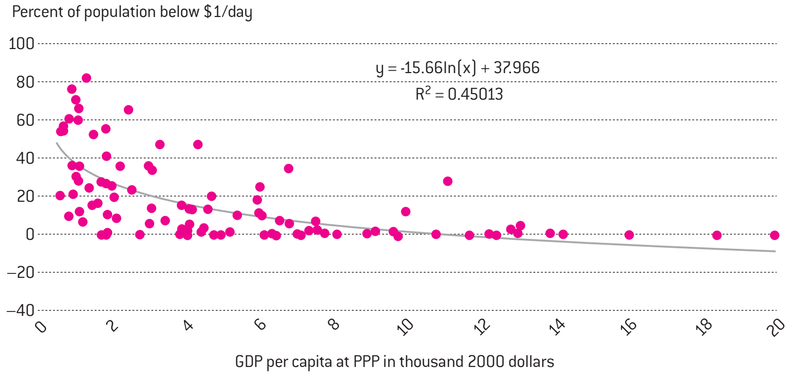
Appendix 1
Cross-Sectional and Lognormal Formulations for Poverty

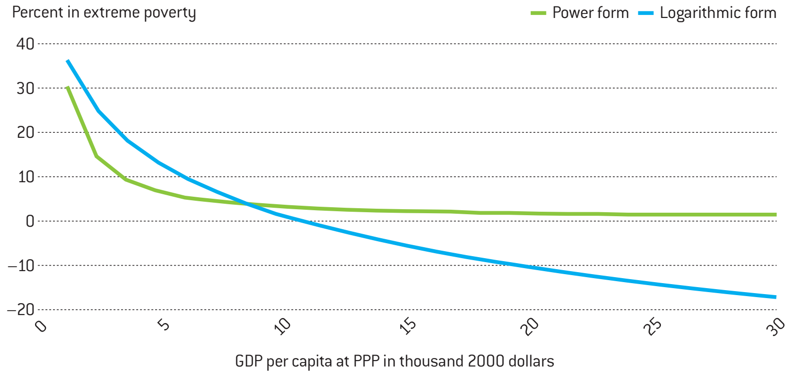
This appendix provides basic information on the two formulations used for forecasting poverty in the IFs model. Appendix 2 elaborates the lognormal approach.

Figure A1.1 Cross-sectional relationship of GDP per capita and extreme poverty



Source: IFs Version 5.47.

Figure A1.2 Cross-sectional formulations linking GDP per capita to poverty rate



Source: IFs Version 5.47.

Cross-Sectional Analysis of Change in Poverty

Looking at the simpler and much less heavily used approach first, Figure A1.1 shows a scatterplot of countries for which there are data on which to build a cross-sectional formulation. The logarithmic curve fit to that data suggests that as countries reach about $10,000 per capita at purchasing power parity (PPP), extreme poverty essentially disappears.

The cross-sectional formulation used within International Futures (IFs) to fill holes for countries without surveys uses the logarithmic form of Figure A1.1 (do not confuse using the logarithmic form with the lognormal approach, discussed below), but statistical analysis added the Gini coefficient to the formulation with the expected positive relationship (taking the adjusted R-squared to 0.62).

$$IncomeLTICS_r = 14.514 - 15.196 * LN(GDPPCP2000_r) + 56.17 * GINI_r$$

where

IncomeLTICS is the percentage living on less than $1

GDPPCP2000 is GDP per capita at PPP in 2000 $

GINI is the Gini coefficient

r is a specific country/region

It should be noted, however, that an exponential or power curve can be fit to the same cross-sectional data with approximately the same R-squared, but it will exhibit slower decline with increasing gross domestic product (GDP) per capita and has a much longer tail of nonzero poverty. Figure A1.2 compares the two quite different functions. When the exponential form is substituted within IFs, the forecasts for poverty reduction are, of course, even less positive. The logarithmic form is normally used in IFs, however, because it appears visually to capture better both the higher levels of poverty at low levels of GDP per capita and to capture the near elimination of extreme poverty by about $10,000 per capita.

