Urban Poverty and Health in Developing Countries: Household and Neighborhood Effects

Mark R. Montgomery
Paul C. Hewett

January 2004

Mark R. Montgomery is Professor of Economics, State University of New York at Stony Brook, and Senior Associate, Policy Research Division, Population Council. Paul C. Hewett is Associate, Policy Research Division, Population Council. Funding for this paper was provided by the Andrew Mellon Foundation and the Hewlett Foundation.

ABSTRACT

In the U.S. and other high-income countries, where most of the population lives in urban areas, there is intense scholarly and program interest in the effects of household and neighborhood living standards on health. Yet very few studies of developing-country cities have examined these issues. This paper investigates whether in these cities, the health of women and young children is influenced by both household and neighborhood standards of living. Using data from the urban samples of some 85 Demographic and Health surveys, and modelling living standards using factor-analytic MIMIC methods, we find, first, that the neighborhoods of poor households are more heterogeneous than is often asserted. To judge from our results, it appears that as a rule, poor urban households do not tend to live in uniformly poor communities; indeed, 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? Applying multivariate models with controls for other socioeconomic variables, we discover that household living standards have a substantial influence on three measures of health: unmet need for modern contraception; birth attendance by doctors, nurses, or trained midwives; and children's height for age. Neighborhood living standards exert significant additional influence on health in many of the surveys we examine, especially in birth attendance. There is considerable evidence, then, indicating that both household and neighborhood living standards can make a substantively important difference to health.

For the foreseeable future, world population growth will be mainly concentrated in the cities and towns of developing countries. According to the United Nations (2000), by the year 2030 the world's population will exceed today's total by 2.06 billion persons, of whom some 1.94 billion will be added to the urban areas of Africa, Asia, and Latin America. If these are the prospects in view, then researchers concerned with poverty and opportunity must increasingly set their concerns in urban contexts.

What might city life imply for levels of reproductive health, and for health inequalities? Using data from the urban samples of some 85 Demographic and Health surveys (DHS), we focus on three indicators of health: the unmet need for modern contraception; attendance of a doctor, nurse, or trained midwife at childbirth; and young children's height for age. The first of these, the unmet need for contraception, is closely linked to the risks of unintended pregnancy; birth attendance is a measure of the risks facing mothers and children at the time of delivery; and height for age is an often-used indicator of the state of child health. Taken together, these measures describe a relatively high-risk period in the lives of women and their children. Our principal objective is to understand how such health measures are affected by urban living standards. To assess the effects, we will consider two dimensions of living standards. One is defined for the household in which the woman and her children reside, and the other for the sampling cluster in which the household resides. Holding household living standards constant, we investigate whether poverty and affluence in the surrounding neighborhood affect health.

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 suggest that some 38 percent of the population of developing-country cities lives 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 by 2020 "significant improvement in the lives of at least 100 million slum dwellers" under the broader goal of ensuring environmental sustainability.[1] But there is, as yet, no consensus in the research community on how "slums" are to be defined, and surprisingly 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, nor 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 of the essence in any definition of slums, current efforts at systematizing slum 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 directly taken into account the concentrations of poverty or affluence in the local neighborhoods that surround households.

In its relative 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

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

rich countries, where neighborhood effects have been the subject of intense scholarly interest over the past two decades. These research efforts have been powerfully motivated by the writings of Wilson, Coleman, and colleagues on social interaction, exclusion, and social capital in poor U.S. neighborhoods (Wilson 1987; Coleman 1988; Massey 1990; White 2001; Sampson et al. 2002). A supporting motivation has emerged within the demographic realm, where multi-level analyses hold considerable methodological appeal, neighborhood effects being a leading example of the forces operating outside households that can exert influence on household-level attitudes and behavior. Hence, on both substantive and methodological grounds there would seem ample reason to explore neighborhood effects in the cities of poor countries.

What, then, can account for their neglect? A fundamental barrier to such research is the lack of data on living standards. Because the DHS program gathers no information on household incomes or expenditures as such, measures of poverty based on these and similar surveys are limited to what can be fashioned from a few proxy variables, including ownership of consumer durables and rather crude assessments 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 explore one of the most promising approaches for distilling the proxies into a single living standards index, termed MIMIC models, a variant of confirmatory factor analysis. In applying this method, we face one difficulty of a methodological nature: the indicators at hand are dichotomous, and standard factor-analytic techniques are inappropriate for such cases. We have developed our own estimation routines to address this problem.

The paper is organized as follows. To begin, we briefly sketch the theory of neighborhood effects in relation to health, drawing from the new report of the National Research Council's Panel on Urban Population Dynamics (2003). The paper's second section gives an overview of the models and statistical issues that must be confronted in fashioning defensible measures of living standards from the crude raw materials at hand, and here we summarize our thinking in an equation system that links urban living standards to health. The third section describes the DHS data, presenting descriptive statistics on the health measures, the basic set of explanatory variables used in the models, and the indicators of household living standards. We then compare living standards and poverty measures for households with summary measures that are calculated at the cluster level, the aim being to understand just how closely household and neighborhood living standards are linked. Following this, 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 paper concludes with thoughts on an agenda for further work.

NEIGHBORHOOD EFFECTS: A REVIEW

Figure 1 for Nairobi may help to frame the issues. In the slums of this city, we see rates of child mortality (shown in the dark bars of the figure) that substantially exceed those found elsewhere in Nairobi, and that 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

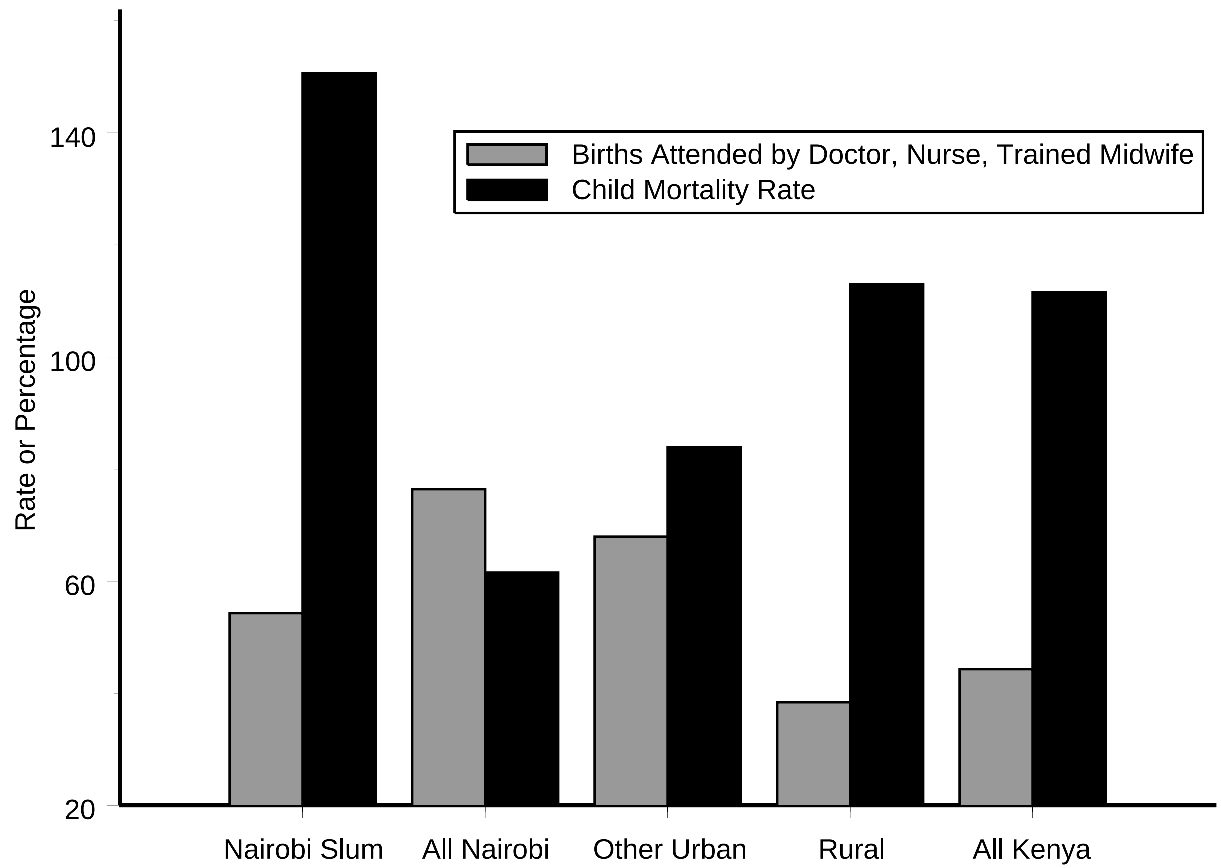


Figure 1 Comparison of birth attendance and child mortality rates (${}_5q_0$) in the Nairobi slums sample with those for all Nairobi, other cities in Kenya, rural areas, and Kenya as a whole. Source: African Population and Health Research Center (2002).

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, the spatial concentration of urban dwellers put them at higher risk of communicable disease. 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 needed to combat communicable disease, and city populations are generally better supplied with modern curative health services. Indeed, on average, as the Panel on Urban Population Dynamics (2003) has shown with DHS data, city populations do exhibit lower levels of child mortality than found in the countryside. When one peers beneath the urban averages, however, striking differentials in health are revealed—poor city dwellers often face health risks that are nearly as bad as what is seen in the countryside, and sometimes (as in Nairobi) the risks are decidedly worse. In this respect, the second set of bars displayed in Figure 1, having to do with birth attendance, conveys a sense of what can be seen more generally in developing countries—large health disparities 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 paper is with urban populations only. Confining attention to the portions of Figure 1 that refer to urban Kenya, we recognize significant differences in health *within* the urban population. These intra-urban inequities have received curiously little attention from researchers, but of course they will be taking on greater weight in all poverty calculations 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 concentrations of poverty found in these slums may apply health penalties beyond what household poverty alone would apply. But the figure does not distinguish poor households in slums from poor households living elsewhere, and it can give no clear testimony as to the effects of spatially concentrated poverty. There is enough here, however, to warrant further exploration.

A sketch of the theories

We cannot do justice to the many pathways by which neighborhood and related contextual effects could exert influence on health. In its new book, the Panel on Urban Population Dynamics (2003) provides 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 briefly 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 disease is concerned, it has long been recognized that the spatial proximity of diverse urban populations can generate negative *health externalities*. Timæus and Lush (1995) provide an unusually penetrating discussion of these externalities. As we have seen for Nairobi, the externalities associated with environmental contamination and communicable disease 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 transport and modern health services (Timæus and Lush 1995; Harpham and Tanner 1995; African Population and Health Research Center 2002).

Less often recognized, but potentially of equal importance, are the *social externalities* that figure into urban life. Individual women and households are connected to others in their neighborhoods through social network ties, and along such social circuits there may flow information about how to recognize and respond to health threats, and where appropriate services can be found. Of course, social network ties will 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). Although we are aware of no recent research on social networks and the diffusion of health information in developing country cities, the work of Behrman et al. (2001) and Casterline et al. (2001) document the network effects on contraceptive use in rural and peri-urban African contexts.[2]

Theories of local reference groups and social comparison are often invoked (if rarely tested) in relation to the psycho–social aspects of health. The idea is that individuals may evaluate their own circumstances by comparing them to what can be observed of the circumstances of others (van den Eeden and Hüttner 1982). When the comparisons are consistently unfavorable, this may bring on 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.

