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Sizing Up the Issues

This study examines the impact of trade policy on global poverty, with an emphasis on how changes in policies in the United States and other industrial countries could help reduce poverty in developing countries. To gauge the problem, this chapter first reviews the extent of global poverty and its trends over time. A key concept, analyzed more formally in appendix 1B below, is the "elasticity of poverty" with respect to growth. The underlying notion is that ultimately it is economic growth that will be the major engine that lifts hundreds of millions out of poverty, and it is important to understand the influences that determine how responsive poverty reduction is to growth. The chapter then develops a concept of "poverty intensity of trade" to identify the potential antipoverty leverage of industrial-country trade policy vis-à-vis different groupings of countries and differing product categories. The final section sets the stage for the subsequent chapters by outlining the broad features of the relationship of growth to trade, a subject that is analyzed more fully in chapter 5.

The Extent and Location of Global Poverty

The World Bank has compiled increasingly comprehensive data on income distribution and poverty by country. This chapter uses this information, in combination with certain procedures to fill in the gaps in the data (see appendix 1A), to arrive at an enumeration of the poor by country, using the definition of $2 per day (1999 purchasing power parity, or

PPP) as the threshold for headcount poverty. Mapping global poverty in this way reveals several important patterns:

- About 2.9 billion people, or about half of the world's population, live below the international poverty line of $2 (PPP) per day.
- Only about 260 million people live in those developing countries that have *average* per capita income at or below this poverty line, so about 90 percent of global poverty reflects inequality *within* the other developing countries.
- An estimated 715 million of the world's poor are located in either the least developed countries (476 million poor), the heavily indebted poor countries (418 million), or sub-Saharan Africa (470 million), three largely overlapping country groupings.
- This in turn means that three-fourths of the world's poor live in countries considered too developed to qualify for any of the special regimes oriented toward benefiting countries in these groupings.
- Just two countries, India and China, account for 1.5 billion of the world's poor, or about half of the total. This number drops to 975 million if a cross-country poverty regression line is used to estimate the two countries' poverty rates, rather than applying the rates reported by the World Bank.
- Together with India and China, another 29 countries with at least 10 million people living in poverty cumulate to 90 percent of the global poor. Four of these have approximately 100 million poor people each (Indonesia, Pakistan, Nigeria, and Bangladesh).

The trend in global poverty is toward slow improvement in relative terms but stagnation in absolute numbers. The World Bank (2001, 21) calculates that the fraction of developing-country (including transition country) population in extreme poverty defined as $1 per day or less (1993 PPP) has fallen, but only slowly, from 28.3 percent in 1987 to 24.0 percent in 1998. This 15 percent reduction in the proportionate share of population in extreme poverty over a decade is encouraging. However, it was almost exactly offset by an 18.1 percent rise in global population during the same period.[1] As a result, the absolute number of people in extreme poverty remained virtually unchanged at 1.4 billion from 1987 to 1998. Although the World Bank does not report a comparable estimate for the trend in poverty under the $2 definition, a similar moderate decline in relative incidence and stagnation in absolute number seems likely.

1. World population may be calculated at 4.99 billion in 1987 and 5.89 billion in 1998 from UNDP (2001).

The two alternative threshold estimates provide a basis for a rough estimate of the first half of a global Lorenz curve (relating cumulative percent of income on the vertical axis to cumulative percent of population on the horizontal axis). Global GDP in 1999 (PPP) amounted to $40.1 trillion (calculated from table 1A.1 and corresponding World Bank estimates for industrial countries). With a corresponding aggregate population of 5.9 billion, global average per capita income in 1999 was $6,800 (1999 PPP).[2] The bottom one-fourth of global population receives $365 per year or less, and the next quartile less than $730. Even overstating their income by imputing all population in the first group at $365 and in the second at $730, the first quartile of global population receives only 1.4 percent of global income, and the next quartile, only 2.7 percent.[3] The upper half of the global income distribution thus receives 95.9 percent of global income, at an average level of $13,000 per capita or 24 times the average for the bottom half.

Poverty Location by Size Groups

On the basis of the full set of country estimates reported in appendix 1A, table 1.1 reports the poverty estimates for 31 large developing countries, each of which accounts for at least 10 million poor by the global definition ($2 per day threshold). In the top tier, India and China have about 860 million and 670 million poor respectively (but see the special estimates below for these two countries). In a second tier, four countries have approximately 100 million in poverty each (Indonesia, Pakistan, Nigeria, and Bangladesh). There then begins a spectrum of another 25 countries with the number of poor declining relatively smoothly from about 50 million in Ethiopia to 10 million in Peru. Together, the 31 countries account for 2.57 billion of the global poor, or 90 percent.

This array of large agglomerations of poor people includes instances of moderate population with very high poverty rates (e.g., Madagascar, with a population of 15 million and 13 million in poverty) as well as large populations with more modest poverty rates (e.g., Brazil, with a population of 168 million and 29 million in poverty). The latter combination means that several upper-middle-income economies account for somewhere between 10 and 40 million poor each, despite their relatively high per capita incomes. These include Mexico, Russia, Brazil, South Africa, Thailand, and Turkey (all with PPP per capita income of about $6,000 or more).

2. For this estimate, it is assumed that average per capita income is $1 per day for Afghanistan, North Korea, Myanmar, Somalia, and Sudan, and $2 per day for Cuba and Iraq; direct estimates are not available for these countries.

3. This assumes that 1.5 billion people receive $365 per year and another 1.5 billion $730 per year, with the remaining 3 billion receiving the rest.

Table 1.1 Countries with more than 10 million people living in poverty ($2 per day basis)

Country	**Population** (millions)	**Per capita income**[a] (dollars)	**Millions living in poverty**	**Poverty rate**[b] (percent)	**Gini coefficient**
India	997.5	2,230	859.9	86.2	0.378
China	1,253.6	3,550	673.2	53.7	0.403
Indonesia	207.0	2,660	136.8	66.1	0.365
Pakistan	134.8	1,860	114.2	84.7	0.312
Nigeria	123.9	770	112.5	90.8	0.506
Bangladesh	127.7	1,530	99.3	77.8	0.336
Ethiopia	62.8	620	48.0	76.4	0.400
Vietnam	77.5	1,860	41.4	53.4[c]	0.361
Mexico	96.6	8,070	41.0	42.5	0.537
Russia	146.2	6,990	36.7	25.1	0.487
Congo, Democratic Republic of	49.8	800	36.2	76.8[d]	n.a.
Egypt	62.7	3,460	33.0	52.7	0.289
Myanmar	45.0	n.a.	32.8	72.8[e]	
Philippines	74.3	3,990	29.2	39.4[c]	0.462
Brazil	168.0	6,840	29.2	17.4	0.600
Sudan	29.0	n.a.	21.1	72.8[e]	n.a.
Tanzania	32.9	500	19.7	59.7	0.382
Afghanistan	26.6	n.a.	19.3	72.8[e]	n.a.
Nepal	23.4	1,280	19.3	82.5	0.367
Kenya	29.4	1,010	18.3	62.3	0.445
Thailand	60.2	5,950	17.0	28.2	0.414
Iran	63.0	5,520	16.8	26.8[c]	0.380
Uganda	21.5	1,160	16.6	77.2	0.392
South Africa	42.1	8,710	15.1	35.8	0.593
Mozambique	17.3	810	13.6	78.4	0.396
Madagascar	15.1	790	13.4	88.8	0.460
Colombia	41.5	5,580	11.9	28.7	0.571
Ukraine	50.0	3,360	11.8	23.7	0.325
Turkey	64.4	6,440	11.6	18.0	0.415
Uzbekistan	24.4	2,230	11.6	47.4[c]	0.333
Peru	25.2	4,480	10.4	41.4	0.462

n.a. = not available

a. In 1999 purchasing power parity dollars per capita.
b. World Bank (2001) poverty rate estimate, unless otherwise noted.
c. Poverty rate calculated from actual Gini and per capita income.
d. Poverty rate calculated from regional Gini and per capita income.
e. Average least developed country poverty rate applied.