In the process of forecasting with the cross-sectionally estimated function, it is necessary to recognize initial differences between the most recent survey-based data for each country and the expected values of the function. These differences could represent a variety of forces, including patterns of government transfers or patterns of social discrimination across ethnic or caste groupings. It is impossible to know if such differences or country-specific shifts relative to the function will persist or not. IFs forecasts assume very slow erosion of the differences for individual countries from the general function over time, thus protecting the country differences (path dependencies) for many years. Specifically, the differences are captured by a multiplicative adjustment factor in the base year of the model.[1]

Lognormal Analysis of Change in Poverty

The use of distributions in forecasting begins with the distinction between a detailed distribution and the simpler parametric representation of such a distribution. By far the most widely used method for detailing distributions of income, wealth, or other quantities is the Lorenz curve (see, again, Figure 3.1 and the discussion of it). Any survey data on income or consumption for a society can be shown in Lorenz curve form with essentially complete accuracy. There is a clear relationship between the Lorenz curve and the expression of shares of income held by quintiles, deciles, or even percentiles of population.

Although it would be possible simply to project forward the quintile or decile shares of a Lorenz curve to specify future income distributions, doing so would have at least two significant weaknesses. First, it would largely freeze those distributions, which can be quite dynamic. Second, it would not directly facilitate the computation of key poverty indexes such as the headcount of those with less than $1 per day.

What we want instead is an analytic representation of the income distribution that can change in form in response to both changing average income levels and changing income distributions, in turn represented by something as simple as the Gini coefficient. Moreover, we want a representational form from which we can conveniently compute specific deciles or quintiles (thereby reconstructing the Lorenz curve) and also compute key poverty measures like the headcount.

Fortunately, there are a number of analytic formulations and estimation techniques that allow us to do exactly that. The most widely used is the lognormal formulation. Chapter 3 discussed it and portrayed it in Figures 3.2–3.3. Although not all national income distributions have lognormal form, something very close to that form is very typical.[2]

A lognormal distribution that fully represents the distribution of income in a society can be specified with only two parameters: average income and the standard deviation of it.[3] Very usefully for forecasting purposes, the Gini coefficient can be used in lieu of the standard deviation. The Lorenz curve and standard poverty measures are then easily computable from the lognormal equation with the two specific parameters.[4]

Given its advantages, the IFs approach to forecasting poverty uses the lognormal formulation, driven by average consumption and the Gini coefficient. More concretely, the procedure in IFs requires specification and use of the general function below.

$$IncomeLTILN_r = f\,(LogNormalDistribution, CperCap_r, GINI_r, NSNARAT_r)$$

where

$$NSNARAT_r = (IncomeLT1LN_r^{t=1}, CperCap_r^{t=1}, GINI_r^{t=1})$$

where

IncomeLT1LN is the percentage living on less than $1 (lognormal)

CperCap is household consumption per capita in 2000 $ at PPP

GINI is the Gini coefficient

NSNARAT is the ratio of national survey poverty level to household consumption from national account data, computed in the initial model yeur (2000)

r is a specific country/region

As with the cross-sectional formulation, the computed value of those living on less than $1 per day in the base year (2000) is fit to initial conditions.

Appendix 2
Using Lognormal Income Distributions

Lognormal Distribution of Income

A variable x is said to be lognormally distributed when its log has a normal distribution. To be lognormally distributed, x always has to be positive. Let us assume that income x has a lognormal distribution, such that $y = \ln(x)$ has a normal distribution with mean μ_x and standard deviation σ_x.

The probability density function (PDF) $f_x(x)$ of the lognormal distribution is given by

(1a)
$$f_x(x) = \frac{1}{x\sigma_x\sqrt{2\pi}} e^{-\frac{1}{2}\left[\frac{\ln x - \mu_x}{\sigma_x}\right]^2}$$

Let us denote the lognormal distribution by $\Lambda(\mu_x, \sigma_x)$ and the normal distribution by $N(\mu_x, \sigma_x)$. The PDF of N is given by

(1b)
$$f_y = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$$

Derivation of the Parameters of Lognormal Distribution from Available Data

J. Aitchison and James Allen C. Brown (1957: 8) note that, the mean, μ of a variable x (e.g., income or consumption), when x has a lognormal distribution, $\Lambda(\mu_x, \sigma_x)$ can be found from the following:

(2)
$$\mu = \exp\left[\mu_x + \frac{1}{2}\sigma_x^2\right]$$

From the Theorem 2.7 of Aitchison and Brown (1957: 13) the Gini coefficient, G for lognormal distribution can be derived as (see Chotikapanich, Valenzuela, and Prasada Rao 1997):

(3)
$$G = 2\Phi\left(\frac{\sigma_x}{\sqrt{2}}\right) - 1$$

where Φ is the standard normal distribution. From the above equation, we can calculate one of the parameters of Λ,

(4)
$$\sigma_x = \sqrt{2}\Phi^{-1}\left(\frac{G+1}{2}\right)$$

Given the mean income, μ, we can use equations (4) and (2) to calculate the other parameter of the lognormal distribution:

(5)
$$\mu_x = \ln(\mu) - \frac{1}{2}\sigma_x^2$$

Calculating Population and Income Shares

Once we find mean μ_x and standard deviation σ_x, we can construct the distribution equation and integrate it for any cutoff of income.