Repeated exposure to such social inequities could erode a poor person's feelings of social confidence, weakening the sense of personal efficacy that is needed to assert claims upon health resources and otherwise to engage in constructive 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 et al. 2003). In U.S. research, some evidence has emerged—not always consistently—indicating that inequality at the county, metropolitan area, and state level is linked to poor health at the individual level. Very little is known of this relationship outside the U.S. context. Other social mechanisms with similar effects include those linked to residential segregation (Massey 1996; White 2001) and to local social capital (Aber et al. 1997; Furstenberg 1993; Furstenberg and Hughes 1997; Astone et al. 1999).

[2]One of the most influential random interventions in the history of family planning, the Taichung experiment of 1963, found strong evidence of information diffusion along social network lines in this Taiwanese city (Freedman and Takeshita 1969). See National Research Council (2001) for an excellent summary of related findings in several areas of demographic research.

Much of this literature has put emphasis on the spatial concentration of poverty, but the effects of spatially concentrated affluence are also drawing attention. Wen et al. (2003: 848) summarize 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 own study, Wen et al. (2003: 856) find 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) can find no separable, significant effect of neighborhood affluence in their Los Angeles study of children's test scores, given controls for the median level of neighborhood family income, which is a significant positive influence on these scores.

In addition to these perspectives on neighborhood effects, one finds a small literature in demography exploring the links between *local services* and health outcomes, with a particular focus on how services may either provide a substitute for, or alternatively complement, the beneficial effects of mother's education (e.g., Sastry 1996). Relatively poor urban neighborhoods may not be attractive to private-sector suppliers of health services and contraception (although vendors offer drugs and supplies even in poor neighborhoods). These neighborhoods may also lack the political clout it takes to secure adequate public-sector services. It is not a given that poor neighborhoods will be under-served by the public sector—in some countries these neighborhoods could be targeted for improved service provision.[3]

How strong is the evidence?

Empirical studies of these effects in developing country cities are far from being common. For Rio de Janeiro, Brazil, research by Szwarcwald et al. (2002) examines a type of multi-level model, in which infant mortality and adolescent fertility rates at the census tract level are posited to depend on the proportion poor and the dispersion of poverty rates across tracts within larger neighborhoods. These authors find substantial dispersion in poverty across the tracts of given Rio neighborhoods, and this variation (or inequality) is only weakly associated with the mean neighborhood poverty rate. Higher neighborhood mean poverty and higher variance both act to increase tract-level infant mortality and adolescent fertility. This is suggestive of a link between local socioeconomic inequality and health, if not quite as persuasive as estimates from multilevel models with both individual and areal characteristics.

[3]There may well be a connection between local social capital and health services—Gilson (2003) applies the concept of "trust" to explain attitudes toward health care providers and institutions. The trust concept may provide one way of measuring the social dimensions of access to effective medical care.

As a number of researchers have noted (e.g., Timæus and Lush 1995; Szwarcwald et al. 2002; Åberg Yngwe et al. 2003; Wen et al. 2003; Drukker et al. 2003), multilevel studies have often but not invariably found neighborhood levels of poverty, income, and related factors to exert significant influence when individual-level covariates are controlled. Collinearity between the individual and spatially aggregated measures can make it difficult to distinguish between individual and neighborhood effects. Ginther et al. (2000), using longitudinal data with a rich set of individual, family, and neighborhood variables, caution that neighborhood measures often lose their significance as more family and individual-level covariates are taken into consideration. Longitudinal studies of these relationships are rare, and randomized intervention studies are rarer still.

But what is an urban neighborhood?

The geographical units for which aggregated data are available—in the U.S., these are census tracts, block groups, and the like—have boundaries that need not correspond closely, or indeed correspond at all, with the sociological boundaries of neighborhoods as determined by patterns of social interaction, contagion, and comparison. Furthermore, as noted above, it may be that social networks exert important influences on individual and family behavior, and these network contacts are not necessarily confined to the space of local neighborhoods.

In an early, memorable, and still provocative piece, Wellman and Leighton (1979) make a point of emphasizing the lack of overlap between social interactions taking place in neighborhoods and those taking place in individual social networks. In their view, social networks encompass and extend well beyond the neighborhood, place-based connections. Writing on health and reference group effects, Wen et al. (2003: 845) acknowledge that, "It is not clear what spatial level is appropriate to examine this relationship." For Sweden, Åberg Yngwe et al. (2003) explore an approach whereby socially-defined reference groups are constituted on the basis of social class, age, and region, rather than in terms of the local geography.

Even the spatial aspect is problematic. Coulton et al. (1997) and Sastry et al. (2002) emphasize the complexities entailed in delineating geographic boundaries for urban neighborhoods. Coulton et al. (1997) asked residents of Cleveland to depict their local neighborhoods in maps, and found that the perceived boundaries often differed substantially from the perimeters of census-based units. There was substantial variance across residents in the spatial extent of their perceived neighborhoods. Despite this variation, when averages of socioeconomic measures (e.g., poverty rates, crime rates, non-marital 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, implying that for Cleveland, at least, tract-level data could serve as useful proxies. We are not aware of any other research on this crucial point.

In this paper, as in so much of the literature on neighborhood effects, definitions of neighborhood are forced upon us by the nature of the available data. DHS surveys collect data within sampling clusters, and we will often refer to these clusters as "neighborhoods." The extent to which DHS sampling clusters represent neighborhoods is, of course, open to debate. In the cities of developing countries, such sampling clusters can be as small as a single multi-unit apartment building, or they can extend more broadly, though 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 paper to identify precisely the routes through which neighborhoods influence health. Data far more 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 will offer interpretations of our findings that stress one or another of the mechanisms described above, and, in closing, will 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. As discussed above, in our application Y will represent one of three measures of health: the unmet need for modern contraception; attendance of a doctor, nurse, or trained midwife at childbirth; and children's height for age. The first two of these are binary variables.

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

$$Y^* = W'\theta + f\delta + \epsilon \tag{1}$$

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 W and an unobservable factor f that we will 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 model the factor $f = X'\gamma + u$, the value of f being determined by a set of exogenous variables X and a disturbance u. Although f is not itself observed, its probable level is signalled 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

[4]According to Fred Arnold (personal communication), in developing countries the enumeration areas used in conducting censuses, which often provide the sampling frame for surveys, typically include 100–200 households. Their spatial extent varies. The logistics of survey-taking—the need for interviewers to conduct a given number of interviews per workday—may imply that urban clusters will generally be compact, especially in high residential density areas.

each such propensity as $Z_k^* = \alpha_k + \beta_k f + v_k$, and, upon substituting for f, obtain K latent indicator equations,

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

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 equation (1) and equations (2) for the living standards indicators. In setting out the model in this way, with latent factors embedded in structural equations, we follow an approach that has been advocated by several researchers (notably Sahn and Stifel 2000; McDade and Adair 2001; Tandon et al. 2002; Ferguson et al. 2003). Filmer and Pritchett (1999, 2001) have developed an alternative approach based on the method of principal components. Although useful in descriptive analyses and very easy to apply, this method is perhaps best viewed as a data-reduction procedure whose main virtue is the ease with which the researcher can collapse multiple indicators into a single index. The principal components approach is otherwise rather limited—it does not cleanly separate the determinants of living standards from the indicators of living standards, and it lacks a firm theoretical and statistical foundation. As a result, the method is not readily generalizable to structural, multiple-equation models such as ours (Montgomery et al. 2000).

For this paper, we will take a two-step approach to estimating the system. Taking all of the disturbances to be normally distributed, the parameters α, β and γ of the indicator equations (2) are estimated by the method of maximum likelihood, as described in Appendix B, using routines that we have written for this purpose.[6] An estimate $\hat{f} = \mathrm{E}[f|X, Z]$ of the factor is derived from these equations alone. The predicted $\hat{f}$ is then inserted into the structural equation (1) just as if it were another observed covariate. Conventional statistical methods are applied to estimate the parameters θ and δ of the structural model.[7]

[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, as discussed in Appendix B. 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 one in each equation.

[6]As will become clear in a moment, it is more accurate to describe the estimation method as "quasi-maximum likelihood," because the estimating equations do not take cross-household, within-neighborhood correlations into account.

Note that the full system (1) and (2) can be viewed as a constrained version of a largish multivariate probit system. To see how estimation techniques for such binary indicator models differ from those for models with continuously-valued indicators, compare Lawley and Maxwell (1962), Bollen (1989), and Jöreskog (2000, 2002). The maximization problem does presents some numerical difficulties, and it appears that maximum likelihood methods have been used less often in problems such as these than minimum-distance estimation.

[7]As in other two-step models with "generated regressors," the standard errors of the estimators $\hat{\theta}$ and $\hat{\delta}$ should be corrected for the use of an estimated $\hat{f}$ in the second step. We employ robust standard errors, which should adequately address this and other sources of heteroskedasticity.

It is important to take note of a key point: we assume that the disturbance terms $\{\epsilon, u, v_1, \ldots, v_K\}$ are mutually independent. The principal worry is that the ϵ disturbance of the health equation might 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 k-th durable, this propensity involves both u and the disturbance v_k) is somehow linked to the disturbance term ϵ of the main health equation. When the indicator equations (2) are estimated separately, as in our approach, then the estimator $\hat{\gamma}$ is consistent for γ, and the $X'\hat{\gamma}$ component of $\hat{f}$ is (in the limit) free from contamination.[8] Hence, one could define $\hat{f} = X'\hat{\gamma}$ and proceed without concern for inconsistency in the health equation estimators. However, when $\hat{f}$ is formed by conditioning not only on X, but also on the indicators Z, then an association of $\hat{f}$ with ϵ could persist even in the limit. When there is a reason to be concerned about this sort of bias, the procedure used to generate $\hat{f}$ must be adjusted. Lacking any compelling reason for suspecting correlation, however, we have not made the adjustments here.

Modelling the living standards factor

With the living standards factor specified as $f = X'\gamma + u$, how should the X variables of this equation be chosen and what relation, if any, should they bear to the W variables that enter the main health equation? How are the X variables, posited to be determinants of living standards, to be distinguished from the $\{Z_k\}$ variables that serve as indicators of living standards?

As Montgomery et al. (2000) note, there is little consensus in the literature about how best to define and model the living standards measures found in surveys such as those fielded by the DHS program, which lack data on consumption expenditures and incomes. With proper consumption data lacking, we think it reasonable to define the set of living standards indicators $\{Z_k\}$ in terms of the consumer durables and housing quality items on which data are gathered. Using these indicators, we construct what McDade and Adair (2001) have termed a “relative affluence” measure of living standards. Producer durables—in a rural sample these would include ownership of livestock and land—are 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 that is drawn from household production.

By this logic, if producer durable variables were available for the urban samples with which we are concerned, we should include them among the X covariates. Unfortunately, as of this writing the DHS survey program has not collected data on urban producer durables as such.[9] To be sure, some publicly-provided services can also be viewed as enabling factors, or inputs, into consumption—notably, the provision of electricity—and we have therefore included electricity in the X living standards determinants. Although

[8] This assumes independence among $\{u, v_1, \ldots, v_K\}$. The X variables themselves are taken to be fully exogenous.

[9] Over the past year, however, the DHS has been experimenting with new urban-sensitive questions on housing ownership and security of tenure in a handful of surveys.

city size may be only a distant proxy for other factors determining consumption—among them, access to multiple income-earning possibilities and heterogeneous labor and product markets—we include city size with the other X variables.

