali 68.5% in Zimbabwe in the first period and from 15.2% in Ethiopia to 86.3% in Zimbabwe in the second period (maps on the left). The high resolution maps allow to clearly visualize the marked within-country variations (maps on the right). The interpretation is very similar to male's dominance in health decision-making, in fact the maps of male's dominance in health decision-making and education seem to be specular, which suggests that high proportions of women with some education might be strongly related to low proportions of women reporting that their husband/partner is the sole decision maker about the women's health. Figure 5 shows the spatial distribution of the urbanization variable in 2002 and 2013. The variable ranges from 0 to 30 and can be interpreted as the level of urbanization per cell. As expected, higher levels of urbanization are more common among large cities (e.g. Lagos, Nairobi, and Harare).

[Figures 4 and 5 here]

In Figure 6, we present maps of change in men's dominance in health decision-making (left) and women's education (right) at the national and local levels. We calculate change as the percentage variation from 2000–2004 to 2011–2015. Maps showing the temporal change at the country level suggest that male dominance in health decision-making has decreased over time in most countries. However, the local-level maps show that the decrease over time has not been homogenous within countries. This invalidates our previous inference based on national estimates, that are inaccurate. In particular, the local-level maps show that some areas have experienced a decline over time in male dominance in household-decision making (red cells), while in others it has increased over time (blue cells). Similarly, the maps of change in women's education show that within-country variation over time is high and that although the proportion of women with at least some education has decreased over time in very few areas (red cells), it has generally increased over time (blue cells), in some areas more than others.

[Figure 6 here]

Sensitivity analysis

We perform the same analysis using different N parameters (i.e., $N_{opt} * 2$ and $N_{opt}/2$) and check that our results do not depend on the choice of N_{opt}. Moreover, we apply the spatial interpolation methods to the same set of indicators to create maps at a lower resolution (i.e., 1 x 1-degree grid cell) and find that our results and inferences are not affected by the number of grid cells in the country.

We also validate our gridded data by aggregating the cell-level estimates at the country level and comparing their density plots with the density plots of the country-level estimates obtained from the micro data. In Figure 5, we present density plots of men's dominance in health decision-making and women's education for the 2000–2004 (left) and 2011–2015 (right). Expect for some values located at the left end of the distribution of women's education (i.e., at low values), the density functions are very similar. Also, the measures are highly correlated, i.e., 0.98 for men's dominance in health decision-making and 0.94 for women's education.

Estimation results

In this section we present the results from the panel data fixed effects model and the SDM panel model estimated for all cells with a value in both periods, i.e. 3,186. The panel data fixed effects model results, shown in Table 2, are those for the fixed-effects model. To test for the presence of spatial dependence, we conduct the LM tests. Both the LM and the robust LM tests, reported at the bottom of Table 2, indicate the presence of spatial dependence within the data. The hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term are rejected at 1% significance level. This suggests that the panel data fixed effects model may suffer from misspecification and, in particular, that a model specification with a spatially lagged dependent variable and a model specification with a spatially autocorrelated error terms variable may be favored over a panel model.

[Table 2 here]

To further test the appropriateness of a spatial model specification, we estimate a panel SDM model, shown in Table 3. The spatial autocorrelation coefficient in the dependent variable λ and the Wald test statistics are reported at the bottom of the table. The former is equal to .91 (p-value<0.001), indicating spatial dependence of male's dominance in health decision-making across cells. This also means that a decrease in male's dominance in health decision-making in neighboring cells leads to a decrease in male's dominance in health decision-making in the reference cell. According to the tests, both the hypothesis $H_0{:}\,\gamma = 0$ and $H_0{:}\,\gamma + \lambda\beta = 0$ are significantly rejected, which suggests that neither the panel SAR model nor the panel SEM model are the most appropriate specification. In other words, the tests indicate that the panel SDM model best describes the data.

[Table 3 here]

We now turn to the interpretation of the direct effects based on the panel SDM model. Women's education has a negative effect on the likelihood that men are the sole decision maker about their wives' health. The effect is statistically significant and indicates that a one-unit increase in the percentage of women with some education in the reference cell decreases the percentage of women reporting that their husband/partner is the sole decision maker about the women's health in that same cell by 0.204. Thus, cells in which women are, on average, more educated tend to have lower values of male dominance in health decision-making. Urbanization (as measured by nighttime light) has a negative effect on the likelihood that men are the only decision makers about women's health in the household. The effect is statistically significant and suggests that cells where urbanization is, on average, greater have lower values of male dominance in decision-making about women's health.

We now compare the impact effects with the point estimates of the panel SDM model. The estimated coefficient of women's education is, in absolute terms, slightly higher for the direct impact estimate of –0.204 than the point estimate of –0.189. The higher coefficient estimate for the direct impact implies that men's dominance in health decision-making are slightly more responsive to an increase in women's education than is found with the point estimate of the panel SDM model. The same applies to the estimated coefficient of urbanization. The difference between the direct effect and the point estimates measures the feedback effect, which is positive and equals to 0.015 (in absolute terms) for women's education and to 0.109 (in absolute terms) for urbanization.

