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Child Health and Infant Mortality in Brazil

by

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Abstract[1]

Child health is a central issue on the public policy agenda of developing countries. Several policies geared to improving child health have been implemented over the years, with varying degrees of success. In Brazil, such policies have led to a significant decline in infant mortality rates over the last 30 years. Despite this improvement, however, mortality rates are still high by international standards and there is substantial variation across Brazilian municipalities, which suggests that differentiated policies should be devised. The aim of this paper is to investigate the determinants of infant mortality at the municipal level, and to provide a more detailed analysis by considering the factors that affect child health at the individual level. To analyze the mortality rate, static and dynamic panel data models are estimated using four censuses covering the period 1970-2000. The demand for child health is addressed through a household decision model, estimated using anthropometric data from the 1996 Standard of Living Survey. The results indicate that sanitation, education and per capita income contributed to the decline in infant mortality in Brazil, the effects being stronger in the long run than in the short run. The fixed effects associated with municipality characteristics help explain the observed dispersion in child mortality rates. The results of the decision model are in line with the mortality model findings: education, sanitation and poverty are the most important explanatory factors of poor child health in Brazil.

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1. Introduction

Child health is a central issue on the public policy agenda of developing countries. In principle, a decline in infant mortality should be a natural consequence of development, provided that the income effect is not offset by changes in the relative price of reducing mortality. On the other hand, if economic growth is to be sustainable an economy's human resources in labor and business must be continually renewed with more skilled individuals. Thus a healthy new generation is a necessary condition for the continuance of growth-generating forces, and child health and infant mortality therefore play a crucial role in development.

Because of that role, several policies geared to improving child health have been implemented over the years in most developing countries, with varying degrees of success. In Brazil, such policies have led to a swift and significant decline in infant mortality rates over the last 30 years. In 1970, infant mortality stood at 123.55 per thousand live births; the figure had fallen to 85.30 by 1980, a decline of 30.96 percent. In the 1990s, the average infant mortality rate fell from 49.45 in 1991 to 34.08 in 2000, a 31.12 percent decline over the decade. In the period 1970-2000, infant mortality fell by 72.42 percent.

Despite this drastic decline, Brazil's infant mortality rate is still quite high in comparison to other countries, and within Brazil there is a significant disparity of rates across states and regions. Table 1 presents a comparison of infant mortality rates for a sample of developed and developing countries, and Table 2 provides infant mortality data for Brazil's various regions. The rate in the Northeast is twice the Brazilian average, and the Brazilian average is four times higher than the rates in developed countries. The dispersion is even more striking at the municipal level.[2] For instance, in some municipalities of the state of Santa Catarina in the Southeastern region, the infant mortality rate in 1991 was 10.46; it declined to 8.5 in 2000. In some municipalities in the Northeastern states, by contrast, the rate was above 130 in 1991 and above 110 in 1998.

[2] *Municipio*, herein rendered as "municipality," is the smallest political division in Brazil, roughly equivalent to a county. According to the 2000 census there are a total of 5,560 *municipios* in Brazil.

Table 1. International Infant Mortality Rates

(per 1,000 live births)

Countries	1990	1999
Latin America		
Argentina	25.2	18.4
Bolivia	80.0	58.8
Brazil	47.8	32.2
Chile	16.0	9.98
Costa Rica	14.8	12.37
Cuba	10.7	6.87
Uruguay	21.20	14.50
Venezuela	24.60	20.20
Europe		
Austria	7.80	4.40
France	7.30	4.80
Germany	7.00	4.82
Greece	9.70	6.02
Hungary	14.80	8.40
Italy	8.20	5.42
Portugal	10.90	5.60
Switzerland	6.80	4.56
United Kingdom	7.90	5.70
North America		
Canada	6.80	5.30
United States	9.40	6.90
Asia		
China	33.06	30.24
India	80.0	70.90
Indonesia	60.0	41.92
Japan	4.60	3.60

Source: World Bank, World Development Indicators (2001).

Table 2. Infant Mortality Rates by Regions of Brazil
(per 1,000 live births)

Regions	1970	1980	1991	2000
North	180.07	135.12	48.93	41.14
Northeast	111.71	71.01	74.35	64.25
Southeast	97.34	61.08	34.42	27.46
South	80.95	51.69	28.93	23.59
Center West	92.22	59.59	38.60	31.00
Brazil	123.55	85.30	49.45	34.08

Source: Fundação IBGE, Census of Population, 1991 and 2000.

In this context, identification of possible socioeconomic factors behind the infant mortality rate might shed some light on the differences in the rates (and hence the differences in child health) between Brazilian municipalities, and might help explain why infant mortality has fallen faster in some municipalities than others. When a model relating infant mortality rates to socioeconomic factors has been estimated, it will be possible to test hypotheses about the individual parameter values, and to understand the relative importance of the variables associated with policy instruments that seek to reduce infant mortality in Brazil.[3]

This paper's main goal is to estimate one such model. Using data from the 1970, 1980, 1991 and 2000 censuses from the Instituto Brasileiro de Geografia e Estatística (IBGE),[4] a regression model is estimated for infant mortality in Brazil at the municipal level. This model is estimated using two different specifications and considering a number of competing estimators. Specifically, first considered are a static model and a dynamic model, which differ only in the effect of the previous period's mortality rate on current rates. The static model was estimated using three different estimation methods: pooled ordinary least squares (OLS), fixed effects (FE), and first difference (FD). The dynamic model was estimated with the same methods, as well as the Arellano and Bond (1991) GMM estimator.

[3] Hobcraft, McDonald, and Rutstein (1984) present a cross-national study corroborating the role of socioeconomic variables in explaining infant mortality.
[4] Alves (2003) uses 1991 and 2000 municipality-level census data to analyze the decline in the infant mortality rate in Brazil between 1991 and 2000.

Analyzing infant mortality at such an aggregate level aids understanding of the factors involved in policy analysis and design, but such analysis might conceal important effects. Hence an additional model is estimated of the demand for child health at the household level, as discussed by Behrman and Skoufias (2004). Because infant mortality and child health are very closely related, modeling the demand for child health facilitates deeper analysis of infant mortality. The wide dispersion in infant mortality rates at the municipal level, for example, may be better understood if micro-level factors affecting those rates are identified.