It is perhaps not unreasonable to liken adult education to a producer durable, education being a type of long-lasting trait that produces a lifetime stream of income and consumption; on these grounds we include the education (and age) of the household head in our specification of the X determinants. In doing so, we are mindful of the "dual roles" played by education in demographic behavior (Montgomery et al. 2000). Education is both a determinant of living standards and a conceptually separable influence on behavior via its links to social confidence, to the ability to process information, and to the breadth and nature of individual social networks. In short, education measures belong with the W variables of the health equations 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 hope 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.[10]

Living standards at the neighborhood level

Evidently there are many issues to confront in specifying living standards models at the individual and household level; yet further issues must be confronted in any effort to define neighborhood (cluster) living standards. Our approach is very simple. With estimates $\hat{f}_{ic}$ in hand for household i in cluster c, we construct 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,

$$\hat{f}_i^c = \frac{1}{n_c} \sum_{j \neq i} \hat{f}_{jc},$$

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

We are exploring two alternative approaches that are better-justified in econometric terms. In one of these, a cluster-level living standards factor f_c is introduced along with the household-level factor f, and modelled in terms of cluster-level variables. This two-factor approach can be implemented in much the same way as the one-factor approach, although estimation entails far greater computational difficulties given the number of indicators and the typical number of households per cluster seen in the DHS data we use. An alternative, not quite as well-justified but perhaps acceptable as a compromise, is to enter the cluster-level variables as indicators (or determinants) of a single household-level living standards factor.

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

Table 1 Mean Values of Urban Unmet Need, Birth Attendance by a Doctor, 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	-.715
Sub-Saharan Africa	48.4	60.2	-1.112
Southeast Asia[d]	21.7	65.2	
South Central Asia	23.4	63.2	-1.241
West Asia	17.4	83.8	-.577
Latin America	22.8	70.4	-.885
TOTAL	35.3	64.5	-1.032

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

[b] Figures shown are percentages of women with births in the last 3 years whose deliveries were attended by a doctor, 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 surveys in this region has collected information on children's height for age.

DATA AND MODEL SPECIFICATION

The data drawn upon in this analysis come from 85 surveys fielded in Phases 2 through 4 of the Demographic and Health Survey (DHS) program.[11] The survey dates range from 1990 through 2001, and in all some 50 countries in 6 developing regions are represented. A list of these countries and their survey years is provided in Table A.1 in Appendix A.

Health measures

Regional summaries of the distributions for the health variables—unmet need for modern contraception, attendance by a physician, nurse, or trained midwife at delivery, and children's height for age—are presented in Table 1. Here and elsewhere in the paper, we use such regional summaries and averages to set the results in context. It should be remembered that the DHS surveys are not strictly representative of any developing region, since in no region have all countries, or even all large countries, participated in the DHS program. Another point to note is that several countries have fielded multiple DHS surveys.

The first column of Table 1 shows the percentages of women who have an unmet need for contraception. An unmet need can be said to exist when a woman who is not currently using contraception expresses a desire to prevent or delay further births (Casterline and Sinding 2000; Westoff and Pebley 1981; Westoff and Bankole 1995). Among those women who report that they wish to stop childbearing altogether or delay the next birth—excluding those not at risk of conception (i.e., those not in union, pregnant, or amenorrheic)—a woman with an "unmet need" is one who uses no modern contraception.

The second health measure in Table 1 is generated from the DHS maternity histories for all births that occurred in the three years before the survey date. For each such birth, information is gathered on who assisted at the delivery of the child, with the possibilities

[11] One survey, for Yemen, provides data on durables and their determinants, but not on the health variables.

Table 2 Coding of educational attainment for multivariate analyses

<table>
<tr><th>Number of surveys</th><th>No Education</th><th>Incomplete Primary</th><th>Completed Primary</th><th>Incomplete Secondary</th><th>Completed Secondary</th><th>Higher</th></tr>
<tr><td>64</td><td colspan="2">Base[a]</td><td colspan="2">Group 2</td><td colspan="2">Group 3</td></tr>
<tr><td>13</td><td colspan="2">Base[a]</td><td colspan="2">Group 2</td><td>Group 3</td><td>Group 4</td></tr>
<tr><td>7</td><td colspan="4">Base[a]</td><td>Group 2</td><td>Group 3</td></tr>
</table>

[a] The base group, which serves as the omitted category in the multivariate models, is defined so as to include no less than 8 percent of the urban sample.

including a doctor, nurse, trained midwife, other midwife, traditional birth attendant, and a relative. This analysis will focus on the women who have had either a doctor, a nurse, or a trained midwife attend each of their deliveries in the last three years. The variable is coded with a "0" if one birth was attended but another was not—hence, in the case of multiple births in the three years before the survey, it measures consistent attendance.

The DHS collects information on the height and weight of each child born in the three years before the survey date.[12] A child's height for age is thought to be a good proxy measure of health status, reflecting both nutrition and disease history (Montgomery et al. 1997). We will focus on height for age among children who are 3 to 36 months of age, the lower age cut-off being chosen to minimize the problems of measurement error that are thought to plague estimates for the youngest children. Height-for-age is standardized by age and sex and is represented in terms of standard deviations from the median of an international reference population.

Explanatory variables

A small set of variables from the DHS is included to serve as socioeconomic controls. Descriptive statistics for these variables are presented in Appendix A; here we discuss the rationale for including the variables and our approach to coding them. The woman's age is coded in the conventional five-year age groups. The urban context is 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 at least 1 million population), and residence in a smaller city (one in the range of 50,000 to 1 million residents). The omitted category for residence is towns, that is, urban places with fewer than 50,000 residents.

To devise a consistent classification of educational attainment is difficult. The educational experiences of women and their husbands vary a great deal over the range of regions and countries covered in this analysis. For example, over 80 percent of woman have completed secondary schooling or more in Kazakhstan and Uzbekistan, whereas only 8 percent and 1 percent have done so in Mali and Burkina Faso, respectively. No single classification scheme can be imposed upon all countries.

[12]The majority of DHS surveys have collected health information on children born in the last five years. We have set the upper limit on age to three years so as to make use of all surveys with these data.

Table 3 Percentages of urban households with living standards indicators, by region.[a]

	North Africa	Sub-Saharan Africa	Southeast Asia	South, 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	67.3	47.7	64.8	52.4	64.9	46.2
Finished flooring	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.

We have chosen to define educational attainment for women and their husbands according to the distribution of attainment within each country. This approach yields three distinct coding schemes, as shown in Table 2. Our aim was to devise a measure with a sizable baseline (omitted) category, with 8 percent of the urban sample taken to be the minimum acceptable size for this category. In the great majority of DHS surveys, the base comprises those with no education or at most incomplete primary school education. For a small minority of surveys, however, mainly from the former Soviet republics, this grouping yielded too small a base category, and 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 3 and Appendix Table A.2. As the appendix table shows, these indicators are available in almost all DHS surveys, 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 exclude such measures in the interest of achieving reasonable cross-country comparability.

HOUSEHOLD AND NEIGHBORHOOD LIVING STANDARDS

Table 4 summarizes the estimated $\hat{\beta}_k$ factor loadings produced by the confirmatory factor models. As can be seen in the table, these coefficients are almost always positive and statistically significant. This is encouraging, in that it supports the interpretation of the factor as reflecting the household's standard of living. Table 5 presents a summary of the effects of the X covariates. These effects are also very much in line with expectations. The provision of electricity is positively associated with living standards, as would be antici-

Table 4 Summary of Confirmatory Factor Loadings ($\hat{\beta}_k$) 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
Measures of Housing Quality			
Sleeping rooms	67	65	2
Finished flooring	78	77	0

[a] The β parameter for ownership of a car is not estimated, but rather normalized to unity; see Appendix B.

pated given its role as a key input. The education of the household head is strongly and positively associated with living standards, and, consistent with age profiles of productivity, we find 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 living standards are generally higher in small and large cities relative to levels found in towns, the smallest urban areas. Evidently there is good statistical support for the notion that the proxy variables collected in the DHS surveys are interpretable as indicators of the household's otherwise unobservable standard of living.

We now examine the relationship between living standards indices estimated at the household level, and aggregated indices computed for the other households residing in the sampling cluster. Recall that the approach is to estimate confirmatory factor scores $\hat{f}_{ic}$ for each household i in urban sampling cluster c in a given Demographic and Health Survey dataset. The sampling cluster averages are computed by separating out the score for each household i and calculating a mean for the other households in the cluster. We also examine the proportion of households in the cluster that fall into the lowest quartile of urban factor scores overall and the proportion falling in the uppermost quartile, again without reference to the i-th household. These proportions are described in what follows as the cluster proportions "poor" and "affluent," with poverty and affluence being defined in relative terms.

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 percent of urban households overall are poor, in examining a set of sampling clusters we are likely to find some clusters with very high concentrations of poverty and others with very few poor households. Likewise, we might well expect to observe a high spatial concentration of affluence.

Table 5 Summary of $\hat{\gamma}$, the Effects of Determinants X on the Living Standards Factor

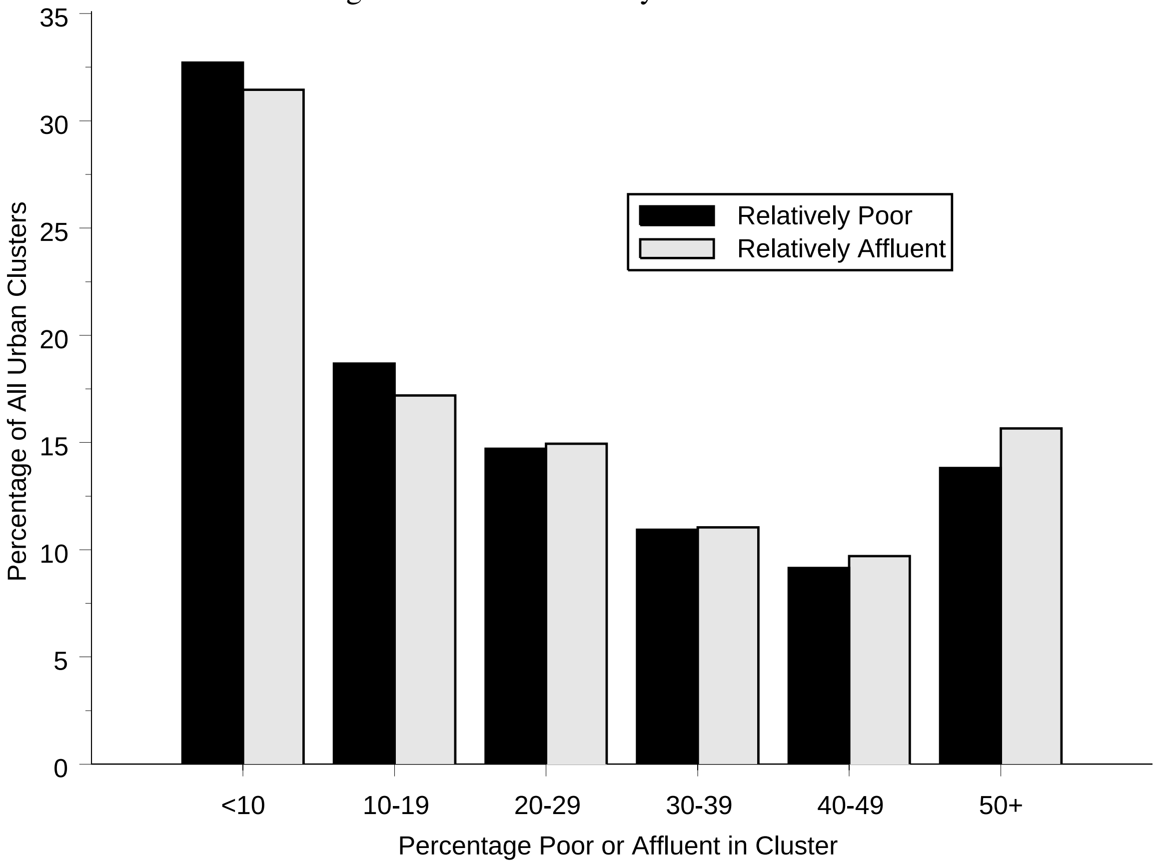
Item	**Estimated**	**Positive and Significant**	**Negative and Significant**
Basic Demographic Variables			
Head is male	85	74	11
Head's age	85	85	0
Head's age, squared[a]	85	0	85
Head's Education[b]			
Completed primary or incomplete secondary	76	76	0
Completed secondary or higher	60	60	0
Completed secondary	19	19	0
Higher	20	20	0
Head's education unknown	12	12	0
Other			
Household has electricity	61	61	0
Residence in small city	71	60	11
Residence in capital city	82	74	7

[a] The living standards factor is estimated to increase with head's age up to an age of 59.7 years, this being the average "turning point" among all estimated models.
[b] See Appendix A for a description of the education coding scheme and the omitted categories.