We next turn to the indirect effects of women's education and urbanization on men's dominance in health decision-making. The indirect effects are, in absolute terms, larger than the point estimates. They refer to the characteristics of neighboring cells and measure to what extent they influence the dependent variable—in our case the proportion of women reporting that their husband/partner is the sole decision maker about the women's health—in any given cell. The indirect effect of –0.388 associated with women's education refers to what happens to the proportion of male dominance in health decision-making in a given cell from having a greater proportion of women with at least some education in all neighboring cells. As for urbanization, we find that the indirect effect is large and negative, but not significantly different from zero. The direct effect of urbanization is negative and statistically significant, while its indirect effect, though still negative, is statistically insignificant. At this point, it is useful to consider the meaning of direct and indirect effects. The direct effect can be interpreted as the effect of a local increase in urbanization, while the indirect effect can be seen as the effect of a global—that is in all neighboring cells—increase in urbanization. Thus, we can assert that men's dominance in household decision making in a given cell decreases over time because women's education is becoming more widespread in neighboring cells. In other words, new gender norms and behaviors can spread even when the characteristics of the carriers do not spread because they are diffused by the forerunners across individuals.

Last column of Table 3 shows the estimated results for the total (sum of the direct and indirect effects) effects. Our results show that decreases in male dominance in decision-making about women's health are mainly driven by women's education. Women's education has a negative total effect on men's dominance in health decision-making, while urbanization, despite having a strong direct effect, does not have any significant total effects.

Finally, we estimate additional alternative models (not shown) as a means of robustness checks. These are models where the spatial weighting matrix is defined differently and, in particular, it is based on the rook's contiguity criterion, that is on shared boundaries only, as opposed to shared edges and vertexes. Results are robust when the neighbors are defined by the queen contiguity of second order (i.e. the neighbors of our neighbors are our neighbors) and by the rook contiguity of first and second order. Results related to the direct and indirect impact of women's education on men's dominance in health decision-making are also robust when the urbanization variable is excluded from the analysis.

Discussion

Drawing on a rich demographic literature on the importance of women's status in the family for health and wellbeing, we explored spatial and temporal variation in men's dominance in decision making on women's health in sub-Saharan Africa. Summary statistics at the aggregate level showed that on average there were declines in men's dominance over decisions about women's health; nonetheless these aggregate statistics masked enormous spatial heterogeneity. For example, our maps of the spatial prevalence of men's dominance showed that some areas in SSA experienced a decline in male dominance in health decision-making, whereas male dominance in health decision-making actually increased in other areas. Furthermore, we found that about 86% of the variation in changes in men's dominance could be attributed to factors that changed within (as opposed to between) countries. This suggested that within country heterogeneity played a meaningful role in shaping observed patterns, which made sense in light of enormous socio-cultural and linguistic heterogeneity within African countries. Nonetheless, we documented that cells with similar values of male dominance tended to be concentrated geographically, and suggested a potential role for processes of social diffusion in spreading of norms about decision-making.

Our spatial panel analysis showed that cell-level prevalence of women's education and urbanization (measured by night time light usage) were negatively associated with men's dominance over women's health decisions. These models also indicated that men's dominance in household decision making in a given cell decreased over time when women's education became more widespread in neighboring cells. This indicated that the spread of women's education played an important role in the diffusion of norms about women's decision-making over space. On the other hand, we did not find evidence of a statistically significant effect of urbanization in neighboring cells on men's dominance in health decision-making. It is possible that education is more important for diffusion of norms related to decision-making because education challenges many conventional gender roles via textbook and learning materials, female teachers as role models, and so on (Caldwell, 1980), whereas exposure to urbanization does not directly challenge these norms as much.

Our analysis contributed to the demographic literature on how women's status is changing in sub-Saharan Africa by demonstrating the importance of considering spatial heterogeneity in measures of women's status—in addition to aggregated indicators or summary statistics—to provide a more complete assessment of changes in women's status over time and space. In doing so, we extended literature which has used spatial methods to map changes in mortality, and education in Africa (Burke, Heft-Neal, & Bendavid, 2016b; Golding et al., 2017; Graetz et al., 2018) to explore spatial trends in other dimensions of family dynamics. We also explicitly tested whether there was evidence of social diffusion of norms about male dominance in decision-making, including an analysis showing that education was an important path through which norms appear to have been diffused spatially. Although a social diffusion perspective has been common to demographic studies of fertility change, it has rarely been applied to studies of how norms about women's status change over time and space.

Our paper has a number of relevant implications for policy and research. In low-income countries, improving women's status has been a central policy concern that features heavily in the United Nations (UN) Millennium Development Goals and UN

Sustainable Development Goals. This has given rise to measures—such as the UNDP women's empowerment indicators— that provide cross-national comparisons of changes in women's status over time. Cross-national comparable indicators of women's status, such as those produced by the UNDP, have been limited in important dimensions. For example, these indicators are only available at the national level, and thus may potentially hide considerable within country heterogeneity, such as between urban and rural areas, and across ethno-linguistic and administrative boundaries. This may make it difficult for policy makers to target key geographic areas of interest for interventions. Furthermore, aggregated indicators reveal very little about the social and demographic processes through which changes in women's status diffuse across time and space. Our analysis demonstrated the importance of taking a spatial perspective to illuminate the social and demographic complexities of how family dynamics in sub-Saharan Africa have changed over time and space.

