URBAN POVERTY AND HEALTH IN DEVELOPING COUNTRIES: HOUSEHOLD AND NEIGHBORHOOD EFFECTS*

MARK R. MONTGOMERY AND PAUL C. HEWETT

In the United States and other high-income countries, there is intense scholarly and programmatic interest in the effects of household and neighborhood living standards on health. Yet few studies of developing-country cities have explored these issues. We investigated whether the health of urban women and children in poor countries is influenced by both household and neighborhood standards of living. Using data from the urban samples of 85 Demographic and Health Surveys and modeling living standards using factor-analytic MIMIC methods, we found that the neighborhoods of relatively poor households are more heterogeneous than is often asserted. Our results indicated that poor urban households do not tend to live in uniformly poor neighborhoods: about 1 in 10 of a poor household's neighbors is relatively affluent, belonging to the upper quartile of the urban distribution of living standards. Do household and neighborhood living standards influence health? Using multivariate models, we found that household living standards are closely associated with three health measures: unmet need for modern contraception, attendance of a trained health care provider at childbirth, and young children's height for age. Neighborhood living standards exert a significant additional influence in many of the surveys we examined, especially for birth attendance.

For the foreseeable future, world population growth will be concentrated mainly in the cities and towns of developing countries. According to the United Nations (2000), by 2030, the world's population will exceed today's total by some 2 billion persons, of whom 1.9 billion will be added to the urban areas of Africa, Asia, and Latin America. With these prospects in view, researchers who are concerned with poverty and health must increasingly set their concerns in urban contexts.

What may city life imply for levels of reproductive health and for health inequalities? Using data from the urban samples of 85 Demographic and Health Surveys (DHS), we focused on three health indicators: the unmet need for modern contraception; attendance of a physician, nurse, or trained midwife at childbirth; and young children's height for age. The unmet need for contraception is closely linked to unintended pregnancy, birth attendance is a measure of the protection given mothers and children at the time of delivery, and height for age is an often-used summary of the state of a child's health. Taken together, these measures describe a relatively high-risk period in the lives of women and their children. Our main objective was to understand how such health measures are affected by urban living standards. To assess the effects, we considered two dimensions of living standards, one defined for the household and the other defined for the sampling cluster in which the household resides. Holding household living standards constant, we investigated whether poverty and affluence in the surrounding neighborhood affect health.

*Mark R. Montgomery, Professor of Economics, State University of New York at Stony Brook, and Senior Associate, Policy Research Division, Population Council, 1 Dag Hammarskjold Plaza, New York, NY 10017; E-mail: mmontgomery@popcouncil.org. Paul C. Hewett, Associate, Policy Research Division, Population Council. Funding for this article was provided by the William and Flora Hewlett Foundation and the Andrew W. Mellon Foundation.

Why are such "neighborhood effects" of interest? Debates on urban poverty in the developing world have often been framed in terms of the living conditions of slum dwellers. Estimates by UN-HABITAT (United Nations Human Settlements Programme) suggest that some 38% of the population of developing-country cities live in slums, with total slum populations numbering 126 million persons in Africa, 433 million in Asia, and 87 million in Latin America (Herr and Karl 2002; Herr and Mboup 2003). The emphasis on slums has been accentuated by the United Nations Millennium Declaration, which specifies a target of achieving "significant improvement in the lives of at least 100 million slum dwellers" by 2020 under the broader goal of ensuring environmental sustainability.[1] But there is, as yet, no consensus in the research community on the definition of *slums* and little knowledge of the relationship between urban poverty overall and the living standards of slum populations. It is not known, for example, what proportion of the developing-country urban poor live in slums or what proportion of slum dwellers can be counted as poor in terms of income and other socioeconomic criteria. Furthermore, although the spatial concentration of poverty would seem to be the essential element of any definition of *slums*, efforts to systematize such definitions (using indicators of access to safe drinking water, adequate sanitation, electricity, and security of housing tenure) have been focused on households and have not much examined the concentrations of poverty or affluence in the neighborhoods that surround households.

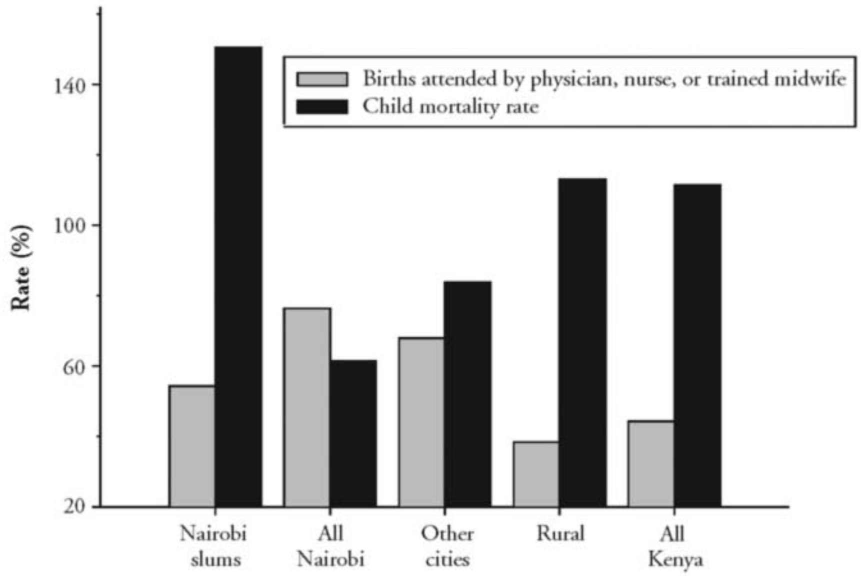
In its neglect of neighborhood effects, the literature on urban poverty in poor countries stands in sharp contrast to that concerned with the United States and other rich countries, where neighborhood effects have attracted intense scholarly interest over the past two decades. These research efforts have drawn much of their motivation from the writings of Wilson, Coleman, and their colleagues on social interaction, exclusion, and social capital in poor U.S. neighborhoods (Coleman 1988; Massey 1990; Sampson, Morenoff, and Gannon-Rowley 2002; White 2001; Wilson 1987). A supporting motivation has emerged within the demographic realm, in which multilevel analyses have had considerable methodological appeal. Neighborhood effects are a leading example of the forces acting outside households that can exert an influence on household-level attitudes and behavior. Hence, on both substantive and methodological grounds, there seems to be ample reason to explore neighborhood effects in the cities of poor countries.

What, then, can account for their neglect? A formidable barrier to such research is the lack of data on living standards. Because the DHS program gathers no information on either household incomes or consumption expenditures, measures of poverty that are based on these and similar surveys are limited to what can be fashioned from a few proxy variables, including ownership of consumer durables and crude summaries of the quality of housing. A lively literature has emerged in the past few years on the merits of various statistical techniques that use such indicators. We explored one of the most promising approaches for distilling the proxies into a single living-standards index, termed MIMIC models ("multiple indicator, multiple cause"), which are a species of confirmatory-factor analysis. In pursuing this approach, we faced one methodological difficulty: the indicators at hand are dichotomous, and standard factor-analytic techniques are inappropriate for such cases. We developed our own estimation routines to address this problem.

This article is organized as follows. To begin, we briefly sketch the theory of neighborhood effects in relation to health, drawing from the report of the National Research Council's Panel on Urban Population Dynamics (2003). The second section presents an overview of the models and statistical issues that must be confronted in constructing defensible measures of living standards from the crude raw materials that are available, and we summarize our thinking in the form of an equation system that links urban living

1. See www.un.org/millenniumgoals for further information on the Millennium Declaration and its associated goals, specific targets, and research programs.

Figure 1. **Comparison of Birth Attendance and Child Mortality Rates ($_5q_0$) in the Nairobi Slums With Those for All Nairobi, Other Cities in Kenya, Rural Areas, and Kenya as a Whole**



African Population and Health Research Centre (2002).

standards to health. The third section describes the DHS data, presenting descriptive statistics on the health measures, the explanatory variables used in the models, and the indicators of household living standards. We then compare the relative living standards and relative poverty measures for households with summary measures that were calculated at the sampling cluster level, the aim being to understand just how closely household and neighborhood living standards are linked. The next section presents multivariate results for the three health measures, with the models based only on household living-standards factors shown first, and models with both household and neighborhood factors following. The article concludes with thoughts on an agenda for further work.

NEIGHBORHOOD EFFECTS: A REVIEW

Figure 1 may help to frame the issues. In the slums of Nairobi, rates of child mortality substantially exceed those found elsewhere in the city and are high enough even to exceed rural rates of mortality. If urban populations have an advantage in health, as is so often asserted, then it seems that this advantage must be very unequally shared. Of course, such urban disadvantages were once widely apparent in the West—in the nineteenth century, it was not uncommon for mortality rates in urban slums to far exceed those of the countryside. In that era, it was well understood that the spatial concentration of urban dwellers somehow put them at higher risk of disease and death. If anything, such urban–rural differences are more striking in today's world because even in poor countries, many cities have managed to provide the basic public health infrastructure that is needed to combat communicable diseases, and city populations are generally better supplied than rural areas with modern curative health services. On average, as the Panel on Urban Population Dynamics

(2003) has shown with DHS data, city populations exhibit lower levels of child mortality than are found in the countryside. When one looks beneath the urban averages, however, striking differences in health are revealed: poor city dwellers often face health risks that are nearly as bad as those seen in the countryside, and sometimes (as in Nairobi) the risks are decidedly worse. In this respect, the bars displayed in Figure 1 having to do with birth attendance represent what can be seen more generally in developing countries, namely, large disparities in health between slum residents and those living elsewhere in the city, but with slum residents being somewhat better shielded from risk than rural dwellers.

Our concern in this article is with urban populations only. Confining our attention to the portions of Figure 1 that refer to urban Kenya, we recognize significant differences in health *within* the urban population. These intraurban inequities have received curiously little attention from demographic researchers, but, of course, they will be taking on greater weight in all calculations of poverty as developing countries continue to urbanize. Because the Nairobi slum populations of Figure 1 exhibit the poorest health in urban Kenya, there is a suggestion that the spatial concentration of poverty found in these slums must apply health penalties beyond those applied by household poverty alone. But the figure does not distinguish poor households in slums from poor households living elsewhere, and it can give no clear testimony to the effects of spatially concentrated poverty. There is enough here, however, to invite further exploration.

A Sketch of the Theories

We cannot do justice here to the many pathways by which neighborhood and related contextual effects could influence health. In its report, the Panel on Urban Population Dynamics (2003) provided an extensive review of these theories, with attention to their implications for neighborhood-level poverty (or living standards) and individual demographic behavior in the cities of developing countries. To summarize this panel's lengthy and complex argument—much of which is dependent on empirical examples from the U.S. experience—one expects neighborhoods to matter for several reasons.

Where communicable diseases are concerned, it has long been recognized that the spatial proximity of diverse urban populations can generate negative *health externalities*. As we showed for Nairobi, the externalities that are associated with environmental contamination and the transmission of diseases could cause the health risks of slum life to rival or exceed those of rural areas, despite the generally easier access of urban residents to emergency transportation and modern health services (African Population and Health Research Center 2002; Harpham and Tanner 1995; Timæus and Lush 1995). Less often recognized, but potentially of equal importance, are the *social externalities* that figure into urban life. Individuals and households are connected to others in their neighborhoods through social network ties, and along such social circuits, information may flow about how to recognize and respond to health threats and where appropriate services can be found. Of course, social network ties often reach beyond the local neighborhood. It has been argued, however, that the social networks of women and the poor are spatially constricted by comparison with those of men and the more affluent. The relative costs of travel may well be greater for the poor, and women with children and domestic responsibilities may find their daily routines largely confined to local neighborhoods (McCulloch 2003; Panel on Urban Population Dynamics 2003).[2]

2. One of the most influential randomized interventions in the history of family planning, the Taichung experiment of 1963, found strong evidence of the diffusion of information along social network lines in this Taiwanese city (Freedman and Takeshita 1969). Although we are aware of no recent research on social networks and the diffusion of health information in developing-country cities, Behrman, Kohler, and Watkins (2001) and Casterline et al. (2001) documented social network effects on contraceptive use in rural and periurban African contexts. See Casterline (2001) for an excellent summary of related findings in several areas of demographic research.

