

Unpacking the Causes of Inequalities in Child Survival: The Case of Cebu, The Philippines

by

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Abstract

The aim of this paper is to “unpack” the socioeconomic causes of inequalities in child survival between poor and better-off children. A two-part model is estimated, comprising a probit to model the child’s prospects of surviving the first year of life, and the second a Weibull to model his survival prospects beyond then. By linking the parameter estimates of the two models with information on the distribution of the various socioeconomic determinants across income groups, it is possible to build up a picture of how far inequalities in each set of determinants contributes to inequalities in survival. The data used are from the Cebu Longitudinal Health and Nutrition Survey. The results point to income inequalities being the largest contributory factor to inequalities in both infant and under-five mortality. Inequalities in mother’s education are also important, as are inequalities in sanitation in the case of infant mortality and inequalities in insurance coverage in the case of survival beyond the first birthday. Inequalities in accessibility and quality of health services, by contrast, appear to contribute very little. In the case of quality, this is not because it does not influence survival, but rather because it does not appear to be especially unequally distributed between poor and better-off households. By contrast, although health services are indeed less accessible for the poor, the impact of proximity on survival varies, from having a strong beneficial effect in the case of a public hospital to an apparently adverse effect in the case of some facilities.

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I. Introduction

Improving the health and nutrition outcomes of the world's poor is currently a major priority of the international development community (cf. e.g. UK Department for International Development 1999; World Bank 1997; World Health Organization 1999). Understandably, much of the focus has been on reducing deaths amongst small children. The gaps in child survival prospects between poor and better-off countries are large. For example, in several sub-Saharan African countries, as many as 200 out of every 1000 children born will die before their fifth birthday; in Sweden, by contrast, the under-five mortality rate is currently only 5 per 1000 live births (World Bank 1999). *Within* countries, too, there are large differences—in Bolivia, for example, there is a fourfold difference between the under-five mortality rates prevailing amongst the poorest fifth of households and that prevailing amongst the richest fifth (Gwatkin et al. 2000). The magnitude of these within-country inequalities also varies—in India and Kenya, for example, the overall under-five mortality rate is similar to that of Bolivia (around 100 per 1000 live births), but there are smaller (threefold and twofold respectively) differences in the rates prevailing in the bottom and top wealth quintiles (Gwatkin et al. op. cit.). Closing these within-country gaps—by securing greater proportional improvements amongst poorer groups—is a major part of the larger challenge of how to improve the health outcomes of the world's poor.

What are the causes of these within-country gaps in child survival outcomes? The determinants of child health outcomes are complex. There are what are sometimes termed the *proximate determinants* of survival—in effect, the arguments of a survival production function (cf. e.g. Moseley and Chen 1984; Schultz 1984). There is extensive knowledge now about what these variables are, and what represents good practice in terms of promoting child survival (cf. e.g. WHO 1998). There is a consensus amongst medical and public health experts on which immunizations and other preventive are desirable, and which practices and interventions are advisable in the event of particular childhood illnesses. There is a consensus amongst public health specialists and nutritionists on which feeding practices best promote survival of young children. There is broad agreement too on which sanitary practices are advisable. And so on. One approach to explaining gaps in childhood survival would be to seek to identify how these behaviors and practices vary across economic groups, and, bearing in mind the sensitivity of survival to each, to decompose the survival gap into components corresponding to each set of proximate determinants. One might then conclude, for example, that in the absence of the large inequalities between poor and nonpoor households in their use of immunization services, there would only have been, say, a threefold gap in the under-five mortality rate rather than, say, a fourfold gap.

Two problems would arise if such a strategy were adopted. The first is technical—to a degree that varies across proximate determinants and varies across households, the proximate determinants of health are within the household's sphere of influence. In a regression framework, therefore, they ought to be treated as endogenous using instrumental variables (IV), and failure to do so could result in serious biases in parameter estimates and the drawing of misleading conclusions (cf. e.g. Cebu Study Team 1991; Rosenzweig and Schultz 1983). A difficulty arises with such methods in the context of child mortality, however. Survival data are best analyzed using duration models, but the use of IV methods with such models is far from straightforward (cf. e.g. Lavy et al. 1996). Moreover, even in the absence of this technical problem, there is a second difficulty that would arise if one were simply to decompose gaps in child survival into gaps in proximate determinants, namely that governments do not influence the proximate determinants of child survival directly but rather only *indirectly* through their influence over the

factors that influence households' health-related behaviors and practices—the so-called *socioeconomic determinants* of survival.¹ For example, it is by influencing the availability, accessibility, quality and prices of health services that governments can influence health service utilization. It is by influencing households' knowledge of health matters and the availability and accessibility of water and sanitation that governments can influence households sanitary practices. And so on. From a policy perspective, therefore, an arguably more useful exercise than that discussed above would be to assess the gaps in the *socioeconomic* determinants of child survival and to assess *their* contribution to inequalities in survival outcomes rather than the contribution of the gaps in the proximate determinants. It is this approach that is adopted in this paper.

The setting for this exercise is Metropolitan Cebu, located on the eastern coast of the Island of Cebu in the central Philippines. In some respects Cebu is unusual—the level of education is high amongst both men and women, the quality of the drinking water is good, and the level of availability of health services is fairly high. All of this helps make for a relatively low under-five mortality rate (78 per 1000 over the period 1981-91) (Wagstaff 2000a,b). The inequality between poor and nonpoor is, however, appreciable—the rate of the poorest quintile is over two a half times that of the richest quintile (Wagstaff op. cit.).

The data are from the Cebu Longitudinal Health and Nutrition Survey (cf. e.g. Cebu Study Team op. cit.; Schwartz et al. 1988). This survey is especially suited to unpacking the causes of inequalities in child survival, since it allows one to link socioeconomic determinants at one point in time to survival over subsequent years. Cross-sectional data, of course, do not allow such a forward-looking exercise to be undertaken. The model estimated is not a simple duration model, but rather a two-part model, in which the child's survival to his first birthday is modeled first using a binary dependent variable model, and his survival time thereafter (if there is any) is modeled using a Weibull duration model. In this particular application, this two-part model predicted survival better than a simple Weibull model and uncovered some interesting differences between the impacts on the first year and impacts on survival subsequently amongst certain socioeconomic determinants. The parameters of the two parts of the model are then used to compute elasticities showing the responsiveness of infant and under-five mortality rates to the various socioeconomic determinants of the model. Finally, simulations and decompositions are undertaken to assess the contributions of inequalities in each set of socioeconomic determinants to the observed inequalities in survival.

II. Modeling Child Survival

Theory

The proximate determinants of child survival (i.e. the variables that have a *direct* influence on survival prospects) are assumed to comprise a vector of household-level variables, x . This includes the utilization of health and related services, diet and feeding practices, sanitary

¹ Governments also influence the quality of care, and this affects the impact of a given unit of health service utilization on health status.

practices, the child's gender and mother's age at the birth of the child, the care and stimulation given to the child, and so on. If s is child survival, the child survival production function is thus:

$$(1) \quad s = s(x).$$

Households exert a good deal of control over the x -vector, so that any attempt to estimate eqn (1) without taking into account the endogeneity of x would result in biased estimates of the impact of the x -variables on survival.