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Fig. 1 Maps of women's geographic location in 2000–2004 (left) and 2011–2015 (right).

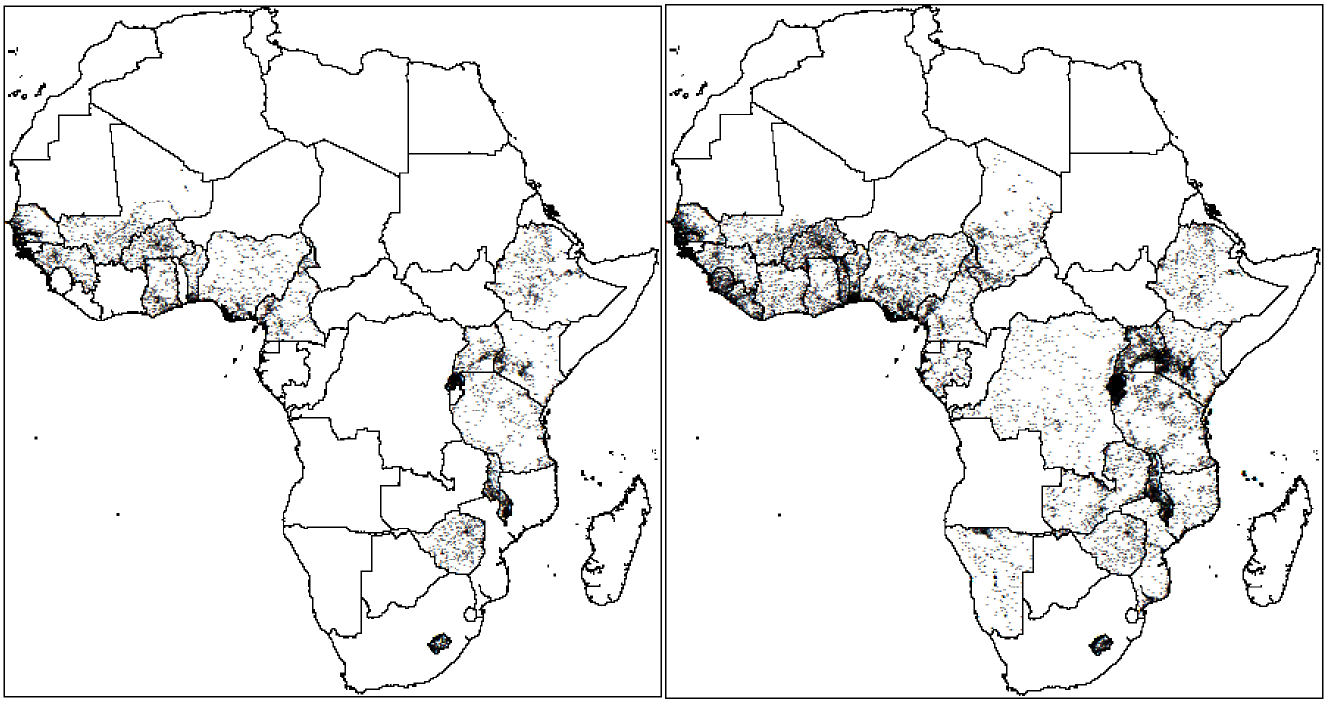

Fig. 2 Maps of prevalence of men's dominance in decision-making about women's health in 2000–2004 at the national (top left) and local (top right) levels and in 2011–2015 at the national (bottom left) and local (bottom right) levels.