The data used to estimate the demand for child health come from the Standard of Living Survey of 1996-1997, which was also conducted by IBGE. This survey, which includes individual anthropometric measurements, covered the Northeast and the Southeast regions of Brazil. The former is known for its low living standards; the latter is much more prosperous, having been the birthplace of Brazil's industrial growth in the late nineteenth and early twentieth centuries.

The Northeast and Southeast regions are each home to about 30 percent of the Brazilian population, but the Northeast accounts for only 22 percent of Brazilian GDP, while the Southeast accounts for 55 percent. The survey therefore covers two regions that differ markedly in terms of economic performance. That circumstance—after controlling for socioeconomic factors—facilitates understanding of the role played by history and geography in inter-regional differences in the demand for child health.

The rest of the paper is organized as follows. Section 2 presents a regression model for the infant mortality rate using municipal-level data, wherein a dynamic panel dimension is used to account for possible endogeneity in the model's explanatory variables. Section 3 estimates the demand for child health using household-level data in order to present additional information on the reasons for the dispersion in infant mortality rates across Brazil. Section 4 present the conclusions drawn from the two analyses and discusses possible policy actions to improve child health in Brazil.

2. A Regression Model for Infant Mortality

This section presents a regression model that relates observed infant mortality rates to explanatory variables such as the proportion of houses with running water, the population's educational level, the number of hospital beds available and the income level. In addition to the effects of these explanatory variables, a fixed-effect parameter is introduced to capture unobserved heterogeneity associated with the municipalities and a time-specific effect.

Representing the municipalities by the subscript i, and the four census years available (1970, 1980, 1990 and 2000) by the subscript t, the model can be written as

$$y_{it} = x_{it}\beta + a_i + \delta_t + u_{it}, \qquad t = 1,2,3,4, \tag{1}$$

where y_{it} is the infant mortality rate, x_{it} is a vector of municipality characteristics, u_{it} is the idiosyncratic error or time-varying error, and β is a vector of parameters. The time-specific effect, represented by δ_t, is equivalent to the coefficient of a dummy variable for each census year, and thus will be incorporated as such in x_{it}. This term captures average trends associated with economic development, such as technological advances, improvements in communications and the diffusion of information, and new cultural trends across the country that lead to better care of newborns and infants.

The fixed effect a_i, on the other hand, is equivalent to the coefficient of a dummy variable for each municipality; for the purposes of this paper a_i represents an unobserved municipality fixed effect or municipality fixed effect. This term captures all unobserved, time-invariant factors that might affect infant mortality rates. In general, the effects of a large variety of factors are potentially included in a_i, from geographical features (such as climate and distance from the sea) to different methods of reporting infant mortality.[5] A particularly important class of such factors comprises cultural attitudes that vary across municipalities; these give rise to different ways of caring for newborn children, thereby affecting infant mortality rates.[6]

2.1 Estimation Methods

Four different estimation methods are considered for the models presented in the previous subsection. The first method simply consists of using OLS with the pooled data. A significant drawback of the pooled OLS estimator is that it requires the assumption that the composite error $v_{it} = a_i + u_{it}$ is uncorrelated with the model's explanatory variables. In general, however, even if

[5] Distance from the sea is important because, until the 1950s, colonization and development were concentrated in the country's coastal areas.
[6] In some of Brazil's southern regions, late European immigration gave rise to a culture that differs from that prevailing in areas where there was little or no European immigration.

it is reasonable to assume that u_{it} is uncorrelated with the explanatory variables, the same is not true for the fixed effect a_i. For instance, an unobserved cultural attitude affecting infant mortality might also have an impact on the population's educational level, implying that the fixed effect is correlated with an explanatory variable. As a result, the pooled OLS estimator would be biased and inconsistent.

The FE and the FD estimators, on the other hand, can accommodate arbitrary correlation between the unobserved effect a_i and the explanatory variables in any time period.[7] The FE estimator consists of transforming the data by centering each variable at its time-specific mean, and then applying least squares to the resulting estimating equation,

$$\ddot{y}_{it} = \ddot{x}_{it}\beta + \ddot{u}_{it}, \qquad t = 1,\ldots,4, \tag{2}$$

where $\ddot{y}_{it} = y_{it} - \overline{y}_i$, with $\overline{y} = T^{-1}\sum_{t=1}^{T} y_{it}$, is the time-demeaned data on y, and similarly for $\ddot{x}_{it}$ and $\ddot{u}_{it}$. Note that because the fixed effect is time-invariant, its centered value is zero for all observations, and thus it is eliminated from the estimating equation. As a result, the model (2) can be estimated by OLS.

The FD estimator, on the other hand, consists of applying least squares to the first difference of the data. Again, invariance of the unobserved effect over time ensures that taking first differences will cause it to be removed from the estimating equation, validating the application of OLS to estimate the model, as in the FE estimator. In fact, these two estimators are very similar overall. The only difference between them is the form of the transformed error's variance and covariance matrix.[8]

It is important to note that although FE and FD estimators accommodate correlation of the unobserved effect and the covariates, they still require additional assumptions to be satisfied.[9] The most important of them in this context is the *strict exogeneity* assumption. This assumption is formally stated by $E(u_{it} | x_{it}, a_i) = 0$, and it implies that u_{it} and x_{it} are not correlated.[10]

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[7] See Wooldridge (2001), pp. 261-78.

[8] Wooldridge (2003), pp. 467-468, shows that when $T = 2$, FE and FD estimators are identical; hence it does not matter which is used; when $t > 2$, FE and FD are not the same. Both are consistent, however, as uncorrelated error term, FE are more efficient than FD.

[9] See Greene (2003), pp. 560-565; and Wooldridge (2003), pp. 481-483.

[10] Actually, instead of considering $E(u_{it} | x_{it}, a_i) = 0$ consideration should be given to $E(u_{it} | \ddot{x}_{it}, a_i) = 0$, where $\ddot{x}_{it}$ is the time-demeaned data in matrix x_{it} as required by the application of the FE estimator procedure.