The proportion of the population with incomes less than or equal to a given level x is given by the distribution function:

(6)
$$\pi(x) = \int_0^x f_x(x)dx$$

The integral $\int_0^x f_x(x)dx$, is the lognormal cumulative distribution function (CDF) at x, that is:

Population fraction below income

(7) $x = \Lambda(x \mid \mu_x, \sigma_x)$

The corresponding income shares (at x) can be obtained from the following first moment distribution (Chotikapanich, Valenzuela, and

Prasada Rao 1997; Aitchison and Brown 1957):

(8)
$$\eta(x) = \frac{1}{\mu}\int_0^x x f_x(x)dx$$

and according to the fundamental theorem of the moment distribution (Aitchinson and Brown 1957: 12), the first moment distribution with parameters (μ_x, σ_x) is the same as the lognormal distribution with parameters ($\mu_x + 0.5\,\sigma_x^2$, σ_x), that is, the income fraction held by people earning below income x,

(9) $\eta(x) = \Lambda\ (x \mid \mu_x + 0.5\ \sigma_x^2, \sigma_x)$

Poverty Measure: Poverty Headcount

Replacing x with the poverty line income, z (e.g., $1 PPP a day, or $365 PPP per year) in equation 7, we obtain the percentage of people living below $1 a day (the headcount index, or H/P, where H is the number of poor and P the total population):

(10) Poverty Headcount Index,
$H/P = \Lambda\ (z \mid \mu_x, \sigma_x)$

Poverty Measure: Poverty Gap

The poverty gap is obtained from the following generalized class of Foster-Gear-Thorbeck (FGT) poverty measures,

(11)
$$P_\alpha = \int_0^z \left[\frac{z-x}{z}\right]^\alpha f_x(x)dx$$

where, α, ≥ 0, $f_x(x)$ is the density function at income x and z is the income at the poverty line.

The above equation returns poverty headcount index for $\alpha = 0$. When $\alpha = 1$, we get the poverty gap (PG), which can be interpreted as the shortfall from the poverty line or the depth of poverty below the line. The poverty gap, expressed as a percentage, can be further simplified to:

(12)
$$PG = \int_0^z \left[\frac{z-x}{z}\right] f_x(x)dx$$

(13)
$$PG = \int_0^z f_x(x)dx - \frac{1}{z}\int_0^z x f_x(x)dx$$

(14)
$$PG = \frac{H}{P} - \frac{\mu}{z}\eta(z)$$

where μ is the mean income (or consumption), using equation 8.

(15)
$$PG = \frac{H}{P} - \frac{\mu}{z}\Lambda\left(z \mid \mu_x + 0.5\sigma_x^2, \sigma_x\right)$$

using equation 9 from above.

Reconciliation Between National Accounts and Survey Data

To reconcile the discrepancy between national accounts (NA) and household survey (HS) figures, International Futures converts its NA mean income (GDP per capita in PPP dollars) to an equivalent HS mean consumption. It does so using a reverse calculation of the mean consumption from the available data on Gini index and the population share with consumption below a dollar PPP a day, both calculated (at the source) by using the HS data.

We know (from the definition section on lognormal distribution above),

(16)
$$\Lambda(x \mid \mu_x, \sigma_x) = \Phi\left(\frac{\ln(x) - \mu_x}{\sigma_x}\right)$$

therefore,

(17)
$$\Lambda(365 \mid \mu_x, \sigma_x) = \Phi\left(\frac{\ln(365) - \mu_x}{\sigma_x}\right)$$

or, population fraction below an income of $1 PPP a day, or $365/year, H/P

(18)
$$= \Phi\left(\frac{\ln(365) - \mu_x}{\sigma_x}\right) \quad \text{or,}$$

(19)
$$\Phi^{-1}\left(\frac{H}{P}\right) = \frac{\ln(365) - \mu_x}{\sigma_x}$$

or,

(20)
$$\mu_x = \ln(365) - \Phi^{-1}\left(\frac{H}{P}\right) * \sigma_x$$

In the above equation $\Phi^{-1}\left(\frac{H}{P}\right), \sigma_x$ is available from World Bank, where it is calculated using HS data on (mostly) consumption. We can calculate μ_x from this equation and obtain a (HS equivalent) mean consumption using equation 2 above.