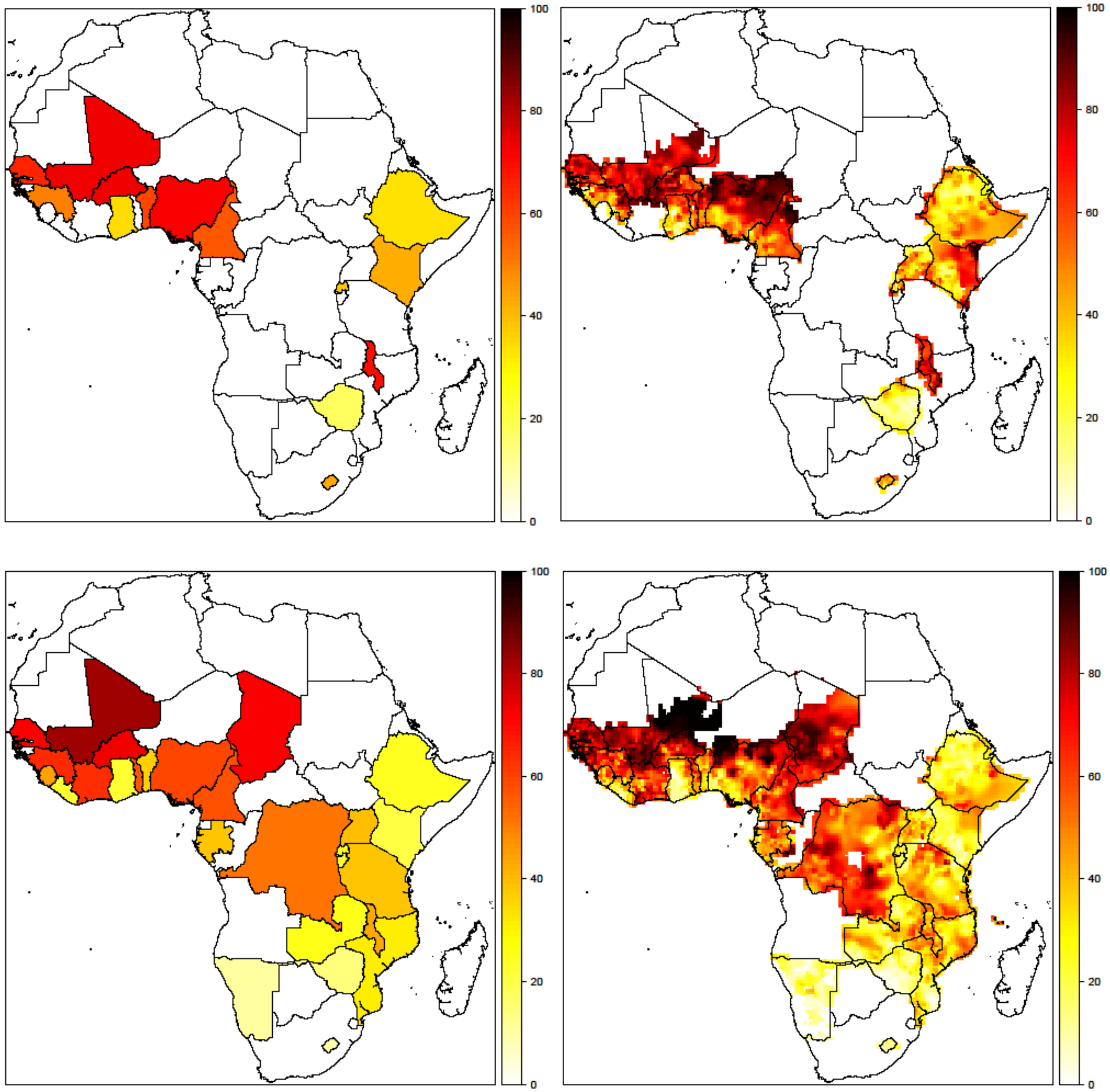

Fig. 3 Maps of local indicator of spatial autocorrelation in men's dominance in decision-making about women's health in 2000–2004 (left) and 2011–2015 (right).

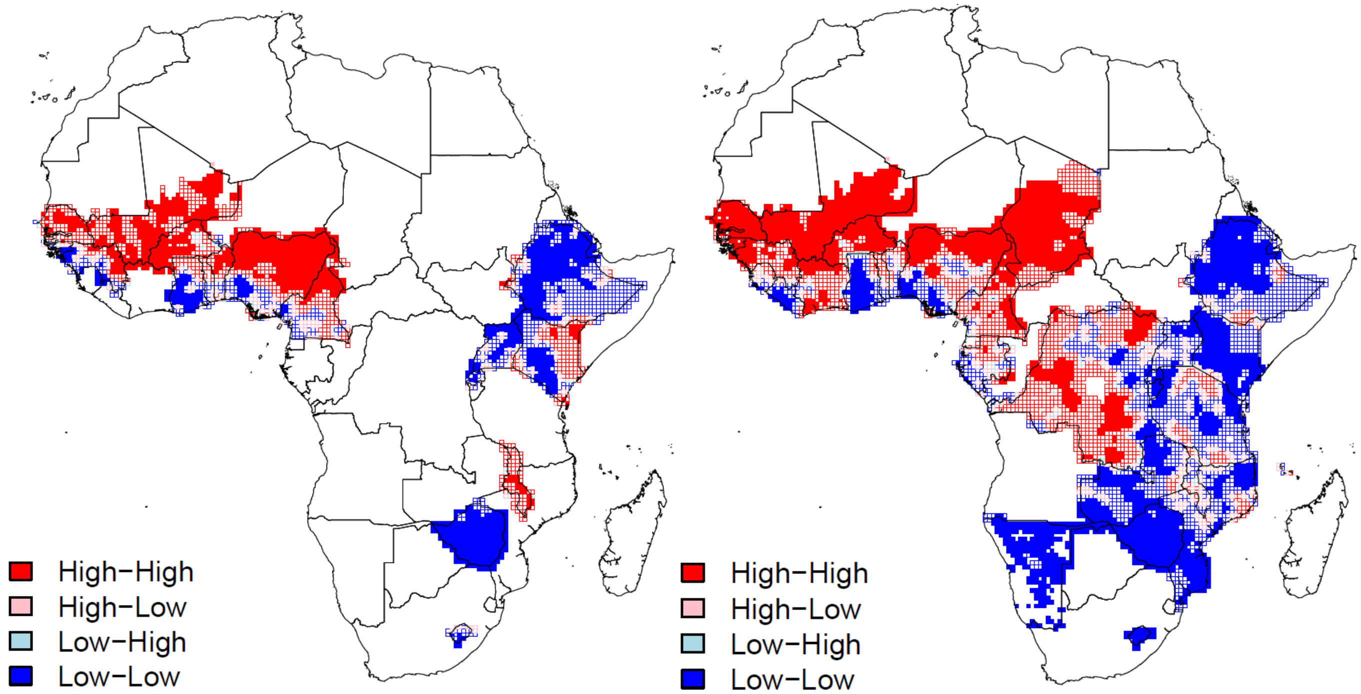

Fig. 4 Maps of prevalence of women's education in 2000–2004 at the national (top left) and local (top right) levels and in 2011–2015 at the nationals (bottom left) and local (bottom right) levels.