Source: World Development Indicators (World Bank 2001).

Table 1.2 reports the poverty estimates for four other groupings of developing countries arrayed by the absolute number of poor people in each. Fifteen countries each having 7 to 10 million poor together have 135 million in poverty. Twenty countries each having 3 to 7 million poor together have 96 million in poverty. And 22 countries each having 1 to 3 million poor together have 47 million in poverty. At the tail of the poverty-

Table 1.2 Economies with number of people living in poverty by range (millions)

Number in poverty	Economies	Total population	Total in poverty
More than 10	See table 1.1	4,193.2	2,570.9
7–10	Ghana, Mali, Burkina Faso, Malawi, Zambia, Cameroon, Niger, Venezuela, Sri Lanka, Angola, Côte d'Ivoire, Zimbabwe, Cambodia, Guatemala, Somalia, Rwanda	209.6	134.7
3–7	Ecuador, Senegal, Romania, Syria, Yemen, Chad, Malaysia, Burundi, Argentina, Haiti, Algeria, Benin, Honduras, Poland, Guinea, Sierra Leone, Azerbaijan, El Salvador, Bolivia, Chile	288.7	96.4
1–3	Central African Republic, Laos, Togo, Nicaragua, Turkmenistan, Eritrea, Papua New Guinea, Congo Republic, Georgia, Kyrgyzstan, Kazakhstan, Liberia, Morocco, Paraguay, Saudi Arabia, Armenia, Lesotho, Moldova, Dominican Republic, Albania, Mongolia, Tunisia	150.4	47.1
0.1–3	See note a	154.0	15.2
Industrial economies[b]		841.6	0
Excluded developing economies[c]		103.6	
Total		**5,941.0**	**2,864.4**

a. Guinea-Bissau, Botswana, Namibia, Costa Rica, South Korea, Gambia, Panama, Jamaica, Bulgaria, Croatia, Macedonia, Mauritania, Latvia, Bhutan, Hungary, Gabon, Jordan, Comoros, Trinidad and Tobago, Lithuania, Estonia, Solomon Islands, Uruguay, Czech Republic, Belarus, Portugal, Mauritius, Equatorial Guinea, Cape Verde, São Tomé and Príncipe, Slovak Republic, Vanuatu, Maldives, Kiribati, Samoa, New Zealand, and Slovenia.

b. Includes Hong Kong and Singapore.

c. Bosnia-Herzegovina, Cuba, Iraq, North Korea, Libya, Oman, Tajikistan, West Bank and Gaza, Yugoslavia (Serbia), Israel, United Arab Emirates, Lebanon, and Kuwait.

Source: World Development Indicators (World Bank 2001).

count distribution, 37 small countries account for an aggregate of 15 million poor.

Table 1.2 also imputes zero incidence of global-scale poverty (i.e., $2 per day or less) to the 840 million people living in industrial countries. Poverty as defined in these economies is at a far higher standard of living (e.g., in the United States the poverty line is set at household income of

$18,000 for a family of four, or $4,500 per capita). It might be considered that the homeless in industrial countries are good candidates for inclusion in the category of under $2 per day. However, the homeless population in these countries is relatively small (one recent estimate for the United States places the figure at 0.8 million; Burt et al. 2001). A more fundamental question, perhaps, is whether the PPP threshold of $2 per day used internationally is really comparable to $2 per day in an industrial country.

It may be that the PPP conversions that are designed to capture the full range of consumption are misleading for a subsistence basket of goods, because it is difficult to envision survival on $2 per day in the United States, for example.[4] In broad terms, nonetheless, the assumption of zero "world-scale" poverty within industrial countries seems appropriate, in part because of their public and charitable infrastructures available to assist the poorest.

Least Developed, Heavily Indebted Poor, and sub-Saharan African Countries

Despite the large share of the world's poor that is located in India, China, and a number of large intermediate-income countries, the most explicit international regimes oriented toward dealing with the poor tend to concentrate on subsets of the poorer countries that exclude many or even most of the global poor. Three regimes in particular have been prominent: the United Nations' list of the least developed countries (LDCs), the heavily indebted poor countries (HIPCs), and the sub-Saharan African countries (SSA). Thus, the European Union's Everything But Arms regime of duty-free imports has been made available to the LDCs; the US African Growth and Opportunity Act (AGOA) has provided preferential entry for SSA; and the Paris Club's forgiveness of bilateral debt and associated forgiveness of multilateral debt have been oriented toward the HIPCs.

Because of their importance for international policies toward poverty alleviation, these three country groupings are examined in table 1.3. The table's first panel reports population and this chapter's poverty estimate for the United Nations' list of LDCs (UNCTAD 2002b). This group of 49 countries accounts for approximately 644 million people, of which approximately 476 million are in poverty by the international ($2) definition.

The second panel of table 1.3 examines the corresponding population and poverty estimates for the HIPCs. Several important poverty concen-

4. A classic linear-programming problem is to identify the least-cost diet subject to nutritional constraints. One recent study using this approach places the minimum-cost diet in the United States at $650 annually for men and $535 for women in 1998 prices (Informs Online 2002). If valid, this would leave only 38 cents per person per day to pay for lodging and clothing after purchasing the minimum-cost diet, subject to a $2 per day ceiling.

Table 1.3 Poverty in least developed, heavily indebted poor, and sub-Saharan African countries

Country and group	Number of countries	Population (millions)	In poverty (millions)
I. Least developed countries (LDCs)[a]	**48**	**644.1**	**476.1**
Of which[b]			
Bangladesh		127.67	99.33
Ethiopia		62.78	47.97
Congo, Democratic Republic of		49.78	36.24
Myanmar		45.03	32.78
Sudan		28.99	21.11
Tanzania		32.92	19.65
Afghanistan		26.55	19.33
Nepal		23.38	19.29
Uganda		21.48	16.58
Mozambique		17.30	13.56
Madagascar		15.05	13.36
Mali		10.58	9.59
Burkina Faso		11.00	9.43
Malawi		10.79	9.18
Zambia		9.88	9.06
Niger		10.50	8.95
Angola		12.36	8.51
Cambodia		11.76	7.47
Somalia		9.71	7.07
Rwanda		8.31	7.03
Senegal		9.29	6.30
Yemen		17.05	6.05
Chad		7.49	5.66
Burundi		6.68	5.50
Haiti		7.80	5.16
Benin		6.11	4.49
Guinea		7.25	4.01
Sierra Leone		4.95	3.69
II. Heavily indebted poor countries (HIPCs)[c]	**41**	**615.5**	**418.5**
Of which, not included in LDCs[b]			
Vietnam		77.52	41.37
Kenya		29.41	18.32
Ghana		18.78	9.74
Cameroon		14.69	9.00
Niger		10.50	8.95
Angola		12.36	8.51
Côte d'Ivoire		15.55	7.68
Somalia		9.71	7.07
Honduras		6.32	4.35
Guinea		7.25	4.01
Bolivia		8.14	3.14
III. Sub-Saharan Africa (SSA)	**46**	**642.7**	**469.7**
Of which, not included in LDC or HIPC[b]			
Nigeria		123.90	112.50
South Africa		42.11	15.07
Zimbabwe		11.90	7.64
IV. Countries in LDCs, HIPCs, or SSA		**1,005.90**	**714.70**

a. Excludes Tuvalu.
b. Countries with 3 million or more living in poverty.
c. Excludes Guyana.