Appendix 3
Deep Drivers of Economic Growth and Distribution

Deep Drivers of Economic Growth

As noted at the beginning of Chapter 4, extrapolation is a good first step to explore possible future poverty levels. Multivariate formulations involving the key proximate causal drivers, namely average income and income distribution, are the appropriate second step. Yet if we want to analyze the leverage of policy interventions, it is necessary to go further by beginning exploration of the deep drivers of the proximate drivers, ideally with tools that frame the deep drivers in terms relatively close to agent action: government spending and regulation, household behavior, technical and other assistance by nongovernmental organizations, or decisions by firms.

Such richness of specification is, of course, the Holy Grail of poverty (and much other policy) analysis and may be as difficult to find as the religious one. In this book we make do with the structures that have been developed within the IFs model. Because of its special importance, this appendix sketches the drivers of GDP per capita (and household consumption).

Chapter 4 summarily described the economic module of IFs as a general equilibrium-seeking model that uses inventories as buffer stocks to provide price signals, so that the model chases equilibrium over time.[5] Its production function represents GDP as a function of production capital, labor, and multifactor productivity (MFP). MPF is a function of human capital (education and health), social capital, governance quality and policies, physical and natural capital (infrastructure and energy prices), and knowledge development and diffusion (R&D and economic integration with the outside world). The cohort-component demographic model determines the size of the labor force, while domestic and foreign savings help determine capital investment. A social accounting matrix (SAM) envelope ties economic production and consumption to simple interactor financial flows, including government taxation or transfers and domestic and international transfers.

In short, many of the desired agent-based policy levers, such as governmental spending and transfers, are available in the structure. In many other cases, such as the levels of governmental corruption or economic freedom, the variables are also included in the model, even without clear roots running to specific actors and agency.

This brief discussion cannot specify the full model, and sources of detailed model elaboration were listed earlier. We invite the reader to call up a window in IFs called "Development Profile," available for any country or grouping. That window shows, for instance, that in Afghanistan in 2000, those aged twenty-five or older had completed an average of only 1.1 years of education. The expected value, based on a cross-sectionally estimated relationship with GDP per capita, was 1.9. The parameter assigned to translate such deviation into impact on productivity, based on the extensive empirical work that many analysts have done on the drivers of productivity, was 0.1 percent lower productivity per year of "missing" education, suggesting that the weakness of Afghanistan in educational performance would cost it nearly 0.3 percent annual growth.[6] Altogether, underperformance with respect to human capital was estimated to be costing Afghanistan about 0.74 percent per year in growth, and underperformance on social capital and governance might cost another 0.15 percent.

Calculations of the impact of social and governmental performance, in spite of extensive empirical work, are obviously uncertain. It is hard to believe, for instance, that weaknesses in social capital and governance were not costing Afghanistan more than 0.15 percent per year in productivity and growth. Because there were no data for Afghanistan on economic freedom, for example, the computed values were set at the level of the expected ones; surely the level of economic freedom in Afghanistan was considerably below the cross-sectionally estimated value in 2000. Fortunately, data are fairly complete on most drivers of productivity for most countries.[7]

In spite of limitations, the approach that the Development Profile illustrates has some significant advantages for the study. First, there is endogeneity in the model's representation of the various drivers of productivity and growth. To illustrate, education and health spending are affected over time by government revenue and expenditure balances, and foreign aid can supplement revenues and increase that spending, but current account deficits may lead to government retrenchment that restricts them. Second, the user of the model can flexibly intervene with respect to these growth drivers and their expected per unit contributions to growth. That is, a user can direct more government spending to education and can also change the empirically often contentious parametric impact of years of education on productivity.

The focus here has been on the drivers of economic growth related to multifactor productivity, but there are many other leverage points in the model. For instance, changes in fertility patterns will, over longer time horizons, affect labor supply, as will changes in the female participation rate in the shorter term. Savings rates and capital investment can be affected by foreign direct investment or worker remittances. Of considerable relevance to the Millennium Project's proposed plan of action and to the Global Compact of the eighth Millennium Development Goal, foreign aid levels can be changed and will affect current account balances and government revenue and spending patterns and balances. Chapter 7 elaborates the leverage points for analysis in considerably more detail.