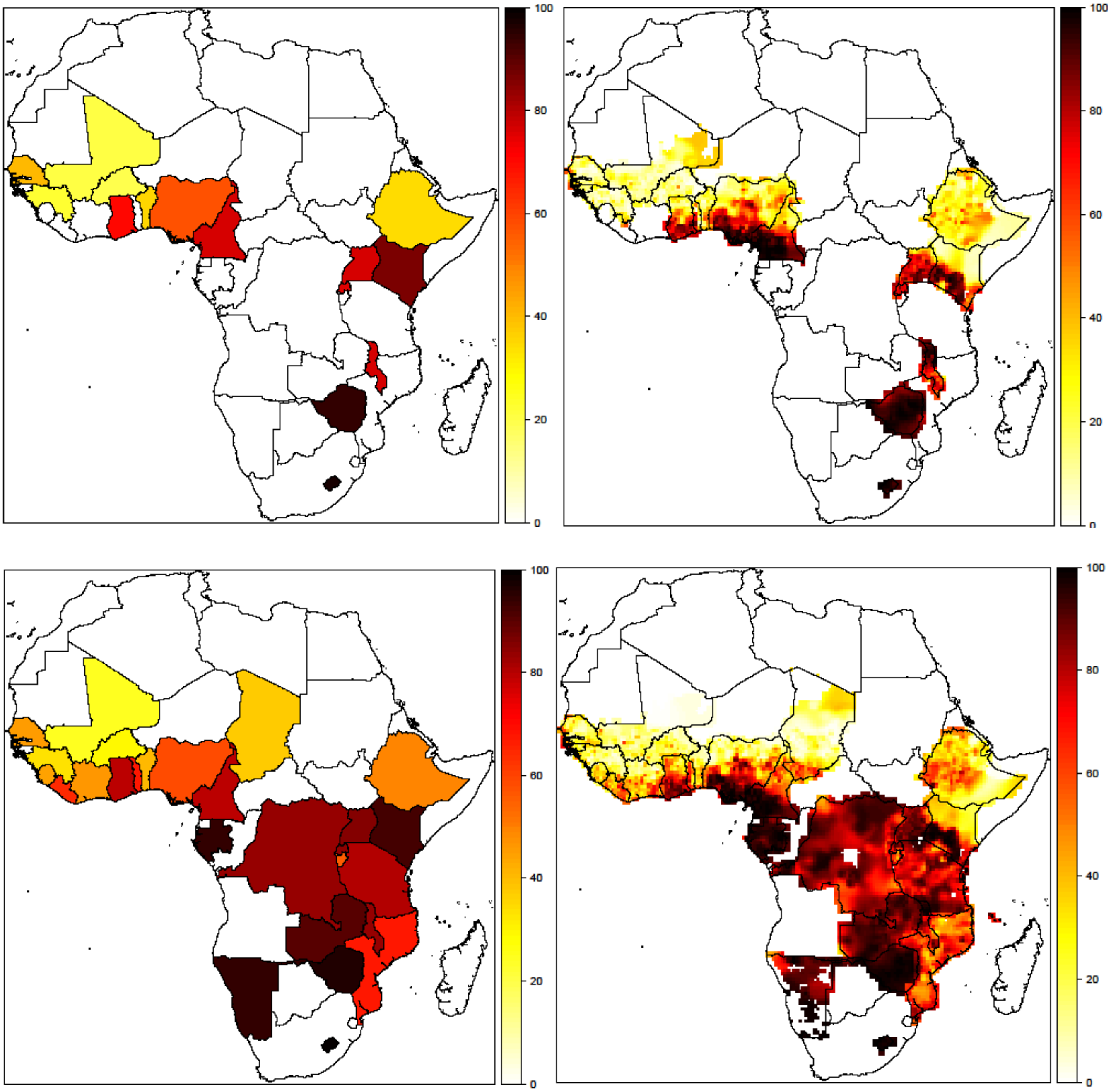

Fig. 5 Spatial distribution of nighttime light intensity in 2003 (left) and 2012 (right).