Source: World Bank (2001) and author's calculations.

trations are to be found in the HIPCs that are omitted from the LDC list, including Vietnam (41 million poor) and Kenya (18 million poor). Conversely, a number of LDCs with sizable poor populations are excluded from the HIPC grouping (in large part because their external borrowing in the past has been insufficient to place them under an unsustainable debt burden), including Afghanistan (19 million poor), Bangladesh (99 million poor), and Nepal (19 million poor). The total for the HIPC group is an aggregate population of 616 million, of which 418 million are in poverty.

The third panel of table 1.3 shows the corresponding aggregates for SSA, at an aggregate population of 643 million and with 470 million in poverty. Three large concentrations of poverty are in the SSA group but are in countries not designated as either an LDC or HIPC: Nigeria, with 112 million poor people; South Africa, 15 million; and Zimbabwe, 8 million.

Because the three groupings have considerable overlap (see table 1A.1), the combined total of the poor for all countries that are members of at least one of the three groupings is 715 million, almost exactly half of the simple sum of the poor for the three groupings individually (1.36 billion). This means, in turn, that the countries that belong to at least one of the three groupings for which the principal international regimes for poverty reduction tend to be oriented account for only 25 percent of the global total of those in poverty (715 million out of 2.86 billion).

India and China

Because of their overwhelming importance for the global total, the poverty estimates for India and China warrant a closer look. The estimates reported in table 1.1 apply the poverty rates reported by the World Bank (2001) to the country populations. Nonetheless, these poverty rates might be seen as on the high side, especially in China, whose per capita income stands at $3,550. Not only is this almost 5 times the $2 per day benchmark, but it is surprisingly close to the $4,500 per capita definition of poverty in the United States.

The World Bank reports the headcount fraction of population in poverty ($2) at 53.7 percent for China and 86.2 percent for India. As a gauge of the possible bias in these estimates, it is useful to apply the cross-country equation A.1 given in appendix 1A relating the poverty rate to per capita income and the Gini coefficient. This equation yields an estimated poverty rate of 39.2 percent for China and 48.4 percent for India. The Indian estimate especially is lower than the World Bank figure. For the two countries combined, substituting these equation-estimated poverty rates reduces the number of the poor from 1.53 billion to 975 million. This alternative estimate also places the number of the poor at almost identical levels for these two largest cases: at 492 million for China and 483 million for India. If these alternative estimates for China and India are applied, the global poverty total is reduced to 2.41 billion, or 16 percent below the main estimate of 2.86 billion.

Implications

The most sobering estimate here is that half of the world's population is in poverty using a $2 per day threshold. This is relatively well known from previous World Bank estimates (World Bank 2001, 3). A less obvious finding, however, is that only about one-fourth of the global poor are to be found in countries that are typically included in the special trade or aid regimes, the LDCs, HIPCs, and SSA.

Another little-known pattern is that by far the great majority (90 percent) of global poverty is to be found in countries whose *average* per capita income is above, and sometimes far above, the international poverty line. This fact indeed contains a hint of why the international special regimes tend to leave out the bulk of the poor: Because donor countries sense that the moderately well-to-do developing countries should be expected to address at least a considerable portion of their own internal problems of poverty rather than expecting the global community to do so.

A more positive reformulation of the same basic point would be that countries with per capita income above the lowest ranges include important cases where growth has been relatively strong, so they enjoy favorable prospects of reducing poverty over time on their own. This implicit perception, for example, would judge that China, whose annual per capita consumption growth has been recorded at 7 percent during the past two decades (World Bank 2001, 276), can deal relatively well on its own with its poor population (whether the figure is about 500 or 675 million).

An alternative prism that could help explain the international policy focus on only about one-fourth of the world's poor is a concern about an implicit "transfer leakage." In the sizable number of countries with intermediate per capita income levels alongside substantial poverty, the strong implication is that the bulk of income goes to the nonpoor. Consider Mexico. The World Bank estimate is that 42.5 percent of its population is in ($2) poverty (table 1.1). Even if all of them were just exactly at this threshold rather than being distributed at and below it, this would imply that whereas Mexico's poor have an average income of $730 annually, the other 57.5 percent of Mexicans enjoy an average income of $13,495, or 18.5 times that of the poor. Moreover, the upper 57.5 percent would account for at least 96 percent of total income.[5] Rich-country policymakers could thus reasonably be concerned that for each dollar of special benefit conveyed generally to Mexico, less than 10 cents would reach those who are

5. On the first calculation: $0.425 \times 730 + 0.575 \times 13{,}495 = 8{,}070$. The second calculation is $(0.575 \times 13{,}495)/8{,}070$. An alternative estimate is that the top 60 percent receive 89 percent of income (World Bank 2001, 283).

at or below the international poverty line. This leakage would typically be considerably lower for a low-income country that is, for example, in the HIPC group.[6] Even so, the leakage could remain relatively large.

Trade Patterns in Relation to Poverty

If industrial-country imports of goods produced by the poor are to serve as a vehicle for the alleviation of global poverty, these imports must come from countries where the poor are located. It is thus germane to examine the pattern relating industrial countries' imports to poverty incidence in their developing-country trading partners. Moreover, as just noted, a particular developing country may have a high incidence of poverty by the headcount measure but have a low share of its national income going to the poor, and hence a high degree of "leakage" to the nonpoor for any countrywide economic variable such as trade.

To explore the trade-poverty relationship, it is useful to measure what may heuristically be called the "poverty intensity of trade." If the entire population of a country is poor, then imports from this country may be said to have 100 percent poverty intensity. Conversely, imports from a nation with zero (world-scale) poverty may be said to have zero poverty intensity. The measure can be calculated first with reference simply to the headcount incidence of poverty. To take account of leakage to the nonpoor, however, a more meaningful measure can be calculated using instead the share of national income accruing to the poor in the supplying developing country. Both measures are only initial approximations meant to give a rough idea of whether the trade flows in question have a potential impact on the poor. A more complete analysis, for example, might seek to consider whether the poor are actually employed as factors of production in the goods traded.

Appendix table 1A.1 reports the percent of population in poverty (by the $2 PPP definition) for 127 developing countries. The table also includes an estimate of the percent of total national income accruing to the poor in each country.[7] These two alternative measures are then multiplied by the

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6. By way of illustration, for Uganda, a calculation along the lines of the Mexican example finds that the above-poverty-line population has an income averaging only 3.7 times that of the poor (vs. 18.5 in Mexico), and that the "leakage" share of total income accruing to the nonpoor amounts to 53 percent rather than 96 percent.