Deep Drivers of Distribution

If the forecasting of economic growth is very difficult, the forecasting of income distribution is even harder. For that reason, many users of the IFs model will prefer to specify changes in the Gini coefficient over time exogenously rather than to rely on the endogenous computations of IFs. Nonetheless, the endogenous computations of IFs do begin to tie deep drivers to the income distribution and therefore allow, once again, some capability for analyzing the possible impact of policy-based interventions.

Forecasting of changes in Gini necessarily involves the forecasting of the differential performance of segments within the population. Based on historical data, the means of different deciles could be extrapolated or in some other way forecast, but that would be, once again, unrelated to specific interventions and not add much simply to extrapolating changes in Gini itself.

Ideally, the forecasting of Gini should be tied to an elaboration of household types as is done with a social accounting matrix. SAMs can distinguish multiple categories of urban and rural households and their changing demographic sizes (as a result, for instance, of rural-to-urban migration) and income structures (as a result of structural change in the economy, of changing patterns of government transfers, and of many other factors). For the purposes of studying longer-term change in global poverty levels, the SAM ideal is tarnished by two realities: (1) in spite of efforts via the UN's system of national accounts, there is no standard household classification system for SAMs, so that they vary widely and are generally used in single-country analysis, not global forecasting; and (2) most models built around SAMs are used for rather short-term analysis and even more commonly for comparative static analysis (for example, comparison of income patterns in a society open to agricultural imports to those in one that is not, without much or any consideration of the dynamic path from one to the other).

Nonetheless, the basic rooting of forecasts of Gini in a SAM retains the tremendous advantage of tying those forecasts to changes in interventions that are clearly policy-relevant. And fortunately, the Global Trade Analysis Project (GTAP) has collected key information, such as share taken of value added, for two classes of households, those based respectively on skilled and unskilled labor, across eighty-seven countries and regions and fifty-seven economic sectors. IFs has drawn heavily on the GTAP data, most recently Version 6, in its own economic model specification, and the IFs SAM is built on the basis of the two household categories. The GTAP database has made it possible to develop forecasts of income by type of household as economies, and therefore value-added shares, shift from agriculture to manufacturing and to services. Moreover, IFs has used the GTAP database to simulate changes not just in sector shares but also in more fundamental economic structures, by making the household shares in each sector a function of GDP per capita levels.

For the calculation of Gini it is necessary, however, to know not just the household income shares, but also their sizes. Unfortunately, the GTAP dataset does not provide numbers on labor force size by skill level within sectors.[8] And data from the Organization for Economic Cooperation and Development (OECD) on labor force size by classifications such as professional and administrative, which could be used to estimate numbers of skilled versus unskilled workers, exist only for well-to-do countries. Within IFs, however, the submodel of formal education helps generate future values of education levels in the adult population, which in turn allow estimates of the size of the skilled and unskilled household sets.

Given the income shares accruing to skilled and unskilled shares of the population from GTAP foundations and the sizes of those portions of the population from the IFs educational model, the Gini index is computed from the simple Lorenz curve that those two incomes and population shares create, scaled to the empirically known initial condition.

As stated at the beginning of this subsection, the formulation for forecasting domestic Gini coefficients for each country, relying on only two household types, is very crude. For that reason, most analysis in this study is done with scenarios of distributional change rather than with endogenous forecasts. Nonetheless, the endogenously computed Gini coefficients carry the advantage of being responsive to many interventions in the model, not least being expenditures on education. Thus it is of interest to explore those computations in some of the analysis.

Appendix 4
Countries in UN Regions and Subregions

Africa				
Eastern Africa	**Middle Africa**	**Northern Africa**	**Southern Africa**	**Western Africa**
Burundi	Angola	Algeria	Botswana	Benin
Comoros	Cameroon	Egypt	Lesotho	Burkina Faso
Djibouti	Central African Republic	Libya	Namibia	Cape Verde
Eritrea	Chad	Morocco	South Africa	Côte d'Ivoire
Ethiopia	Congo, Rep. of	Sudan	Swaziland	Gambia
Kenya	Congo, Dem. Rep. of the	Tunisia		Ghana
Madagascar	Equatorial Guinea			Guinea
Malawi	Gabon			Guinea-Bissau
Mauritius	São Tomé and Príncipe			Liberia
Mozambique				Mali
Réunion				Mauritania
Rwanda				Niger
Seychelles				Nigeria
Somalia				St. Helena (UK)
Uganda				Senegal
Tanzania				Sierra Leone
Zambia				Togo
Zimbabwe				