In practice, it is often the case that this assumption is not satisfied. For instance, municipalities with a high infant mortality rate are generally those with the worst living conditions, and thus are more likely to receive investments to improve public services such as running water and education. As a result, the explanatory variables representing those services at the municipal level might be endogenous, and thus correlated with the idiosyncratic error term u_{it}. In such a case, the pooled OLS, FE and FD will be inconsistent.

An important case in which the strict exogeneity assumption fails is in a dynamic specification, where the mortality rate in the previous period, $y_{i(t-1)}$, affects the current rate. As pointed out by Wooldridge (2001), strict exogeneity never holds when there are lagged dependent variables in the model. The presence of the lagged dependent variable causes no harm to pooled OLS if the idiosyncratic error term presents no autocorrelation. FE and FD estimators, however, are biased and inconsistent even without the presence of the autocorrelated error term. Note that the disturbance of the error term for the FD model is $\Delta u_{it} = u_{it} - u_{i(t-1)}$ and this error is correlated with $y_{i(t-1)}$. The same will happen with the FE model; $\ddot{u}_{it} - \bar{u}_i$, $\bar{u}_i$ has $u_{i(t-1)}$ among its components, leading $\bar{u}_{it}$ to be correlated with the lagged dependent variable $y_{i(t-1)}$.

Coping with the endogeneity problem demands that instruments be found for the endogenous explanatory variables. That is exactly what the Arellano and Bond (1991) GMM estimation method does, since it uses lagged explanatory variables and lagged differenced variables as instruments. Thus a drawback of the Arellano-Bond procedure is that two census years of observation, 1970 and 1980, are lost.[11]

Consider the dynamic panel data model:

$$y_{it} = y_{i(t-1)}\gamma + x_{it}\beta_1 + w_{it}\beta_2 + a_i + u_{it} \tag{3}$$

where γ, β_1 and β_2 are the parameters to be estimated, $y_{i(t-1)}$ is the lagged dependent variable, x_{it} is the vector of potentially endogenous variables, and w_{it} the vector of predetermined and/or exogenous variables. Taking the first difference of equation (3), the following is obtained:

$$\Delta y_{it} = \Delta y_{i(t-1)}\gamma + \Delta X_{it}\beta + \Delta u_{it}. \tag{4}$$

where $X_{it} = [x_{it}\ w_{it}]$ and $\beta' = [\beta_1\ \beta_2]$.

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[11] The vector x_{it} might have some variables that are endogenous and some that are not. In each situation a new estimation procedure can be derived. See Arellano and Bond (1991).

As mentioned earlier, estimation of equation (4) by OLS generates an inconsistent estimator because $E(\Delta y_{i(t-1)}\Delta u_{it}) \neq 0$. Arellano and Bond (1991) suggest a GMM procedure to estimate equation (4) using the instrument matrix:

$$Z_i = \begin{bmatrix} [y_{i1}] & 0 & \cdots & 0 & \Delta X_{i3} \\ 0 & [y_{i1}, y_{i2}] & \cdots & 0 & \Delta X_{i4} \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & \Delta X_{i(T-1)} \\ 0 & 0 & \cdots & [y_{i1},\ldots,y_{i(T-2)}] & \Delta X_{iT} \end{bmatrix} \tag{5}$$

The use of instruments does not account for the differenced error term in (4). In fact $, E(\Delta u_i \Delta u'_i) = \sigma_v^2 (I_N \otimes A)$ where $\Delta u'_i = (u_{i3} - u_{i2},\ldots,u_{iT} - u_{i(T-1)})$, and

$$A_i = \begin{bmatrix} 2 & -1 & 0 & \cdots & 0 & 0 \\ -1 & 2 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & 0 & \cdots & -1 & 2 \end{bmatrix} \tag{6}$$

where A is a $(T-2)\times(T-2)$ matrix. As long as the residuals are not correlated, moment conditions can be built for any pre-determined variable of the X matrix. Specifically, for a matrix of instruments $Z = [Z'_1,\ldots,Z'_N]'$, the moment conditions are given by $E[Z'_i \Delta u_i] = 0$.

Arellano and Bond's GMM estimator can be obtained using a two-step procedure: pre-multiplying the differenced equation (4) in vector form by Z' gives:

$$Z'\Delta y = Z'[\Delta y_{t-1}\ \Delta X][\gamma_1\ \beta] + Z'\Delta u. \tag{7}$$

Then the first step is to apply Generalized Least Squares (GLS) on (7), which yields consistent estimates of γ and β, and the residuals. In the second step, the residual estimates obtained in the first step are used to construct the estimated variance and covariance matrix of the moment conditions so that the application of GLS may obtain the optimal GMM estimator.[12]

[12] See Arellano (2003), pp. 129-138, Baltagy (2001), pp. 131-135, for a discussion and derivation of the GMM estimator for the dynamic panel data model.

2.2 Empirical Results

Table 3 summarizes the data used in the empirical analysis. It presents the mean, standard deviation, minimum and maximum of each explanatory variable used in the models estimated later in this section.

Table 3. Summary of the Variables Used in Regressions

	Mean	S.d.	Min.	Max.
Mortality rate				
1970	123.6	52.8	27.9	303.7
1980	85.3	44.9	21.7	257.9
1991	49.5	25.0	10.6	130.7
2000	34.1	18.5	5.4	109.7
Family income				
1970	0.2	0.2	0.0	1.0
1980	0.5	0.3	0.0	1.0
1991	0.6	0.1	0.1	0.9
2000	0.8	0.1	0.4	1.0
Sewerage				
1970	24.0	21.5	0.1	100.0
1980	35.1	28.2	0.0	100.0
1991	47.6	30.7	0.0	99.4
2000	62.9	30.4	0.0	100.0
Years of education				
1970	1.4	0.8	0.0	5.6
1980	2.1	1.1	0.1	7.2
1991	3.0	1.3	0.2	8.8
2000	4.0	1.3	0.8	9.7

* Per capita income as proportion of the legal minimum wage in September 1991.

** Proportion of houses connected to running water and sewerage systems.

Source: IBGE, Census of Population (1970, 1980, 1991, 2000).