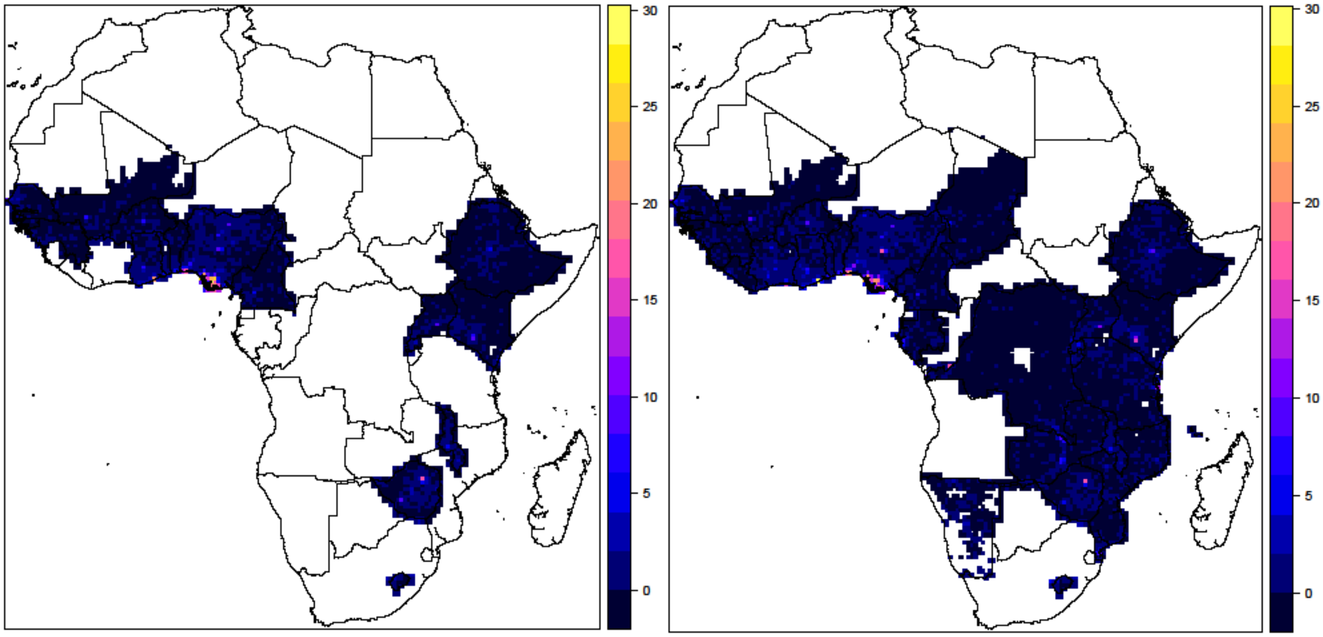

Fig. 6 Maps of change between 2000–2004 and 2011–2015 in men’s dominance in decision-making about women’s health (left) and women’s education (right).