Asia				
Eastern Asia	**South-Central Asia**	**South-Eastern Asia**	**Western Asia**	
China	Afghanistan	Brunei	Armenia	Saudi Arabia
Hong Kong	Bangladesh	Cambodia	Azerbaijan	Syria
Korea, Dem. Rep. of	Bhutan	Indonesia	Bahrain	Turkey
Korea, Rep. of	India	Laos	Cyprus	United Arab Emirates
Japan	Iran, Islamic Rep. of	Malaysia	Gaza Strip	Yemen
Macau	Kazakhstan	Myanmar	Georgia	
Mongolia	Kyrgyzstan	Philippines	Iraq	
Taiwan	Maldives	Singapore	Israel	
	Nepal	Thailand	Jordan	
	Pakistan	Timor-Leste	Kuwait	
	Sri Lanka	Vietnam	Lebanon	
	Tajikistan		Oman	
	Turkmenistan		Palestine	
	Uzbekistan		Qatar	

Oceania			
Australia-New Zealand	**Melanesia**	**Micronesia**	**Polynesia**
Australia	Fiji	Guam (US)	Samoa
New Zealand	New Caledonia	Kiribati	Cook Islands
	Papua New Guinea	Marshall Islands	French Polynesia
	Solomon Islands	Micronesia	Niue
	Vanuatu	Nauru	Pitcairn (NZ)
		Northern Mariana Islands (US)	Western Samoa
		Palau	Tokelau (NZ)
			Tonga
			Tuvalu (UK)
			Wallis and Futuna Islands (F)

Europe			
Eastern Europe	**Northern Europe**	**Southern Europe**	**Western Europe**
Belarus	Channel Islands (UK)	Albania	Austria
Bulgaria	Denmark	Andorra	Belgium
Czech Republic	Estonia	Bosnia and Herzegovina	France
Hungary	Faeroe Islands (DK)	Croatia	Germany
Poland	Finland	Gibraltar (GB)	Liechtenstein
Moldova	Iceland	Greece	Luxembourg
Romania	Ireland	Holy See	Monaco
Russia	Isle of Man (UK)	Italy	Netherlands
Slovak Republic	Latvia	Macedonia	Switzerland
Ukraine	Lithuania	Malta	
	Norway	Portugal	
	Sweden	San Marino	
	United Kingdom	Serbia and Montenegro	
		Slovenia	
		Spain	

Latin America and the Caribbean			
Caribbean		**Central America**	**South America**
Anguila (UK)	Martinique (F)	Belize	Argentina
Antigua and Barbuda	Monserrat (UK)	Costa Rica	Bolivia
Aruba (NE)	Netherlands Antilles (NE)	El Salvador	Brazil
Bahamas	Puerto Rico	Guatemala	Chile
Barbados	St. Kitts and Nevis	Honduras	Colombia
British Virgin Islands (UK)	St. Lucia	Mexico	Ecuador
Cayman Islands (UK)	St. Vincent & the Grenadines	Nicaragua	Falkland Island (Malvinas) (UK)
Cuba	Trinidad and Tobago	Panama	French Guiana (F)
Dominica	Turks and Caicos Islands (UK)		Guyana
Dominican Republic	US Virgin Islands (US)		Paraguay
Grenada			Peru
Guadeloupe (F)			Suriname
Haiti			Uruguay
Jamaica			Venezuela

Northern America
Bermuda (UK)
Canada
Greenland
St. Pierre and Miquelon (F)
United States

Source: http://www.unsystem.org/scn/Publications/4RWNS/Appendix02.pdf.

Appendix 5
Points of Leverage in International Futures (IFs)

Using IFs to explore specific interventions or a strategic package of them (see especially Chapter 7) requires information on the parameters used in the interventions. From the Scenario Tree of IFs, it is possible to use the Parameter Search feature to identify the branch of the tree with a desired parameter. More easily, the specific interventions for this study were packaged with other scenario files, available to the Tree via the Scenario Files/Open/Other and Add Scenario Components menu options. Please look under World Integrated Scenario Sets/HDR Plus 50. In the list below, the parameters used in Chapter 7 have an asterisk. The analyses of the study are replicable with the following parameters.