Eqn (1) is not, in any case, especially helpful in trying to understand the causes of poor-nonpoor inequalities in child survival, since it simply pushes the question back one stage—it begs the question of what causes poor and nonpoor households to use health services differently, feed their children differently, and do on. In making choices over the x variables, households are influenced by two sets of variables. The first are the various household-level variables, such as the household's resources (income, education, etc.), its insurance coverage, its access (in terms of time costs) to health services, and so on. We label these variables y . The second set of variables, denoted by z , comprise various community-level variables, including the availability and quality of health services in the community, the transport and local infrastructure, and so on.² The (input) demand function for the x -variables is thus:

$$(2) \quad x = x(y, z).$$

Substituting the input demand function (2) in the survival production function (1) yields a reduced-form survival demand function:

$$(3) \quad s = s[x(y, z)] = f(y, z).$$

Variables that lower the shadow price of child survival—such as parents' education and health insurance coverage—ought to increase the household's 'demand' for child survival (cf. e.g. Grossman 1972). By contrast, variables that *raise* the shadow price of survival—such as poor local sanitary conditions and poor quality health services—would be expected to be *negatively* associated with survival in the survival demand function.

Eqn (3) is less likely to be plagued by endogeneity than the survival production function (though not, as will be seen below, necessarily completely free from it), since households exert a smaller influence over, say, the quality of health services locally than they do over their use of health services. Furthermore, this equation is more useful as a basis for explaining poor-nonpoor survival inequalities, since it links survival outcomes to the variables that ultimately explain these outcomes. It is this equation that underlies the empirical work that follows.

Econometric Model

The data on child survival used in the empirical work that follows come from complete fertility histories—the date of birth and death if applicable of each child is recorded, rather than

² It is possible that some community-level variables (e.g. the environment) have a direct influence on health. These are not analyzed in the present study.

just the number of children ever born and the number surviving (an incomplete fertility history). It makes sense in such a context to use a duration model (cf. e.g. Lavy et al. op. cit.). Rather than relying completely, however, on a duration model, this paper employs a two-part model, the first modeling the survival probability for the first year of life, the second modeling the survival over the following nine years, conditional, of course, on the child having survived the first year. This approach, which is analogous to the two-part models used in the analysis of health service utilization (cf. Manning et al. 1981), allows for the possibility that the variables in the survival demand function can have a different impact on the child's survival chances in the first year than on his survival prospects thereafter.

The chances of surviving the first year are modeled using a probit model. Survival beyond the first year up to the child's tenth birthday is modeled using a Weibull model with covariates (cf. e.g. Greene 1993; Lavy et al. op. cit.). Let $S(t)$ be the survival function at time t , and $I(t)$ be the hazard rate at time t . The latter measures the rate at which the survival function decreases over time, and is equal therefore to $-d\ln S(t)/dt$. The basic Weibull model assumes the existence of a basic time-invariant hazard rate, I , to which the hazard rate at a time t is linked by the equation:

$$(4) \quad I(t) = I p(I t)^{p-1},$$

where p is a parameter, with $p < 1$ indicating that $I(t)$ falls continuously over time, while $p > 1$ indicates the opposite. In the case of child survival, it is likely that p will be less than one, since $S(t)$ drops sharply in the first year and then starts to level out. It is linked to the basic hazard, I , and the parameter p by the function:

$$(5) \quad S(t) = e^{-(I t)^p},$$

so a higher basic hazard reduces the proportion of children surviving to any specific age. The econometric model then seeks to explain variations in I . The model takes the form:

$$(6) \quad -\ln I_i = \mathbf{b}x_i,$$

where I_i is the basic hazard rate for child i , \mathbf{b} is a vector of parameters, and x_i a vector of determinants of child survival. Notice the dependent variable is decreasing in the hazard and hence increasing in survival duration—a positive \mathbf{b} thus indicates a longer life. Although the hazard rate is unobserved at the individual level, survival times *are* observed. Using this information, a maximum likelihood estimator can be derived, the application of which results in estimates of the coefficient vector \mathbf{b} as well as the parameter p (cf. e.g. Greene op. cit.). This estimator takes into account any censoring—children who were alive in 1991 but had not yet reached their tenth birthday and who had therefore not been exposed to the risk of death for the full nine-year period over which the Weibull model is estimated.

III. The Data

The Setting

The data are from Metropolitan Cebu, located on the eastern coast of the Island of Cebu in the central Philippines. The area covered includes the city of Cebu (the second largest in the Philippines), coastal towns, and a number of mountain and coastal villages. The Philippines in general, and Cebu in particular, do better on key determinants of child survival than many other lower middle income countries. The population is relatively literate and well educated, and the corresponding gender gap is either negligible (in the case of literacy) or in *favor* of women (in the case of years of education).³ The quality of drinking water is also good (cf. e.g. VanDerslice et al. 1994), the availability and quality of health services is better than in many developing countries, and even in the 1980s around one fourth of households some form of health insurance.

The Survey

The Cebu Longitudinal Health and Nutrition Survey (LHNS), which began in 1982 and had its latest sweep in 1999, focuses on 33 of the 243 *barangays* (small communities) in the Metro Cebu area.⁴ Of the 33 *barangays*, 17 were classified as urban and 16 as rural.⁵ The prospective respondents were all pregnant women residing in the selected *barangays* expected to deliver a live birth any time between 1 May 1983 and 30 April 1984. The sample initially consisted of 3711 women. Information on the children born to these women was collected at the time of the birth, and thereafter through a series of follow-up interviews. Extensive information was collected on the mother and on other members of the household at the time of the first interview, and again in 1991, 1994 and 1999. In the empirical work that follows, the child mortality data are from the complete birth histories provided by the participating women when re-interviewed in 1991, while the household-level information is from the baseline household survey conducted in 1983/84. Extensive surveying of the community around the mother's home was also undertaken at the same dates—the topics covered included infrastructure, water and sanitation, local schools, women's groups, etc. In addition to the household and community surveys, four health service facility surveys were conducted in 1983, 1984, 1986, and 1988. These varied somewhat in the number of facilities covered and the information sought—the first and third were general surveys, while the second and third focused on specific topics. In the empirical work that follows, data from the third (1986) survey was used, since this contained

³ The 1999 WDI reports the rates of illiteracy amongst men and women in the Philippines to be 5% and 6% respectively, compared to 10% and 22% in lower middle income countries generally. Schwartz et al. (1988) report an overall average years of schooling of seven years in the Cebu LHNS sample, which, as Dargent-Molina et al. (1994) note, is high by developing country standards. Furthermore, Schwartz et al. (op. cit.) report *higher* average years of schooling amongst the mothers in their Cebu sample than amongst the men in the sample, in both urban and rural areas.