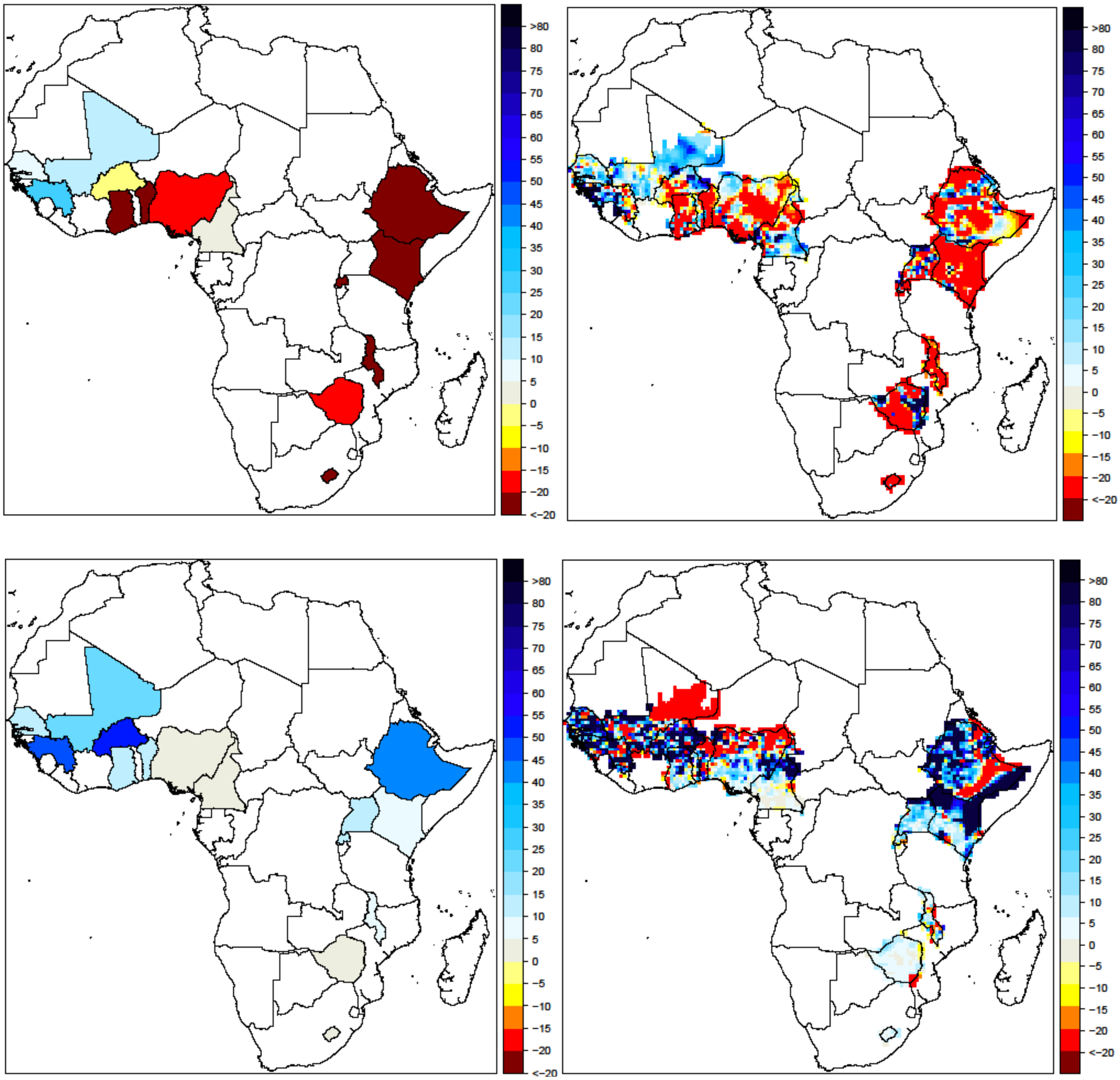

Fig. 7 Density plot of country-level estimates and cell-level estimates aggregated at the country level.

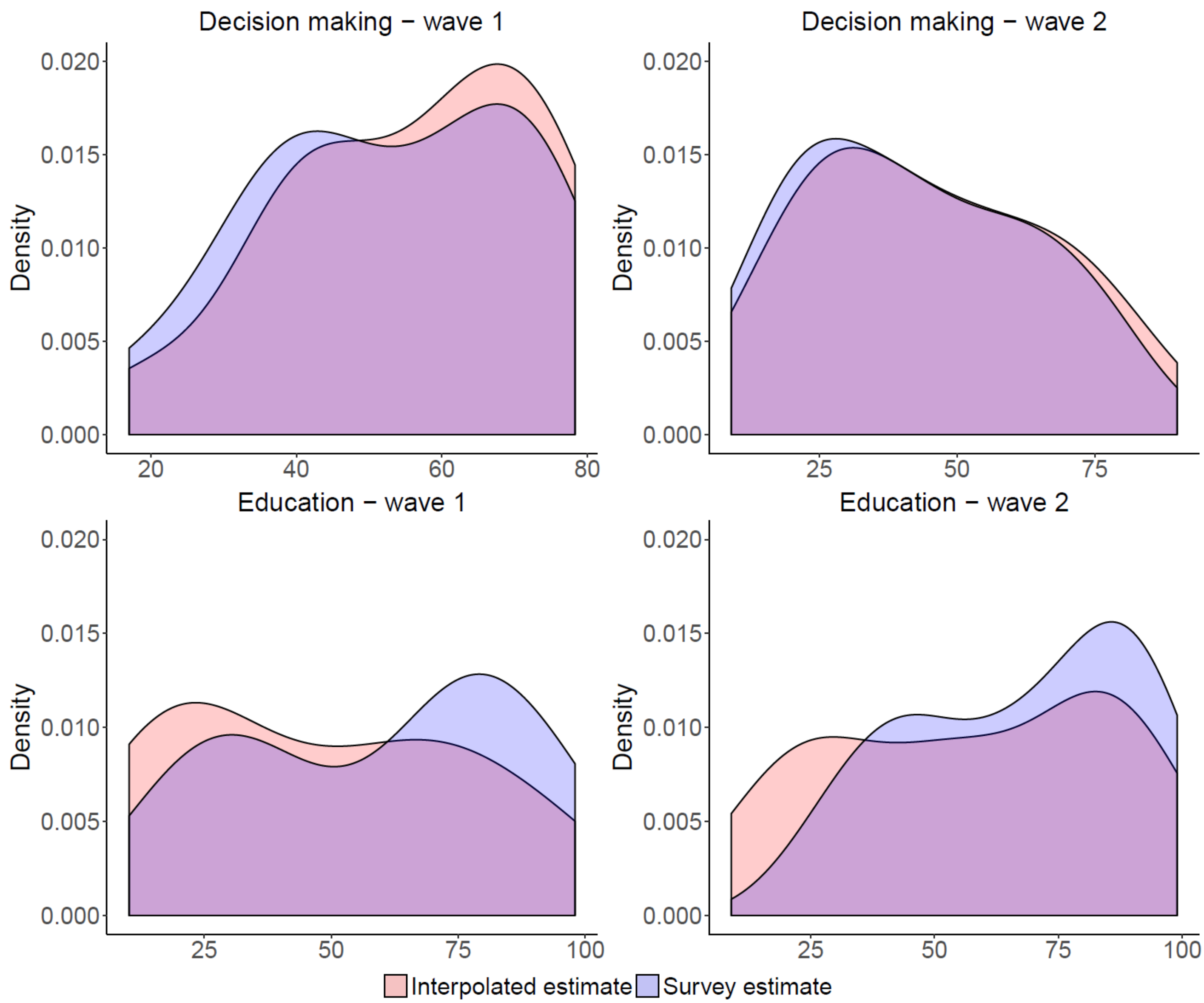

Table 1 Characteristics of the DHS samples.