Parameters that control population			
Source/type	**Parameter**	**Definition**	**Comment**
Population	tfrm*, non-OECD	Total fertility rate multiplier	

Parameters that control domestic interventions			
Source/type	**Parameter**	**Definition**	**Comment**
Education	gdsm*, education, non-OECD	Education spending multiplier	
Health	gdsm*, health, non-OECD	Health spending multiplier	
Economic freedom	econfreem*, non-OECD	Economic freedom multiplier	
Governance effectiveness	goveffectm*, non-OECD	Governance effectiveness multiplier	
Corruption	govcorruptm*, non-OECD	Corruption multiplier	Higher is less corrupt
Infrastructure	infraroadm* infraelecm*, infratelem*, infranetm*,non-OECD	Infrastructure multipliers: roads, electricity, telecommunications, networking	
Renewable energy	enpm*, other renewable, non-OECD	Energy production multiplier	
R&D	gdsm*, R&D, non-OECD	R&D spending multiplier	
Trade protection	protecm*, non-OECD	Protectionism multiplier	
Female labor	labfemshrm*,non-OECD	Female labor participation rate multiplier	
Investment	invm*, Afr-Subsahar, Asia-SoCent	Investment rate multiplier	
Government transfers	govhhtrnwelm*,unskilled, non-OECD	Government welfare transfers multiplier	

Parameters that control international interventions			
Source/type	**Parameter**	**Definition**	**Comment**
High trade	protecm*, non-OECD	Protectionism multiplier	
Export promotion	xshift*, Afr-Subsahar, Asia-SoCent	Export shift/promotion parameter	
FDI flows	xfdistockm*, non-OECD (minus China) xfdiwgrm*	Foreign direct investment inward stocks multiplier; world FDI growth rate	
Portfolio flows	xportfoliom*, non-OECD xportwgrm*	Portfolio inward stocks multiplier; world portfolio investment growth rate	
Remittances	wmigrm*	Global migration multiplier	
Foreign aid	aiddon*, OECD	Aid donations as percent of GDP	
IFI Flows	xwbloanr*, ximfcreditr*	World Bank loan growth rate multiplier; IMF credit growth rate multiplier	
Technology	mfpadd*, non-OECD	Multifactor productivity addition	

1 Normally in IFs, "adjustment shifts" calculated in the first year are allowed to erode back to basic functional specifications over 50 to 100 years. For the analysis of this report, the country-specific poverty shifts were left intact over the forecast horizon.

2 Bourguignon (2003: 7) noted that a lognormal distribution is "a standard approximation of empirical distributions in the applied literature." He further decomposed the growth and distributional change effects in poverty reduction and explored the interaction between them.

3 The lognormal is not the only parameterization possible of the income distribution. Other forms include polynomial functions (used by Dikhanov 2005), a generalized quadratic model (Villasenor and Arnold 1989), and the Beta model (Kakwani 1980). Datt (1991) has derived formulations for computing the common aggregate poverty measures from multiple parameterizations of the Lorenz curve. In representing income distribution it is also possible to use nonparametric techniques, such as the Gaussian kernel density function (Sala-i-Martin 2002b).

4 Qu and Barney (2002) used the basic procedure for forecasting in the T21 model, and Kemp-Benedict, Heaps, and Raskin (2002) used it in POLESTAR for the computation of malnutrition.

5 Kornai (1971) analyzed the weaknesses of traditional equilibrium models. In addition to allowing much faster computation and representing some of the real world's actual disequilibrium, chasing equilibrium in a recursive structure avoids the artificial assumption that a time path consists of a series of comparative static solutions.

6 Some parameters work with the standard errors and others with the absolute gap between expected and computed values, depending largely on the preference of the empirical studies from which the parameters came (Hughes 2005 documents the sources of the parameters).

7 A correction factor automatically adjusts the sum of the computed contributions to economic growth so that the adjusted aggregate computed productivity performance matches apparent performance in multifactor productivity of recent years (growth minus the effects of change in labor and capital stock). That means that the model will, all else being equal, calculate growth rates in the forecasts that are comparable to growth rates in the past.

8 The availability only of value-added shares of the two types of labor, not sector-specific labor force sizes, was confirmed via e-mail on December 9, 2005, by Betina Dimaranan, who documents the labor data.