Theories of local reference groups and social comparisons are often invoked (if rarely formally tested) in relation to the psychosocial aspects of health. The idea is that individuals may evaluate their own circumstances by comparing them with what can be observed of the circumstances of others (van den Eeden and Hüttner 1982). Comparisons that are consistently unfavorable may provoke feelings of resentment and inequity, producing stresses and anxieties that undermine mental health. There is reason to think that such mechanisms can affect health more broadly. In the view of Wilkinson (1996:215), "It is the social feelings which matter, not exposure to a supposedly toxic material environment. The material environment is merely the indelible mark and constant reminder of one's failure, of the atrophy of any sense of having a place in a community, and of one's social exclusion and devaluation as a human being." For the poor, repeated exposure to such social inequities could erode feelings of social confidence and weaken the sense of personal efficacy that is needed to sustain health-seeking behavior.

The role of relative socioeconomic standing, as measured by individual income in relation to the income distribution of the surrounding community or wider social group, is still largely untested, especially for spatial units as small as neighborhoods (Wen, Browning, and Cagney 2003). In U.S. research, some evidence has emerged—not always consistently—to indicate that inequality at the county, metropolitan-area, and state levels is linked to poor health at the individual level. Little is known about such relationships in developing countries. Other social mechanisms with similar implications include residential segregation (Massey 1996; White 2001), local social capital, and community organizations (e.g., Aber et al. 1997; Astone et al. 1999; Furstenberg 1993; Furstenberg and Hughes 1997).

Much of this literature has emphasized the spatial concentration of poverty, but the effects of spatially concentrated affluence are also drawing attention. Wen et al. (2003:848) summarized Wilson's work as showing the benefits of economic heterogeneity for urban communities:

> In his [Wilson's] model, the prevalence of middle/upper-income people positively correlates with the material and social resources necessary to sustain basic institutions in urban neighborhoods like the family, churches, schools, voluntary organizations, and informal service programs. . . . These institutions are pillars of local social organization that help to nurture neighborhood solidarity and mobilize informal social control.

In their study, Wen et al. (2003) found that neighborhood affluence exerts a significant positive influence on health net of other covariates, including neighborhood-level poverty, income inequality, aggregated educational attainment, and lagged levels of neighborhood health. However, Pebley and Sastry (2003) could find no separable, significant effect of neighborhood affluence in their study of children's test scores in Los Angeles, given the median level of neighborhood family income, which had a significant positive influence on the scores.

In addition to these approaches to neighborhood effects, a small literature in demography has explored the links between *local services* and health outcomes, with a particular focus on how services may either substitute for or complement the beneficial effects of mother's education (e.g., Sastry 1996). Relatively poor urban neighborhoods may not provide attractive markets for private-sector suppliers of modern health services, leaving health needs to be met by an assortment of local practitioners, including pharmacists, vendors of drugs, and purveyors of traditional medicines. Poor neighborhoods may also lack the political clout needed to secure adequate public-sector services.

But What Is an Urban "Neighborhood"?

The geographic units for which aggregated data are available—in the United States, these are census tracts, block groups, and the like—have boundaries that may not correspond closely, or indeed correspond at all, with the sociological boundaries of neighborhoods as determined by patterns of social interaction, contagion, and comparison. Wellman and Leighton (1979) questioned whether in urban areas, neighborhoods effectively mark the boundaries of social interchange—they emphasized the lack of overlap between social interactions that take place in neighborhoods and those that take place in individual social networks arrayed across the urban space. Writing on health and reference-group effects, Wen et al. (2003:845) acknowledged, "It is not clear what spatial level is appropriate to examine this relationship." For Sweden, Åberg Yngwe et al. (2003) explored an approach in which socially defined reference groups were constituted on the basis of social class, age, and region, rather than in terms of local geography.

Coulton et al. (1997) and Sastry, Pebley, and Zonta (2002) underscored the complexities of establishing geographic boundaries for urban neighborhoods. Coulton et al. asked residents of Cleveland to depict their local neighborhoods on maps and found that the perceived boundaries often differed substantially from the boundaries of census-based units. There was also substantial variation among residents in the spatial extent of their perceived neighborhoods. Despite this variation, when averages of socioeconomic measures (e.g., poverty rates, crime rates, and nonmarital fertility) were calculated for the perceived neighborhoods and then compared to figures for the census tracts, the composition of the tracts proved to be similar to that of the units sketched out by local residents. For Cleveland, at least, it seems that census tracts can serve as useful proxies for socially defined neighborhoods. We are not aware of any other research on this crucial point.

As a number of researchers have noted (e.g., Åberg Yngwe et al. 2003; Drukker et al. 2003; Szwarcwald, de Andrade, and Bastos 2002; Timæus and Lush 1995; Wen et al. 2003), multilevel studies have often but not invariably found that neighborhood levels of poverty, income, and related factors exert a significant influence when individual-level covariates are controlled. Among other things, collinearity between the individual and spatially aggregated measures can make it difficult to distinguish between individual and neighborhood effects. Ginther, Haveman, and Wolfe (2000) showed that neighborhood measures tend to lose significance as more family- and individual-level covariates are taken into consideration. Longitudinal data (or data from randomized experimental interventions) are of great value in addressing the neighborhood self-selection problems that arise in any study of place-based determinants of health (Oakes 2004), but such data are rarely available for developing-country cities.[3]

Here, as in so much of the literature on neighborhood effects, definitions of *neighborhood* were forced upon us by the nature of the available data. The DHS program collects data within sampling clusters, which we refer to as "neighborhoods." The extent to which DHS sampling clusters represent neighborhoods is, of course, open to debate. In the cities of developing countries, sampling clusters are occasionally as small as a single multiunit apartment building or can extend more broadly, although they would seldom be as broad in spatial terms as rural sampling clusters.[4] Unfortunately, the spatial perimeters of DHS sampling clusters are not documented in any accessible format, and it would be a substantial undertaking to retrieve the relevant maps even for recently fielded surveys. Further substantial effort would be needed to determine the nature of social interactions that take place within and outside these spatial perimeters.

For many reasons, then, it is well beyond the scope of this article to identify precisely the routes through which neighborhoods influence health. Data that are far more

3. See Montgomery and Ezeh (2005) for further discussion of key concepts and measurement issues for urban neighborhoods of developing countries, with an extensive review of recent multilevel studies.

4. According to Fred Arnold of ORC/Macro (personal communication 2003), in developing countries, the enumeration areas that are used in conducting censuses, which often provide the sampling frame for surveys, typically include 100–200 households, but their spatial extent varies.

detailed and extensive than those collected in the DHS would be required for a full accounting. In making a preliminary survey of the data sources at hand, we offer interpretations of our findings that emphasize one or another of the mechanisms described earlier, and in closing, we outline priorities for future research.

STATISTICAL OVERVIEW

The specifications to be explored here take the form of equation systems in which a given health variable, denoted by Y, is the main object of interest. In our applications, Y represents one of three measures of health: the unmet need for modern contraception; attendance of a physician, nurse, or trained midwife at childbirth; and children's height for age. The first two of these measures are binary variables.

For the unmet-need and birth-attendance models, we write the health equation in latent variable form, as

$$Y^* = \mathbf{W}'\boldsymbol{\theta} + f\delta + \varepsilon, \tag{1}$$

with the observed dependent variable $Y = 1$ if $Y^* \geq 0$ and $Y = 0$ otherwise. For the children's height variable, which is continuously distributed, we can think of Y as being equivalent to Y^*. The determinants of Y^* include a vector of explanatory variables $\mathbf{W}$ and an unobservable factor f that we take to represent the household's standard of living—more in a moment on when this will be a tenable interpretation. Another unobservable, ε, serves as the disturbance term of this structural equation.

We posit a model of the factor f whereby $f = \mathbf{X}'\boldsymbol{\gamma} + u$, the value of f being determined by a set of exogenous variables $\mathbf{X}$ and a disturbance term u. Although f is not itself observed, its probable level is signaled through the values taken by $\{Z_k\}$, a set of K indicator variables. These are binary indicators in our application, and it is conventional to represent them in terms of latent propensities Z_k^*, with $Z_k = 1$ when $Z_k^* \geq 0$ and $Z_k = 0$ otherwise. We write each such propensity as $Z_k^* = \alpha_k + \beta_k f + v_k$, and, upon substituting for f, obtain K latent indicator equations,

$$\begin{aligned}
Z_1^* &= \alpha_1 + \mathbf{X}'\boldsymbol{\gamma} + u + v_1 \\
Z_2^* &= \alpha_2 + \beta_2 \cdot \mathbf{X}'\boldsymbol{\gamma} + \beta_2 u + v_2 \\
&\cdot \\
&\cdot \\
&\cdot \\
Z_K^* &= \alpha_K + \beta_K \cdot \mathbf{X}'\boldsymbol{\gamma} + \beta_K u + v_K .
\end{aligned} \tag{2}$$

In this set of equations, the β_k parameters show how the unobserved factor f takes expression through the indicators.[5] Whether f is actually interpretable as a living-standards index depends on the signs that are exhibited by these parameters.

The full equation system thus comprises the health Eq. (1) and Eqs. (2) for the living-standards indicators. In setting out the model in this way, with latent factors embedded in

---

5. Note that no β_1 coefficient appears in the first of the indicator equations; it has been normalized to unity. Further normalizations are also required. In latent variables models such as these, the sizes of the variances σ_u^2 and $\sigma_{v_k}^2$ are not identifiable. For the indicator equations, we apply the normalization rule $\beta_k^2\sigma_u^2 + \sigma_{v_k}^2 = 1$, so that the variance of $\beta_k u + v_k$ equals unity in each equation.

structural equations, we follow an approach that has been recommended by several researchers (notably Ferguson et al. 2003; McDade and Adair 2001; Sahn and Stifel 2000; Tandon et al. 2002). Filmer and Pritchett (1999, 2001) have explored an alternative approach using the method of principal components. Although useful in descriptive analyses and easy to apply, this method is perhaps best viewed as a simple data-reduction procedure. The principal-components approach is otherwise limited; among other things, it does not cleanly separate the determinants of living standards from the indicators of living standards.[6] As a result, a principal-components specification is not readily embedded in structural, multiple-equation systems such as ours (Montgomery et al. 2000).