Table 3 reveals some interesting aspects of the Brazilian development process in the last three decades. The most striking is the way in which the dispersion of the mortality rates has evolved, as indicated by the minimum and maximum. In 1970, the maximum was about 11 times the minimum mortality rate, in contrast to the 20-fold difference evident in 2000. The increased dispersion is also reflected in the mortality rate's coefficient of variation (standard deviation divided by the mean). It rose from 0.43 in 1970 to 0.54 in 2000.

Household per capita income and the number of years of schooling have increased consistently over the period considered. The proportion of households with access to running water systems also increased significantly between 1970 and 2000, with declining coefficients of variation over the period.

2.2.1 Static Model for Infant Mortality

Table 4 presents the results of the application of pooled OLS, FE and FD estimators to model (1). The variables included in x_{it} are: running water services, measured by the proportion of houses with running water and running water disposal service; educational level, measured by the average years of schooling of the municipality's population; the logarithm of per capita income;[13] and a set of dummy variables accounting for the time effects on the infant mortality rate.

The results in Table 4 reveal that pooled OLS coefficient estimates and signs are in line with *a priori* expectations. They indicate that municipality income (represented by *log of income*), average years of schooling (represented by *education*) and the proportion of households served by running water and running water systems (represented by *running water*) contribute to a decline in infant mortality rates. The coefficients associated with the time dummies reflect the fall in infant mortality rates over time. During the 30 years between the four censuses, the infant mortality rate fell by 47.3 percent solely as a result of forces captured by the action of time, such as technological progress and cultural changes.[14]

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[13] Where per capita income is approximated by division of total value-added produced by the municipal divided by its population.

[14] Desai and Alva (1998) show that the mother's education has a strong impact on infant mortality rates. A decline in illiteracy rates is accompanied by an improvement in women's education.

Table 4. Static Model Coefficient Estimates

	Pooled OLS		Fixed Effects		First Difference	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Constant	73,515	1.25	84,523	1.06	-23,922	1.04
Log of Income	-33,836	0.61	19,753	0.61	-14,797	0.82
Education	-5,691	0.27	-0.028	0.55	1,493	0.59
Sewage	-0.161	0.01	0.103	0.01	0.018	0.01
D2	3,286	0.74	18,847	0.92	-	-
D3	-14,909	0.75	50,640	1.50	-9,369	0.97
D4	-14,920	0.81	63,338	2.05	9,932	0.73
R2	0.692		0.526		0.259	
Sample size	17301		17301		11503	

* Not Significant. All other coefficients significant at less than the 1% level. Asymptotic standard errors robust to general cross-section and time series heteroskedasticity.

The results reported in Table 4 indicate that the FE and FD estimators produced some coefficient signs contrary to expectations. The coefficient of *running water* ranges from negative and highly significant in the pooled OLS to positive and significant in the FE, and to positive but not significant in the FD. Recall that, despite the FD and FE transformations, reference is made to the structural equation in order to interpret the coefficients. Hence the positive sign for *running water* indicates that, after removing the effects of the other explanatory variables, infant mortality rates increase as more houses are connected to urban systems for the disposal of running water. This result is certainly counterintuitive.

A possible explanation of the positive and significant impact of running water treatment could be some sort of model misspecification. Education and income, for example, could be correlated with a relevant omitted variable. One way of addressing this problem is to introduce the lagged dependent variable into the model. As well as accounting for omitted factors, use of the lagged infant mortality rates as an explanatory variable introduces dynamic effects into the model, allowing inertial effects on infant mortality rates to be captured.

Another kind of misspecification might be the failure of the strict exogeneity assumption. As pointed out by Wooldridge (2001), if the differences between FD and FE are large and cannot be attributed to sampling variation, this endogeneity is probably a problem.[15] Comparing the FD and FE estimates reported in Table 4, there appears to be support for this conjecture. Hence, in the rest of this section, the estimation of a dynamic model is considered by means of the Arellano and Bond (1991) estimator, which accommodates both forms of misspecification.

2.2.2 Dynamic Model for Infant Mortality

First, the dynamic model was estimated by means of the same methods used to estimate the static model. In other words, the lagged dependent variable was simply introduced as an explanatory variable in the static model discussed earlier. The first six columns of Table 5 present the estimates of equation (3) by pooled OLS, FE and FD. The pooled OLS results show that the lagged dependent variable has a significant and positive coefficient. An estimated coefficient, positive and smaller than one, indicates that there is an adjustment process along census years. Coefficients associated with *education*, *log income* and the time dummies agree with *a priori* expectations, replicating the conclusions obtained with the static model. Nonetheless, it is worth noting that the magnitude of the effects declined substantially when the lagged mortality rate was included.

In order to account for endogeneity, two alternative forms of the Arellano and Bond estimator are considered. The results obtained are presented in the last four columns of Table 5. The results labeled "Model 1" refer to the use of an instrument matrix exactly like that presented in the Z matrix in (5)—that is, the model deals only with the endogeneity derived from the presence of the lagged dependent variable used as regressor in equation (3). The results labeled "Model 2," by contrast, refer to a model that treats all explanatory variables as endogenous. In this case the Z matrix has additional instruments to cope with the endogeneity of these variables. Each of these instruments is formed in the same way. Only with the lagged dependent variable is addressed here.[16]

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[15] See Wooldridge (2001), p. 284.

[16] For instance, taking $T = 3$, for any vector of the $\Delta x_{i3} = x_{i3} - x_{i2}$ matrix of explanatory variable, the instrument would be x_{i2} because it will not be correlated with, for all $s < t$, and uncorrelated with Δx_{i3}. $\Delta u_{i3} = u_{i3} - u_{i2}$.