Although these are reasonable expectations, the DHS results provide something less than resounding support for them. We see a greater degree of heterogeneity in cluster composition than might have been anticipated. We document this heterogeneity in several ways. Consider Figure 2, which presents the distributions of DHS sampling clusters by the cluster proportion of relative poverty and relative affluence. (Region-specific results, not shown, are very similar to the averages shown here.) In about one-third of urban clusters, fewer than 10 percent of households are poor. Likewise, in about 31 percent of clusters fewer than 10 percent of households are relatively affluent (that is, in the upper quartile of all urban households). These two left-most bars are suggestive of some spatial concentration of poverty and affluence. However, as we consider the full range of the distributions, we see less evidence of extreme spatial concentration. We simply do not find very many clusters that are more than half poor or more than half affluent.[13]

[13]By construction, of course, only one-quarter of urban households in any survey are relatively poor, and only one-quarter are relatively affluent. The definition of poverty and affluence in terms of quartiles places some constraints on distributions like those seen in the figure. A complicating factor is that DHS sampling clusters vary in population size. In an extreme case, a relatively small number of very large clusters could house most of the urban poor or the urban affluent. A more refined analysis than we can undertake here would take such complications into account.

Figure 2 Distribution of sampling clusters by percentages of relatively poor and relatively affluent households. Averages over all DHS surveys.



Figures 3 and 4, which refer to all surveys in our analysis, may further clarify the situation. In the first of these figures, we characterize the neighbors of poor households. If 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 predominantly 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 percent of its neighbors are poor. To be sure, this is well above the percentage of poor in the urban population as a whole (25 percent by our definition of poverty), 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 percent of a poor household's neighbors) and even for neighbors who are affluent, those who are in the top-most quartile of the urban distribution. A poor Latin American household has, on average, about 1 neighboring household in 10 which is affluent.

Figure 4 depicts the neighbors of these affluent households. Again, as expected, slightly more of these neighbors are themselves affluent than in the urban population at large, and the affluent households have somewhat fewer poor neighbors (who make up about 20 percent of the neighbors of affluent families). But a household's affluence is

Figure 3 Who are the neighbors of the urban poor?

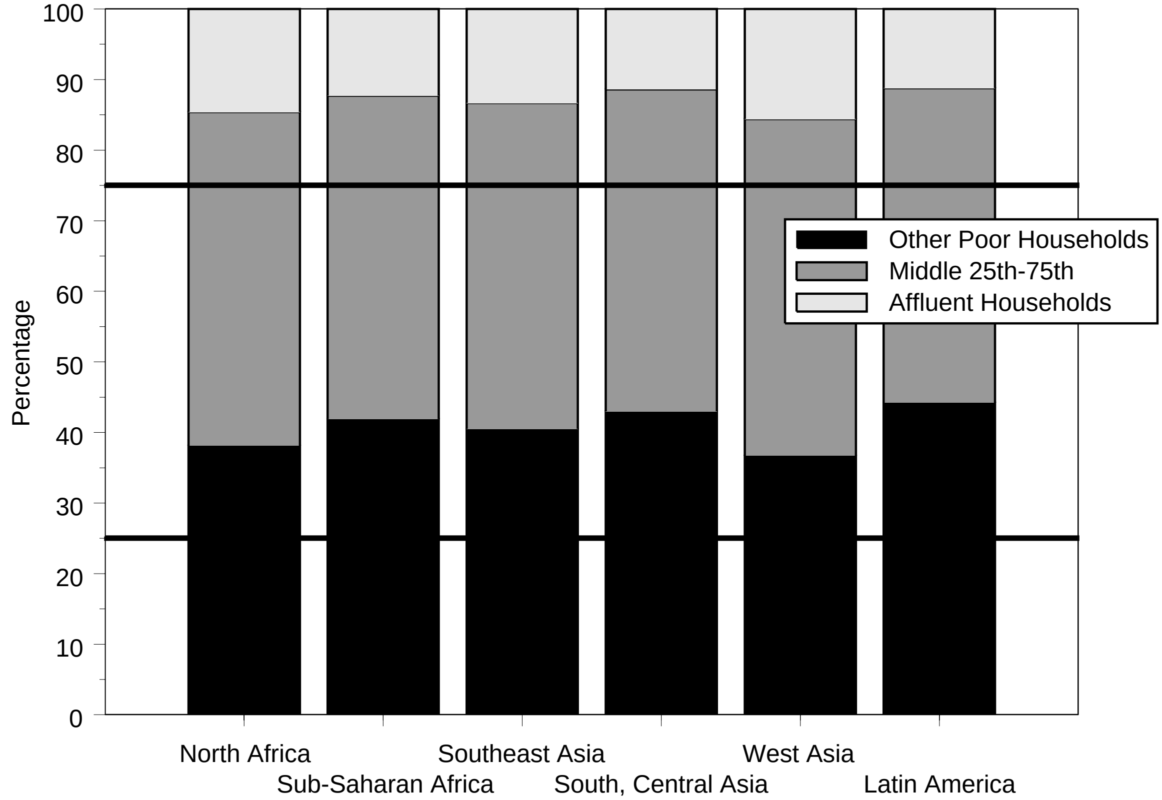


Figure 4 Who are the neighbors of the urban affluent?

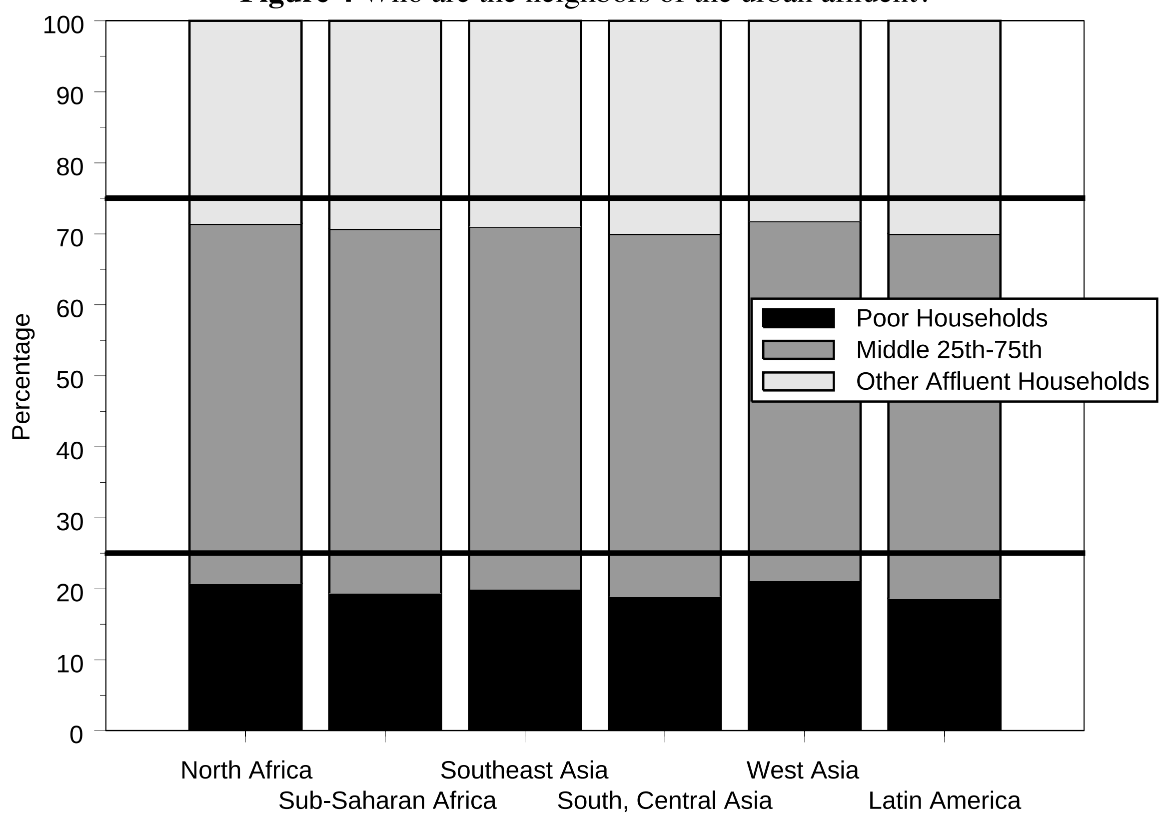


Table 6 Correlations of household and cluster factor scores, by region

Region	Correlation of Household Factor Score With		
	Mean of Cluster Scores[a]	Proportion of Cluster Poor	Proportion of Cluster Affluent
North Africa	.50	-.45	.43
Sub-Saharan Africa	.56	-.48	.51
Southeast Asia	.53	-.49	.46
South Central Asia	.60	-.53	.54
West Asia	.47	-.41	.41
Latin America	.58	-.53	.50

[a] Household's own score omitted from the calculation.

not strongly predictive of neighborhood composition—these are small differences from the 25th and 75th percentile benchmarks. The spatial concentration of affluence is less clearly evident than we would have anticipated given the images of extreme social–spatial polarization that appear so often in the literature.

Table 6 depicts the central tendencies and heterogeneities in terms of correlations between the living standards factor score for a household, on the one hand, and a set of cluster-level measures of living standards, on the other. (Recall that the household's own score is removed from the cluster-level measures.) Considering the correlation between the household's factor score and the mean within the cluster, we find the expected positive correlation in the second column of Table 6. But these correlations, though positive, are not especially high, the highest being .60 in the surveys from South and Central Asia. The correlations of household living standards scores with the cluster proportions poor and better off (shown in the last two columns of the table) are likewise in the expected direction but modest in size.

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 find 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 inhabiting the same local space will interact, or even serve as relevant points of comparison. The Latin American literature is especially instructive on non-spatial 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.[14]

Unmet Need, Birth Attendance, and Height for Age

In the multivariate empirical work reported below, we began by examining measures of the lower and upper quartiles of the factor score distributions, focusing on the

[14]Fred Arnold and 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. He reports seeing many discrepancies between these two types of spatial units (personal communication). It is not yet known whether what is true for Mumbai is true more generally.

households that we have termed relatively poor and relatively affluent and on the corresponding cluster proportions. To date, however, we have not uncovered empirical evidence suggesting that these measures add insight 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 poverty and affluence effects from the effect of neighborhood medians in their study of Los Angeles neighborhoods.) Although further work needs to be done on specifications involving relative poverty and affluence, the models to which we now turn are specified in simpler terms.

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

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

where Φ is the standard normal cumulative distribution function, 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 over all except the i-th 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, and for this model we add indicators of the child's sex, age, and the square of age (recall that these are children no more than 36 months old). Robust standard errors are employed throughout.