⁴ The 33 *barangays* were selected using a stratified single-stage sampling procedure.

⁵ This represents an oversampling of the urban *barangays*—in reality, only 39% of the *barangays* in Metro Cebu were urban. This oversampling is not taken into account in what follows. Nor has it apparently been taken into account in the others studies using the Cebu LHNS. See e.g. Schwartz et al. (1988).

information on the availability of medicines, vaccines, oral rehydration solutions and tablets, and female contraceptives.⁶

The Survival and Income Data

The children included in the analysis are all those born over the period 1981-91, numbering 6645 in total. Information on survival was obtained from the complete birth histories in the 1991 follow-up survey. Life table methods using half-yearly intervals produce sample average infant and under-five mortality rates of 38.7 and 78.9 respectively, with relative standard errors of 6% and 4% respectively—well within the bounds of what is considered reasonable for standard errors in this field (cf. e.g. Curtis 1995).

As with all the variables in the analysis, the interest here is not just with the sample average but with the distribution across income classes. A broad measure of income was constructed from the 1983/4 baseline survey within the CLHNS. This included wage and non-wage income of all household members, in-kind income received from non-family members, the value of home-grown vegetables and other produce, and the rental value of the family's home and other consumer durables. The total was equivalized to take into account inter-household differences in household size. The two extreme positions on equivalization are (a) to assume that there are no economies of scale in household consumption (it costs two people twice as much to live as one) and (b) to assume that there are maximum economies of scale (two can live as cheaply as one). These two extremes, and certain intermediate positions, can be represented by the following relationship between equivalent consumption and actual consumption:

$$(7) \quad E = A/H^e$$

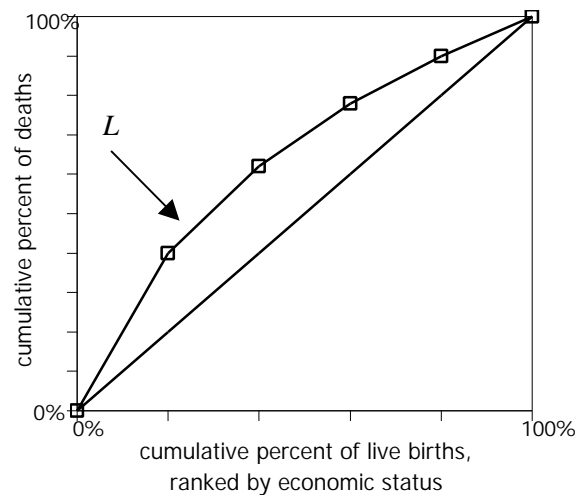
where E is equivalent consumption, A is actual consumption, H is household size, and e an equivalence scale elasticity (cf. Buhmann et al. 1988). Under the assumption that there are no economies of scale, e is set equal to 1, and equivalent consumption is simply per capita consumption. Under the assumption that two (or three, or four, or five,...) can live as cheaply as one, e is set equal to 0, and equivalent consumption is simply aggregate household consumption. Although it is not uncommon to find e set equal to one (the per capita adjustment), a more plausible position, at least in countries where a sizeable proportion of consumption is on non-food items, is that there are some economies of scale, but that the elasticity e is greater than zero. In their survey of equivalence scales in OECD countries, Buhmann et al. (op. cit.) found that most equivalence scales could be approximated quite closely by eqn (7) and that, on average, the implied value of the elasticity e was around 0.4. Hentschel and Lanjouw (1996), in their work on Ecuador, experiment with three values of e : 0.4, 0.6, and 1.0. In what follows, we set e equal to 0.5, which seems a reasonable intermediate position.

Inequalities by income in mortality and the socioeconomic determinants thereof are measured here using a concentration index (Wagstaff et al. 1991; Kakwani et al. 1997; Wagstaff

⁶ The non-synchronization of the household and facility surveys clearly rules out the use of panel data approaches to link changes in survival to changes in the availability of health services. Such an approach has been advocated by Pitt et al. (1993) to overcome any endogeneity introduced by selective placement of facilities—see below.

2000a,b). The curve labelled L in Figure 1 is a mortality concentration curve. It plots the cumulative proportion of deaths (on the y-axis) against the cumulative proportion of children at risk (on the x-axis), ranked by income, beginning with the most disadvantaged child. If the curve L coincides with the diagonal, all children, irrespective of their household income, enjoy the same mortality rates. If, as is more likely, L lies above the diagonal, inequalities in mortality favor the better-off children; we will call such inequalities *prorich*. If L lies below the diagonal, we have *propoor* inequalities in mortality (inequalities to the disadvantage of the better-off). The further L lies from the diagonal, the greater the degree of inequality in mortality across quintiles of economic status. The concentration index, denoted below by C , is defined as twice the area between L and the diagonal. C takes a value of zero when L coincides with the diagonal and is negative (positive) when L lies above (below) the diagonal. Computational and inference issues surrounding the index C have been discussed elsewhere and need not be repeated here (Kakwani et al. op. cit.). The same method can be used to measure inequalities in the *determinants* of mortality.

Fig 1: Mortality concentration curve



The values of C for the infant and under-five mortality rates for Cebu for the period 1981-91 are -0.096 and -0.160 respectively. Both are significantly different from zero at conventional levels (the t -ratios are 2.31 and 3.45 respectively). Of the other eight countries investigated in Wagstaff (2000a,b), only two have a more unequal under-five mortality distribution, namely Brazil and Nicaragua.

The Other Socioeconomic Determinants of Survival

Table 1 lists the means and concentration indices of the socioeconomic variables included in the survival model. The selection of variables follows closely previous microeconomic demand studies of child mortality (cf. e.g. Benefo and Schultz 1996; Frankenberg 1995; Lavy et

al. op. cit.; Pitt et al. 1993; Rosenzweig and Wolpin 1982). The child's gender is included, as is the mother's age at the child's birth, along with age squared. The functional form used here allows for non-linearities in the relationship between child survival and mother's age at birth, the expectation being an inverse u-shaped relationship. The concentration index for mother's age at birth is negative but only marginally so, indicating that poor women tend to have their children at a slightly earlier age than better-off women. The number of siblings is excluded on the grounds that households *choose* this variable, along with their decisions that influence childhood survival (cf. e.g. Benefo and Schultz op. cit.). Mother's education at the baseline survey is included categorically, the three categories being college education (12% of mothers), high school (30% of mothers), and less than high school (the latter is the omitted category). The educational attainment of women in Cebu is quite high, as is the average years of schooling—7 years overall (Schwartz et al. 1988). The concentration indices indicate that a high school diplomas amongst mothers and especially college degrees amongst mothers are concentrated in better-off households.⁷ The presumption is that by making mothers more efficient producers of child health, education will increase child survival. Some 32% of children live in households with health insurance of one type or another—the concentration index indicates this is fairly concentrated amongst better-off households. This would be expected to be negatively associated with child survival, since insurance lowers the cost at the point of use of using health services.