Table 5. Dynamic Panel Data Model Estimates

							Arellano-Bond GMM			
	Pooled OLS		Fixed Effect		Differenced Variables		Model 1		Model 2	
Variables	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Constant	66.758	1.33 **	84.533	1.185	-13.662	1.239 **	-8.532	129 **	-9.128	1.31 **
Mortality t-1	0.494	0.01 **	-0.012	0.008	-0.109	0.007 **	0.5151	0.011 **	0.499	0.01 **
Log income	-22.123	0.86 **	-19.755	0.669 **	-15.744	0.848 **	-14.365	1.288 **	-15.429	1.12 **
Education	-1.333	0.21 **	0.111	0.623	1.077	0.66	-2.524	0.974 **	-2.302	0.969 **
Sewerage	-0.043	0.01 **	0.1	0.013 **	0.011	0.013	-0.041	0.019 *	-0.037	0.019 *
D_2	-54.691	1.18 **	-17.833	1.336 **	-	-	-	-	-	-
D_3	-63.437	1.10 **	-50.088	1.795 **	-22.869	1.254 **	-	-	-	-
D_4	-54.618	1.05 **	-63.662	2.315 **	-3.897	1.087 **	17.68	0.73 **	17.8	0.72 **
R^2	0.7928		0.5258		0.2542		-		-	
Sample size	15756		15756		9958		7292		7292	

Reported standard errors are heteroskedasticity-robust.

* Significant at the 1% level.

** Significant at the 5% level.

The first striking result of the Arellano-Bond results when compared to the pooled OLS, FE and FD is the change in signs of the *running water* and *education* coefficients; they are negative in the Arellano-Bond estimates but positive in the FE and FD estimates.

Education is the most important factor—one additional year of schooling entails a 7.35 percent reduction in infant mortality. One additional year of education will bring about a decline in the infant mortality rate from the 34.08 evident in 2000 to 31.56. An increase in the number of households connected to sources of treated water and running water also has a positive effect on infant mortality, although the impact is small compared to that of education and per capita income.

3. Demand for Child Health

As discussed in the introduction, the purpose of this section is to provide a more detailed analysis of infant mortality rates by complementing the previous section's model with analysis of the demand for child health. This analysis is based on the specification and estimation of an equation for the demand for child health as discussed by Behrman and Skoufias (2004).

3.1 Data Description

The dataset used to estimate the demand for child health was the 1996-97 Living Standards Survey conducted by IBGE. Socioeconomic and anthropometric measurements were collected at the household level between September 1996 and March 1997 for two regions of Brazil: the Northeast and the Southeast (IBGE, 1998). For this paper, the authors selected from the survey only those children aged 0-12 who were related to family members in the household.

As discussed earlier, health levels are not observable, and thus the authors follow Kassouf (1994) and Kassouf and Senour (1996), using Z-scores as proxies for level of health. As indicated by Kassouf and Senour (1996), there are three types of anthropometric Z-score: weight-for-height (WH); weight-for-age (WA); and height-for-age (HA). Each of these is associated with very specific types of malnutrition and thus with health status. Low Z-scores for weight-for-height and weight-for-age indicate poor health as a result of current acute malnutrition; a low Z-score for height-for-age indicates poor health as a result of (chronic) malnutrition, also known as "stunting."

Low or high Z-scores are the result of comparisons with normal, healthy populations. Z-scores equal to or above -1 are taken to indicate healthy individuals.[17] Z-scores below -1 are usually associated with unhealthy children. In general, the lower a child's score, the worse his or her health problems are likely to be. These health problems can be classified as severe, moderate, and mild. Children with anthropometric measures between one and two standard deviations below the mean (that is, scores between -1 and -2) are likely to have mild health problems. Those with measures between two and three standard deviations below the mean (Z-scores between -2 and -3) are likely to have moderate health problems. Children with Z-scores below -3 are likely to have severe health problems.

[17] In Brazil, overweight-related health problems are not yet a cause for serious concern, in contrast to circumstances in developed economies such as the United States and European countries.

Table 6. Percentage of Children by Z-score

Z-Score Range	Health Condition	HA			WH			WA		
		Total	NE	SE	Total	NE	SE	Total	NE	SE
<-3	Severe	4.67	4.5	4.9	0.96	1.3	0.5	0.47	0.63	0.25
[-3,-2)	Moderate	7.92	9.75	5.45	2.39	2.35	2.45	4.57	6.29	2.25
[-2,-1)	Mild	19.35	22.3	15.39	10.13	10.87	9.15	21.27	24.65	16.74
>-1	Normal	68.06	63.44	74.26	86.52	85.48	87.91	73.69	68.43	80.76

Source: IBGE, Standard of Living Survey, 1996.

The Z-scores for children aged 0-12 are presented in Table 6. The information in this table suggests that low HA scores represent a major problem: 12.6 percent of children in the sample suffer from moderate to severe health problems. Table 6 also indicates that there is considerable inequality between the richer and the poorer regions: the percentage of low HA scores is 14.3 percent in the Northeast and 10.4 percent in the Southeast.[18] Finally, the data indicate that the situation does not change if the health level is measured by WA or by WH scores. All three indicators suggest that stunting affects a high percentage of children in the sample, with obvious consequences for child health. The situation is particularly severe in the Northeast; the health level in the Southeast, although higher than in the Northeast, is still lower than in developed economies.[19] Stunting is generally associated with adverse economic conditions; its abundance indicates that a large percentage of children in Brazil, especially in the Northeast, suffer from various infectious diseases such as diarrhea, cholera and respiratory illnesses.

Table 7 presents the mean and standard deviation of the variables used to estimate the anthropometric demand equations, and the Heckman Selection Model applied to estimate household full income. The variables included in the model that explain individuals' decision to participate in the labor force were: *age*; age^2; the number of years of formal schooling, *education*; a variable that indicates the individual's position in the household (*Hh* for the head of the household and *sun* for *son*/*daughter*; other positions within the household are omitted); *white*

[18] Using 1989 data, Kassouf and Senour (1996) found a value of 16 percent for children aged two to five. Their sample is representative of Brazil as a whole, while the sample used in this study covers only two regions of the country for 1996/7. In Section 2 the authors show that infant mortality rates dropped sharply in Brazil between 1970 and 2000. It could be that the discrepancy between these two percentages is due to improvements in child health reflected by the rapid decline in infant mortality rates.

[19] For healthy child populations this percentage is 2.5 percent.

to capture the effect of race (the other races, Asian and *parda,*[20] are omitted); *southeast*, a dummy variable to distinguish the two regions of the survey, whose value is one if the household is in the Southeast region and zero otherwise; *urban*, a dummy variable indicating whether the household is in an urban area (value of one) or a rural area (value of zero); *Lnlabor*, the logarithm of non-labor income; *son 12*, indicating the number of young children (children less than 12 years old) in the family; and *We* and *Wage*, the spouse's education and age, respectively.