To distill a great number of coefficient estimates into a few readily interpretable quantities, we summarize them in the following way. For each health outcome variable, we limit discussion to the estimated effects of the household and cluster factor scores, making comments only in passing on the estimates for 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 unmet need analysis. To summarize the effects of living standards we calculate the predicted probability that woman i has an unmet need given her W_{ic} covariates and given a factor score $\hat{f}_{ic}$ that we fix at the value for the 25th percentile of the urban factor score distribution (i.e., the distribution across all urban households in the survey in question). We construct another predicted probability using the same W_{ic} covariates but with the factor score now set to the value corresponding to the 75th percentile of the score distribution. (The 25th and 75 percentile points are chosen to be suggestive of a relatively poor and a relatively affluent urban household.) We average the predictions $P_{i,25}$ and $P_{i,75}$ over the urban estimation sample used in the survey, thereby obtaining two averages P_{25} and P_{75}. The difference between these, $P_{25} - P_{75}$, is one illustration of the size of the factor score's effect in a given DHS sample. We term this the "absolute difference" in the predicted probabilities of unmet need. In the tables to follow, the absolute difference is expressed in terms of percentage points. A second illustrative device is constructed by dividing the absolute difference by the average level of unmet need in the survey's urban sample, giving $(P_{25} - P_{75})/\bar{P}$. We describe this second measure as the "difference relative to the mean." It may convey a sense of the proportional effect of the factor score, and we report these relative differences in terms of percentages.

A similar approach is taken in describing the effects of the cluster-level factor score means, although in this case, the 25th and 75th percentile points are taken from the distribution of cluster mean scores *across clusters*. Because cluster means *are* means, they tend to have more concentrated distributions than the individual household scores, and we take this into account in choosing values to represent relatively poor and relatively better off clusters.

Models with household factors only

Tables 7 to 9 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 surveys in the unmet need analysis (Table 7), is positive and significant in some 63 of the 76 surveys where birth attendance is examined (Table 8), and is positive and significant in 49 of 73 surveys for children's height for age (Table 9). The proportions of significant findings are strikingly similar to those for mother's education, as can be seen in the notes to the tables.

The substantive implications of the household scores are summarized in the remaining columns of these tables. We first focus on the absolute effect, comparing predicted values for households at the 25th percentile of the score distribution (the "poor" households) with those at the 75th percentile (the "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 unmet need analyses (Table 7), we see that the average difference in the unmet need percentage 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. Comparing the regions, the largest absolute effects are found in sub-Saharan Africa and Latin America. When these absolute effects are translated into relative terms (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 percent 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.

Much the same story emerges from the analyses of birth attendance and children's height for age, which are summarized in Tables 8 and 9. The estimated influence of the household living standards factor on birth attendance is large in terms of the percentage point differences between relatively poor and affluent households, and these absolute differences imply differences relative to mean attendance that range from 7.6 percent in West Asia to 47.6 percent for the significant cases of South and Central Asia. In the height for age models (Table 9), where 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 .291 standard deviations of children's height. These differences are quite large in relative terms, especially in Latin America. Clearly, even within urban sectors

Table 7 Summary of Estimates of Unmet Need using Confirmatory Factor Scores

Region	**Factor Score Negative and Significant**[a]	**Effect of Household Factor Score: Absolute Difference**[b]		**Difference Relative to Mean**[c]	
		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 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 results for women's education and the education of the spouse or partner. Women's education exerts a negative and significant influence on unmet need in 2 of 4 surveys for North Africa, 28 of 42 in sub-Saharan Africa, 3 of 6 in Southeast Asia, 4 of 12 in South Central Asia, 3 of 4 in West Asia, and 10 of 16 in Latin America. Spouse's education is negative and significant far less often: in none of the surveys from North Africa, Southeast Asia, and South Central Asia, in 16 of 39 surveys from sub-Saharan Africa, 1 of 4 surveys in West Asia, and 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 unmet need among households at the 75th percentile.

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

Table 8 Summary of Estimates of Birth Attendance by a Doctor, Nurse, or Trained Midwife, using Confirmatory Factor Scores

Region	Factor Score Positive and Significant[a]	Effect of Household Factor Score: Absolute Difference[b]		Difference Relative to Mean[c]	
		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, 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	12.3	19.5	21.8

The surveys for Ethiopia 1999, Niger 1998 and Philippines 1998 did not collect birth attendance data. Models for Armenia 2000, Jordan 1997, Kazakhstan 1995, Kazakhstan 1999, Kyrgyz Republic 1997 and Uzbekistan 1996 could not be estimated due to near-universal birth attendance.

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

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

[c] Expressed in percentages of women with all births attended by a trained nurse or doctor in the urban samples.

Table 9 Summary of Estimates of Children's Height for Age using Confirmatory Factor Scores

Region	Factor Score Positive and Significant[a]	Effect of Household Factor Score: Absolute Difference[b]		Effect of Household Factor Score: Difference Relative to Mean[c]	
		All	Significant	All	Significant
North Africa	1 of 3	.123	.252	19.7%	45.2%
Sub-Saharan Africa	25 of 39	.322	.398	29.7	36.1
South, Central Asia	5 of 11	.212	.322	23.2	20.9
West Asia	3 of 5	.211	.224	42.7	49.5
Latin America	15 of 15	.328	.328	42.6	42.6
TOTAL	49 of 73	.291	.355	31.8	37.6

[a] This column may be compared with 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 for North Africa, 11 of 39 in sub-Saharan Africa, 6 of 11 in South and Central Asia, 3 of 5 in West Asia, and 12 of 15 in Latin America. Husband's education is positive and significant in 1 of 3 North African surveys, 3 of 37 surveys in sub-Saharan Africa, 2 of 11 in South Central Asia, 2 of 5 in West Asia, and 5 of 15 in Latin America.

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

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

that are generally better supplied with transport options and health services, a household's standard of living can make a considerable difference in its 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 model, retaining all covariates and the household's own factor score. The results are summarized in Tables 10–12. We first describe the number of surveys in which a significant effect is found for the cluster variable, and also check the significance of the household scores to see if separate household and cluster effects can be discerned. We then proceed to describe the influence of the cluster scores, comparing predicted values at the 25th percentile of the cluster score distribution (the "poor" clusters) with those at the 75th percentile ("affluent" clusters).

In general, the cluster-level factors are not statistically significant as often as the individual household factors were, and in fact, 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, in relatively few cases does the inclusion of a cluster-level average remove statistical significance from the household factor.) For unmet need, the cluster mean score is significant in 16 of the 84 surveys examined; it is significant in 53 of the 76 cases for birth attendance; and in 22 of 73 cases for children's height for age. Although smaller in the typical case, the absolute effects of the cluster scores still exert a reasonably strong influence on the three measures of health, with the effects being most striking in the case of birth attendance. If the absolute effects are translated into relative terms, they are seen to be of substantive importance.

How does the general pattern of findings square with the theories of neighborhood effects that were outlined earlier? The three pathways of influence that have been mentioned in the literature involve health externalities associated with communicable disease; social externalities stemming from localized patterns of interaction, information flow, and the like; and the effects of local service provision.

We had expected to find the clearest expression of neighborhood effects in the children's height analyses, because here is where one would think health externalities and the risks of contagion in poor neighborhoods would be most apparent. There are numerous significant and relatively large effects seen in height for age (Table 12), especially in Latin America, but on the whole the cluster measure attains significance in under one-third of all surveys. It may be that cluster mean values of living standards scores are too many steps removed from the epidemiological mechanisms that produce within-neighborhood contagion. Direct measures of health in the cluster (e.g., percentages of children with recent fevers or diarrhea) might better isolate this particular pathway of influence. Also, note that the models do not include access to piped water and improved sanitation, and these measures of services need to be examined before any strong conclusions can be drawn.

In our view, the results linking neighborhood living standards to birth attendance are surprisingly strong. We do not think that contagion effects in the narrow epidemiological sense can be involved here. But neighborhood patterns of social interaction and information exchange could make a substantial difference in the extent to which city res-

Table 10 Summary of Estimates of Unmet Need using Household and Cluster Average Factor Scores

Region	Cluster Score Negative and Significant	Household Score Negative and Significant	Effects of Mean Cluster Score: Absolute Difference[a]		Effects of Mean Cluster Score: Difference Relative to Mean[b]	
			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, 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.

Table 11 Summary of Estimates of Birth Attendance by a Doctor, Nurse, or Trained Midwife, using Household and Cluster Average Factor Scores

Region	Cluster Score Positive and Significant	Household Score Positive and Significant	Effects of Mean Cluster Score: Absolute Difference[a]		Effects of Mean Cluster Score: Difference Relative to Mean[b]	
			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, 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

[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 doctor, nurse, or trained midwife in the urban samples.

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

Table 12 Summary of Estimates of Height for Age using Household and Cluster Average Factor Scores

Region	Cluster Score Positive and Significant	Household Score Positive and Significant	Effects of Mean Cluster Score: Absolute Difference[a]		Difference Relative to Mean[b]	
			All	Significant	All	Significant
North Africa	3 of 3	1 of 3	.174	.174	25.4%	25.4%
Sub-Saharan Africa	5 of 39	22 of 39	.107	.253	11.3	25.8
South, Central Asia	2 of 11	5 of 11	.151	.145	17.0	9.1
West Asia	2 of 5	3 of 5	.104	.181	21.7	39.7
Latin America	10 of 15	14 of 15	.182	.244	24.9	35.0
TOTAL	22 of 73	45 of 73	.132	.222	16.3	29.7

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

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

idents assess the risks of childbirth, feel comfortable with modern medical professionals, and are motivated to pay for their services. (Household abilities to pay are indicated in the strong effects of the household-level factor scores.) These are examples touching on the social epidemiology of health and health-seeking behavior. Our results for urban communities may thus parallel what Pebley et al. (1996) found for rural Guatemalan villages: strong associations among community residents in birth attendance that appear to stem from shared norms about appropriate care in childbirth.

There may be other explanations for the patterns we have found. As 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. These possible pathways cannot be examined in great depth with DHS data, but we have not yet exploited all of the DHS measures available. For example, many DHS surveys have fielded community modules even in urban areas, and these may shed light on the local availability of health services.

Conclusions

This paper can be read as a progress report on a far-from-completed research agenda. We have found strong evidence that household living standards, as measured by confirmatory factor scores, exert substantial influence on 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 significant is strikingly similar to that for women's education) and these effects are clearly of substantive importance. Our measures of living standards at the level of the cluster attained statistical significance less often, but when they were significant, these cluster effects were also found to be of substantive importance. To judge from our results, there is sufficient reason to believe that both dimensions of living standards can be important influences on health in the cities and towns of developing countries. It seems that the health of poor households can depend not only on their own standards of living, but also on the economic composition of their neighborhoods.

As we think about the meaning of these empirical results, it is worth remembering just how crude some of the key measures are. The concept of a living standard is measured only imperfectly by a few simple indicators $\{Z_k\}$ and determinants X. The concept of neighborhood is also very imperfectly measured by the use 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. The notion of living standards at the neighborhood level is measured through simple averages of the household-level factors, and as we have noted, more could be done to strengthen this aspect of the econometric models.

Our conceptualization of neighborhood composition is simplistic—more attention could be paid to their social composition, as reflected in the percentages of local residents who are educated, for example (Coleman 1988; Kaufman et al. 2002; Kravdal 2003). Theories of social and environmental interaction and externalities (Panel on Urban Population Dynamics 2003) indicate a need for the collection of social network and spatial data that lie well outside the scope of the DHS program, and which will require new sorts of surveys to be fielded in the cities of developing countries. Much could be learned, we believe, through application to these cities of the conceptual and measurement tools being applied to poor urban communities in the United States. We would like to think that when relatively strong results emerge from models with rather weak measures, as they have here, more tightly-focused investigations might well turn up even stronger findings.

As our descriptive analyses have shown, the neighborhoods of poor urban households often contain considerable percentages of non-poor households, and even appreciable percentages of the affluent, 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. To the extent that heterogeneity brings social, economic, and political resources within the reach of the poor, it may suggest greater potential for neighborhood-based interventions than some might have thought.