There then follows in Table 1 a vector of drinking-water variables. These are measured at the level of the household. In each case, an attempt is made to capture not just the type of facility available but also its location (inside the house and therefore private, or outside the house or yard and therefore public). The omitted category is water from a stream, river, or rain water. Some 9% of children live in households reliant on this source—the value of C of -0.117 indicates that these are poor households. Another 10% of children live in households with piped water or a private pump, the concentration index of 0.321 indicating that this source is heavily concentrated amongst better-off households. Almost half of the children in the sample (49%) relied on pumped water in a public place, and the remaining 10% relied on an open well. The latter group especially tended to poor households. The remaining 23% of children lived in households relying on drinking water from a vendor—these were predominantly better-off households. Improvements in drinking water availability and a closer location are likely to have a mixture of effects on survival, including reductions in exposure to pathogens whilst drinking, changes in feeding practices (the introduction of food other than breast milk becomes less risky), improvements in sanitary behavior such as handwashing, and reductions in the time taken to obtain drinking water. Overall, it seems likely that survival will improve with better and/or closer drinking water.

The sanitation variables also aim to capture both the type and location of the facility. One third of children live in households with no sanitation facilities at all (the omitted category). These, unsurprisingly, are poor households, and the concentration index indicates that there is an even greater degree of concentration amongst the poor in this variable than in the variable indicating lack of a drinking water source. At the other extreme, another third of children live in households with a private flush WC or water-sealed toilet. These, unsurprisingly, are better-off

⁷ The value of C for the omitted category is -0.173 . This can be computed from the data in table 1, since a weighted average of the concentration indices of a vector of categorical variables (with the sample proportions as weights) is equal to one.

households. In between, 7% and 19% of children live in households reliant on a public water-sealed toilet and public latrine respectively. Both are somewhat more common amongst better-off households. Only 5% of children live in households reliant on an open pit—these, unsurprisingly, tend to be poor ones. Improvements in sanitation are clearly likely to reduce the risk of a child's death.

The CLHNS contains detailed information on the accessibility of a variety of different types of health facility, measured in terms of travel time from the household's dwelling. The average travel time is around 20-25 minutes, but from the concentration indices it is apparent that the poor tend to have to travel for longer. No information on travel time to a public hospital is available at household level, but the community survey contains data on the distance from the center of the barangay to the nearest public hospital. Here too, it is evident that the poor face higher time costs. Since increased travel time raises the shadow price of child health, the expectation is that it will be inversely associated with the length of survival.

In addition to the household survey, the CLHNS also undertook various health facility surveys. For reasons indicated above, the data used here have been taken from the 1986 survey. This covered 79 public and private facilities, ranging from large and small hospitals, though area health centers (in urban areas) and rural health units (in rural areas), down to health centers (in urban areas) and barangay health stations (in rural areas) (Office of Population Studies et al. 1989). The interest here was in generating community-level data capturing the variation across barangays in the availability and quality of health services. At hospital level, there is relatively little variation that can be captured from the data that is not already captured by the accessibility variables—there is only one public hospital located in the 33 barangays surveyed, and all of the eight surveyed private hospitals serving the barangays are located elsewhere in Metro Cebu. The same is true of most of the maternity hospitals, private clinics and puericulture centers. For these facilities, one can capture the variation across households in accessibility, but it is not obvious how one might capture availability and quality. Primary care facilities, by contrast, *do* vary across the 33 sampled barangays—some barangays have no facility; others have one; others still have more than one (e.g. a rural health unit *and* a barangay health station).

From the facility surveys, community-level data were generated on primary care staffing levels per 1000 population. Staffing levels proved to be highly correlated across staff categories at the facility level. A principal components analysis revealed two clear factors, the first loading highly on physicians, nurses, midwives, sanitary inspectors, *mananabangs* (untrained birth helpers or hilots) and nutritionists, and the second loading highly on health aides, family planning “motivators” and paramedics. Two aggregates were therefore constructed, the first being the sum of the personnel in the first group, the second being the sum of personnel in the second group. These two aggregates were multiplied by the opening hours of the facility in question. These measures of staffing hours at the facility level were then aggregated across facilities in each barangay and expressed on a per-1000-population basis to obtain measures of total primary care staffing hours *per capita* for the barangay. The negative (albeit small) concentration indices indicate that areas with poorer households appear, on average, to be

slightly *better* endowed with primary health care personnel, though this masks an inverted u-shaped pattern to the quintile distribution.⁸

In addition to the staffing measures, “quality” variables were constructed for primary health care facilities. For each facility, data were collected on whether or not the facility typically stocked vitamins (including iron and iodine supplements), vaccines (measles, tetanus, polio, DPT, and BCG), oral rehydration therapies, and female contraceptives. Within each category, there was a high degree of correlation at the facility level (facilities that typically stocked DPT also typically stocked polio vaccines), and for each category a summary measure was defined at the barangay level indicating whether *any* of the facilities in the barangay typically stocked *any* of the items in the category in question. Table 1 indicates that 36% of children born over the period 1981-91 lived in barangays where vitamins were normally stocked. The figures for vaccines, ORT and female contraceptives are 54%, 74% and 70% respectively. Surprisingly, with the exception of ORT, there is a slight tendency for poorer children to live in areas with *higher* propensities to stock drugs—the variation is very slight, however.

IV. Estimation Results

Parameter Estimates

Table 2 reports the parameter estimates of the probit and Weibull models. In both models, the standard errors are estimated taking into account the clustered nature of the sample design. It makes sense (cf. e.g. Deaton 1997) in such situations to view the error term as the sum of a cluster-specific (i.e. *barangay*-specific) component and a child-specific component—although the error will be uncorrelated across children in different barangays, it is unlikely to be uncorrelated across children in the same barangay. The probit and Weibull routines need modification in such a case to ensure accurate standard errors.⁹

A male child is somewhat more likely to survive the first year of life (though not significantly so), but has a somewhat lower (though not significantly lower) survival expectation over the next nine years conditional on reaching his first birthday. The age of the mother at the child’s birth has the expected u-shaped relationship for the probability of surviving the first year but has the opposite shaped-relationship with survival beyond the age of one. Neither is significant, however. The children of college-educated women have a better chance of surviving to their first birthday, while children whose mothers are high school graduates and especially those whose mothers are college graduates have significantly better survival prospects beyond

⁸ This is not inconsistent with Schwartz et al. (1988), who report higher proportions of facilities in rural areas using trained midwives to deliver babies, and with the remarks in the survey background document (Office of Population Studies et al. 1989) to the effect that the larger population in urban areas often cancels out the staffing advantages they have over rural areas.