7. The estimate is an upper bound because it treats all of the poor as having the full $2 per day income. Thus, the income share of the poor, S_p, is estimated as $S_p = (730H)/y^*$, where H is the headcount fraction of population in poverty and y^* is the average PPP per capita income, subject to a ceiling of $S_p = 1.0$. This follows from the fact that total income of the poor is $NH \times 730$, where N is total population, while total income is Ny^*.

fraction of industrial countries' imports from developing countries as a group that comes from each of the individual developing countries, to obtain a weighted average "poverty intensity of imports" from developing countries for each of the major industrial-country groupings (table 1.4).[8]

Table 1.4 is first useful in highlighting the principal developing-country exporters. China, South Korea, Mexico, Russia, and Malaysia alone account for 46 percent of developing-country exports to world markets. In contrast, the aggregates for the three special-regime poor-country groupings are striking in revealing how little trade is actually involved. Thus, in 2000 total exports of the LDCs stood at a meager $35 billion, only 2.1 percent of the developing-country total. Of total imports from developing countries, those from LDCs accounted for only 1.8 percent for the United States and 2.4 percent for the European Union. Although the HIPC totals are somewhat larger and the SSA totals even larger, both remain small. Imports from SSA made up only 4.5 percent of total imports from developing countries into the United States, and 6.7 percent for the European Union.

Finally, the aggregates also reveal that only about 60 percent of developing-country exports goes to industrial-country markets, and the rest goes to developing countries.[9] The 40 percent developing-country market share for developing-country exports significantly exceeds these countries' share in global GDP, at market prices (not PPP), reflecting the typically higher shares of trade in GDP for developing countries than in especially the largest industrial countries (the United States, Japan, and the European Union as a unit).[10] This suggests that in the search for international trade as a vehicle for alleviating global poverty, it should be kept in mind that increased market opportunities in developing countries' own markets, especially those of middle-income economies, have a potentially important role to play.

8. The poverty-intensity indexes are thus, for each importing area: $P_h = 100 \times [(\Sigma_i M_i H_i)/M]$, for the headcount weighting, and $P_s = 100 \times [(\Sigma_i M_i S_{pi})/M]$, for the income-share weighting, where M_i is imports from country i and M is total imports from developing countries.

9. The IMF (2001a, 10) similarly reports that 57.8 percent of developing-county exports go to industrial-country markets. Note, however, that the substantially larger magnitude for "developing-country" exports in the DOTS total ($2.34 trillion in 2000, vs. $1.72 trillion in table 1.4) reflects the exclusion in the present study of Hong Kong, Singapore, and Taiwan from the "developing country" set, as well as such high-income oil-exporting economies as Kuwait and United Arab Emirates. Exports in 2000 of the three largest omitted exports amounted to $202 billion for Hong Kong, $138 billion for Singapore, and $135 billion for Taiwan; IMF (2001a) and Central Bank of China (Taiwan), www.cbc.gov.tw.

10. The South-South trade share is about the same as the 43 percent share of developing and transition economies in global purchasing parity GDP (IMF 2001b, 187). However, it is nominal market GDP, not PPP GDP, that matters for world trade markets.

Table 1.4 Imports from developing countries, 2000

Country or group	World	United States	Canada	Japan	European Union
Amount (billions of dollars)	1,717.7	434.0	18.5	143.5	416.6
Of which:					
Argentina	26.6	3.0	0.2	0.4	4.6
Brazil	56.1	13.4	0.6	2.5	15.0
China	249.2	52.2	3.2	41.7	38.2
Czech Republic	28.9	0.8	0.1	0.1	19.9
Hungary	28.1	1.5	0.0	0.2	21.1
India	44.2	10.0	0.8	2.4	10.5
Indonesia	62.1	8.5	0.4	14.4	8.7
Iran	27.5	0.2	0.1	4.9	7.1
South Korea	171.8	37.8	2.4	20.5	23.5
Malaysia	98.2	20.2	0.8	12.8	13.4
Mexico	166.5	147.7	3.4	0.9	5.6
Philippines	38.2	11.4	0.3	5.6	6.8
Poland	31.6	1.0	0.2	0.1	22.2
Russia	103.0	8.0	0.1	2.8	36.9
Saudi Arabia	75.2	13.0	0.6	12.9	13.2
Thailand	69.1	14.7	0.8	10.2	10.9
Turkey	27.8	3.1	0.2	0.1	14.5
Venezuela	34.0	17.3	0.4	0.2	1.6
Least developed countries (LDCs)	35.4	8.0	0.2	1.0	10.0
Heavily indebted poor countries (HIPCs)	57.1	10.3	0.4	3.4	15.5
Sub-Saharan Africa (SSA)	83.3	19.6	0.7	2.5	28.1
Total, relative to importing area					
GDP (percent)		4.4	2.7	3.1	5.0
Total imports[a] (percent)		35.1	7.7	38.0	40.9
Poverty intensity[b]					
Total					
Headcount weighting	32.21	38.11	35.98	35.74	26.07
Income-share weighting	7.77	8.16	8.41	7.82	6.88
Least developed countries					
Headcount weighting	66.2	69.2	73.8	64.6	69.7
Income-share weighting	49.0	44.1	49.7	58.0	50.3
Heavily indebted poor countries					
Headcount weighting	61.7	66.1	61.6	56.7	62.3
Income-share weighting	41.4	38.7	34.6	31.7	41.2
Sub-Saharan Africa					
Headcount weighting	62.1	70.3	66.8	50.7	57.5
Income-share weighting	43.8	55.8	49.2	27.8	36.9

a. For the European Union, this refers to imports from non-EU countries.
b. Maximum possible: 100 percent; see the text.

Sources: Country exports to market in question, as reported in IMF (2002a); this study, table 1A.1.

The final panel in table 1.4 indicates that, weighting by supplier-country headcount poverty shares, 32 percent of worldwide imports from developing countries come from the global poor. This poverty intensity is the highest for the United States, at 38 percent. It is approximately the same level for Canada and Japan, but lower at 26 percent for the European Union. The explanation for the EU figure is that a larger share of EU imports comes from Central and Eastern European economies, such as Russia, Poland, Hungary, and the Czech Republic, which tend to have relatively low poverty headcount ratios (25, 10, 4, and 2 percent, respectively).

The income-share poverty weighting, in contrast, places the percent of imports from the poor considerably lower: at about 8 percent for all the importing areas except the European Union, where it stands at about 7 percent. The difference between the poverty headcount weighting and the income-share weighting is the largest for the United States (38.1 percent vs. 8.2 percent), reflecting the large share of US imports coming from Mexico and China, in combination with the relatively low ratios of the poverty group's income share to headcount share in both of these key economies.

For the three poor-country regime groupings (LDCs, HIPCs, and SSA), the poverty-intensity estimates are considerably higher. The headcount-weighted measures show a range of 60 to 70 percent of imports from these countries as being from the poor, almost twice the rate for developing countries as a whole. The increase is even greater for poverty-intensity weighting by income shares of the poor. By this measure, about half of the imports from the three special regime groupings come from the poor, or about seven times the rate for developing countries as a whole.