To appreciate this potential, consider a health intervention whose aim is to improve the lives of the urban poor. Should such a program be situated in a neighborhood where nearly all residents are poor, and where health needs are 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; they may also possess a stronger base of local associations. The middle- and upper-income residents of such communities could conceivably serve as "bridges" to politicians, government agencies, and sources of outside funding and expertise. For these reasons, social and economic heterogeneity could well have the effect of amplifying the positive effects of health interventions. In theory, at least, programs set in such heterogeneous neighborhoods could yield more benefits for the poor than if they were sited in uniformly poor neighborhoods. But there are also risks in situating health interventions in mixed-income communities. Program benefits could 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 characteristic of the neighborhoods of the developing-country urban poor, it will present both challenges and opportunities for program targeting.

References

Åberg Yngwe, Monica, Jon Fritzell, Olle Lundberg, Finn Diderichsen, and Bo Burström. 2003. "Exploring relative deprivation: Is social comparison a mechanism in the relation between income and health?" *Social Science and Medicine* 57(8): 1463–73.

Aber, J. Lawrence, Martha A. Gephart, Jeanne Brooks-Gunn, and James P. Connell. 1997. "Development in context: Implications for studying neighborhood effects," in Jeanne Brooks-Gunn, Greg J. Duncan, and J. Lawrence Aber (eds.), *Neighborhood Poverty*, vol. I: Context and Consequences for Children, pages 44–61, New York: Russell Sage Foundation.

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, Kenya: African Population and Health Research Center.

Astone, Nan M., Constance A. Nathanson, Robert Schoen, and Young J. Kim. 1999. "Family demography, social theory, and investment in social capital," *Population and Development Review* 25(1): 1–31.

Behrman, Jere, Hans-Peter Kohler, and Susan Watkins. 2001. "Social networks, family planning, and worrying about AIDS," Paper presented at the 2001 Annual Meetings of the Population Association of America, Washington, DC.

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

Caldeira, Teresa P. R. 1999. "Fortified enclaves: The new urban segregation," in James Holston (ed.), *Cities and Citizenship*, pages 114–138, Durham and London: Duke University Press.

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

Casterline, John B., Mark R. Montgomery, Dominic K. Agyeman, Peter Aglobitse, and Gebre-Egziabher Kiros. 2001. "Social networks and contraceptive dynamics in southern Ghana," Paper presented at the 2001 Annual Meetings of the Population Association of America, Washington, DC.

Casterline, John B. and Steven W. Sinding. 2000. "Unmet need for family planning in developing countries and implications for population policy," *Population and Development Review* 26(4): 691–724.

Coleman, James S. 1988. "Social capital in the creation of human capital," *American Journal of Sociology* 94(Supplement): S95–S120.

Coulton, Claudia, Jill Korbin, Tsui Chan, and Marilyn Su. 1997. "Mapping residents' perceptions of neighborhood boundaries: A methodological note," Working Paper, Center on Urban Poverty and Social Change, Case Western Reserve University.

Drukker, Marjan, Charles Kaplan, Frans Feron, and Jim 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: 825–841.

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

Ferguson, B. D., A. Tandon, E. Gakidou, and C. J. L. Murray. 2003. "Estimating permanent income using indicator variables," Global Programme on Evidence for Health Policy Discussion Paper no. 42, Geneva: World Health Organization.

Filmer, Deon and Lant Pritchett. 1999. “The effect of household wealth on educational attainment: Evidence from 35 countries,” *Population and Development Review* 25(1): 85–120.

—. 2001. “Estimating wealth effects without expenditure data—or tears: An application to educational enrollments in states of India,” *Demography* 38(1): 115–132.

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

Furstenberg, Frank F. 1993. “How families manage risk and opportunity in dangerous neighborhoods,” in William J. Wilson (ed.), *Sociology and the Public Agenda*, pages 231–258, Newbury Park, CA: Sage Publications.

Furstenberg, Frank F. and Mary Elizabeth Hughes. 1997. “The influence of neighborhoods on children’s development: A theoretical perspective and a research agenda,” in Jeanne Brooks-Gunn, Greg J. Duncan, and J. Lawrence Aber (eds.), *Neighborhood Poverty*, vol. II: Policy Implications in Studying Neighborhoods, pages 23–47, New York: Russell Sage Foundation.

Gilson, Lucy. 2003. “Trust and the development of health care as a social institution,” *Social Science and Medicine* 56(7): 1453–68.

Ginther, Donna, Robert Haveman, and Barbara Wolfe. 2000. “Neighborhood attributes as determinants of children’s outcomes: How robust are the relationships?” *Journal of Human Resources* 35(4): 603–33.

Harpham, Trudy and M. Tanner (eds.). 1995. *Urban Health in Developing Countries: Progress and Prospects*, New York: St. Martin’s Press.

Heckman, James J. 1981. “Statistical models for discrete panel data,” in Charles F. Manski and Daniel McFadden (eds.), *Structural Analysis of Discrete Data with Econometric Applications*, chap. 3, pages 114–178, Cambridge, MA: MIT Press.

Herr, Harvey and Guenter Karl. 2002. “Estimating global slum dwellers: Monitoring the millenium development goal 7, target 11,” Monitoring Systems Branch, Global Urban Observatory, UN-HABITAT, Nairobi.

Herr, Harvey and Gora Mboup. 2003. “Slum dweller estimation methodology,” Unpublished paper (in progress), UN-HABITAT, Nairobi.

Jöreskog, Karl G. 2000. “Latent variable scores and their uses,” Unpublished paper, available at http://www.ssicentral.com/lisrel.column6.pdf.

—. 2002. “Structural equation modeling with ordinal variables using LISREL,” Unpublished paper, available at http://www.ssicentral.com/lisrel/corner.htm.

Kaufman, Carol E., Shelley Clark, Ntsiki Manzini, and Julian May. 2002. "How community structures of time and opportunity shape adolescent sexual behavior in South Africa," Policy Research Division *Working Paper* no. 159. New York: Population Council.

Kravdal, Øystein. 2003. "Community mortality in India: Individual and community effects of women's education and autonomy," East-West Center Working Papers, Population Series, No. 112, Honolulu, Hawaii.

Lawley, D. N. and A. E. Maxwell. 1962. "Factor analysis as a statistical method," *Statistician* 12(3): 209–29.

Massey, Douglas S. 1990. "American apartheid: Segregation and the making of the underclass," *American Journal of Sociology* 96(2): 329–357.

—. 1996. "The age of extremes: Concentrated affluence and poverty in the twenty-first century," *Demography* 33(4): 395–412.

McCulloch, Andrew. 2003. "An examination of social capital and social disorganisation in neighbourhoods in the British household panel study," *Social Science and Medicine* 56(7): 1425–38.

McDade, Thomas W. and Linda S. Adair. 2001. "Defining the 'urban' in urbanization and health: A factor analysis approach," *Social Science and Medicine* 53: 55–70.

Montgomery, Mark R., Michele Gragnolati, Kathleen A. Burke, and Edmundo Paredes. 2000. "Measuring living standards with proxy variables," *Demography* 37(2): 155–174.

Montgomery, Mark R., Cynthia Lloyd, Paul C. Hewett, and Patrick Heuveline. 1997. "The consequences of imperfect fertility control for children's survival, health, and schooling," Demographic and Health Surveys *Analytical Reports* no. 7. Calverton, MD: Macro International.

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

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

Pebley, Anne R., Noreen Goldman, and Germán Rodríguez. 1996. "Prenatal and delivery care and childhood immunization in Guatemala: Do family and community matter?" *Demography* 33(2): 231–247.

Pebley, Anne R. and Narayan Sastry. 2003. "Concentrated poverty vs. concentrated affluence: Effects on neighborhood social environments and children's outcomes," Paper presented at the 2003 Annual Meetings of the Population Association of America. School of Public Health and Department of Sociology, UCLA.

Press, William H., Saul A. Teukolsky, William T. Vetterling, and Brian P. Flannery. 1992. *Numerical Recipes in FORTRAN: The Art of Scientific Computing*, New York: Cambridge University Press, second ed.

—. 1996. *Numerical Recipes in Fortran 90: The Art of Parallel Scientific Computing*, vol. 2, New York: Cambridge University Press.

Sahn, David E. and David C. Stifel. 2000. "Poverty comparisons over time and across countries in Africa," *World Development* 28(12): 2123–55.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. 2002. "Assessing "neighborhood effects": Social processes and new directions in research," *Annual Review of Sociology* 28: 443–78.

Sastry, Narayan. 1996. "Community characteristics, individual and household attributes, and child survival in Brazil," *Demography* 33(2): 211–229.

Sastry, Narayan, Anne Pebley, and Michela Zonta. 2002. "Neighborhood definitions and the spatial dimension of daily life in Los Angeles," Paper presented at the 2002 Annual Meetings of the Population Association of America, Atlanta, Georgia.

Szwarcwald, Célia Landmann, Carla Lourenço Tavares de Andrade, and Francisco Ináci Bastos. 2002. "Income inequality, residential poverty clustering and infant mortality: A study in Rio de Janeiro, Brazil," *Social Science and Medicine* 55(12): 2083–2092.

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, Geneva: World Health Organization.

Timæus, Ian M. and Louisiana Lush. 1995. "Intra-urban differentials in child health," *Health Transition Review* 5(2): 163–190.

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

Wellman, Barry and Barry Leighton. 1979. "Networks, neighborhoods, and communities: Approaches to the study of the community question," *Urban Affairs Quarterly* 14(3): 363–390.

Wen, Ming, Christopher R. Browning, and Kathleen A. Cagney. 2003. "Poverty, affluence, and income inequality: Neighborhood economic structure and its implications for health," *Social Science and Medicine* 57: 843–860.

Westoff, Charles F. and Arkinrinola Bankole. 1995. "Unmet need 1990–1994," Tech. rep., Macro International, Inc.

Westoff, Charles F. and Anne R. Pebley. 1981. "Alternative measures of unmet need for family planning in developing countries," *International Family Planning Perspectives* 7(4): 126–136.

White, Michael J. 2001. "Demographic effects of segregation," in *Encyclopedia of the Social and Behavioral Sciences*, vol. 19, pages 13250–13254, Elsevier Science.