For this article, we take a two-step approach to estimating the full system. Assuming the disturbances to be normally distributed, we estimate the parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ of the indicator Eqs. (2) by the method of maximum likelihood, using routines that we have written for this purpose.[7] For each household i, an estimate $\hat{f}_i = E\left[f_i \mid \mathbf{X}_i, \mathbf{Z}_i\right]$ of the factor is derived from the indicator equations alone, using Gaussian quadrature to calculate the expected value. The predicted $\hat{f}_i$ is then inserted into the health Eq. (1) just as if it were another observed covariate. Conventional statistical methods are applied to estimate the parameters $\boldsymbol{\theta}$ and δ of the health model.[8]

It is important to acknowledge a key point: we assume that the disturbance terms of the equations, $\{\varepsilon, u, v_1, \ldots, v_K\}$, are mutually independent. The principal worry is that the ε disturbance of the health equation may be correlated with u or one of the v_k disturbances. A correlation involving ε could arise if the propensity to own a given consumer durable (for the kth durable, this propensity involves both u and the disturbance v_k) is somehow linked to the disturbance term of the main health equation. When the indicator Eqs. (2) are estimated separately, as in our approach, then the estimator $\hat{\boldsymbol{\gamma}}$ is consistent for $\boldsymbol{\gamma}$, and the $\mathbf{X}'\hat{\boldsymbol{\gamma}}$ component of $\hat{f}$ is (in the limit) free from contamination.[9] Hence, one could define $\hat{f} = \mathbf{X}'\hat{\boldsymbol{\gamma}}$ and proceed without concern for inconsistency in the health-equation estimators. However, when $\hat{f}$ is formed by conditioning not only on $\mathbf{X}$ but also on the indicators $\mathbf{Z}$, then an association of $\hat{f}$ with ε could persist even in the limit. If there is reason to be concerned about this sort of bias, the procedure that is used to generate $\hat{f}$ must be adjusted. Lacking any compelling reason for suspecting correlation, however, we did not make the adjustments here.

Modeling the Living-Standards Factor

With the living-standards factor specified as $f = \mathbf{X}'\boldsymbol{\gamma} + u$, how should the $\mathbf{X}$ variables of this equation be chosen, and what relation, if any, should they bear to the $\mathbf{W}$ variables

6. When only a handful of indicators $\{Z_k\}$ are available in a given data set, the principal-components method produces living-standards distributions that tend to be concentrated at a relatively small number of discrete points. This feature of the approach can make it difficult to identify with confidence the distribution's quartiles, quintiles, and the like. The MIMIC approach, however, makes use of living-standards determinants $\mathbf{X}$ as well as the indicators. With the aid of this additional source of variation, it generates predicted living-standards distributions that more closely approximate continuous distributions, in which quartiles and even deciles tend to be clearly discernible.

7. See our companion paper (Montgomery and Hewett 2004) for the development of the likelihood function and notes on estimation. The maximization problem does present some numerical difficulties, and it appears that maximum-likelihood methods have been used less often in problems such as these than has minimum-distance estimation. To see how estimation techniques for such binary indicator models differ from those for models with continuously valued indicators, compare Bollen (1989), Jöreskog (2000, 2002), and Lawley and Maxwell (1962). Our estimation method is properly described as "quasi-maximum likelihood," because the estimating equations do not take cross-household, within-neighborhood correlations into account.

8. As in other two-step models with "generated regressors," the standard errors of the estimators $\boldsymbol{\theta}$ and δ must be corrected for the use of an estimated $\hat{f}_i$ in the second step. We used robust standard errors, which should adequately address this and other sources of heteroskedasticity.

9. That is, $\mathbf{X}'\hat{\boldsymbol{\gamma}}$ is free of large-sample bias, assuming independence among $\{u, v_1, \ldots, v_K\}$. The $\mathbf{X}$ variables themselves are taken to be fully exogenous.

that enter the main health equation? How are the **X** variables, posited as determinants of living standards, to be distinguished from the $\{Z_k\}$ variables that serve as indicators of living standards?

As Montgomery et al. (2000) noted, there is little consensus in the literature on how best to define and model the living-standards measures that are found in surveys such as those fielded by the DHS program, which lack data on consumption expenditures and incomes. In the absence of proper data on consumption, we think it reasonable to define the set of living-standards indicators $\{Z_k\}$ in terms of the consumer durables and housing-quality items for which data are gathered. Using these indicators, we constructed what McDade and Adair (2001) termed a "relative affluence" measure of living standards, which is at least loosely analogous to a measure of consumption. Producer durables—which, in a rural sample, would include ownership of livestock and land—were deliberately excluded from the $\{Z_k\}$ set because while they may help determine final consumption, producer durables are not themselves measures of that consumption. They are a means to an end, or, to put it differently, producer durables are better viewed as inputs in household production functions, rather than as measures of the consumption drawn from household production.

By this logic, if producer durable variables were available for the urban samples with which we are concerned, we would have considered including them in the **X** covariates. Unfortunately, the DHS program has not collected data on urban producer durables as such in its core questionnaire.[10] Some publicly provided services can also be viewed as enabling factors, or inputs, into consumption—notably, the provision of electricity—and we therefore included electricity in the **X** living-standards determinants. Although city size may be only a distant proxy for other factors that determine consumption—among them, access to multiple income-earning possibilities and heterogeneous labor and product markets—we included city size with the other **X** variables.

It is perhaps not unreasonable to liken adult education to a producer durable, since education is a type of long-lasting characteristic that produces a lifetime stream of income and consumption. On these grounds, we included the education (and age) of the household head in our specification of the **X** determinants. In doing so, we were mindful of the "dual roles" played by education in demographic behavior (Montgomery et al. 2000). Education is at once a determinant of living standards and a conceptually separable influence on health via its links to social confidence, to the ability to process information, and to the breadth and nature of individual social networks. In short, educational measures belong with the **W** variables of the health equation, as well as in the set of **X** variables that act as determinants of living standards. Model identification is not threatened by variables that are common to both **X** and **W**, but we hoped to strengthen the empirical basis for estimation by using the education of the household head as a determinant of living standards and the education of the woman and her spouse as determinants of health.[11]

Living Standards at the Neighborhood Level

Evidently there are many issues to confront in specifying living-standards models at the household level, and further issues must be confronted in any effort to define neighborhood (cluster) living standards. Our approach is simple. With estimates $\hat{f}_{ic}$ in hand for household i in cluster c, we constructed a cluster-level measure for household i by averaging $\hat{f}_{jc}$ over all households $j \neq i$ that reside in the cluster; that is,

$$\hat{f}_i^c = \left(1/n_c\right) \sum_{j \neq i} \hat{f}_{jc},$$

10. Recently, however, the DHS has been experimenting with new urban-sensitive questions on housing ownership and security of tenure in a handful of surveys.

11. In most of our samples, there is sufficient variation in headship for this strategy to produce distinct educational variables in the indicator and health equations.

with n_c being the number of households in the cluster less 1. In our descriptive work, we also constructed measures of the proportion of cluster households falling into the lowest and highest quartiles of the urban distribution of living standards.

Summary

The outcome of the MIMIC procedure is an estimate $\hat{f}$ of each household's *relative* standard of living, with the comparison population for each survey composed of all urban households covered in that survey. In what follows, we treat $\hat{f}$ in explicitly relative terms, summarizing its estimated effects by calculating predicted health outcomes for households at given percentiles of the urban living-standards distributions. Viewed in one way, this approach simplifies the task of comparing results across countries that differ in absolute standards of living: in each case, urban households in the lowest quartile are examined in relation to those in the middle or upper quartiles. Attention to such relative measures is well justified. As the theories reviewed earlier indicate, there is ample reason to believe that in developing as well as developed countries, inequality and relative forms of social comparison can exert an important influence on health. But when viewed in another way, our insistence on relative comparisons may be thought confusing: after all, a household falling in the lowest urban quartile in a poor developing country is probably more severely deprived, when judged in absolute terms, than one in the lowest quartile of a middle-income country. The difficulty is how to quantify and separate out the absolute component, given the data at hand.

Unlike measures of income and consumption expenditures, the indicators $\{Z_k\}$ and determinants $\mathbf{X}$ supplied in the DHS data sets are not readily converted to measures of absolute deprivation. To aid in the interpretation of the results, we grouped our estimates according to geographic regions within the developing world, hoping in so doing to keep variation in absolute living standards within reasonable bounds. (We explored further breakdowns by country per capita income levels within regions but found that the additional disaggregation yielded no new insights.) Perhaps it is inevitable that surveys that offer only crude proxies for living standards—which are analyzed with living standards conceived as being inherently unobservable—provide no obvious means of separating absolute from relative effects.

Even so, further attention to this point is in order. We are encouraged by the work of Gordon et al. (2003), who devised measures of severe absolute deprivation using data from the DHS and similar surveys fielded in UNICEF's Multiple Indicator Cluster Survey program. Unfortunately, health outcomes—including children's height for age, immunization percentages, and parental responses to child illness—are among the key measures of absolute deprivation in this research. Such indices of deprivation would be statistically endogenous in models such as ours, in which health outcomes are specified as dependent variables.

DATA AND MODEL SPECIFICATION

The data for this analysis were drawn from 85 surveys that were fielded in Phases 2–4 of the DHS program.[12] The survey dates ranged from 1990 through 2001, and 50 countries in six developing regions are represented (see Appendix Table A1 for a list).

Health Measures

Regional summaries of the distributions for the health variables—the unmet need for modern contraception; attendance by a physician, nurse, or trained midwife at delivery;

12. One survey, for Yemen, provided data on durables and their determinants, but not on the health variables.

Table 1. Mean Values of Urban Unmet Need; Birth Attendance by a Physician, Nurse, or Trained Midwife; and Children's Height for Age, by Region

Region	Unmet Need[a]	All Recent Births Attended[b]	Height for Age[c]
North Africa	20.8	64.4	–0.715
Sub-Saharan Africa	48.4	60.2	–1.112
Southeast Asia[d]	21.7	65.2	
South and Central Asia	23.4	63.2	–1.241
West Asia	17.4	83.8	–0.577
Latin America	22.8	70.4	–0.885
Total	35.3	64.5	–1.032

[a]Expressed in percentages of women at risk of unmet need.

[b]Expressed in percentages of women with births in the past three years whose deliveries were attended by a physician, nurse, or trained midwife.

[c]Expressed in standard deviations from an international reference median, with –1.0 being one standard deviation below that median.

[d]No DHS in this region have collected information on children's height for age.

and children's height for age—are presented in Table 1. Here and in what follows, we use such regional summaries and averages to set the results in context. The first column of Table 1 shows the percentages of women who have an unmet need for contraception. Among women who reported that they wanted to stop childbearing altogether or to delay the next birth—excluding those who were not at risk of conception (i.e., pregnant, amenorrheic, or not in union)—a woman with an "unmet need" was one who used no modern contraception (Casterline and Sinding 2000; Westoff and Bankole 1995; Westoff and Pebley 1981). The second health measure in Table 1 was generated from the DHS maternity histories for all births that occurred in the three years before the survey date. For each such birth, information was gathered on who assisted at the delivery of the child, with the possibilities including a physician, nurse, trained midwife, other midwife, traditional birth attendant, and relative. This analysis focuses on the women whose deliveries in the past three years were attended by a physician, nurse, or trained midwife. The variable was coded 0 if one birth was attended but another was not; hence, in the case of multiple births in the three years before the survey, the variable measures consistent attendance.[13]

The DHS program also collects information on the height and weight of each (surviving) child who was born in the three years before the survey date.[14] A child's height for age is thought to be a good proxy measure of health status, reflecting both nutrition and disease history. We focused on height for age among children aged 3–36 months, with the lower age cutoff chosen to minimize the problems of measurement error that are believed to plague estimates for the youngest children (Montgomery et al. 1997). Height for age was standardized by age and sex and is represented in terms of standard deviations from the median of an international reference population.

13. An ordered-probit analysis with inconsistent attendance as a distinct outcome category produced results that were similar to those of the simple probit models reported later.

14. Although the majority of DHS have collected such information on children who were born in the past five years, we set the upper limit on age to three years to make use of all available surveys with data on height.