This contrast to the large leakage to the nonpoor in imports from major developing-country exporters such as China, Mexico, and South Korea seems likely to be an important explanation for why the special-treatment regimes have been limited to these economies, even though they account for only about one-fourth of the world's poor. Namely, special opportunities granted to the LDCs, HIPCs, and SSA are much more heavily focused on the poor than would be the case for such access to developing countries generally. Of course, another and perhaps more important reason is that, as suggested by their extremely small shares in total trade, these economies' exports are not large enough to induce much disruption or reaction in industrial-country markets.

The differences among the four industrial-country groupings in import poverty intensity are somewhat greater for the three special-regime groupings than for developing countries overall. In particular, the income-share-weighted poverty intensity for US imports from SSA, at 56 percent, is considerably above the 37 percent for the European Union. The high US figure reflects especially the high share of Nigeria in US imports from SSA (48 percent, compared with 19 percent for the European Union), coupled with the high estimated income share of the poor in Nigeria (86 percent). This pattern in turn reflects lesser concentration in oil for EU imports from SSA, and greater imports from such economies as South Africa and Côte d'Ivoire where the income share of the poor is considerably lower.[11]

For developing countries as a whole, the estimates in table 1.4 suggest that there are not large differences among the major industrial-country groupings in the extent to which their imports are oriented toward the poor, especially when the measurement is on an income-share basis. A noteworthy nuance is that the low poverty incidence of Eastern Europe more than offsets the high poverty incidence of Africa in yielding a somewhat lower poverty intensity of imports into the European Union than into the other major industrial-country areas, but again this difference is not large when the income-share weights are applied.

Another basis for identifying differences among the industrial-country importers is to simply compare the magnitude of imports from developing countries relative to GDP or total imports of each major industrial-country area. These ratios are reported in the middle panel of table 1.4. Here the pattern is somewhat the reverse, because imports from developing countries are a moderately higher share of total imports (from nonmembers) for the European Union than for the United States (40.9 vs. 35.1 percent), and the same holds true for imports relative to GDP (5.0 and 4.4 percent of GDP, respectively). The comparisons are ambiguous for Japan, because at 38 percent, the developing-country share of total imports stands intermediate between the US and EU ratios, whereas at 3.1 percent imports from developing countries are considerably lower as a share of GDP. The latter thus reflects the relatively low overall ratio of imports to GDP for Japan, rather than a low share for developing countries in Japan's imports. Canada is the outlier of the industrial countries, because its imports from developing countries are far smaller relative to total imports (at 7.7 percent) than is true for the other industrial-country areas; and even relative to GDP, Canada's imports from developing countries are the lowest among the industrial-country areas. This likely reflects Canada's greater similarity to many developing countries in its role as a natural resource–exporting economy.

Finally, the poverty intensity of trade can also be examined with respect to product sectors, again measuring by the poverty characteristics of the supplying countries rather than the factor composition of production or other measures. Table 1.5 reports these estimates for US imports from developing countries in 2001. The estimates identify the top 23 product categories for these imports, using variously 2- and 3-digit Standard Inter-

11. Note, however, that the imputation method, whereby all the poor are attributed the threshold income of $730, compared with the relatively low per capita income in Nigeria, probably understates the income share of the nonpoor, because many of the poor could be receiving well below the $730 threshold.

Table 1.5 Poverty intensity of principal US imports from developing countries, 2001

Import category	Imports (billions of dollars)	Poverty intensity: By number	Poverty intensity: By income share
Petroleum (33)	64.7	39.13	17.47
Apparel (84)	49.8	47.16	12.38
Computers (752)	26.9	35.09	5.09
Telecommunications (764)	22.6	32.96	4.42
Motor vehicles (781)	21.9	29.37	2.64
Semiconductors (776)	15.5	26.18	3.75
Toys (894)	14.9	50.75	10.24
Footwear (85)	13.1	48.60	10.08
Office machinery (759)	11.5	36.70	5.92
Furniture (821)	10.7	46.17	8.14
Textiles (65)	8.7	47.74	12.28
Vehicle parts (784)	6.6	39.24	4.57
Electrical goods (773)	6.6	41.84	4.95
Televisions (761)	6.6	38.68	3.98
Iron and steel (67)	5.8	27.84	4.03
Radios (762)	5.8	42.74	6.86
Electrical appliances (772)	5.5	40.74	5.34
Pearls (667)	3.1	68.80	21.03
Copper (682)	2.3	31.62	3.95
Coffee (071)	1.4	41.33	9.76
Tobacco (12)	1.0	29.14	9.71
Cocoa (072)	0.6	49.22	16.80
Sugar (061)	0.6	35.30	7.96
Subtotal	306.2	39.81	9.60
All others	164.8	39.47	6.74
Total	**471.0**	**39.69**	**8.60**

Note: The number in parentheses following the import category is the Standard International Trade Classification category.

Source: Import values are from USITC (2002).

national Trade Classification (SITC) categories. These products account for 65 percent of total US imports from developing countries.

The table shows that the largest import value from these economies is in petroleum, at $65 billion. Next is apparel, at $50 billion. The next four categories reflect the dramatic change in import composition during the past several years, because these goods are far from the traditional stereotypes of products in which developing countries have a comparative advantage: computers, telecommunications goods, motor vehicles, and semiconductors, summing to $87 billion. The next two categories revert to more traditional developing-country specialties—toys and footwear. Close behind is another familiar category, textiles. Somewhat surprisingly, the classical developing-country commodity products do not appear in the ranking until the bottom of the list, where copper, coffee, tobacco, cocoa, and sugar are found to total only $6 billion.

The table then applies the headcount and income-share poverty measures by supplying country (from table 1A.1) to calculate the corresponding poverty-intensity estimates by product. The most poverty-intensive product is "pearls, precious and semiprecious stones" (SITC 667). These are heavily concentrated in imports from India (66 percent of US imports from developing countries) and South Africa (15 percent). Both countries have a high poverty headcount incidence, and India has a relatively high share of income going to the poor.

A more important surprise in the table is that the next most poverty-intensive good is also the import with the largest value: petroleum. This result reflects the fact that except for Saudi Arabia (which accounts for 19 percent of US oil imports from developing countries), the principal oil exporters have high poverty headcount incidence (Algeria, Colombia, Mexico, and Venezuela) and, in the case of Angola and Nigeria, relatively high poverty income shares.

The finding that oil is a relatively poverty-intensive product is perhaps counterintuitive and warrants certain caveats. The control of oil (and other natural-resource) rents may be more highly concentrated than the general distribution of income. In particular, unskilled labor is the main factor endowment of poor households, and unskilled labor will tend to have a smaller share in value added from oil than in agriculture and most manufacturing sectors. In some countries such as Nigeria, moreover, a high incidence of corruption may concentrate oil income, although in other countries such as Mexico and Venezuela the state ownership of oil probably tends to make the distribution of its income more in line with the general distributional incidence of public spending.

In principle, any special cooptation of oil income by the rich should already have been taken account of in the poverty share estimate. In practice, however, as noted above, this is an upper-bound estimate that assumes all of the poor receive a full $2 per day. The resulting potential overstatement of the share of the poor in national income could be particularly problematical in some of the oil-producing economies (e.g., Nigeria, where this estimation approach yields 86 percent as the share of the poor in national income). Despite these limitations, the relatively high poverty-intensity estimate for oil serves as a reminder that oil imports do tend to come disproportionately from poor countries.