⁹ Estimation was undertaken using the probit and Weibull routines in STATA, using the cluster option, with the *barangay* serving as the clustering variable. For both the probit and the Weibull models, the standard errors are typically larger with the cluster option—on average, 6% larger in the case of the Weibull model, and 3% in the case of the probit model.

their first birthday. Household income exerts a significantly positive impact on both the probability of a child reaching his first birthday and his survival beyond that, while health insurance is significantly associated with longer survival after the first birthday (but not the probability of reaching it).

The coefficients on the drinking water variables tell a somewhat different story for infant mortality than they do for survival beyond the first birthday. Surprisingly, if a child lives in a household whose drinking water source is not a river, a spring or rainwater (the omitted catch-all category), his chances of reaching his first birthday are *worse* than they would otherwise be, but his survival prospects *beyond* his first birthday (if he reaches it) are *better* than they would otherwise be. It is possible that this may be due to households with better water weaning earlier than they would otherwise, with deleterious effects on the probability of the child surviving his first year. Results from the CLHNS reported by VanDerslice et al. (1994) do indeed show that weaning patterns do vary according to the water and sanitation facilities of the household. In the Weibull model, the relative magnitudes of the coefficients are interesting, suggesting a relatively small beneficial impact of public pump drinking water compared to other sources, including an open well. Private sanitation has a clear strong and significant effect on the probability of a child reaching his first birthday and impacts positively (though not significantly) on his survival prospects beyond then. By contrast, there is some evidence that a household using formal *public* sanitation facilities (water-sealed toilet or latrine) may be worse for its children's survival prospects than its using an open pit or no proper facilities at all.

The coefficients on the travel time and distance variables tell a mixed story but one that is, on the whole, as predicted by theory. Only two coefficients are significant—those on the variable indicating the distance to a public hospital in the probit and Weibull models—and both are, as hypothesized, negative. Five of the remaining coefficients are negative but insignificant. These results are actually somewhat *more* consistent with theoretical expectations than results reported in previous studies in this field. Lavy et al. (op. cit.) report a *positive* and significant coefficient on the distance-to-facility variable in their Weibull model for rural Ghana and an insignificant negative coefficient for their urban sample, while Benefo and Schultz (op. cit.) report positive and significant effects of distance to the nearest health clinic on child *mortality* in Côte d'Ivoire but insignificant coefficients in their Ghana sample.

Turning finally to the effects of the quality and availability of health facilities, the results are also somewhat mixed, but are, on the whole, also in line with theory. Only three of the twelve coefficients are significant. Vaccine availability has a strong positive and significant effect on the probability of surviving to one's first birthday, but not thereafter (indeed, the coefficient in the Weibull model is negative). This is somewhat surprising—it is often argued (cf. Koenig et al. 1991) that immunization programs are likely to have a *smaller* potential impact on infant mortality than on survival prospects subsequently. It is possible that the estimated effect here reflects a targeting on infants by facilities that have vaccines to the detriment of the children who have already reached their first birthday. There is a positive and significant estimated effect of "other" health workers on survival beyond the first birthday, but this group does not have a significant effect on the chances of surviving to the first birthday. The number of physicians and related workers does not have a significant impact in either model. By contrast, the availability of female contraceptives has a significant and positive effect on survival

duration of children who have reached their first birthday. This presumably reflects the impact of female contraception on the number and spacing of children.

The effects of health facility quality and availability on child mortality reported in previous studies using similar methods are also somewhat mixed. In their India paper, Rosenzweig and Wolpin (op. cit.) reported negative and significant effects on child mortality of family planning facilities and dispensaries, but a negative and insignificant effect of hospitals, and a *positive* and significant effect of other health facilities. In their Weibull models for Ghana, Lavy et al. (op. cit.) report a positive and significant coefficient on hours of baby services provided by clinics in their rural sample, but a *negative* and significant coefficient on drug availability in their rural sample, and no significant coefficients on the other variables or on these two variables in their urban sample.

One explanation advanced for mixed results such as these is that, contrary to what is assumed in these studies, the spatial distribution of health facilities (their availability and quality) may not be random and hence the estimates of their effects on survival may be biased through endogeneity (cf. e.g. Pitt et al. op. cit.). The argument would be that the barangay-specific component of the error term, mentioned above, is known to policymakers and used by them in the spatial allocation of public facilities and funds, with barangays prone to high child mortality getting better facilities. If this is the case, the barangay-specific error will—contrary to what has implicitly been assumed—be correlated with the values of the health facility variables. The estimates of their effects on child survival will be downward biased, possibly so much so that the estimated coefficient is negative when the true impact is positive. In their studies of mortality in Indonesia, Pitt et al. (op. cit.) and Frankenberg (op. cit.) employed a fixed effects methodology to eliminate the community-specific effect, and hence eliminate the endogeneity problem, by relating *changes* in mortality to *changes* in health facilities.¹⁰ In the present context, however, the use of a fixed-effects approach would mean compromises on the modeling in other respects. It would mean the abandonment of the duration model and the use instead of a model lending itself to differencing. It would mean throwing away the facility data on “quality”, as well as the data on personnel, since these were not collected in the previous or subsequent facility surveys. And since the methodology sweeps out not only the unobserved community-specific effect but also any time-invariant covariates, it would mean being unable to get estimates of the coefficients on any variables that are genuinely time-invariant *and* any variables that would have to be *assumed* to be time-invariant. Several variables would fall into the latter category, since the CLHNS is a longitudinal survey rather than a panel study, so that although key health and nutrition outcomes and certain other variables *were* tracked over time, their tracking was not sustained over the entire period of the study and, more importantly, the socioeconomic information of the household was collected only at two points in the period under investigation—1982/83 and 1991. In what follows, therefore, we stick with the parameter estimates of Table 2.

¹⁰ Pitt et al.’s use of fixed effects leaves the estimated positive effect of health clinics on child mortality unaffected, but does turn a positive (and significant) effect of family planning clinics into a negative (but insignificant) effect. Frankenberg’s use of fixed effects turns a negative but insignificant coefficient on maternity clinics into a negative and significant coefficient, and a positive and insignificant coefficient on physicians into a negative and significant coefficient. However, it also turns a negative (albeit insignificant) coefficient on health workers into a *positive* (and close-to-significant) coefficient.

But the possible biases do need to be borne in mind, especially those on the health facility variables.

Elasticities

Interpretation of the coefficients are far from straightforward—the scales of the covariates vary enormously, and the dependent variables are unobserved index variables (a latent index in the case of the probit and the negative of the log of the hazard rate in the case of the Weibull). Table 3 presents elasticities for the infant, 1-5 and under-five mortality rates derived numerically from the parameter estimates in Table 2. In all cases, the elasticities are evaluated at the sample mean. In the case of mother’s education, drinking water and sanitation, the elasticities indicate the impact of raising the category in question by a given percentage, whilst reducing the remaining categories proportionately.