Table 2. Percentages of Urban Households With Living-Standards Indicators, by Region[a]

Item	North Africa	Sub-Saharan Africa	Southeast Asia	South and Central Asia	West Asia	Latin America
Consumer Durables						
Car	17.4	12.9	12.7	24.6	28.3	16.3
Television	92.6	37.4	62.6	69.9	95.8	79.0
Refrigerator	79.4	23.9	37.2	67.9	91.9	51.8
Radio	83.9	76.6	77.2	57.4	72.6	84.6
Bicycle	17.6	21.0	48.9	31.7	10.8	27.4
Motorcycle	10.3	12.6	30.5	12.9	0.1	8.9
Housing Quality						
Sleeping rooms[b]	67.3	47.7	64.8	52.4	64.9	46.2
Finished floors	94.7	76.9	75.8	47.3	79.7	77.2

[a]Unweighted means, based on households with a woman eligible for the unmet-need analysis, using surveys that gathered data on the indicator.

[b]Percentages of households with more sleeping rooms than the (weighted) urban median.

Explanatory Variables

We included a small set of variables from the DHS to serve as socioeconomic controls. Descriptive statistics for these variables are presented in Montgomery and Hewett (2004); here we discuss the rationale for including the variables and our approach to coding them. The woman's age was classified in the conventional five-year age groups. The urban context was indicated by a pair of dummy variables for residence in the country's capital or another large city (defined by the DHS as a city with a population of at least 1 million) and residence in a smaller city (with a population of 50,000–1 million residents). The omitted category for residence is towns, that is, urban places with fewer than 50,000 residents.

The educational experiences of women and their husbands or partners vary a great deal over the range of regions and countries covered in this analysis. For example, over 80% of women have completed secondary schooling in Kazakhstan and Uzbekistan, whereas only 1% have done so in Mali and Burkina Faso. Rather than force countries into a single classification scheme, we chose to define educational categories according to the distribution of attainment within each country. In the great majority of DHS, the base comprises those with no education or, at most, incomplete primary education. For a small minority of surveys, however, mainly from the former Soviet republics, this grouping yielded too small a base category, so the base was expanded to include those who completed primary school or attended, but did not complete, secondary school.

Living-Standards Indicators

The set of living-standards indicators $\{Z_k\}$ includes the consumer durables and housing items shown in Table 2. These indicators are available in almost all surveys that have been fielded in the recent phases of the DHS program, although some countries lack one or two of them. Some surveys include additional consumer items (e.g., possession of soap or a cooking stove), but we excluded such measures in the interest of achieving reasonable cross-country comparability.

HOUSEHOLD AND NEIGHBORHOOD LIVING STANDARDS

Table 3 summarizes the estimated $\hat{\beta}_k$ factor loadings produced by the MIMIC models. As can be seen in the table, these coefficients are almost always positive and statistically significant. This result is encouraging in that it supports the interpretation of the factor as

Table 3. Summary of Confirmatory-Factor Loadings (β_k) for Consumer Durables and Housing Quality[a]

Item	Estimated	Positive and Significant	Negative and Significant
Consumer Durables			
Television	71	69	1
Refrigerator	76	75	0
Radio	83	82	0
Bicycle	79	75	4
Motorcycle	57	54	1
Housing Quality			
Sleeping rooms	67	65	2
Finished floors	78	77	0

[a]The β parameter for ownership of a car is not estimated but normalized to unity.

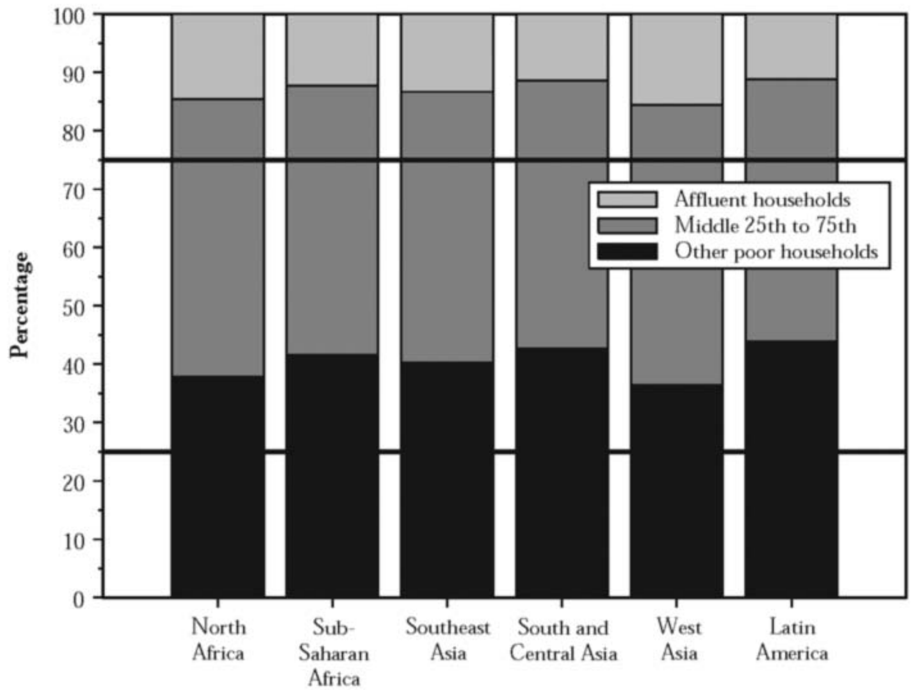
an expression of the household's relative standard of living. Table 4 presents a summary of the effects of the **X** living-standards determinants. These effects are also much in line with expectations. The provision of electricity is positively associated with relative living standards, as would be anticipated, given its role as a key input. The education of the household head is also strongly and positively associated with living standards, and, consistent with age profiles of productivity, we found that living standards increase with the head's age up to about age 60 and decrease thereafter. City-size variables show weaker effects overall, but the estimates indicate that relative living standards are generally higher in large and small cities by comparison with the levels found in towns, the smallest urban areas. Evidently there is good statistical support for the notion that the proxy variables

Table 4. Summary of γ, the Effects of Determinants X on the Living-Standards Factor

Item	Estimated	Positive and Significant	Negative and Significant
Demographic Variables for Head			
Male	85	74	11
Age	85	85	0
Age squared[a]	85	0	85
Head's Education			
Completed primary or incomplete secondary	76	76	0
Completed secondary or higher	60	60	0
Completed secondary	19	19	0
Higher	20	20	0
Unknown	12	12	0
Other			
Household has electricity	61	61	0
Residence in a small city	71	60	11
Residence in a capital or large city	82	74	7

[a]The living-standards factor was estimated to increase with the head's age up to age 59.7, which is the average "turning point" among all the estimated models.

Figure 2. Who Are the Neighbors of Relatively Poor Households?



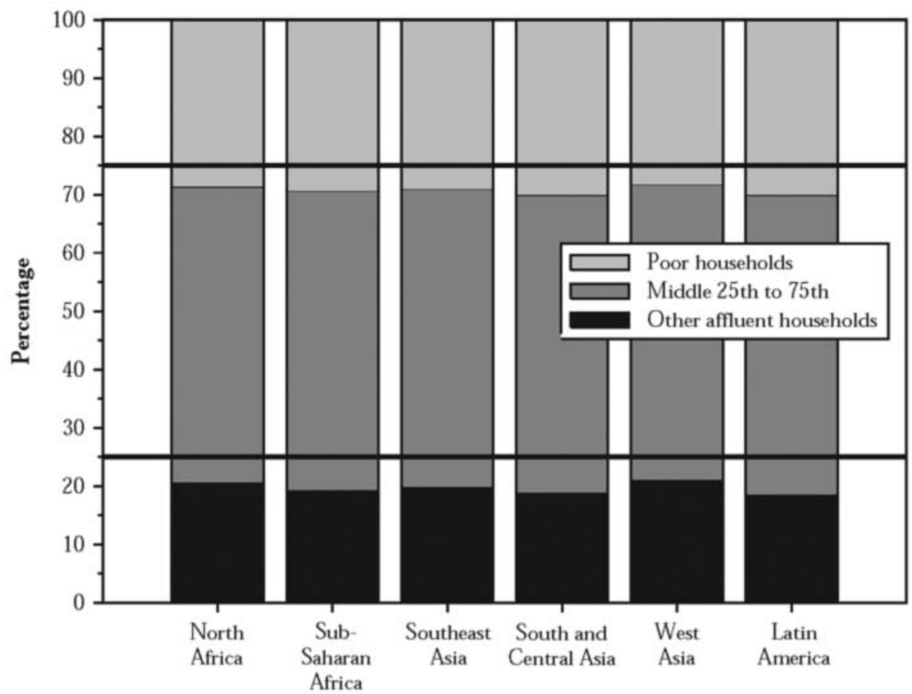
collected in the DHS are interpretable in terms of the household's otherwise unobservable standard of living.

We now examine the relationship between living-standards indexes that were estimated at the household level and aggregated indexes that were computed for the other households in the sampling cluster. Recall that the approach is to estimate factor scores $\hat{f}_{ic}$ for each household i in urban sampling cluster c in a given DHS data set. We computed the sampling cluster averages by separating out the score for each household i and calculating a mean for the remaining households in the cluster. We also examined the proportion of households in the cluster that fall into the lowest quartile of urban factor scores overall (in the survey in question) and the proportion that fall into the uppermost quartile, again without reference to the ith household. These proportions are described in what follows as the cluster proportions "relatively poor" and "relatively affluent."

In considering the DHS sampling clusters, we might ask first whether there is evidence that relative poverty and affluence are indeed spatially concentrated. It is reasonable to expect that if 25% of urban households overall are relatively poor (by definition), in examining a set of sampling clusters, we are likely to find some clusters with high concentrations of poverty and others with few relatively poor households. Likewise, we might well expect to observe a high spatial concentration of (relative) affluence.

Although these are reasonable expectations, the DHS results provide something less than resounding support for them. There is more heterogeneity in cluster composition than might have been anticipated. This greater heterogeneity is documented in several

Figure 3. **Who Are the Neighbors of Relatively Affluent Households?**



ways. In about one-third of urban clusters, less than 10% of households are relatively poor. Likewise, in about the same percentage of clusters, less than 10% of households are relatively affluent (i.e., in the upper quartile of all urban households). But in considering the full range of the distributions, we see little evidence of extreme spatial concentration. Few clusters are more than half poor or half affluent (in relative terms).

Figures 2 and 3 may further clarify matters. In Figure 2, we characterize the neighbors of relatively poor households. If such poor households were indeed generally surrounded by other poor households—as in the images of slums and shantytowns that are invoked in so many discussions of urban poverty—then we would expect to find that their neighbors are almost all poor. As the figure shows, this is far from being the case. In Latin America, the average poor household lives in a neighborhood in which about 44% of its neighbors are poor. To be sure, this is well above the percentage of poor in the urban population as a whole (25% by our definition), but it leaves substantial room for neighbors who are in the 25th–75th percentiles of the living-standards distribution (in Latin America, this "middle" group accounts for about 45% of a poor household's neighbors) and even for neighbors who are relatively affluent, those in the top-most quartile of the urban distribution. A relatively poor Latin American household has, on average, about 1 neighbor in 10 who is relatively affluent.

Figure 3 depicts the neighbors of these affluent households. Again, as expected, slightly more of the neighbors are themselves relatively affluent than in the urban population at large, and affluent households have somewhat fewer poor neighbors (who make up about 20% of the neighbors of affluent families). But a household's affluence is not strongly predictive of its neighborhood composition—these are minor departures from the 25th and 75th percentile benchmarks. The spatial concentration of relative affluence is less clearly evident than would be anticipated, given the images of extreme social-spatial polarization that appear so often in the literature.