The other product categories with relatively high poverty intensity are goods more intuitively expected: cocoa, apparel, textiles, toys, and footwear, all of which have a poverty-income-share intensity of 10 percent or above. Conversely, and as also would be expected, the high-technology complex of goods that bulks large in the dollar totals tends to have very low poverty intensity, in the range of 3 to 5 percent on the income-share measure. This reflects the characteristics of the principal suppliers. Thus, in

Table 1.6 Poverty intensity of principal developing-country exports to the world, 2000 (percent)

Export category	Exports (billions of dollars)	Poverty intensity: By number	Poverty intensity: By income share
Wheat (041)	2.17	15.68	1.73
Rice (042)	3.41	47.21	13.04
Maize (044)	2.58	32.44	6.22
Sugar (061)	4.34	31.40	7.45
Coffee (071)	9.43	44.05	15.47
Cocoa (072)	3.19	51.42	22.73
Cotton textile fibers (263)	4.01	50.09	22.82
Jute textile fibers (264)	0.06	74.76	35.59
Electrical appliances (772)	0.00	35.73	6.14
Pearls (667)	16.41	62.01	21.84
Copper (682)	14.97	25.94	5.74
Computers (752)	70.58	30.91	5.04
Office machinery (759)	48.31	33.84	5.68
Televisions (761)	25.18	34.71	5.34
Radios (762)	16.52	41.06	7.41
Telecommunications (764)	60.39	33.48	5.53
Electrical goods (773)	18.80	33.70	5.11
Semiconductors (776)	93.33	23.36	3.47
Motor vehicles (781)	45.71	21.56	2.18
Vehicle parts (784)	16.76	26.17	3.30
Furniture (821)	25.59	38.48	7.23
Toys (894)	36.81	51.02	10.52
Tobacco (12)	5.23	35.43	13.67
Oil seeds (22)	6.11	27.65	8.45
Petroleum (33)	289.33	32.30	13.63
Textiles (65)	61.00	41.01	10.66
Iron and steel (67)	52.04	25.04	4.25
Apparel (84)	144.10	43.80	11.00
Footwear (85)	32.53	46.27	10.49

Note: The number in parentheses following the export category is the Standard International Trade Classification category.

Source: Export values from United Nations (2002).

semiconductors, 29 percent of US imports from developing countries is from Malaysia, 23 percent from South Korea, 23 percent from the Philippines, and 9 percent from Mexico, all countries with low poverty income shares (although Mexico and the Philippines boost the headcount measure).

Table 1.6 reports the headcount and income-share poverty intensities by product category, weighting by developing-country exports to all markets. These are generally close to the corresponding estimates for US imports from developing countries.

There are two major implications of these poverty-intensity estimates. The first is that trade policy in industrial countries is likely to be most efficiently directed toward reducing global poverty when it is specifically tailored to encourage imports from poor countries. For poor countries that have already been identified in special international regimes (i.e., the

LDCs, HIPCs, SSA), about 50 percent of import value is associated with people who are poor at the global threshold of $2 per day, weighting by income shares of the poor (rather than their higher "headcount" shares). In contrast, for imports from all developing countries, this share is only about 8 percent, because the bulk of these imports is from middle-income countries where the income share of the poor is low even if the headcount incidence of poverty is not. This contrast suggests that whatever their past shortcomings, regimes of special trade access for poor countries warrant renewed consideration for enhancement as a means of addressing global poverty. These programs are reviewed in chapter 2.

At the same time, the considerably lower poverty intensity for imports from those middle-income and other developing countries that are not members of the three major low-income groupings should not be interpreted as implying that opening markets to their exports holds little scope for reducing poverty. On the contrary, it will be shown in chapters 4 and 5 that global trade liberalization could reduce global poverty substantially. Similarly, it should be kept in mind that three-fourths of the world's poor live in countries not included in the LDC, HIPC, or SSA groupings.

The second major area for policy implications concerns the product category estimates of poverty intensity. These provide a guide to the sectors in which changes in industrial-country protection could be most effective in alleviating (liberalization) or aggravating (heightened protection) global poverty. As expected, apparel, textiles, light manufactures such as toys and footwear, and some tropical products (cocoa) have a relatively high poverty intensity. About 10 to 20 percent of trade value is associated with the globally poor in these products, given the income shares of the poor in the countries of origin. A crucial and surprising poverty-intensive product is petroleum, which not only has a high intensity (17 percent on the income-share basis) but is also the largest product by value in industrial-country imports from developing countries ($65 billion).

One product serves to illustrate the relevance of taking product-sector poverty intensity into account in policy decisions. One of the high-profile issues at the September 2003 meeting of the World Trade Organization's trade ministers in Cancún, Mexico, was the request by several African countries for the elimination of US subsidies for cotton production (and interim compensation pending such elimination). As indicated in table 1.6, "cotton textile fibers" are one of the most poverty-intensive products exported by developing countries, at about 23 percent, weighting by the income share of the poor. There was thus a good case on the grounds of fighting global poverty for beginning the attack on farm subsidies with cotton.[12]

12. US negotiators instead suggested the integration of cotton into the textiles-apparel arrangements. As discussed in chapter 5, however, the Cancún talks broke down, primarily over the issue of agricultural subsidies and protection more generally and the question of extension of World Trade Organization rules to new areas (the "Singapore issues" concerning investment, competition, trade facilitation, and government procurement).

It is appropriate, nonetheless, to conclude this section on the "poverty intensity of trade" with the reminder that this concept is essentially indicative rather than rigorous. The concept could be fleshed out more fully with empirical estimates of the factor shares for factors of production involved in export products, by country and by sector, and/or with a more complete analysis of the actual shares of the poor in national incomes. A more detailed analysis could reduce the estimate of the poverty intensity of oil, for example, by capturing a disproportionate share of the rich in resource rents. Conversely, for some products (e.g., perhaps cocoa), a more accurate estimate might boost the measured poverty intensity. The main purpose of the concept, however, is merely to shed light on the potential for trade to affect global poverty directly. For this purpose, even the broad-brush calculations here would seem to provide a relatively reliable basis for refocusing attention on the approach of giving special trade opportunities to poor countries. It is partly on the basis of the concept of poverty intensity of trade that this study suggests a two-track policy strategy, with immediate free market access for imports from the "at-risk" poor countries, and phased multilateral free trade for all other countries (chapter 6).

Poverty, Growth, and Trade

The ultimate source of global poverty reduction is sustained economic growth. To complete this initial review of the principal issues involved in the trade-poverty relationship, it is thus important to highlight the basic interrelationships in, and analytical controversies surrounding, the trade-growth-poverty nexus.

Does Growth Reduce Poverty?

There is relatively widespread agreement that sustained economic growth in developing countries is essential to the reduction of global poverty. The World Bank (2001, 47, 54) has synthesized numerous household survey studies to arrive at the following general relationship: A 1 percent increase in real per capita income reduces the incidence of poverty by 2 percent. This "growth elasticity of poverty" is higher (in absolute terms) where the degree of income equality is greater, and lower where it is lower (with the central elasticity reaching about 3 where the Gini coefficient of concentration is as low as 0.2, and only about 1.5 where the Gini is as high as 0.6).[13]

13. The intuition on this point is that an equal income distribution means the households are tightly bunched, so more of them will pass over a given poverty threshold for a given percentage increase in income. (I am indebted to François Bourguignon for this perception.)