Table 7. Description of the Variables

Variables	Mean	s.d.
WA	-0.091	1,427
HA	-0.306	1,729
WH	0.296	1,761
Southeast	0.427	0.495
Running water	0.663	0.473
Urban	0.694	0.461
Electricity	0.876	0.329
Garbage	0.594	0.491
White	0.434	0.496
Asian	0.002	0.044
Parda	0.507	0.500
Child sex	0.509	0.499
Child age	6,209	3,784
Log full income	2,973	2,005
WH father	7,918	4,945
WH mother	9,178	4,929
Mother age < 16	0.998	0.044
Number of brothers	2,198	1,904
Number of children < 12	2,700	1,904
Mother education	6,154	4,219
Private health insurance	0.198	0.398

Source: IBGE, Standard of Living Survey, 1996.

[20] In the Brazilian census, *parda* is the general denomination for the various degrees of white-black racial mixes.

3.2 Opportunity Cost of Labor and Full Income

Full income, defined by Becker (1965, 1981) as the opportunity cost of available labor time per month, plus any other kind of non-labor income received per month by the household's members, was calculated for each household in the sample. The hourly wage was multiplied by the number of hours per month available to those household members who can participate in the labor force. Some of the men and women in the sample did not participate in the labor force; hence the opportunity cost of time for those not employed had to be estimated. The opportunity costs are the wage rates that the individuals who are not in the labor force would have received had they been employed. In the wage rate estimation, all men and women aged between 16 and 70 were used.

In order to estimate the wage rate that the individuals not in the labor force would have received, wage equations for men and women were estimated separately, using Heckman's (1979) two-step procedure to eliminate the sample selection bias. The first step in the Heckman procedure is to use a *probit* for labor force participation. The first-step coefficients are then used to compute a correction term, which is included as a covariate in the wage equation.

Table 8 presents the estimated selection equation and wage equation for men and women. The results indicate that labor force participation is negatively related to non-labor income. In the case of women, a 1 percent increase in non-labor income reduces the participation rate by 0.072 percent. Women in the Southeast have a higher rate of labor force participation, and married women a lower rate. The significance and sign of $num\ children < 12$ show that the presence of small children in the family is a deterrent to women's labor force participation. This result is consistent with other studies on the subject, such as Mroz (1987) and Killingsworth and Heckman (1986). It is worth noting that some other variables associated with urban-rural dummies, such as urban/rural Southeast and urban/rural Northeast, were included in the model but were not statistically significant. The urban-rural for both regions, however, was significant. The same is true of race, which is why only white was included.

The wage equations results for men and women, respectively, are presented in the last two columns of Table 8. In both cases the dependent variable for the wage equation was the logarithm of hourly wage. The sign and significance level of the estimated coefficients seem to be consistent with *a priori* expectations. Moreover, the LR tests reported in both tables show that the sample selection would have led to bias in the coefficients had the estimation procedure not been taken into account.

The wage equation for women shows that almost all variables are statistically significant and have the expected signs. Married women earn less than single women, and white women earn more per hour than black or *parda* women, an indication of discrimination in the job market. Education and experience contribute positively to wages, and men and women in the Southeast earn higher wages.

Using the coefficient estimates reported in Table 8, the predicted wage rates were computed for each individual in the sample aged between 16 and 70. Full income was then estimated by multiplying the wage estimate for each member of the household by 720 (the total number of hours in a month), plus any non-labor income. Note that full income is an exogenous variable in the demand equation because it does not depend on the allocation of time by the household members, while the wage rate is a given in the labor market.[21]

The estimation of hourly wages and the full income raise some identification questions in estimating the demand for child health. The strategy used in this paper differs from that used by Kassouf and Senour (1996) in two main respects. First, in the selection equation the latter authors did not include the number of young children in the family, which proved to be highly significant in the present model. Second, Kassouf and Senour included relation variables (such as head of household, wife, daughter, and so on) and characteristics of the spouse both in the selection and in the wage equations, but not in the demand equations. They advocate use of both the predicted logarithm of wage and full income as explanatory variables in the equation for the anthropometric demand for child health.

[21] The procedure reported here is commonly used in wage equation estimation. Kassouf (1994) and Kassouf and Senour (1996), for example, used this procedure to estimate a model for the role of parents in child nutrition in Brazil. The present authors use the same arguments as the former authors to emphasize the exogenous role of full income as an exogenous variable in the demand for child health.

Table 8. Coefficient Estimates from Heckman's Sample Selection Model

	Selection Equation		Wage Equation	
	Men	Women	Men	Women
Constant	0.104	-0.281	-2.851 **	-3.383 **
	(0.64)	(-1.89)	(-13.32)	(-15.26)
Age	0.012	0.015	0.009	0.015
	(1.83)	(2.53)	(-1.10)	(1.86)
Age2	0.000 **	0.000 **	0.000	0.000
	(-2.86)	(-3.33)	(-1.00)	(-2.22)
Education	0.024 **	0.0430 **	0.122 **	0.118 **
	(4.33)	(8.58)	(21.77)	(18.95)
Household Head	0.239 **	-0.049	0.194 *	-0.374 **
	(2.64)	(-0.69)	(2.29)	(-4.00)
Son or Daughter	-0.125	-0.329 **	-0.095	-0.499 **
	(-1.73)	(-5.03)	(1.11)	(-5.66)
Southeast	0.164 **	0.128 **	0.425 **	0.492 **
	(4.40)	(3.64)	(8.88)	(9.81)
White	0.042	-0.002	0.129 **	0.181 **
	(1.08)	(-0.06)	(2.77)	(3.67)
Urban	0.177 **	0.128 **	0.177 **	0.577 **
	(4.05)	(2.93)	(4.05)	(9.42)
Wife	-	0.078	-	-0.068
	-	(0.66)	-	(0.82)
Student	0.023	0.044		
	(0.38)	(0.80)		
Num Children <12	-0.262 **	-0.176 **		
	(-11.65)	(-8.07)		
Log Household Income	-0.139 **	-0.08 **		
	(-7.88)	(-5.28)		
Spouse Education	0.002	-0.015 **		
	(0.30)	(-2.67)		
Spouse Age	-0.004 **	-0.001		
	(-2.87)	(-0.45)		
Lambda	0.311 **	0.777 **		
	(2.56)	(6.71)		
Rho	0.312 **	0.654 **		
	(2.73)	(9.54)		
Sigma	1.000 **	1.189 **		
	(3.24)	(21.81)		
N	5578	6223		
Censored Obs.	3408	3889		

Heteroskedastic-robust standard errors in parenthesis.
* Significant at the 5% level.
** Significant at the 1% level.