In summary, having taken the estimated factor score to be a measure of the standard of living and having examined the internal composition of clusters in this dimension, we found some support for the hypothesis of spatial concentration of poverty and affluence, but not as much support as we had expected to find. Two cautions are in order. First, there can be no presumption that households that inhabit the same local space will interact or even serve as relevant points of comparison. The Latin American literature is especially instructive on nonspatial forms of exclusion and segregation (e.g., Caldeira 1999, 2000). Second, as we have already noted, sampling clusters are not the same thing as neighborhoods, and little, if anything, is known of their correspondence in DHS sampling designs.[15]

UNMET NEED, BIRTH ATTENDANCE, AND HEIGHT FOR AGE

In the multivariate empirical work reported in this section, we began by examining measures of the lower and upper quartiles of the factor-score distributions, focusing on the households that we have termed relatively poor and relatively affluent and on the corresponding cluster proportions. We uncovered no consistent evidence to suggest that these measures add insights beyond what can be gleaned from models with individual factor scores and cluster mean scores. (Pebley and Sastry [2003] also found it difficult to isolate the effects of poverty and affluence from the effect of neighborhood medians in their study of Los Angeles neighborhoods.) The models to which we now turn were therefore specified in terms of household scores and cluster means.

The analyses of unmet need and birth attendance are based on probit regressions for the ith household in sampling cluster c, which can be expressed as

$$\Pr\left(Y_{ic}=1\middle|\mathbf{W}_{ic},\hat{f}_{ic},\hat{f}_i^c\right)=\Phi\left(\mathbf{W}_{ic}'\theta+\hat{f}_{ic}\delta+\hat{f}_i^c\delta_c\right),$$

where Φ is the standard normal cumulative distribution function, $\mathbf{W}_{ic}$ denotes the set of explanatory variables measured at the household level, $\hat{f}_{ic}$ is the estimated factor score for the household, and $\hat{f}_i^c$ is the average of these scores in c, excluding the ith household in the cluster. The model of children's height for age is a simple regression model; the explanatory variables include those used for unmet need and birth attendance, to which we added the child's sex, age in months, and the square of age (recall that these children were no older than 36 months). Robust standard errors were used throughout.

To distill an enormous number of coefficient estimates into a few readily interpretable quantities, we summarize these estimates as follows. For each health measure, we confine our discussion mainly to the effects of the household and cluster factor scores, and with the exception of education, comment only in passing on the estimates for the other explanatory variables. We describe how often the factor score coefficients attain statistical significance and how often they are both significant and of the expected sign.

We then illustrate the size of the living-standards effect in two ways. Consider the analysis of unmet need. To summarize the effects of living standards, we calculated the predicted probability that woman i has an unmet need, given her $\mathbf{W}_{ic}$ covariates and given

15. Fred Arnold and his colleagues at the DHS have examined the case of Mumbai, India, where maps of survey enumeration areas can be overlaid on the maps of urban slum communities that have been drawn up by Indian planners and social scientists. Arnold reported seeing many discrepancies between these two types of spatial units (personal communication 2003). It is not yet known whether what is true for Mumbai is true more generally.

a factor score $\hat{f}_{ic}$ that we fixed at the value for the 25th percentile of the distribution of the urban factor score (i.e., the distribution across all urban households in the survey in question). We constructed another predicted probability using the same $\mathbf{W}_{ic}$ covariates but with the factor score set to the value corresponding to the 75th percentile of the score distribution. (The 25th and 75th percentile points were chosen to be suggestive of relatively poor and relatively affluent urban households.) We averaged the predictions $P_{i,25}$ and $P_{i,75}$ over the urban estimation sample used in the survey, thereby obtaining two averages, $\bar{P}_{25}$ and $\bar{P}_{75}$. The difference between these, $\bar{P}_{25} - \bar{P}_{75}$, illustrates the size of the factor score's effect in a given DHS sample. We termed this the "absolute difference" in the predicted probability of unmet need. In the tables that follow, the absolute difference is expressed in terms of percentage points. The second illustrative device was constructed by dividing the absolute difference by the average level of unmet need in the survey's urban sample, giving $(\bar{P}_{25} - \bar{P}_{75})/\bar{P}$, which we termed the "difference relative to the mean." This measure may convey a sense of the proportional effect of the factor score, and we report these relative differences in terms of percentages.

We used a similar approach in describing the effects of the means of the cluster-level factor score, although in this case, we took the 25th and 75th percentile points from the distribution of cluster mean scores *across clusters*. Because cluster means *are* means, they tend to have more concentrated distributions than do the individual household scores, and we took this fact into account in choosing values to represent relatively poor and relatively affluent clusters.

Models With Household Factors Only

Tables 5–7 summarize the results from models using the household factor scores together with the set of socioeconomic controls. There is an impressive consistency in the findings across the three measures of health. First, the factor scores are generally statistically significant and take the expected sign in each of the health equations. As can be seen in the second columns of these tables, the household score is negative and significant in 64 of the 84 DHS in which unmet need was analyzed (Table 5), is positive and significant in 63 of the 76 surveys in which birth attendance was examined (Table 6), and is positive and significant in 49 of the 73 surveys with data on children's height for age (Table 7). The proportions of significant findings are strikingly similar to those for women's education, as can be seen in the notes to the tables.[16]

The substantive implications of the household scores are summarized in the remaining columns of these tables. We first focus on the absolute differences, comparing predicted values for households at the 25th percentile of the score distribution (the "relatively poor" households) with those at the 75th percentile (the "relatively affluent"), and then examine the effects relative to the mean of each dependent variable. The estimated effects are reported for all surveys and separately for the surveys in which a statistically significant coefficient was found. For the analysis of unmet need (Table 5), the average difference in the percentage of unmet need that is implied by this comparison is 7.4 percentage points in the full sample (see the "Total" row) and 8.7 percentage points in the sample with significant results. Among the regions, the largest absolute effects were found in sub-Saharan Africa and Latin America. When these absolute effects are translated into relative terms (the last two columns of the table), we see that an absolute difference of 6.3 points in the Latin American results is equivalent to 31.1% of the mean level of unmet need. The relative effects of the household factor for the other regions are generally smaller than this but are still of considerable substantive importance.

16. Note the minor differences in the total number of surveys in which effects can be estimated for a given covariate—these differences are due to the occasional instance of perfect collinearity with another explanatory variable or perfect association with the dependent variable.

Table 5. Summary of Estimates of Unmet Need for Modern Contraception Using Confirmatory-Factor Scores

		Effect of Household Factor Score			
		Absolute Difference[b]		Difference Relative to the Mean[c]	
Region	Factor Score Negative and Significant[a]	All	Significant	All	Significant
North Africa	3 of 4	4.0	4.9	18.9	22.0
Sub-Saharan Africa	31 of 42	9.5	11.5	22.9	28.1
Southeast Asia	5 of 6	4.5	5.7	17.3	24.8
South and Central Asia	6 of 12	5.2	7.1	22.7	26.6
West Asia	3 of 4	3.9	4.8	22.5	28.0
Latin America	16 of 16	6.3	6.3	31.1	31.1
Total	64 of 84	7.4	8.7	23.8	28.1

[a]This column may be compared with the results for women's education and the education of the husband or partner. Women's education exerts a negative and significant influence on unmet need in 2 of 4 surveys in North Africa, 28 of 42 in sub-Saharan Africa, 3 of 6 in Southeast Asia, 4 of 12 in South and Central Asia, 3 of 4 in West Asia, and 10 of 16 in Latin America. Husbands' education is negative and significant far less often: in none of the surveys in North Africa, Southeast Asia, and South and Central Asia; in 16 of 39 surveys in sub-Saharan Africa; in 1 of 4 surveys in West Asia; and in 4 of 16 surveys in Latin America.

[b]Expressed in percentage points. The difference is between predicted unmet need among households at the 25th percentile of the urban household factor score distribution and predicted unmet need among households at the 75th percentile.

[c]Expressed in the percentage of mean unmet need in the urban samples.

Much the same story emerges from the analyses of birth attendance and children's height for age, which are summarized in Tables 6 and 7. The estimated influence of the household living standards on birth attendance is large in terms of the percentage-point differences between poor and affluent households, and these absolute differences imply differences relative to mean attendance that range from 7.6% in West Asia to 47.6% for the significant cases of South and Central Asia. In the height-for-age models (Table 7), in which absolute effects are expressed in terms of standard deviations from the reference median, the implied difference between an affluent and a poor household is on the order of 0.291 standard deviations of children's height. These differences are quite large in relative terms, especially in Latin America. Clearly, even within urban populations that are generally far better supplied with transportation options and health services than are rural populations, a household's standard of living can make a considerable difference to its health.

With household living standards controlled, women's education exhibits a substantial additional influence of its own on all three measures of health. As we describe in the notes to the tables, women's education significantly reduces unmet need in 50 of the 82 surveys that we examined, is positively associated with birth attendance in 58 of 76 surveys, and exhibits a positive and significant association with children's height for age in 33 of 73 surveys. By contrast, the education of the woman's spouse or partner achieves significance much less often (in 21 of 81 surveys for unmet need, 27 of 73 for birth attendance, and only 13 of 71 for children's height). The influence of women's education on health is evidently separable from its association with household living standards, a finding consistent with the view that education also influences health through social confidence, the ability to process information, and related mechanisms. Our findings lend less-consistent support to this view where men's education is concerned, although significant effects did surface in a number of surveys. The MIMIC

Table 6. Summary of Estimates of Birth Attendance by a Physician, Nurse, or Trained Midwife Using Confirmatory-Factor Scores

		Effect of Household Factor Score			
	Factor Score Positive and	Absolute Difference[b]		Difference Relative to the Mean[c]	
Region	Significant[a]	All	Significant	All	Significant
North Africa	4 of 4	7.1	7.1	11.6	11.6
Sub-Saharan Africa	31 of 39	10.7	12.9	18.7	20.2
Southeast Asia	4 of 5	10.8	14.3	14.9	19.5
South and Central Asia	8 of 8	18.8	18.8	47.6	47.6
West Asia	3 of 4	4.4	5.3	7.6	9.4
Latin America	13 of 16	7.9	9.4	13.8	16.4
Total	63 of 76	10.4	9.4	19.5	21.8

The surveys for Ethiopia 1999, Niger 1998, and Philippines 1998 did not collect data on birth attendance. Models for Armenia 2000, Jordan 1997, Kazakhstan 1995, Kazakhstan 1999, Kyrgyz Republic 1997, and Uzbekistan 1996 could not be estimated because of near-universal birth attendance by a trained professional.

[a]This column may be compared with the results for women's education. Women's education exerts a positive and significant influence on birth attendance in 4 of 4 surveys in North Africa; 24 of 39 surveys in sub-Saharan Africa; 4 of 5 surveys in Southeast Asia; 8 of 8 surveys in South and Central Asia; 4 of 4 surveys in West Asia; and 14 of 16 surveys in Latin America. Husbands' education is positive and significant in 3 of 4 surveys in North Africa; 10 of 36 surveys in sub-Saharan Africa; 3 of 5 surveys in Southeast Asia; 3 of 8 surveys in South and Central Asia; 2 of 4 surveys in West Asia; and 6 of 16 surveys in Latin America.

[b]Expressed in percentage points. The difference is between predicted birth attendance among households at the 75th percentile of the distribution of the urban household factor score and birth attendance among households at the 25th percentile.