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

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

A FURTHER DESCRIPTION OF DHS SURVEYS AND DATA

Table A.1 Demographic and Health Surveys, Phases 2 to 4

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

Table A.2 Number of DHS surveys with consumer durables and housing quality variables available, by region

	North Africa	**Sub-Saharan Africa**	**Southeast Asia**	**South, Central Asia**	**West Asia**	**Latin America**
Surveys with Consumer Durables						
Refrigerator	4	39	5	7	4	16
Television	4	40	6	12	4	16
Radio	4	42	5	12	3	16
Bicycle	4	42	6	12	2	12
Motorcycle	2	41	5	8	2	12
Car	2	41	6	6	4	13
Surveys with Housing Quality Measures						
Number of sleeping rooms	3	36	3	6	3	15
Finished flooring	4	42	6	9	4	16
Number of DHS Surveys	4	42	6	12	4	16

Table A.3 Descriptive Statistics on Residential Status

Region	**Capital or Large City**	**Small City**
North Africa	35.6	40.7
Sub-Saharan Africa	43.6	30.8
Southeast Asia	30.2	35.2
South, Central Asia	34.3	30.0
West Asia	40.6	30.0
Latin America	40.4	31.8

Table A.4 Descriptive Statistics On Women's Age and Spousal Age Differences

Region	**Women's Age (Percentages)**							**Husband's Age Minus Wife's (years)**
	15–19	**20–24**	**25–29**	**30–34**	**35–39**	**40–44**	**45–49**	
North Africa	1.5	9.1	17.3	21.4	22.2	16.8	11.7	3.5
Sub-Saharan Africa	6.4	18.5	21.8	19.1	16.8	11.1	6.3	4.3
Southeast Asia	1.3	10.8	20.0	21.9	20.9	15.6	9.5	1.1
South, Central Asia	4.5	14.7	20.6	20.6	18.0	13.8	7.8	3.8
West Asia	2.1	12.2	20.0	20.7	20.1	15.5	9.4	3.8
Latin America	4.8	15.0	19.9	20.9	18.2	13.4	7.9	3.0
TOTAL	5.0	16.0	20.8	20.1	18.0	12.7	7.5	3.7

Table A.5 Descriptive Statistics on Women's Educational Attainment

Region	No Education	Incomplete Primary	Completed Primary	Incomplete Secondary	Completed Secondary	Higher
64 surveys	Base		Group 2		Group 3	
North Africa	54.4		21.6		24.0	
Sub-Saharan Africa	50.2		41.5		8.2	
Southeast Asia	20.8		46.5		32.7	
South, Central Asia	49.5		31.5		19.0	
West Asia	25.7		57.7		16.7	
Latin America	48.9		34.3		16.8	
TOTAL	47.5		39.7		12.8	
13 surveys	Base		Group 2		Group 3	Group 4
North Africa	44.0		16.1		27.7	12.2
Sub-Saharan Africa	18.2		49.6		19.0	13.2
West Asia	14.6		36.5		24.3	24.6
Latin America	20.7		42.8		20.6	16.0
TOTAL	23.6		38.7		21.9	15.8
7 surveys	Base				Group 2	Group 3
Southeast Asia	43.2				21.7	35.1
South, Central Asia	8.5				63.5	28.0
West Asia	3.1				72.7	24.3
TOTAL	17.6				52.9	29.5

Table A.6 Descriptive Statistics on Husband's Educational Attainment

Region	No Education	Incomplete Primary	Completed Primary	Incomplete Secondary	Completed Secondary	Higher
61 surveys	Base		Group 2		Group 3	
North Africa	41.0		28.4		30.6	
Sub-Saharan Africa	39.0		41.8		19.2	
Southeast Asia	13.2		42.8		44.0	
South, Central Asia	32.2		32.5		35.3	
West Asia	7.8		71.7		20.4	
Latin America	41.5		36.9		21.7	
TOTAL	35.8		40.6		23.6	
13 surveys	Base		Group 2		Group 3	Group 4
North Africa	34.4		19.2		26.8	19.6
Sub-Saharan Africa	19.8		46.6		19.1	14.4
West Asia	9.9		30.3		26.3	33.4
Latin America	17.2		41.8		19.6	21.4
TOTAL	19.5		37.8		21.2	21.5
7 surveys	Base				Group 2	Group 3
Southeast Asia	41.8				23.5	34.7
South, Central Asia	7.8				61.7	30.4
West Asia	6.5				66.9	26.5
TOTAL	17.3				51.5	31.1

B ESTIMATING ONE-FACTOR MODELS WITH MULTIPLE BINARY INDICATORS

The application for which this appendix is written involves using a set of binary consumer durables measures—termed "indicators" here and in the text—to shed light on an otherwise unobserved construct, the household "standard of living." Many other applications of the basic ideas come to mind. For instance, one can think of multiple indicators of health, each of which reflects an individual's underlying "healthiness."

In our application, every household i in the sample provides a vector Z_i containing K observed binary indicators, with each of these being denoted by Z_{ik}. To begin, we describe a multiple indicators model in which the indicators are expressions of an unobserved factor $F_i = u_i$, which we take to represent household i's standard of living. Many of the estimation details are discussed in this simple context, as are the procedures used to estimate u_i given the observed values of the indicators. The last section of the appendix sets out an expanded model in which $F_i = X_i'\gamma + u_i$, allowing covariates X_i to play a role in determining the standard of living. The expanded model is the so-called MIMIC specification, this being an acronym for "multiple indicators, multiple causes." Throughout the discussion, the indicators are assumed to be dichotomous rather than continuously-valued.

The Multiple Indicators model

In this specification each element of the indicator vector Z_i is assumed to depend on an unobserved factor $F_i = u_i$. Consider Z_{ik}, one of the k indicators. This observed indicator is linked to its latent counterpart Z_{ik}^* via two equations, the first being

$$\begin{aligned} Z_{ik}^* &= \alpha_k + \beta_k F_i + v_{ik} \\ &= \alpha_k + \beta_k u_i + v_{ik}. \end{aligned} \tag{B-1}$$

In equation (B-1), α_k is a cut-point parameter and β_k is a coefficient indicating how the unobserved factor u_i takes expression through the k-th indicator. The latent variable Z_{ik}^* is then linked with its observed counterpart Z_{ik} through the second relation

$$Z_{ik} = \begin{cases} 1 & \text{if } Z_{ik}^* > 0, \\ -1 & \text{if } Z_{ik}^* \leq 0. \end{cases}$$

Although unconventional, this $\{1, -1\}$ coding scheme simplifies both the analytics and the programming.

In what follows, we will indicate the dependence of the vector Z_i on u_i using the notation $P_i(u_i)$, with P_i being the joint probability distribution associated with Z_i conditional on the (unknown) value of u_i. The unconditional probability associated with Z_i is derived by "integrating out" the unobserved random factor. We will assume that the factor u_i is normally distributed with mean zero and variance ρ. Given this, the unconditional probability is expressed by the integral

$$\int_{-\infty}^{\infty} (2\pi)^{-1/2} \rho^{-1/2} e^{-\frac{1}{2\rho} u_i^2} P_i(u_i)\, du_i. \tag{B-2}$$

Unfortunately, the integral is not available in a closed form, and numerical approximation methods are required to evaluate it.

Background on quadrature

The method of Gaussian quadrature is often applied when one desires a good approximation to an integral of the type

$$\int_{-\infty}^{\infty} e^{-\epsilon^2} P(\epsilon) d\epsilon$$

where the function $P(\epsilon) > 0$ and the integral in question cannot be represented in a closed form. (Note that, for the moment, the i subscript has been suppressed.) The quadrature method approximates this integral by a weighted summation over a pre-selected number of quadrature points. The method is explained in illuminating detail by Press et al. (1992, 1996), who provide additional references as well as programming subroutines that calculate the quadrature points and the weights associated with them.

To put equation (B-2) in this form, we need only make a change of variables

$$\epsilon = \frac{u}{\sqrt{2}\rho^{1/2}},$$

with $\rho^{1/2}$ being the standard deviation of u. The transformation implies $u^2 = 2\rho\epsilon^2$ and

$$\frac{du}{d\epsilon} = \sqrt{2}\rho^{1/2}.$$

Upon making the change of variables, we obtain

$$\pi^{-1/2} \int e^{-\epsilon^2} P(\sqrt{2}\rho^{1/2}\epsilon) d\epsilon,$$

which is in the required form apart from the constant $\pi^{-1/2}$. The quadrature method approximates the integral by the sum

$$\sum_{j=1}^{n_q} w_j P(\sqrt{2}\rho^{1/2} e_j),$$

whose index j ranges over $n_q > 1$ quadrature points. The quadrature points e_j are symmetric about zero, as are the weights w_j with which they are associated. The number of points n_q is under the control of the researcher, but the quality of the approximation generally improves as the number of points increases.

Maximum likelihood estimation: General approach

Let L_i^* represent the contribution made by household i to the sample likelihood function and let L_i be the contribution to the sample log-likelihood. The contribution depends on covariates specific to household i and on a set of parameters θ, one of which is the variance ρ of the random factor. (The other parameters will be discussed shortly.) To display these dependencies more explicitly than we have thus far, we write

$$L_i^* = \pi^{-1/2} \sum_{j=1}^{n_q} w_j P_i(\theta_0, \sqrt{2}\rho^{1/2} e_j).$$

In this notation, θ_0 contains all unknown parameters save ρ, and we let the full set of parameters be denoted by $\theta = (\theta_0, \rho)'$.

Estimation of the parameters θ proceeds by maximizing the full log-likelihood function $L = \sum_i \ln L_i^* = \sum_i L_i$. A key step is to derive the *score vector*, which is the vector of derivatives $\partial L/\partial\theta$, with

$$\frac{\partial L}{\partial \theta} = \sum_i \frac{\partial L_i}{\partial \theta}.$$

Note that household i's contribution to the score is

$$\frac{\partial L_i}{\partial \theta} = \frac{\sum_j w_j \frac{\partial P_{ij}}{\partial \theta}}{\sum_j w_j P_{ij}}.$$

It will prove helpful to re-express this derivative in the form

$$\frac{\partial L_i}{\partial \theta} = \frac{\sum_j w_j P_{ij} \frac{\partial \ln P_{ij}}{\partial \theta}}{\sum_j w_j P_{ij}},$$

because the derivatives of $\ln P_{ij}$ with respect to θ are generally similar to their counterparts in models without random factors.

Estimation of the model

For convenience, we repeat here the latent variable equation (B-1),

$$Z_{ik}^* = \alpha_k + \beta_k u_i + v_{ik}. \tag{B-1}$$

In constructing probability expressions for the observed indicators Z_{ik}, we assume that the disturbance term v_{ik} of equation (B-1) is normally distributed with mean zero and variance $\sigma_{v_k}^2$. We take u_i and v_{ik} to be independent of each other for all i and k, and assume that the elements of $\{v_{ik}, k = 1, \ldots, K\}$ are mutually independent. Hence, although the various Z_{ik}^* are inter-correlated, their correlations stem from a common dependence on the u_i factor. Conditional on u_i, the latent variables Z_{ik}^* are independent, as are their observable Z_{ik} counterparts.

In probit structures such as these, the sizes of the disturbance variances are not identified and some normalization rule must be imposed. Following in the spirit of Heckman (1981: 129), we choose the rule to be $\beta_k^2\rho + \sigma_{v_k}^2 = 1$. This is a convenient rule to apply if one begins with $\hat{\alpha}_k$ estimates from standard probit models, since those estimates are based on an assumed disturbance variance of unity. Note that under the normalization rule, the variance of v_{ik} is $1 - \beta_k^2\rho$. We also define $\beta_1 \equiv 1$ for reasons to be explained below.

Equation (B-1), which defines the latent indicator Z_{ik}^*, may now be multiplied through by $r_k = (1 - \beta_k^2\rho)^{-1/2}$ to give a result expressed in the usual probit form. We can see that

$$r_k Z_{ik}^* = r_k(\alpha_k + \beta_k u_i) + r_k v_{ik}$$

is in the desired form since $r_k v_{ik}$ is standard normal. The probability associated with the observed dependent variable Z_{ik}, conditional on the random factor u_i, is then

$$\Pr\big(Z_{ik} = z_{ik} | u_i\big) = \Phi\big(z_{ik} r_k \cdot (\alpha_k + \beta_k u_i)\big),$$

where Φ is the standard normal cumulative distribution function, and we have made use of our unconventional $\{1, -1\}$ coding scheme for Z_{ik} and the symmetry of the normal distribution. The product of such probabilities over all indicators for household i is

$$P(u_i) = \prod_{k=1}^{K} \Phi\big(z_{ik} r_k \cdot (\alpha_k + \beta_k u_i)\big).$$

Recall that to integrate out the unobservable random effect u, we need the quadrature approximation to an integral of the general form,

$$\int_{-\infty}^{\infty} (2\pi)^{-1/2} \rho^{-1/2} e^{-\frac{1}{2\rho} u^2} P(u) du.$$

Applying the change of variables and using n_q quadrature points, we obtain

$$L_i^* = \pi^{-1/2} \sum_{j=1}^{n_q} w_j P_i(\theta_0, \sqrt{2}\rho^{1/2} e_j) = \pi^{-1/2} \sum_{j=1}^{n_q} w_j P_{ij},$$

in which $\theta_0 = (\alpha, \beta)'$, this being a vector of length $2K - 1$ containing all unknown parameters except for ρ, the variance of the factor (recall that $\beta_1 \equiv 1$). When we need to see the roles of the parameters more clearly, we write out the expression for P_{ij} in full, as

$$P_{ij} = P_i(\theta_0, \sqrt{2}\rho^{1/2} e_j) = \prod_{k=1}^{K} \Phi\big(z_{ik} r_k \cdot (\alpha_k + \beta_k \sqrt{2}\rho^{1/2} e_j)\big).$$

Below we will refer to this expression as $P_{ij}(\theta)$, a notation in which the vector $\theta = (\alpha, \beta, \rho)'$, of length $2K$, contains all of the model's unknown parameters.