This paper adopts a different identification procedure, inasmuch as young children are included in the selection equation. Specifically, the mother's education was included as an explanatory variable in the wage equation, and thus a decision was made to exclude the estimated wage rate in the demand for health. They also included *convenio* as an additional explanatory variable representing families' private health insurance coverage.[22]

3.3 Estimated Anthropometric Demand Equations

As discussed earlier, there are three types of Z-scores: height-for-age, weight-for-height and weight-for-age. Each of these scores corresponds to one dimension of health associated with long-run, medium-run and short-run or chronic malnutrition, respectively. As a result, there are three candidates to proxy the children's health level. An anthropometric demand for child health is estimated for each of these cases.

Table 9 presents the OLS results of the estimation of the reduced-form anthropometric demand for child health equations. The t-statistics reported in Table 9 were calculated using White's (1980) heteroskedastic-consistent covariance matrix estimator.[23] Some aspects of these results are worthy of note. Children living in the Southeast region, other factors held constant, have better health than children living in the Northeast region.[24]

Apparently, living in urban areas is not particularly important in explaining health levels. This explanatory variable, *urban*, is not significantly different from zero in the height-for-age and weight-for-age equations. Nonetheless, it is significantly positive, at the 10 percent level, in the weight-for-height equation, which suggests that it may have some impact on health. This result is somewhat in line with the findings of Thomas and Strauss (1992), indicating a positive effect of urbanization on child height-for-age, but it contrasts with the results of Kassouf and Senour (1996), which indicate that urbanization has a negative impact on child health.

[22] The authors believe that it is hard to defend the exogeneity of the mother's education both in the child health demand equation and in the wage equation; omission of variables related to ability is a fact in both equations. In both cases the estimated coefficient in the anthropometric demand equation would be biased and inconsistent. The endogeneity argument also applies to the *convenio* variable. The decision to acquire private insurance is part of the decision-making process of the demand for health, and families with a history of child disease will be more eager to acquire health insurance than others. See Alves and Timmins (2003) for a discussion of this issue in the context of an analysis of the Brazilian health system.

[23] OLS with constant variance did not seem to be supported by the sample data. Standard errors changed substantially when White robust standard errors were estimated.

[24] This result is consistent with the results presented in Section 2, which indicate that the Northeast is well behind other regions of the country in terms of child health.

The effects of infrastructure on child health are mixed. Except for running water, all variables capturing the provision of infrastructure either have a positive and significant effect or such provision is not significant. The results presented in Table 9 show that *running water* has a positive effect, at the 10 percent level, on the height-for-age equation.[25] However, there is a negative impact of *running water* on the weight-for-age and weight-for-height equations, at the 10 percent and 1 percent level, respectively.

The variable *electricity* has a strongly significant positive impact on height-for-age and weight-for-age, but no significant impact on the weight-for-height scores. Thus children in households supplied with electricity, *ceteris paribus*, have better health levels than those in households with no electrical supply. The same is true of weight-for-age. In the weight-for-height equation, the coefficient of electricity is not significant.

Garbage collection, represented by the variable *garbage*, has a significant positive impact on health as reflected in the weight-for-height and weight-for-age equations. In the height-for-age case, however, its effect was not significant. With the exception of the unexpected result for the *running water* variable, therefore, the results here indicate that the infrastructure variables have a positive impact on child health. Better infrastructure, other factors held constant, improves child health.

The results in Table 9 indicate that race might not be particularly important in explaining health differences. There is some indication that white children have somewhat better health levels than black, *pardo* and Asian children when weight-for-height and weight-for-age scores are used as proxies. Asian children seem to perform more poorly than other races when weight-for-height is used, but there is no significant difference when the other two proxies are applied. All the other race coefficients are not statistically different from zero. In contrast, *gender* does seem to have a significant impact on health: all three proxies for health are negatively related to gender: girls are healthier than boys. Interestingly, this result contrasts with the findings of Kassouf and Senour (1996), which suggest that no health differences are due to gender.[26]

[25] To some extent this result corroborates the findings in Section 2 indicating the positive impact of running treated water on the decline in infant mortality.
[26] See Kassouf and Senour (1996), p. 824.

Table 9. Anthropometric Health Demand Equations

	HA	WA	WH
Constant	-0.526	-0.944 *	-0.38
	(-0.89)	(-2.03)	(-0.595)
Southeast	0.012	0.118 *	0.198 *
	-0.21	(2.55)	(2.77)
runwater	0.154	-0.098	-0.315 **
	-1.88	-1.59	(-3.25)
urban	-0.17 *	-0.009	0.154
	(-2.03)	(-0.141)	-1.21
electricity	0.575 **	0.321 **	-0.07
	(6.19)	(4.94)	(-0.645)
garbage	0.000	0.239 **	0.374 **
	(-0.00)	(4.00)	(4.08)
White	-0.225	0.165	0.38 *
	(-1.89)	-1.65	(2.58)
Asian	0.621	0.371	-1.6
	-1.01	-1.08	(-1.36)
Parda	-0.142	0.093	0.192
	(-1.22)	-0.96	-1.32
Sex	-0.154 *	-0.137 **	-0.13 *
	(-3.03)	(-3.42)	(-2.13)
childage	-0.012	-0.05 **	-0.038 **
	(-1.79)	(-8.80)	(-3.90)
log full income	0.326	0.222 **	-0.013
	(5.86)	(5.29)	(-0.18)
WHfath	0.007	0.022 **	0.029 **
	-1.24	(5.01)	(4.52)
WHmoth	0.024 **	0.04 **	0.027 **
	(4.51)	(8.87)	(4.20)
Educfath	0.01	0.01	0.005
	-1.32	-1.55	-0.56
educmoth	0.018 *	0.033 **	0.022 *
	(2.00)	(2.93)	(1.96)
agemoth16	-1.92 **	-1.03 *	-0.028
	(-3.57)	(-2.41)	(-0.05)
R-square	0.100	0.166	0.055
F-stat.	27.44	48.18	10.97
N	3976	3976	3022

Heteroskedasticity-robust t statistics in parenthesis.