[c]Expressed in the percentages of women with all births attended in the urban samples.

Table 7. Summary of Estimates of Children's Height for Age Using Confirmatory-Factor Scores

		Effect of Household Factor Score			
	Factor Score Positive and	Absolute Difference[b]		Difference Relative to the Mean[c]	
Region	Significant[a]	All	Significant	All	Significant
North Africa	1 of 3	0.123	0.252	19.7	45.2
Sub-Saharan Africa	25 of 39	0.322	0.398	29.7	36.1
South and Central Asia	5 of 11	0.212	0.322	23.2	20.9
West Asia	3 of 5	0.211	0.224	42.7	49.5
Latin America	15 of 15	0.328	0.328	42.6	42.6
Total	49 of 73	0.291	0.355	31.8	37.6

[a]This column may be compared with the results for women's education. Women's education exerts a positive and significant influence on children's height for age in 1 of 3 surveys in North Africa, 11 of 39 surveys in sub-Saharan Africa, 6 of 11 surveys in South and Central Asia, 3 of 5 surveys in West Asia, and 12 of 15 surveys in Latin America. Husbands' education is positive and significant in 1 of 3 surveys in North Africa, 3 of 37 surveys in sub-Saharan Africa, 2 of 11 surveys in South and Central Asia, 2 of 5 surveys in West Asia, and 5 of 15 surveys in Latin America.

[b]Expressed in standard deviations, the units in which height for age is expressed. The difference is between child's predicted height among households at the 75th percentile of the distribution of the urban household factor score and predicted height among households at the 25th percentile.

[c]Expressed in the percentages of mean height for age in the urban samples.

Table 8. Summary of Estimates of Unmet Need for Modern Contraception Using Household and Cluster Average Factor Scores

			Effect of Mean Cluster Score			
			Absolute Difference[a]		Difference Relative to the Mean[b]	
Region	Cluster Score Negative and Significant	Household Score Negative and Significant	All	Significant	All	Significant
North Africa	2 of 4	3 of 4	2.1	2.9	10.1	13.2
Sub-Saharan Africa	5 of 42	24 of 42	2.0	8.1	4.3	23.9
Southeast Asia	0 of 6	5 of 6	0.3	—	4.0	—
South and Central Asia	2 of 12	7 of 12	1.5	3.0	6.1	18.6
West Asia	3 of 4	3 of 4	3.4	4.9	19.4	28.1
Latin America	4 of 16	14 of 16	1.8	5.8	7.8	22.3
Total	16 of 84	56 of 84	1.8	5.6	5.6	22.3

[a]Expressed in percentage points. The difference is between predicted unmet need among households at the 25th percentile of the distribution of urban cluster means across clusters and unmet need among households at the 75th percentile of this distribution.

[b]Expressed in percentages of mean unmet need in the urban samples.

factor estimate is partly determined by the education of the head of household (Table 4), and it may be that collinearity with $\hat{f}$ tends to mask much of the direct effect of men's education on the three measures of health.

Models With Both Household and Cluster Factor Scores

To weigh the evidence for "neighborhood effects," we now add the cluster means of the household factor scores to the models, retaining all other covariates and the household's own factor score. The results are summarized in Tables 8–10. We first describe the number of surveys in which we found a significant effect for the cluster variable and report the significance of the household scores to determine whether separate household and cluster effects can really be discerned. We then describe the influence of the cluster scores, comparing predicted values at the 25th percentile of the distribution of the cluster score (the "relatively poor" clusters) with those at the 75th percentile ("relatively affluent" clusters).

In general, the cluster-level factors are not statistically significant as often as the individual household factors, and the significance of the household factors is little affected by the inclusion of the cluster measures. (Each table includes a column indicating how often the household factors are significant; as can be seen, the inclusion of a cluster-level average removed statistical significance from the household factor in only a few cases.) For unmet need, the cluster mean score is negative and significant in 16 of the 84 surveys (Table 8), positive and significant in 53 of the 76 cases for birth attendance (Table 9), and positive and significant in 22 of 73 cases for children's height for age (Table 10). When they are significant, however, the absolute and relative effects of the cluster scores indicate that neighborhood living standards can exert a substantively important influence on health, with the effects being most striking in the case of birth attendance.

How does the general pattern of these findings square with the theories of neighborhood effects that we outlined earlier? The three main pathways of influence that we mentioned involve health externalities that are associated with communicable diseases; social externalities that stem from localized patterns of interaction, information flow, and the like; and the effects of the provision of local services.

Table 9. Summary of Estimates of Birth Attendance by a Physician, Nurse, or Trained Midwife Using Household and Cluster Average Factor Scores

			Effect of Mean Cluster Score			
			Absolute Difference[a]		Difference Relative to the Mean[b]	
Region	Cluster Score Positive and Significant	Household Score Positive and Significant	All	Significant	All	Significant
North Africa	3 of 4	4 of 4	8.9	11.0	13.6	16.2
Sub-Saharan Africa	23 of 39	16 of 39	7.6	11.3	14.8	21.6
Southeast Asia	4 of 5	4 of 5	8.1	9.4	10.8	12.7
South and Central Asia	6 of 8	7 of 8	7.8	8.1	19.4	19.6
West Asia	3 of 4	3 of 4	3.2	3.2	4.4	3.6
Latin America	14 of 16	11 of 16	7.5	8.2	12.5	13.8
Total	53 of 76	45 of 76	7.5	9.5	13.9	17.3

The surveys for Ethiopia 1999, Niger 1998, and Philippines 1998 did not collect data on birth attendance. Models for Armenia 2000, Jordan 1997, Kazakhstan 1995, Kazakhstan 1999, Kyrgyz Republic 1997, and Uzbekistan 1996 could not be estimated because of near-universal birth attendance by a trained professional.

[a]Expressed in percentage points. The difference is between predicted birth attendance among households at the 75th percentile of the distribution of urban cluster means across clusters and birth attendance among households at the 25th percentile of this distribution.

[b]Expressed in percentages of women with all births attended by a physician, nurse, or trained midwife in the urban samples.

Table 10. Summary of Estimates of Height for Age Using Household and Cluster Average Factor Scores

			Effect of Mean Cluster Score			
			Absolute Difference[a]		Difference Relative to the Mean[b]	
Region	Cluster Score Positive and Significant	Household Score Positive and Significant	All	Significant	All	Significant
North Africa	3 of 3	1 of 3	0.174	0.174	25.4	25.4
Sub-Saharan Africa	5 of 39	22 of 39	0.107	0.253	11.3	25.8
South and Central Asia	2 of 11	5 of 11	0.151	0.145	17.0	9.1
West Asia	2 of 5	3 of 5	0.104	0.181	21.7	39.7
Latin America	10 of 15	14 of 15	0.182	0.244	24.9	35.0
Total	22 of 73	45 of 73	0.132	0.222	16.3	29.7

[a]Expressed in standard deviations. The difference is between predicted height for age among households at the 75th percentile of the distribution of urban cluster means across clusters and predicted height for age among households at the 25th percentile of this distribution.

[b]Expressed in the percentages of mean height for age in the urban samples.

We had expected to find the clearest expression of neighborhood effects in the analyses of children's height because that is where one would think health externalities and the risks of contagion in poor neighborhoods would be most apparent. We found numerous significant and relatively large effects on height for age (Table 10), especially in Latin America, but, on the whole, the cluster measure attains significance in under one-third of the surveys. It may be that cluster means of living-standards scores are simply too many steps removed from the epidemiological mechanisms that tend to produce within-neighborhood contagion. Direct measures of health in the cluster (e.g., the percentages of children with recent fevers or diarrheas) may better isolate this particular pathway of influence.

By contrast, the links between neighborhood living standards and birth attendance are surprisingly strong. We do not think that the effects of contagion in a narrow epidemiological sense can be involved here. But neighborhood patterns of social interaction and information exchange could make a crucial difference in how city residents assess the risks of childbirth and determine whether the residents feel comfortable with modern medical professionals and are motivated to pay for modern services. (The ability of households to pay is indicated in the strong effects of the household-level factor scores.) These are examples that touch on the social epidemiology of health and health-seeking behavior. Our results for urban communities may thus parallel what Pebley, Goldman, and Rodríguez (1996) found for rural Guatemalan villages: strong associations among community residents in birth attendance that stem from shared norms and views about appropriate care during childbirth. There may be other explanations for the patterns that we found. As we noted earlier, relatively poor urban neighborhoods may not be well equipped with private-sector health services, and even public-sector clinics and hospitals may be located elsewhere if governments make little effort to target services to the poor. The difference between the social and service environments could be examined further if inventories of urban health services according to their distance from the DHS sampling clusters were available; unfortunately, such data have not been gathered routinely in the DHS program.

Summary

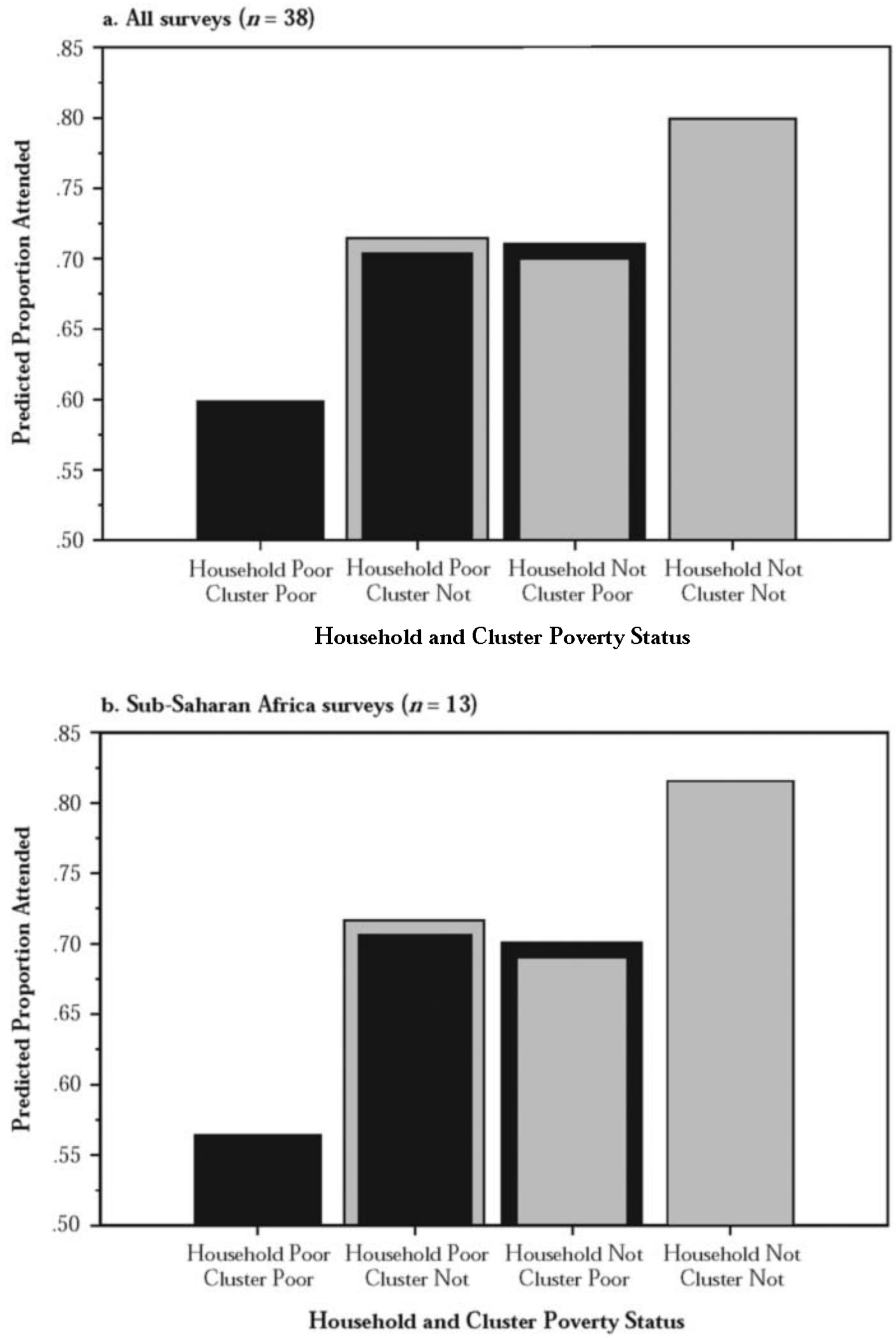
Figure 4 summarizes the implications of household and cluster living standards for birth attendance, using averages of predicted probabilities for all surveys in which both the household living-standards factor and the cluster factor were significant (Figure 4a) and separately for the sub-Saharan and Latin American surveys. The bars in the figure represent the probabilities of birth attendance for poor households in poor clusters, nonpoor households in these poor clusters, and poor and nonpoor households in the nonpoor clusters.[17] As can be seen, the least-protected households are the poor households in poor clusters, and the best-protected are the nonpoor households in nonpoor clusters. But poor households in nonpoor clusters are about as well protected (in terms of birth attendance) as the nonpoor households in poor clusters. Social or medical resources may be accessible in the better-off clusters that bring substantial benefits to poor households.