Growth might not lead to poverty alleviation if it were typically associated with an ever-increasing inequality of income. Although for a long time development economists feared that this was exactly the pattern for growth in the early stages of development, by the late 1990s the stylized fact had emerged that sustained growth has tended to be neutral with respect to the resulting distribution of income.[14] Thus, in their prominent compilation of data on income inequality, Deininger and Squire (1996, 566) found that "for the ninety-five growth spells for which we have information on income shares, we find no systematic link between growth and inequality, but we do find a strong positive relationship between growth and poverty reduction." Dollar and Kraay (2001a, 1) found that "the share of income accruing to the bottom quintile does not vary systematically with average income." As discussed below, however, subsequent research has suggested that although within-country distribution has tended to be stable on the scale of several decades, it showed a trend toward equalization in the first part of the postwar period, followed by a return toward greater inequality in the period 1980–2000.

The Paradox of Persistent Global Poverty

There does appear to be a major paradox to be explained, either by a renewed trend toward inequality or otherwise. The paradox is that *the main estimates of global poverty show a smaller decline during the 1990s than would be predicted by the growth-poverty relationship.* As discussed above, the central estimate of the elasticity of poverty incidence with respect to growth is –2. The decline in the World Bank's measure of the incidence of poverty in developing and transition economies (at the $1 per day threshold) is from 28.3 percent in 1987 to 24.0 percent in 1998. But this decline was too small to match the observed growth combined with the central poverty elasticity.

From 1990 to 2000, real gross domestic product in the low- and middle-income economies grew at an annual average rate of 3.6 percent, while their population grew at an average rate of 1.6 percent (World Bank 2002e, 233, 237). Real per capita income growth averaged 2.0 percent. With a poverty elasticity of 2, this pace would be expected to reduce the inci-

14. The well-known "Kuznets curve" postulated that income distribution first becomes more unequal and then reverts to greater equality as development proceeds (Kuznets 1955). The argument was that in the absence of a significant surplus, poor economies necessarily start from relatively equal distributions; that as urbanization and modern-sector development occur, the shift in the share of population and the economy to the urban sector increases the weight of the more unequal part of the economy; but that eventually incomes are high enough to facilitate political interventions to alleviate poverty (and increasing capital boosts the marginal product and thus pay of labor). Development experience, however, has shown that, especially in some of the Asian economies where early land reform helped equalize assets, sustained growth has not necessarily been accompanied by rising inequality.

dence of poverty by 4 percent a year. But at this pace, the poverty incidence fraction should have fallen by 35 percent, or from 28.3 to 18.4 percent (instead of 24.0 percent), during the 11-year period 1987–98.[15] So the incidence of severe global poverty fell less than half as much as should have been expected in the 1990s.[16]

This is the *time-series* paradox of persistent poverty. A further analysis suggests there is also a *cross-section* paradox, because most middle-income countries have more poverty than would be expected under the most common statistical form (i.e., lognormal) for income distribution, as developed below.

At least two possibilities could help explain the time-series paradox. First, perhaps the World Bank's estimates have a time-trend bias that increasingly overstates poverty. Second, perhaps the usual postwar constancy of within-country income concentration has changed into a trend toward rising inequality.

Misleading Data?

Bhalla (2002) has carried out a major empirical study concluding that the World Bank's poverty data have failed to capture the actual pace of poverty reduction. The core of his argument is that the World Bank accepts the average incomes reported in household surveys, but that this income has increasingly fallen below the average income implied by national accounts data. He does not have an explanation for this generalized pattern, but he is confident enough that the national accounts are right and the sample means are wrong to conclude that in fact the incidence of severe poverty in developing countries fell from his estimated 30 percent (vs. the World Bank's 28.3 percent) in 1987 to 13 percent in 2000 (vs. the World Bank's 24 percent) (Bhalla 2002, 3). If he is right, the time-series paradox disappears.

Attempting to resolve whether Bhalla or the World Bank is right, and more generally the extent to which sample survey data as opposed to national accounts data should be relied upon, would unduly detain the present study.[17] A few thoughts, however, are nonetheless worth mentioning.[18] On the one side, the seeming overstatement of estimated poverty in

15. That is, $28.3/(1.04)^{11} = 18.4$.

16. Or by only 43 percent: $(28.3 - 24.0)/(28.3 - 18.4) = 0.43$.

17. The principal author on the World Bank side of the debate, Martin Ravallion, has provided a detailed critique of the Bhalla method (Ravallion 2002). Bhalla (2003) has provided a rejoinder. The dispute turns on such arcane issues as whether or not Bhalla has sufficiently taken into account the 1993 change in the official Indian national accounts statistics raising consumption estimates (and resultingly reducing the ratio of the sample survey to national accounts).

18. This is in addition to the key points made by Deaton (2003), as discussed below.

India and China when compared with international patterns, as analyzed earlier in this chapter, is suggestive of important problems in the key data for global poverty, although it does not address the question of the trend bias.[19] Also on this side, there are certainly reasons why sample surveys might be expected to report a declining share of national accounts income over time. Thus, rising shares of national income spent by governments on education and health, for example, would not tend to show up in household surveys of income and consumption.[20] In addition, the practice of "top coding" income brackets in surveys, so that the highest-income families report only that they receive more than a given threshold (rather than the actual income level), means that an increasing share of income may go to households in the top bracket and that imputation of their income increasingly falls short of the actual total.[21]

On the other side of the debate, it is unclear whether Bhalla sufficiently addresses the likely concentration of sample income understatement in the higher income brackets. If not, his approach of using the sample survey distributions but applying them to the mean income levels from national accounts would tend to bias upward the income levels of the lower-income households, biasing downward measured poverty.

Deaton (2003) has examined this controversy, in part on the basis of data from some 550 surveys of industrial and developing countries during the period 1980–2000. His most striking finding is that the ratio of mean survey consumption to mean national accounts consumption systematically falls as income rises. The ratio actually exceeds unity in SSA, where nonmarket consumption is often captured less fully in national accounts than in surveys. For all countries, however, the average ratio of survey to national accounts consumption is 0.86 unweighted and 0.77 weighting by country population; and for the Organization for Economic Cooperation and Development (OECD), the ratio is only three-fourths. The gap is even wider for income, for which the ratio is only 60 percent, but for which there is no systematic pattern as income rises. In the United States, the trend in the consumption gap is pronounced; the ratio of the survey to national accounts fell from 80 percent in 1984 to 64 percent in 2001. For all non-OECD countries, population-weighted PPP consumption from surveys has grown at only half the rate reported in the Penn World Tables for national accounts.

19. Indeed, removing China decreases rather than increases the pace of poverty reduction (leaving it at a decline from 28.5 percent in 1987 to 26.2 percent in 1998; World Bank 2001, 23).

20. Note that this is not offset by simply excluding government consumption from household income in Bhalla's method, in which "household income has to be approximated by per capita GDP" (Bhalla 2002, 104–05).

21. I am indebted to Gary Burtless for these observations. Note, however, that top coding may not be a frequent practice in surveys for developing countries.