The scores

Recall that household i's contribution to the full score vector is

$$\frac{\partial L_i}{\partial \theta} = \frac{\sum_j w_j P_{ij} \frac{\partial \ln P_{ij}}{\partial \theta}}{\sum_j w_j P_{ij}}.$$

Now, $\ln P_{ij}(\theta)$ is itself the sum over k of the logs of the probabilities specific to indicator k:

$$\ln P_{ij}(\theta) = \sum_{k=1}^{K} \ln \Phi\big(z_{ik} r_k \cdot (\alpha_k + \beta_k \sqrt{2}\rho^{1/2} e_j)\big). \tag{B-3}$$

Hence, for the α parameters we take derivatives of equation (B-3) to obtain

$$\frac{\partial \ln P_{ij}}{\partial \alpha_k} = \frac{\phi_{ik,j}}{\Phi_{ik,j}} z_{ik} r_k, \tag{B-4}$$

with $\phi_{ik,j}$ being the derivative of $\Phi_{ik,j}$ with respect to its argument. Both $\phi_{ik,j}$ and $\Phi_{ik,j}$ are evaluated at the point $z_{ik} r_k W_{kj}$, with $W_{kj} = \alpha_k + \beta_k \sqrt{2}\rho^{1/2} e_j$. Note that the expression involves only parameters specific to the k-th indicator.

For the β parameters, we face a more complicated derivation because r_k depends on β_k. For $k \geq 2$ (again recall that $\beta_1 \equiv 1$), the result is

$$\frac{\partial \ln P_{ij}}{\partial \beta_k} = \frac{\partial \ln P_{ij}}{\partial \alpha_k} \cdot \left(W_{kj} r_k^2 \beta_k \rho + \sqrt{2} \rho^{1/2} e_j. \right) \tag{B-5}$$

As for the derivative with respect to ρ, a parameter that enters all of the indicator equations, if we recall that r_k is also a function of ρ we obtain

$$\frac{\partial \ln P_{ij}}{\partial \rho} = \sum_{k=1}^{K} \frac{\partial \ln P_{ij}}{\partial \alpha_k} \cdot \frac{\beta_k}{2} \left(W_{kj} r_k^2 \beta_k + \sqrt{2} \rho^{-1/2} e_j \right). \tag{B-6}$$

These results provide all the ingredients needed to estimate the model.

Notes on identification

In setting out the multiple indicator model, we have imposed a number of restrictions, and some comment is in order on why these are needed and how the restrictions help to identify the parameters. Note first that the restriction $\beta_1 = 1$ is something more than a trivial normalization. Consider a model with a given set of $\{\beta_k\}$ parameters. Because the unobserved factor u_i is symmetrically distributed about zero, given normality, a second model that is observationally equivalent to the first can be constructed by reversing the signs of all of the β_k parameters while leaving their magnitudes untouched. Fixing $\beta_1 = 1$ eliminates this possibility. However, in choosing to set the first of the β_k parameters to unity, we are making the assumption that the first indicator Z_{i1} is known to be positively associated with the unmeasured factor. If there is any doubt about this assumption, another indicator should be used in its place.

A second point to note is that the variances of the composite disturbance terms—by "composite" we mean $u_i + v_{i1}$ for the first indicator and $\beta_k u_i + v_{ik}$ for the k-th—are not identified in latent variable models with binary indicators. By setting each of the composite variances to unity, we are imposing restrictions that acknowledge this fact.

Consider, then, a two-indicator model. The unknown parameters of this model are α_1, α_2, β_2, the factor's variance ρ, and the disturbance variances $\sigma^2_{v_1}$ and $\sigma^2_{v_2}$, giving a total of six parameters. Two restrictions are imposed via the unit variance assumptions, and this reduces the number of unknowns to four. However, the data at hand provide us with only three quantities that can be calculated: conventional single-equation probit models supply consistent estimates of α_1 and α_2, and the covariance between $Y^*_{i,1}$ and Y^*_{i2} can be estimated consistently by a bivariate probit. Unless further assumptions can be made, the two-indicator model is clearly under-identified.

Counting up parameters and calculable quantities for a three-indicator model shows that this model is just-identified. After imposing variance restrictions, we are given six parameters to estimate. Three conventional probits identify the α_k parameters, and three applications of bivariate probit supply estimates of the three cross-equation covariances. By the same logic, models with four indicators or more are over-identified. Each additional indicator adds a new pair of α_k, β_k parameters to estimate, to be sure, but each indicator also makes available a new set of cross-equation covariances that help in estimating all of the β_k parameters and the ρ parameter.

If many indicators are available, some of the assumptions made above can be relaxed. For instance, if the model is over-identified given the assumption of zero covariance between disturbance components v_{ij} and v_{ik}, $j \neq k$, then additional parameters can be introduced to allow for a limited number of non-zero covariances.

Numerical optimization issues

Our experience in estimating these models suggests that on occasion they present numerical difficulties. In particular, we have encountered cases in which one of the normalizing factors $r_k = (1 - \beta_k^2 \rho)^{-1/2}$ behaves badly as the result of a steady drift upward in its β_k. We have not been able to diagnose the root cause of the problem; fortunately, it is generally easy to correct. To arrest the tendency for one or more of the β_k to drift upward, we have programmed special checks that are applied during the course of optimization, which temporarily reduce the absolute amount of change permitted in the parameters once such drift is detected. Slowing things down in this way generally allows the optimization to regain its footing and things usually proceed smoothly thereafter. As a further safeguard, we have estimated the models using an initial grid search over ρ, estimating all other parameters for each ρ value in the grid. The best estimates $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\rho}$ emerging from this grid search are presented as starting values to a full maximum likelihood estimation routine.

Estimating the unobserved factor

Even though the factor u_i is unobserved, we can estimate its value from the values of the observed indicators Z_i for that observation. The procedure is little more than an application of Bayes' Rule. We seek the conditional expectation

$$E(u_i|Z_i) = \int u\, P(u|Z_i)\, du, \tag{B-7}$$

in which the conditional density $P(u|Z_i)$ is the density for the factor u given the indicator vector Z_i for the i-th household. By Bayes' Rule,

$$P(u|Z_i) = \frac{P(u, Z_i)}{P(Z_i)} = \frac{P(Z_i|u)\phi(u)}{P(Z_i)}, \tag{B-8}$$

with $\phi(u)$ being the normal density function for a factor with mean 0 and variance ρ. Note that $P(Z_i)$ is the contribution made by observation i to the sample likelihood.

Given realized values $Z_i = z_i$, the numerator of $P(u|Z_i)$, as it is expressed on the right-hand side of equation (B-8), can be written as

$$\prod_{k=1}^{K} \Phi\big(z_{ik} r_k \cdot (\alpha_k + \beta_k u)\big) \cdot \phi(u), \tag{B-9}$$

and the denominator of equation (B-8) is the integral of (B-9) over u.

To calculate the conditional expectation of u, we start with the quadrature approximation to $\int u\, P(Z_i|u)\phi(u)\, du$, which is

$$\pi^{-1/2} \sum_{j=1}^{n_q} w_j(\sqrt{2}\rho^{1/2} e_j) \cdot \prod_{k=1}^{K} \Phi\left(z_{ik} r_k \cdot (\alpha_k + \beta_k \sqrt{2}\rho^{1/2} e_j)\right). \tag{B-10}$$

In this expression, the first component in parentheses, $\sqrt{2}\rho^{1/2} e_j$, stands in for u. To complete the quadrature approximation to equation (B-7), we divide equation (B-10) by the approximation to $P(Z_i)$, which is

$$\pi^{-1/2} \sum_{j=1}^{n_q} w_j \prod_{k=1}^{K} \Phi\left(z_{ik} r_k \cdot (\alpha_k + \beta_k \sqrt{2}\rho^{1/2} e_j)\right). \tag{B-11}$$

These calculations are carried out using the estimated $\hat{\alpha}_k$, $\hat{\beta}_k$, and $\hat{\rho}$ parameters. (The factor u, being normally distributed, takes on negative as well as positive values. It may be that quadrature approximations to the conditional expectation of u perform poorly unless the integrand $uP(u|Z_i)$ is positive. An easy solution is to add a large positive constant to u (i.e., to its proxy $\sqrt{2}\rho^{1/2} e_j$ that appears immediately after the summation sign in equation (B-10)) and then subtract that constant after the integral has been calculated.)

The Multiple Indicator, Multiple Cause model

With all of this as background, we may now generalize things by allowing the unobserved factor to be determined by a set of observed exogenous variables X_i as well as an unobserved component u_i. This MIMIC model ("multiple indicator, multiple cause") may be represented as $F_i = X_i'\gamma + u_i$, where F_i is the latent factor, the X_i covariates are its observed determinants, and u_i is its unobserved determinant, assumed to be independent of X_i. In this approach, the latent indicator Z_{ik}^* is written out as

$$\begin{aligned} Z_{ik}^* &= \alpha_k + \beta_k F_i + v_{ik} \\ &= \alpha_k + \beta_k X_i'\gamma + \beta_k u_i + v_{ik}. \end{aligned} \tag{B-12}$$

We apply the unit variance restrictions as before,

$$r_k Z_{ik}^* = r_k \left(\alpha_k + \beta_k X_i'\gamma + \beta_k u_i\right) + r_k v_{ik}, \tag{B-13}$$

and obtain

$$\ln P_{ij} = \sum_{k=1}^{K} \ln \Phi\left(z_{ik} r_k (\alpha_k + \beta_k X_i'\gamma + \beta_k \sqrt{2}\rho^{1/2} e_j)\right), \tag{B-14}$$

also much as before.

The forms of the scores in the α_k and β_k dimensions are essentially unchanged. For the other parameters, however, we have

$$\frac{\partial \ln P_{ij}}{\partial \gamma} = \sum_{k=1}^{K} \frac{\partial \ln P_{ij}}{\partial \alpha_k} \cdot \beta_k \cdot X_i, \tag{B-15}$$

a vector of the same dimension as the X_i vector, and

$$\frac{\partial \ln P_{ij}}{\partial \rho} = \frac{\partial \ln P_{ij}}{\partial \alpha_k} \cdot \left(W_{kj} r_k^2 \beta_k \rho + X_i' \gamma + \sqrt{2} \rho^{1/2} e_j \right) \tag{B-16}$$

with $W_{kj} = \alpha_k + \beta_k X_i' \gamma + \beta_k \sqrt{2} \rho^{1/2} e_j$. This definition of W_{kj} would also be used in the modified versions of equations (B-4) and (B-5).

As for estimating the unobserved factor, there is little to distinguish the MIMIC model from the standard model. In this case we aim to estimate $F_i = X_i' \gamma + u_i$ conditional on Z_i and X_i. We employ $\hat{\gamma}$ for the first term and then apply the procedures that were outlined above to predict u_i.