CONCLUSIONS

This article can be read as a progress report on a far-from-completed research agenda. We have found strong associations between the relative living standards of urban households, as measured by MIMIC factor scores, and the unmet need for modern contraception, birth attendance, and children's height for age. The effects are generally statistically significant (not always, to be sure, but the fraction that is significant is strikingly similar to that for women's education), and these associations are clearly of substantive importance. Measures of living standards at the level of the cluster attained

17. The predicted values are taken from the models described in Table 9, which contain only the "main effects" of the household and cluster living-standards factors. We also estimated models that include interactions between the household and cluster factors, but found that these interactions attained statistical significance in only eight surveys. It seems, therefore, that a simple, additive, main-effects model adequately summarizes these data.

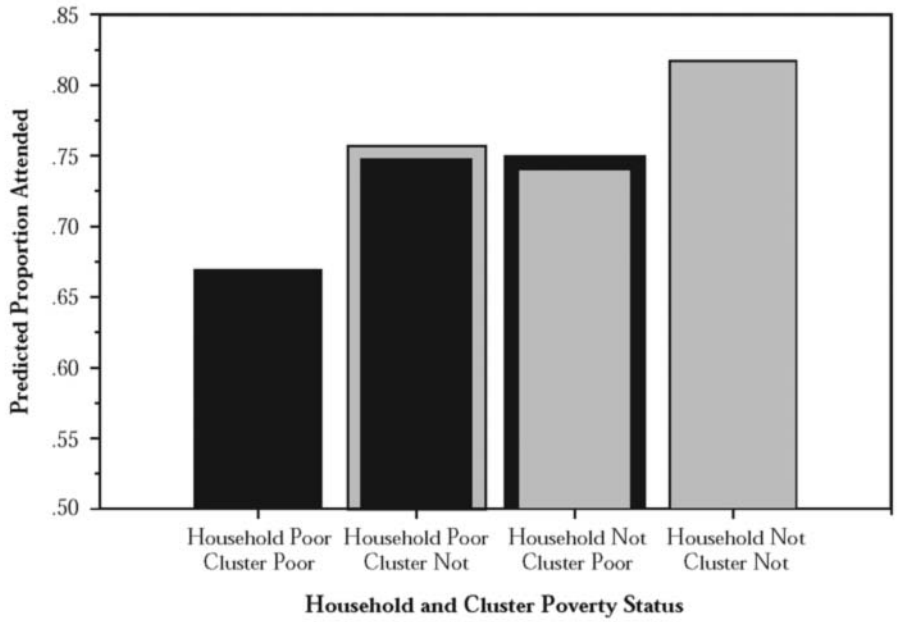
Figure 4. Predicted Proportion of Births Attended, by Household and Cluster Poverty: Results for Surveys in Which Both Household and Cluster Factor Scores are Significant



n n

n n

c. Latin America surveys (n = 11)



statistical significance less often, but when they were significant, the cluster effects were also found to be of substantive importance. To judge from our results, there is good reason to believe that both the household and neighborhood dimensions of living standards matter. It seems that the health of poor households can depend not only on the households' own standards of living but also on the economic composition of the neighborhoods in which they live.

In reflecting on the meaning of these results, it is worth remembering just how crude some of the key measures are. The standard-of-living concept is measured only imperfectly by a few simple indicators $\{Z_k\}$ and determinants $\mathbf{X}$. The concept of *neighborhood* is also imperfectly measured by the boundaries of DHS sampling clusters. We hope that the mismatches between neighborhood (a social construct) and sampling clusters (a statistical device) are not so great as to threaten the conclusions of this research, but we know of no direct evidence on this point. Our conceptualization of neighborhood composition is simplistic—in a fuller treatment, more attention could be paid to neighborhood social composition, as reflected in the percentages of local residents who are educated, for example (Coleman 1988; Kaufman et al. 2002; Kravdal 2003). And all our results refer to poverty, affluence, and living standards in relative terms only. With the data at hand, we could not easily distinguish relative from absolute deprivation and were therefore prevented from pursuing this important distinction.

As our descriptive analyses have shown, the neighborhoods of relatively poor urban households often contain considerable percentages of nonpoor households and even appreciable percentages of relatively affluent households, with some 1 in 10 of a poor household's neighbors typically belonging to the upper quartile of the urban distribution.

This neighborhood heterogeneity in living standards has not been much remarked upon in demographic analyses of developing-country cities. But is it really surprising that city neighborhoods in developing countries are heterogeneous? For the United States, it has long been known that spatial segregation by income is much less pronounced than is segregation by race (e.g., White 1987). Research by Hardman and Ioannides (2004) on the American Housing Survey, using data on the 10 closest neighbors of each sampled household, has revealed substantial income heterogeneity within these micro-neighborhoods. Likewise, a detailed study of Cali, Colombia, in the mid-1990s (World Bank 2002) found considerable income heterogeneity within *manzanas*, which are small blocks of housing that are classified into what had previously been regarded as homogeneous socioeconomic strata. Upon closer inspection, however, in the lowest socioeconomic stratum of *manzana* in Cali, 1 household in 5 was discovered to have a per capita income that placed it in the top 40% of the distribution for the city as a whole. In the highest stratum of *manzana*, about 1 household in 10 had a per capita income that placed it in the bottom 40% of the city's income distribution. Not enough is yet known of the empirical realities to say whether the images of uniformly poor slums and uniformly affluent communities that are so often portrayed in the literature have misrepresented the diversity within city neighborhoods, but enough is known for these characterizations to be viewed skeptically.[18]

To the extent that such diversity brings social, economic, and political resources within the reach of the poor, it may enhance the potential for neighborhood-based interventions. Consider a health intervention that aims to improve the lives of the urban poor. Should such a program be situated in a neighborhood in which nearly all residents are poor and health needs are the greatest? Or is there reason to consider mixed-income sites as well? Mixed-income communities may be able to supply more volunteers for community-based organizing activities and may possess a stronger base of local associations. The middle- and upper-income residents of such communities could conceivably serve as "bridges" to politicians, governmental agencies, and sources of outside funding and expertise. For these reasons, neighborhood social and economic heterogeneity could well amplify the positive effects of health interventions. In theory, at least, programs that are set in such heterogeneous neighborhoods could yield more benefits for the poor than those that are located in uniformly poor neighborhoods. But there are also risks in situating health interventions in mixed-income communities. Program benefits can be siphoned off by upper-income residents, and it could prove difficult to sustain community motivation for pro-poor activities when better-off residents have the means to purchase health care. These are obviously difficult and situation-specific issues.

If the heterogeneity that we have documented is found to be characteristic of the neighborhoods of the developing-country urban poor, it will present both challenges and opportunities for health research, programs, and policies. In the realm of research, theories of urban social and environmental interaction and externalities (Panel on Urban Population Dynamics 2003) have indicated the need to collect social network and detailed spatial data that lie well outside the current scope of the DHS program and that will require new types of surveys to be fielded in the neighborhoods of developing-country cities. Much could be learned, we believe, by applying to developing-country cities the conceptual and measurement tools that are now being applied to poor urban communities in the United States.

---

18. A complicating factor is that the composition of neighborhoods can be fluid. In urban Uruguay (not in our DHS sample), according to Baker (2001), city neighborhoods were once thought to be internally heterogeneous, with households of different income levels sharing much the same public space and services, which contributed to a sense of social cohesion. More recently, however, evidence has been found of increasing polarization, with the former residents of Montevideo's middle-class neighborhoods moving to poorer peripheral areas of the city that are disconnected from services and beneficial social networks.

Appendix Table A1. Demographic and Health Surveys, Phases 2–4

Region or Country	Survey Year	Region or Country	Survey Year
North Africa		Southeast Asia	
Egypt	1992, 1995, 2000	Indonesia	1991, 1994, 1997
Morocco	1992	Philippines	1993, 1998
Sub-Saharan Africa		Vietnam	1997
Benin	1996	South, Central, West Asia	
Burkina Faso	1992, 1998	Armenia	2000
Cameroon	1991, 1998	Bangladesh	1993, 1996, 1999
Central African Republic	1994	India	1992, 1998
Chad	1996	Jordan	1997
Comoros	1996	Kazakhstan	1995, 1999
Côte d'Ivoire	1994, 1998	Kyrgyz Republic	1997
Ethiopia	1999	Nepal	1996, 2000
Ghana	1993, 1998	Pakistan	1990
Guinea	1999	Turkey	1993, 1998
Kenya	1993, 1998	Uzbekistan	1996
Madagascar	1992, 1997	Yemen	1991
Malawi	1992, 2000	Latin America	
Mali	1995, 2001	Bolivia	1993, 1998
Mozambique	1997	Brazil	1996
Namibia	1992	Colombia	1990, 1995, 2000
Niger	1992, 1998	Dominican Republic	1991, 1996
Nigeria	1999	Guatemala	1995, 1999
Rwanda	1992, 2000	Haiti	1994, 2000
Senegal	1992, 1997	Nicaragua	1997
South Africa	1998	Peru	1991, 1996, 2000
Tanzania	1991, 1996, 1999		
Togo	1998		
Uganda	1995, 2000		
Zambia	1992, 1996		
Zimbabwe	1994, 1999		

REFERENCES

Aber, J.L., M.A. Gephart, J. Brooks-Gunn, and J.P. Connell. 1997. "Development in Context: Implications for Studying Neighborhood Effects." Pp. 44–61 in *Neighborhood Poverty, Volume I: Context and Consequences for Children,* edited by J. Brooks-Gunn, G.J. Duncan, and J.L. Aber. New York: Russell Sage Foundation.

Åberg Yngwe, M., J. Fritzell, O. Lundberg, F. Diderichsen, and B. Burström. 2003. "Exploring Relative Deprivation: Is Social Comparison a Mechanism in the Relation Between Income and Health?" *Social Science and Medicine* 57:1463–73.