<table>
<tr><th rowspan="2">Country</th><th rowspan="2">Year</th><th rowspan="2">Survey Type</th><th rowspan="2">Number of Clusters</th><th colspan="2">N_{opt}</th></tr>
<tr><th>Decision Making</th><th>Education</th></tr>
<tr><td>Benin</td><td>2001</td><td>DHS</td><td>247</td><td>78</td><td>94</td></tr>
<tr><td>Benin</td><td>2011</td><td>DHS</td><td>746</td><td>138</td><td>177</td></tr>
<tr><td>Burkina Faso</td><td>2003</td><td>DHS</td><td>397</td><td>166</td><td>146</td></tr>
<tr><td>Burkina Faso</td><td>2010</td><td>DHS</td><td>541</td><td>231</td><td>234</td></tr>
<tr><td>Burundi</td><td>2010</td><td>DHS</td><td>376</td><td>83</td><td>173</td></tr>
<tr><td>Cameroon</td><td>2004</td><td>DHS</td><td>464</td><td>121</td><td>195</td></tr>
<tr><td>Cameroon</td><td>2011</td><td>DHS</td><td>577</td><td>145</td><td>268</td></tr>
<tr><td>Cote d'Ivoire</td><td>2011</td><td>DHS</td><td>341</td><td>112</td><td>116</td></tr>
<tr><td>Chad</td><td>2014</td><td>DHS</td><td>624</td><td>225</td><td>184</td></tr>
<tr><td>Comoros</td><td>2012</td><td>DHS</td><td>242</td><td>46</td><td>80</td></tr>
<tr><td>Democratic Republic of the Congo</td><td>2013</td><td>DHS</td><td>492</td><td>148</td><td>227</td></tr>
<tr><td>Ethiopia</td><td>2005</td><td>DHS</td><td>528</td><td>110</td><td>149</td></tr>
<tr><td>Ethiopia</td><td>2011</td><td>DHS</td><td>571</td><td>136</td><td>183</td></tr>
<tr><td>Gabon</td><td>2012</td><td>DHS</td><td>331</td><td>60</td><td>189</td></tr>
<tr><td>Ghana</td><td>2003</td><td>DHS</td><td>410</td><td>89</td><td>110</td></tr>
<tr><td>Ghana</td><td>2014</td><td>DHS</td><td>423</td><td>79</td><td>173</td></tr>
<tr><td>Guinea</td><td>2005</td><td>DHS</td><td>291</td><td>93</td><td>120</td></tr>
<tr><td>Guinea</td><td>2012</td><td>DHS</td><td>300</td><td>118</td><td>115</td></tr>
<tr><td>Kenya</td><td>2003</td><td>DHS</td><td>398</td><td>118</td><td>129</td></tr>
<tr><td>Kenya</td><td>2014</td><td>DHS</td><td>1579</td><td>130</td><td>364</td></tr>
<tr><td>Lesotho</td><td>2004</td><td>DHS</td><td>380</td><td>108</td><td>121</td></tr>
<tr><td>Lesotho</td><td>2014</td><td>DHS</td><td>399</td><td>96</td><td>168</td></tr>
<tr><td>Liberia</td><td>2013</td><td>DHS</td><td>322</td><td>98</td><td>147</td></tr>
<tr><td>Malawi</td><td>2004</td><td>DHS</td><td>520</td><td>140</td><td>139</td></tr>
<tr><td>Malawi</td><td>2010</td><td>DHS</td><td>827</td><td>165</td><td>255</td></tr>
<tr><td>Mali</td><td>2001</td><td>DHS</td><td>399</td><td>175</td><td>164</td></tr>
<tr><td>Mali</td><td>2012</td><td>DHS</td><td>413</td><td>215</td><td>137</td></tr>
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<tr><td>Rwanda</td><td>2014</td><td>DHS</td></tr>
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<tr><td>Senegal</td><td>2014</td><td>DHS</td></tr>
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<tr><td>Tanzania, United Replublic of</td><td>2010</td><td>DHS</td><td>458</td><td>76</td><td>342</td></tr>
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<tr><td>Uganda</td><td>2011</td><td>AIS</td></tr>
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<tr><td>Zimbabwe</td><td>2010</td><td>DHS</td><td>393</td><td>101</td><td>241</td></tr>
</table>

Table 2 Results from panel data fixed effects model.

	Men's dominance
Women's education	-0.399***
	(0.025)
Urbanisation	-1.300*
	(0.541)
LM spatial lag	12,075.603***
LM spatial error	12,334.636***
Robust LM spatial lag	63.998***
Robust LM spatial error	323.031***
N	6,372

*p<.05; **p<.01; ***p<.001

Table 3 Results from panel SDM.

			Marginal effects		
	β	γ	Direct effect	Indirect effect	Total effect
Women's education	-0.189***	0.137***	-0.204***	-0.388**	-0.592***
	(0.022)	(0.027)	(0.021)	(0.141)	(0.144)
Urbanisation	-0.899*	0.576	-1.008*	-2.867	-3.875
	(0.403)	(0.544)	(0.411)	(3.919)	(4.036)
λ			0.913***		
			(0.008)		
H_0: $\gamma=0$			26.88***		
H_0: $\gamma+\lambda\beta=0$			7.40*		
AIC			21,884.67		
BIC			21,921.07		
Log-likelihood			-10,936.34		
N			6,372		

*p<.05; **p<.01; ***p<0.001