The variable with the highest elasticity in all equations is income, the elasticity in each case being well over unity in absolute size. The elasticity on mother’s age is also large, especially for infant mortality. Also noteworthy is the relatively large elasticity on the availability of female contraception for mortality in the 1-5 age bracket—a ten percent increase in the proportion of primary care facilities carrying female contraceptives would reduce mortality amongst the 1-5 age group by 3%. Also noteworthy is the elasticity on vaccine availability in the case of infant mortality—a ten percent increase in the proportion of primary care facilities carrying vaccines would reduce proportion of children dying before their first birthday by just over 2%. There are also relatively large elasticities on the variables capturing a college education, health insurance, drinking water from a public pump, and a private flush WC or water-sealed toilet, though these are not all of the expected sign.

V. Unpacking Inequalities in Child Survival

The concentration indices in section IV, coupled with the parameter estimates in the previous section, provide an insight into the inequalities that give rise to inequalities in child survival. For example, it does *not* appear to be the case that inequalities in vaccine availability are responsible for survival inequalities—not because vaccine availability does not have any perceptible influence on child survival, but rather because there do not appear to be major inequalities in access to vaccines between poor and better-off households in Cebu. By contrast, the inequality in child survival *does* appear to be due to inequalities in mothers’ educational attainment—poor children do, indeed, have less well educated mothers, and mother’s education appears to raise the probability of a child reaching his first birthday *and* his survival expectation thereafter. Likewise, the poor tend to have to travel further to a public hospital and this appears to reduce their children’s survival prospects. Such comments do not, however, give a sense of the *magnitude* of these contributions. For example, are inequalities in mother’s education or inequalities in distance to a public hospital more important in explaining inequalities in survival? We cannot say, on the basis of the discussion so far, how important these two factors are in explaining inequality, either relative to one another, or relative to other contributory factors. It is to this issue we now turn.

Simulating the Effects of Equalizing the Determinants of Childhood Mortality

An obvious way of approaching this question is to ask what would happen to survival inequalities if each set of socioeconomic determinants in turn were equalized across the income distribution. So, for example, what would the distribution of under-five mortality have been if all mothers of the children in the sample had reached the same educational attainment? We compare this counterfactual distribution with the other possible counterfactual distributions generated by equalizing each set of determinants in turn. The equal distributions we impose are those obtained by giving all five quintiles the values of the determinants of the top quintile. The simulated results are derived from the two-part model parameter estimates in table 2, and are obtained by applying the parameter vectors to the counterfactual distributions of the vectors y and z , and then re-running the life table to obtain the counterfactual values of the infant, 1-5 and under-five mortality rates for each quintile.

Table 4 presents the results of these exercises. In each case, the largest effects on inequality are produced by equalizing income, resulting in reductions, in absolute size, of C of 88%, 64% and 76% for the IMR, 1-5 mortality rate and the under-five mortality rate respectively. This reflects both the degree of income inequality in the sample and the high income elasticity for all three mortality rates. Inequalities in mother's education also appear to account for relatively large portions of the inequalities in childhood survival, though their contributions are much less pronounced than those of income inequalities. Inequalities in sanitation appear to be a relatively important contributory factor to inequalities in infant and under-five mortality, while inequalities in health insurance coverage appear to be a relatively important contributory factor to inequalities in 1-5 and under-five mortality. All are far less important, however, than inequalities in income and mother's education.

Inequalities in accessibility, availability and quality of health facilities appear to contribute very little to inequalities in child survival in Cebu, the only perceptible effect being in the case of inequalities in accessibility contributing to inequalities in survival prospects for years one through five. The relative unimportance of inequalities in health service availability and quality stems from the apparent absence of any inequalities to the disadvantage of poor households, rather than any apparent lack of impact of availability and quality on survival prospects—quality, especially, has been estimated to have relatively large negative elasticities with respect to under-five mortality. The results for drinking water are more complex. For example, a public water-pump and an open well have been estimated to have positive elasticities with respect to under-five mortality, and to be more common amongst the worse-off. But these effects are offset by the fact that water from a private pump or piped source, though more common amongst the better-off, has a *positive* elasticity with respect to under-five mortality.

Decomposing the Causes of Inequalities in Childhood Mortality

There is an alternative approach. Our measure of inequality, the concentration index, is additively decomposable in the following sense. Suppose we are analysing the distribution of a variable y across income groups, and y is the sum of two variables y_1 and y_2 . Then the concentration index for y , C_y , can be shown to be equal to

$$(8) \quad C_y = (\bar{y}_1 / \bar{y})C_1 + (\bar{y}_2 / \bar{y})C_2,$$

where C_1 and C_2 are the concentration indices for y_1 and y_2 respectively. Thus C_y is a weighted average of the concentration indices for y_1 and y_2 , where the weights are the average “shares” of y_1 and y_2 in y .¹¹ This is helpful if the variable whose distribution across income groups we are investigating can be thought of as being made of the sum of set of contributory factors. Of course, what we relate linearly in the regression analyses to the contributory factors in this case is not the mortality rate per se, but rather the underlying latent variable in the case of the probit model and $-\ln I$ in the case of the Weibull. But as it is only these variables that account for any variation in the modelled infant and 1-5 mortality rates across income groups (p has been assumed in this exercise to be invariant), we could just as well examine inequalities in the underlying latent variables. We thus treat the latent variable underlying the probit and $-\ln I$ —or, more accurately, their expected values—as analogous to y in eqn (8). The “shares” are obtained by computing $b\bar{x}$ for each of the x ’s, and then dividing the result by the expected value of the latent variable underling the probit or of $-\ln I$.

The results of these decompositions are presented in Table 5. The overall values of the concentration index for both the underlying latent variables are positive, reflecting the higher chances that a better-off child has of reaching his first birthday and his lower hazard rate and hence better survival prospects beyond then. The broad picture in terms of the causes of inequalities in child survival is the same as emerged from the simulation exercise. Income inequality is by far the biggest contributory factor to mortality inequality, both in the first year of life and beyond then. As this is the *partial* effect of income, holding constant water, sanitation, etc., this result is somewhat surprising and raises the question of what channels this income effect operates through. Inequality in mother’s education is the next biggest contributory factor in the case of mortality beyond the first birthday, but also a very close second to sanitation in the case of infant mortality. The other factors, with the exception of insurance coverage inequality in the case of mortality beyond the first year of life, contribute negligibly to the inequality in child mortality, and in some cases—drinking water, for example—contribute negatively, meaning literally that inequalities would have been larger in the absence of the proric inequalities in good drinking water.

VI. Summary and Implications

The aim of this paper has been to “unpack” the causes of inequalities in child survival between poor and nonpoor children, where “causes” are interpreted not in terms of the proximate determinants, such as health service usage, and feeding and sanitary practices, but rather in terms of the socioeconomic causes, such as household income, education, insurance coverage, water and sanitation, and the accessibility, availability and quality of health services locally.