African Population and Health Research Center. 2002. *Population and Health Dynamics in Nairobi's Informal Settlements: Report of the Nairobi Cross-Sectional Slums Survey (NCSS) 2000*. Nairobi: African Population and Health Research Center.

Astone, N., C.A. Nathanson, R. Schoen, R., and Y.J. Kim. 1999. "Family Demography, Social Theory, and Investment in Social Capital." *Population and Development Review* 25:1–31.

Baker, J.L. 2001. "Social Exclusion in Urban Uruguay." Working paper. Latin America and Caribbean Region, World Bank, Washington, DC.

Behrman, J., H.-P. Kohler, and S. Watkins. 2001. "Social Networks, Family Planning, and Worrying About AIDS." Paper presented at the 2001 annual meeting of the Population Association of America, Washington, DC, March 29–31.

Bollen, K. 1989. *Structural Equations With Latent Variables*. New York: John Wiley & Sons.

Caldeira, T.P.R. 1999. "Fortified Enclaves: The New Urban Segregation." Pp. 114–38 in *Cities and Citizenship,* edited by J. Holston. Durham, NC: Duke University Press.

———. 2000. *City of Walls: Crime, Segregation, and Citizenship in São Paulo*. Berkeley: University of California Press.

Casterline, J.B., ed. 2001. *Diffusion Processes and Fertility Transition: Selected Perspectives*. Washington, DC: National Academies Press.

Casterline, J.B., M.R. Montgomery, D.K. Agyeman, P. Aglobitse, and G.-E. Kiros. 2001. "Social Networks and Contraceptive Dynamics in Southern Ghana." Paper presented at the 2001 annual meeting of the Population Association of America, Washington, DC, March 29–31.

Casterline, J.B. and S.W. Sinding. 2000. "Unmet Need for Family Planning in Developing Countries and Implications for Population Policy." *Population and Development Review* 26: 691–723.

Coleman, J.S. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94(Suppl.):S95–S120.

Coulton, C., J. Korbin, T. Chan, and M. Su. 1997. "Mapping Residents' Perceptions of Neighborhood Boundaries: A Methodological Note." Working Paper. Center on Urban Poverty and Social Change, Case Western Reserve University, Cleveland, OH.

Drukker, M., C. Kaplan, F. Feron, and J. van Os. 2003. "Children's Health-Related Quality of Life, Neighbourhood Socio-economic Deprivation and Social Capital. A Contextual Analysis." *Social Science and Medicine* 57:825–41.

Ferguson, B.D., A. Tandon, E. Gakidou, and C.J.L. Murray. 2003. "Estimating Permanent Income Using Indicator Variables." Discussion Paper No. 42. Global Programme on Evidence for Health Policy, World Health Organization, Geneva.

Filmer, D. and L. Pritchett. 1999. "The Effect of Household Wealth on Educational Attainment: Evidence From 35 Countries." *Population and Development Review* 25:85–120.

———. 2001. "Estimating Wealth Effects Without Expenditure Data—Or Tears: An Application to Educational Enrollments in States of India." *Demography* 38:115–32.

Freedman, R. and J.Y. Takeshita. 1969. *Family Planning in Taiwan: An Experiment in Social Change*. Princeton, NJ: Princeton University Press.

Furstenberg, F.F. 1993. "How Families Manage Risk and Opportunity in Dangerous Neighborhoods." Pp. 231–58 in *Sociology and the Public Agenda,* edited by W.J. Wilson. Newbury Park, CA: Sage.

Furstenberg, F.F. and M.E. Hughes. 1997. "The Influence of Neighborhoods on Children's Development: A Theoretical Perspective and a Research Agenda." Pp. 23–47 in *Neighborhood Poverty, Volume II: Policy Implications in Studying Neighborhoods,* edited by J. Brooks-Gunn, G.J. Duncan, and J.L. Aber. New York: Russell Sage Foundation.

Ginther, D., R. Haveman, and B. Wolfe. 2000. "Neighborhood Attributes as Determinants of Children's Outcomes: How Robust Are the Relationships?" *Journal of Human Resources* 35:603–33.

Gordon, D., S. Nandy, C. Pantazis, S. Pemberton, and P. Townsend. 2003. *Child Poverty in the Developing World*. Bristol, England: Policy Press.

Hardman, A. and Y.M. Ioannides. 2004. "Income Mixing and Housing in U.S. Cities: Evidence From Neighborhood Clusters of the American Housing Survey." Working paper. Department of Economics, Tufts University, Medford, MA.

Harpham, T. and M. Tanner, eds. 1995. *Urban Health in Developing Countries: Progress and Prospects*. New York: St. Martin's Press.

Herr, H. and G. Karl. 2002. "Estimating Global Slum Dwellers: Monitoring the Millennium Development Goal 7, Target 11." Monitoring Systems Branch, Global Urban Observatory. Nairobi: UN-HABITAT.

Herr, H. and G. Mboup. 2003. "Slum Dweller Estimation Methodology." Unpublished paper. Nairobi: UN-HABITAT.

Jöreskog, K.G. 2000. "Latent Variable Scores and Their Uses." Unpublished paper. Available on-line at http://www.ssicentral.com/lisrel.column6.pdf

———. 2002. "Structural Equation Modeling With Ordinal Variables Using LISREL." Unpublished paper. Available on-line at http://www.ssicentral.com/lisrel/corner.htm

Kaufman, C.E., S. Clark, N. Manzini, and J. May. 2002. "How Community Structures of Time and Opportunity Shape Adolescent Sexual Behavior in South Africa." Working Paper No. 159. Policy Research Division, Population Council, New York.

Kravdal, Ø. 2003. "Community Mortality in India: Individual and Community Effects of Women's Education and Autonomy." East-West Center Working Papers, Population Series, no. 112. East-West Center, Honolulu, HI.

Lawley, D.N. and A.E. Maxwell. 1962. "Factor Analysis as a Statistical Method." *Statistician* 12:209–29.

Massey, D.S. 1990. "American Apartheid: Segregation and the Making of the Underclass." *American Journal of Sociology* 96:329–57.

———. 1996. "The Age of Extremes: Concentrated Affluence and Poverty in the Twenty-first Century." *Demography* 33:395–412.

McCulloch, A. 2003. "An Examination of Social Capital and Social Disorganisation in Neighbourhoods in the British Household Panel Study." *Social Science and Medicine* 56: 1425–38.

McDade, T.W. and L.S. Adair. 2001. "Defining the 'Urban' in Urbanization and Health: A Factor Analysis Approach." *Social Science and Medicine* 53:55–70.

Montgomery, M.R. and A.C. Ezeh. 2005. "Urban Health in Developing Countries: Insights From Demographic Theory and Practice." Pp. 317–60 in *The Handbook of Urban Health,* edited by S. Galea and D. Vlahov. New York: Springer.

Montgomery, M.R., M. Gragnolati, K.A. Burke, and E. Paredes. 2000. "Measuring Living Standards With Proxy Variables." *Demography* 37:155–74.

Montgomery, M.R. and P.C. Hewett. 2004. "Urban Poverty and Health in Developing Countries: Household and Neighborhood Effects." Working Paper No. 184. Policy Research Division, Population Council, New York. Available on-line at www.popcouncil.org/publications

Montgomery, M.R., C. Lloyd, P.C. Hewett, and P. Heuveline. 1997. "The Consequences of Imperfect Fertility Control for Children's Survival, Health, and Schooling." Demographic and Health Surveys Analytical Reports No. 7. Macro International, Calverton, MD.

Oakes, J.M. 2004. "The (Mis)estimation of Neighborhood Effects: Causal Inference for a Practicable Social Epidemiology." *Social Science and Medicine* 58:1929–52.

Panel on Urban Population Dynamics, National Research Council. 2003. *Cities Transformed: Demographic Change and Its Implications in the Developing World,* edited by M.R. Montgomery, R. Stren, B. Cohen, and H. Reed. Washington, DC: National Academies Press.

Pebley, A.R., N. Goldman, and G. Rodríguez. 1996. "Prenatal and Delivery Care and Childhood Immunization in Guatemala: Do Family and Community Matter?" *Demography* 33:231–47.

Pebley, A.R. and N. Sastry. 2003. "Concentrated Poverty vs. Concentrated Affluence: Effects on Neighborhood Social Environments and Children's Outcomes." Paper presented at the 2003 annual meeting of the Population Association of America, Minneapolis, MN, May 1–3.

Sahn, D.E. and D.C. Stifel. 2000. "Poverty Comparisons Over Time and Across Countries in Africa." *World Development* 28(12):2123–55.

Sampson, R.J., J.D. Morenoff, and T. Gannon-Rowley. 2002. "Assessing 'Neighborhood Effects': Social Processes and New Directions in Research." *Annual Review of Sociology* 28:443–78.

Sastry, N. 1996. "Community Characteristics, Individual and Household Attributes, and Child Survival in Brazil." *Demography* 33:211–29.

Sastry, N., A. Pebley, and M. Zonta. 2002. "Neighborhood Definitions and the Spatial Dimension of Daily Life in Los Angeles." Paper presented at the 2002 annual meeting of the Population Association of America, Atlanta, GA, May 9–11.

Szwarcwald, C.L., C.L.T. de Andrade, and F.I. Bastos. 2002. "Income Inequality, Residential Poverty Clustering and Infant Mortality: A Study in Rio de Janeiro, Brazil." *Social Science and Medicine* 55:2083–92.

Tandon, A., E. Gakidou, C.J.L. Murray, and B. Ferguson. 2002. "Cross-Population Comparability and PPPs: Using Micro-data on Indicators of Consumer Durables." Evidence and Information for Policy Cluster draft paper. World Health Organization, Geneva.

Timæus, I.M. and L. Lush. 1995. "Intra-urban Differentials in Child Health." *Health Transition Review* 5:163–90.

United Nations. 2000. *World Urbanization Prospects: The 1999 Revision: Data Tables and Highlights*. New York: Department of Economic and Social Affairs, Population Division, United Nations.

van den Eeden, P. and H.J.M. Hüttner. 1982. "Multi-level Research." *Current Sociology* 30(3): 1–182.

Wellman, B. and B. Leighton. 1979. "Networks, Neighborhoods, and Communities: Approaches to the Study of the Community Question." *Urban Affairs Quarterly* 14:363–90.

Wen, M., C.R. Browning, and K.A. Cagney. 2003. "Poverty, Affluence, and Income Inequality: Neighborhood Economic Structure and Its Implications for Health." *Social Science and Medicine* 57:843–60.

Westoff, C.F. and A. Bankole. 1995. *Unmet Need 1990–1994*. Demographic and Health Surveys Comparative Studies. Calverton, MD: Macro International.

Westoff, C.F. and A.R. Pebley. 1981. "Alternative Measures of Unmet Need for Family Planning in Developing Countries." *International Family Planning Perspectives* 7(4):126–36.

White, M.J. 1987. *American Neighborhoods and Residential Differentiation*. New York: Russell Sage Foundation.

———. 2001. "Residential Concentration/Segregation, Demographic Effects of." Pp. 13250–54 in *International Encyclopedia of the Social and Behavioral Sciences,* Vol. 19, edited by N.J. Smelser and P.B. Baltes. Oxford, England: Elsevier Science.

Wilkinson, R. G. 1996. *Unhealthy Societies: The Afflictions of Inequality*. London: Routledge.

Wilson, W.J. 1987. *The Truly Disadvantaged: The Inner City, the Underclass and Public Policy*. Chicago: University of Chicago Press.

World Bank. 2002. *Cali, Colombia: Toward a City Development Strategy*. Washington, DC: World Bank.