* Significant at the 5% level.

** Significant at the 1% level.

The variable *child age* has a negative sign in all three equations, even though it is not significant in the height-for-age equation. The coefficient of the logarithm of per capita full income, indicated by *log full income* in Table 9, is positive and highly significant in the height-for-age and weight-for-age equations. In the weight-for-height equation it was not significant. These results indicate that stunting and wasting are positively associated with poverty. Higher per capita income leads to better health, as predicted by the reduced form (12) of the theoretical model. To the extent that weight-for-height captures the long-run impact of malnutrition, the results reported for this variable make a great deal of sense. Poverty takes a long-term toll on children's health, and low income per person in the household leads to a lower health status in the long run.

In all the equations, the weight-for-height of the parents is an important factor in explaining health differences. It has positive effects on health, with the exception of the father's weight-for-height in the height-for-age equation. This finding suggests that genetics plays a role in health differences among children, but it is important to note the substantial likelihood that the parents' long-run overall poverty manifests itself in the weight-for-height Z-scores. These variables have been used as proxies for unobserved family background characteristics.[27] It is important to control for family characteristics when analyzing the estimation of the demand for child health. Behrman and Wolfe (1984) and Behrman (1990), for instance, argue that the impact of education may be overestimated because of unobserved endowment and family background.

Low-income families in developing countries are usually large. In the present sample, low-income households have larger families than high-income households. The parents of low-income families have to care for and feed more children than the parents of high-income families.[28] Number of siblings, however, was not introduced into the explanation of child health because parents decide on the number of children in the household. This variable is an integral part of the household decision-making process and thus suffers from an endogeneity problem.

The variable *mother age* < 16, indicating whether the mother is younger than 16, also has a detrimental effect on child health when measured by height-for-age and weight-for-age. When health is measured by the weight-for-height, however, it has no significant impact. Younger

[27] See Thomas and Strauss (1992), p. 317; and Kassouf and Senour (1996), p. 825.
[28] In the sample, the 10 percent highest income bracket has 2.3 children per household, while the lowest 10 percent has 2.6.

mothers are less experienced in dealing with children, and their children exhibit poorer health levels.[29]

The variable *mother education* has a positive and significant coefficient in all of the demand equations. This result is quite strong, as would be expected given several other studies indicating the positive impact of the mother's education on improvements in child health in developing countries. See, for example, Behrman and Wolfe (1984), Thomas, Strauss and Henriques (1990), Alderman and Garcia (1993), Behrman and Deolalikar (1988), Kassouf and Senour (1996) and Kassouf (1994).

The inclusion of full per capita income and mother's education and full income might look contradictory, because the mother's education enters as an explanatory variable into the mother's wage equation while the predicted mother's wage enters into the composition of household full income. The mother's education is included in the health demand equations in an effort to capture the net contribution of the mother's education to child health. In the full income variable the mother's education explains child health indirectly. The mother's education would therefore have both a direct and an indirect dimension, the latter of which derives from the value of education in the job market. In this study, however, the results indicate that the direct effect of the mother's education is not particularly strong, and thus the indirect effect might be stronger than would be expected.

The father's education also has a positive impact on child health, albeit to a lesser extent than the mother's education. The gender variable, sex, indicates that boys have a poorer health status than girls in all demand equations. In all of them the variable age has a negative and significant coefficient, indicating that as a child ages his or her health tends to deteriorate.

4. Conclusion

Infant mortality rates declined significantly in Brazil between 1970 and 2000, but they remain high relative to other developing countries. There are wide variations within the country, moreover, and the rates in some regions are well above the national average. The rate in the Northeast is twice the national average. Census data, disaggregated at the municipality level, were used to estimate a model explaining how infant mortality rates behaved over time, as well

[29] Horton (1988) found a positive relation between mother's age and child health; Strauss (1990) did not.

as across Brazilian municipalities. The model explores the panel dimension of the dataset, comprising four census years and using the municipality as the unit of observation.

Fixed-effect and first-difference estimators were used. However, even with estimators taking into account the correlation between the error term and explanatory variables due to omitted factors, the results indicated that some endogeneity remains. A dynamic panel data model was adopted, in which infant mortality rates in the previous census were used as an explanatory variable to account for possible explanatory variable omission. The results of the dynamic model estimation, however, indicated that some endogeneity persisted, introducing inconsistency into the parameter estimation. Estimation procedures were implemented to account for this problem, whereby instruments were used in a GMM framework to account for endogenous explanatory variables. The results indicated that variables related to education, basic sanitation services (such as the household's connection to running water and sewerage services) and per capita income were important factors in explaining the behavior of infant mortality rates in Brazil.

Among these factors, education is by far the most important. One additional year of schooling leads to a more than 7 percent decline in the average infant mortality rate. Improvements in sanitation services, meaning the greater availability of treated running water and sewerage services, also lead to a fall in infant mortality. Economic growth as measured by per capita income is another strong factor in reducing the rate.

The estimation of the child demand equations, using Z-scores as a measure of child health, brought additional inference to corroborate the findings of the infant mortality analysis. The household data allowed for a deeper analysis, and variables such as education could be separated by the level of education embodied in the household by each parent. It is unquestionable that the mother's education is a strong and direct factor in improving child health. The father's education also contributes, but to a lesser degree.

The mother's age is another important determinant of child health. The results indicate that the children of younger mothers have poorer health. Variables related to infrastructural services, such as running water and sewerage, electricity and garbage collection, were also found to play an important role in improving child health, although their effect is not as clear-cut as the parents' education.

From a policy perspective, the conclusion is clear: education, the improvement of sanitary services and higher per capita income brought about by economic growth are all important to improving child health in Brazil.

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