¹¹ One way to see this is to reason by analogy with the tax progressivity literature. Kakwani’s (1977) progressivity index is defined as the concentration index for taxes less the Gini coefficient for pre-tax income. The index for, say, direct and indirect taxes combined, is a weighted average of the indices for direct and indirect taxes, where the weights are the shares of direct and indirect taxes in the combined revenue raised from these two taxes (cf. e.g. Lambert 1993, p.180). Since the same pre-tax Gini is used to compute the two progressivity indices, it follows that the concentration index for both taxes combined is a weighted average of the concentration indices for the two taxes.

A key component to this exercise is the model linking child survival to these determinants of survival. For this, a two-part model was used, the first part capturing the child's prospects of surviving to his first birthday (modeled using a probit), and the second capturing his survival prospects beyond then (modeled using a Weibull on the subset of children surviving to their first birthday). The Cebu LHNS provides a rich source of data for this modeling exercise, allowing survival over the period 1981-91 to be related to the household's circumstances in 1983, and the accessibility, availability and quality of local primary care services in 1986. Household income emerged as a significant determinant in both models, and produced very large elasticities for infant, 1-5 and under-five mortality. Proximity to a public hospital also emerged as significant in both models, the elasticities suggesting that a ten percent increase in distance is associated with a 2% increase in all three mortality rates. Vaccine availability and female contraceptive availability in local primary care facilities emerged as significant influences on respectively the survival prospects of infants and children who had reached their first birthday. Mother's education and health insurance coverage also emerge as significant determinants of survival beyond the first birthday.

By linking the parameter estimates of the two models with information on the distribution of the various socioeconomic determinants across income groups, it is possible to build up a picture of how far inequalities in each set of determinants contributes to inequalities in survival. For example, as mentioned, mother's education and insurance both proved to be significant determinants of survival beyond the child's first birthday, and since both are fairly heavily concentrated amongst better-off households, it can be concluded that these prorich inequalities both contribute to the observed prorich inequalities in survival prospects. To get a sense of the *magnitude* of the contributions of these and other determinants, two exercises were undertaken, both of which led to the same conclusions. The first involved undertaking a series of simulation exercises, replacing, for each set of determinants in turn, the average values of the bottom four quintiles with those of the top quintile, and then computing the resultant distribution of mortality rates. This provides a sense of what inequalities in survival would have been if, say, there had been no inequalities in mother's education, but all the inequalities in the other determinants had remained in force. The second exercise involves decomposing the summary inequality index—the concentration index—into terms corresponding to the contributions of each set of determinants. This is not possible to do for the mortality rate itself, since the models used are estimated on individual survival data, but *can* be done for the latent variables underlying the probit and Weibull models, which are, of course, assumed to be linearly related to the covariates. This exercise gives an idea of how much of the overall inequality in survival (as captured by the underlying latent variable) is attributable to inequalities in, say, mother's education.

Both exercises point to income inequalities being, *ceteris paribus*, by far the largest contributory factor to inequalities in both the infant and 1-5 mortality rates. Inequalities in mother's education are also important, as are inequalities in sanitation in the case of infant mortality and inequalities in insurance coverage in the case of survival beyond the first birthday. Inequalities in accessibility and quality of health services, by contrast, appear to contribute very little to inequalities in child survival in Cebu. In the case of quality, this is not because it does not influence survival, but rather because it does not appear to be especially unequally distributed between poor and nonpoor households. In the case of accessibility, on the other hand, the explanation is different—the poor do, indeed, have to travel further or at least longer to get to health facilities, but the impact of accessibility on survival varies, from having a strong adverse

effect in the case of proximity to a public hospital to an apparently beneficial effect in the case of proximity to a pharmacy and traditional midwife.

There are, of course, several caveats to these results. First, they tell us nothing about the routes through which inequalities in the various socioeconomic determinants get translated into inequalities in survival. Part of the income story may well be, for example, that poor households simply lack the means to pay for the transport costs and out-of-pocket payments associated with health service usage. Second, the results are potentially highly specific to Cebu. As mentioned in the Introduction, with its high levels of education amongst both men and women, and its relatively well-endowed health services, Cebu is far from typical of the developing world. Unpacking the causes of inequalities in child survival in, say, Burkina Faso might lead to quite different conclusions. Third, the results shed light on the causes of inequalities, and their relative importance, but do not provide ready policy solutions. For this one would want to ask how a specific—and ideally fully costed—set of policies would impact on the inequalities in survival between poor and nonpoor children. That is a rather different exercise, but one to which the modeling exercise undertaken in this paper ought to lend itself rather well.

VII. References

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Table 1: Variable definitions, means and concentration indices

Variable	Variable definition	Sample mean	Conc. index
Male	Child male	0.48	0.002
Mother's age	Mother's age at birth of child	27.83	-0.005
Education high school	Mother has high school education	0.30	0.117
Education college	Mother has college education	0.12	0.522
Log equiv income	Log of equivalent household income	2.76	0.084
Health insurance	Health insurance coverage of one type or another	0.32	0.169
DW private pipe/pump	Drinking water pipe/pump private	0.11	0.310
DW public pump	Drinking water pump public	0.49	-0.021
DW open well	Drinking water open well	0.09	-0.145
DW vendor	Drinking water from vendor	0.23	0.007
Private WC	Private flush WC or water-sealed toilet	0.35	0.165
Public water-sealed toilet	Public water-sealed toilet	0.07	0.033
Public latrine	Public latrine	0.19	0.042
Open pit	Open pit	0.05	-0.128
Travel time to RHU/CHO	Travel time to RHU/CHO	21.20	-0.072
Travel time to pharmacy	Travel time to pharmacy	22.40	-0.081
Travel time to priv doc	Travel time to private doctor	25.99	-0.081
Travel time to priv midwife	Travel time to private midwife	21.92	-0.013
Travel time to mananbang	Travel time to mananbang (hilot)	21.80	-0.055
Travel time to manananabang	Travel time to manananabang (less trained hilot)	25.58	-0.043
Dist to publ hospital	Distance to public hospital from barangay center	5.76	-0.073
Other staff hours	Hours of availability per 1000 population of others health workers	254.89	-0.079
Doctor hours	Hours of availability per 1000 population of doctors and related staff	203.90	-0.044
Vitamin	Vitamin availability in local primary care clinics	0.36	-0.004
Vaccine	Vaccine availability in local primary care clinics	0.54	-0.008
ORT	ORT availability in local primary care clinics	0.74	0.003
Female contraceptives	Fem. contraception avail. in local primary care clinics	0.70	-0.004
Urban	Urban dummy	0.72	0.062

Table 2: Parameter estimates of probit and Weibull models

Variable	Probit 0-1 year		Weibull 1-10 years	
	Coef.	z	Coef.	z
Male	0.050	0.74	-0.132	-0.50
Mother's age	0.041	0.92	-0.154	-0.53
Mother's age squared	-0.001	-0.89	0.003	0.58
Education high school	-0.031	-0.42	0.670	1.94
Education college	0.139	1.27	2.563	2.97
Log equiv income	0.256	2.98	1.749	3.13
Health insurance	-0.026	-0.30	0.788	2.11
DW private pipe/pump	-0.360	-1.69	0.318	0.36
DW public pump	-0.195	-1.13	0.541	0.68
DW open well	-0.388	-1.97	0.952	0.86
DW vendor	-0.126	-0.67	0.831	1.17
Private WC	0.166	1.67	0.434	0.99
Public water-sealed toilet	0.064	0.45	-0.445	-0.78
Public latrine	-0.102	-0.85	-0.422	-0.98
Open pit	0.080	0.58	0.410	0.68
Travel time to RHU/CHO	0.002	0.99	-0.006	-0.65
Travel time to pharmacy	0.002	1.01	0.017	1.55
Travel time to priv doc	-0.001	-0.35	-0.008	-1.07
Travel time to priv midwife	-0.001	-0.53	-0.004	-0.27
Travel time to mananbang	0.002	1.27	0.010	1.49
Travel time to manananabang	0.001	0.60	0.002	0.35
Dist to publ hospital	-0.016	-2.37	-0.078	-1.71
Other staff hours	0.000	-0.97	0.001	2.40
Doctor hours	0.000	-1.53	0.000	0.74
Vitamin	0.017	0.29	0.095	0.30
Vaccine	0.193	3.63	-0.603	-1.63
ORT	0.017	0.18	-0.025	-0.07
Female contraceptives	-0.059	-0.69	1.049	3.53
Urban	-0.043	-0.60	-0.852	-1.33
<i>N</i>	6313		6072	
<i>p</i>			0.459	
lnL	-1054.44		-1384.99	
Pseudo R^2	0.030			

Table 3: Elasticities of infant, 1-5 and under-five mortality rates

Variable	IMR	1-5 MR	U5MR
Male	-0.052	0.029	-0.016
Mother's age	-0.585	0.281	-0.204
Education high school	0.036	-0.030	0.007
Education college	-0.040	-0.128	-0.079
Log equiv income	-1.446	-1.962	-1.673
Health insurance	0.018	-0.112	-0.039
DW private pipe/pump	0.083	-0.015	0.040
DW public pump	0.209	-0.118	0.065
DW open well	0.079	-0.040	0.027
DW vendor	0.063	-0.085	-0.002
Private WC	-0.128	-0.069	-0.102
Public water-sealed toilet	-0.009	0.013	0.001
Public latrine	0.042	0.036	0.039
Open pit	-0.060	0.012	-0.028
Travel time to RHU/CHO	-0.088	0.059	-0.023
Travel time to pharmacy	-0.093	-0.166	-0.125
Travel time to priv doc	0.030	0.091	0.057
Travel time to priv midwife	0.048	0.036	0.043
Travel time to mananbang	-0.100	-0.093	-0.097
Travel time to manananabang	-0.053	-0.025	-0.041
Dist to publ hospital	0.197	0.204	0.200
Other staff hours	0.015	-0.059	-0.017
Doctor hours	0.036	-0.031	0.006
Vitamin	-0.013	-0.015	-0.014
Vaccine	-0.227	0.149	-0.062
ORT	-0.027	0.009	-0.011
Female contraceptives	0.091	-0.328	-0.094
Urban	0.068	0.281	0.162

Table 4: Simulations showing effects of equalizing mortality determinants

IMR	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	average	CI	Av % ch	CI % ch
Predicted	52.1	43.5	38.4	33.2	24.2	38.3	-0.139		
Same mother's education	47.6	39.5	35.0	30.6	24.2	35.3	-0.126	-8%	-9%
Same incomes	26.2	26.1	25.5	25.1	24.2	25.4	-0.016	-34%	-88%
Same health insurance	53.0	43.9	38.6	33.4	24.2	38.6	-0.141	1%	2%
Same drinking water	55.8	45.7	41.0	35.6	24.2	40.4	-0.145	6%	5%
Same sanitation	47.4	40.1	35.5	31.6	24.2	35.8	-0.123	-7%	-11%
Same medicine availability	52.6	44.7	39.4	34.0	24.2	39.0	-0.138	2%	0%
Same staff hours	51.1	42.9	37.3	32.5	24.2	37.6	-0.137	-2%	-1%
Same distance to med facils	53.1	44.2	39.6	33.2	24.2	38.8	-0.142	1%	2%

I-5 MR	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	average	CI	Av % ch	CI % ch
Predicted	55.2	40.1	30.6	24.6	12.8	32.7	-0.246		
Same mother's education	35.1	26.2	21.3	18.5	12.8	22.8	-0.184	-30%	-25%
Same incomes	20.9	19.7	17.5	16.8	12.8	17.5	-0.088	-46%	-64%
Same health insurance	49.6	37.7	29.6	23.6	12.8	30.6	-0.229	-6%	-7%
Same drinking water	56.3	40.8	31.3	25.0	12.8	33.2	-0.248	2%	1%
Same sanitation	52.8	38.6	29.2	24.0	12.8	31.5	-0.241	-4%	-2%
Same medicine availability	55.4	39.9	30.9	24.6	12.8	32.7	-0.246	0%	0%
Same staff hours	57.4	41.5	32.3	25.6	12.8	33.9	-0.248	4%	1%
Same distance to med facils	53.2	39.2	30.5	24.3	12.8	32.0	-0.240	5%	-3%

USMR	quintile 1	quintile 2	quintile 3	quintile 4	quintile 5	average	CI	Av % ch	CI % ch
Predicted	107.4	83.6	69.0	57.8	36.9	70.9	-0.188		
Same mother's education	82.7	65.7	56.3	49.1	36.9	58.1	-0.149	-18%	-21%
Same incomes	47.1	45.8	43.0	41.9	36.9	43.0	-0.045	-39%	-76%
Same health insurance	102.6	81.6	68.1	57.0	36.9	69.2	-0.180	-2%	-4%
Same drinking water	112.1	86.5	72.3	60.6	36.9	73.7	-0.191	4%	2%
Same sanitation	100.2	78.8	64.7	55.6	36.9	67.2	-0.178	-5%	-5%
Same medicine availability	108.0	84.6	70.3	58.6	36.9	71.7	-0.188	1%	0%
Same staff hours	108.6	84.4	69.6	58.0	36.9	71.5	-0.190	1%	1%
Same distance to med facils	106.3	83.3	70.0	57.5	36.9	70.8	-0.186	5%	-1%

Table 5: Decompositions showing contributions to inequality in survival of inequalities in determinants

	probit 0-1	Weibull 1-10
CI predicted total	0.037	0.047
Mother's education	0.004	0.014
Income	0.033	0.031
Health insurance	-0.001	0.003
Drinking water	-0.003	-0.001
Sanitation	0.005	0.001
Drug availability	0.000	0.000
Staff hours	0.001	-0.001
Distance to med facils	-0.001	0.001
Mother's age and child's gender	0.000	0.000
Urban	-0.001	-0.003