The UN Conference on Trade and Development (UNCTAD 2002a, 48) similarly shows that national accounts consumption data yield a higher incidence of poverty than survey consumption data at very low per capita income levels (below $500 PPP at 1985 prices) but a lower incidence of poverty than the survey data at higher income levels. In these data, which apparently combine time-series and cross-section information, a central regression curve relating poverty incidence to PPP per capita income places $1 per day poverty incidence at 80 percent for $300 PPP income using national accounts data but only at 50 percent using survey data. Conversely, at $900 PPP income, the national accounts place this poverty at 10 percent, while survey data place it at 33 percent.[22] UNCTAD prefers the national accounts basis, which yields a higher incidence of poverty for the LDCs than the levels normally reported on the basis of surveys.[23]

For his part, Deaton judges that "there can be no general presumption in favor of one or other of the surveys and the national accounts" (2003, 17).[24] He also judges that "it would be incorrect to apply inequality or distributional measures, which are derived from surveys which measure one thing, to means that are derived from the national accounts, which measure another" (p. 35), a critique that applies to Bhalla's method. In particular, national accounts include the imputed rental value of owned housing, as well as financial services that are indirectly imputed. Both of these are income-elastic and so constitute a larger fraction of the consumption of the rich than of the poor, so this would seem to be a specific source of bias that would overstate the income and consumption of the poor if means from national accounts were applied to survey income distributions.

Deaton's bottom line is that "the downward bias in survey measures of consumption almost certainly bias upward the World Bank's estimates [of poverty, such that] the rate of decline is probably downward biased. Yet there is essentially no choice but to use the surveys, because only the surveys provide direct measures of the living standards of the poor" (p. 37).

Overall, it would seem reasonable to judge that the World Bank estimates understate the pace of decline in global poverty, but it seems unlikely that they do so by as much as Bhalla in particular argues. Indeed, the simplest assumption about the nonreporting of consumption and income in surveys would seem to be along the following lines. Households at the poverty line and below report relatively accurately, because they

22. For $2 per day poverty, the crossover is at about $600 PPP per capita. At $1,350 per capita, e.g., national accounts place this poverty at 25 percent, whereas surveys place it at 45 percent.

23. Choice of the national accounts would seem, however, to provide a substantial overstatement of poverty at very low income levels because of the problem of failure to capture nonmarket consumption, as noted above.

24. One implication, which Deaton notes but does not emphasize, is that global economic growth may have been considerably slower than the national accounts data indicate.

have little to hide. Households above the poverty line have a greater incentive to understate (e.g., because of fear of taxation), and the degree of underreporting rises monotonically with income. Under these circumstances, the sample will unambiguously understate inequality.[25]

If this simple model of reporting is accurate, then Bhalla has it backwards: National accounts data should be used to obtain the missing income in surveys, and this missing income should be allocated to the nonpoor, especially the higher brackets, rather than using national accounts means and applying unchanged survey distributional data. This model also implies that true inequality has tended to rise, and that the constancy of survey-based inequality is misleading.

In sum, Bhalla has usefully alerted researchers to the possibility of a bias in the time trend of the World Bank poverty data. Deaton has provided additional evidence that suggests systematic decline in survey consumption relative to national accounts consumption as income rises. The implication is that at least some of the time-series paradox of persistent poverty may be attributable to misleading data. Nonetheless, and as implied by Deaton, on balance it seems likely that in making adjustments to the survey estimates, Bhalla has overstated the pace of decline in global poverty.

Rising Inequality?

Another explanation of the time-series paradox may be simply that within-country inequality increased during the 1990s when the World Bank data showed so little poverty reduction, such that a simple application of growth data to the usual poverty elasticity (which assumes a constant degree of inequality) would overstate expected poverty reduction. It

25. In contrast, where all households accurately report income but there is a higher incidence of absence from the sample by higher-income households (rising nonresponse), the sample measure of inequality need not be biased downward. Mistiaen and Ravallion (2003) show that if nonresponse rises monotonically with income, the sample Lorenz curve will cross the population Lorenz curve, making inequality comparisons ambiguous. (Nonetheless, empirically they find for the United States that nonresponse does rise monotonically with income, and that "correcting for selective compliance appreciably increases mean income and inequality" [p. 1].) Deaton (2003) shows that for the lognormal income distribution, under the restrictive assumption that, above a threshold income, the logarithm of the probability of nonresponse rises linearly with the logarithm of income, the sample has the same variance (and hence inequality) as the population but the sample mean is biased downward.

A stronger statement can be made about the Pareto distribution, which has the form: $N = Ay^{-b}$, where N is the number of households with income of y or greater. The Gini coefficient for this distribution is $G = 1/[2b - 1]$ (Cline 1972, 227). Because neither N nor y appears in the Gini coefficient, it can be said that this distribution is fractal: A sample from any portion of it will yield the same Gini coefficient as a sample from any other portion. So a monotonic rise of nonresponse with income would not bias the sample measure of the Gini if the distribution is Pareto.

does indeed appear that, in contrast to the earlier stylized fact of constant within-country distribution, more recent research has tended to identify a trend of rising inequality in the 1980s and 1990s. Cornia and Kiiski (2001, 1) find that, for 73 developing, industrial, and transition economies constituting four-fifths of world population, "over the past two decades inequality rose in two-thirds of these 73 countries . . . [in] a clear departure from . . . trends recorded since the end of World War II." The authors suggest, but do not test, the hypothesis that the upturn in inequality was associated with market-oriented "Washington Consensus" policies.[26]

New statistical tests using the World Institute for Development Economics Research (WIDER) database on inequality confirm these more recent findings, that there have been two subperiods of first declining and then rising within-country inequality. A simple ordinary-least-squares regression of the following form may be estimated:

$$G_{it} = a + bt + c_i D_i + dtD_{EE} \tag{1.1}$$

where G_{it} is the Gini coefficient for country i in year t; a is a constant; b is the overall coefficient relating the Gini coefficient to time; D_i is a separate dummy variable for each country; and D_{EE} is a dummy variable if the country is an Eastern European or former Soviet Union economy. If there is a trend toward rising within-country inequality, the regression coefficient b will be positive. The inclusion of an Eastern European dummy allows for divergence in these economies from the general trends, in view of the strong indications that the transition process was associated with a rise in inequality.

Table 1.7 reports the results of applying this regression equation to 526 observations on country-year Gini coefficients (expressed in percentage form), spanning the period 1950 through 2000 and including observations for 76 countries.[27] In the upper panel, the unweighted regression for the full period finds a small but statistically significant negative coefficient on time (where $t = 1$ for 1950, rising to 51 for 2000). Approximately the same coefficient is found for the period 1950–79. This result supports the proposition of stable or slightly declining inequality in this period.

In contrast, for the period 1980–2000, the coefficient of the Gini on time turns positive, and it is again statistically significant. In this period, each additional year is associated with a rise in the Gini coefficient of 0.118. For

26. Galbraith and Kum (2002) use United Nations Industrial Development Organization data on average wages in industry to estimate that there was a declining trend in within-country inequality in the 1960s and 1970s, followed by a rising trend in the 1980s and 1990s. However, it would seem questionable to place much weight on the industrial wage data, given the small share of industry in employment in most countries and the paucity of detail available from the two or three dozen industrial category averages available.

27. The data are from WIDER (2000).

Table 1.7 Regression results: Time trend of Gini coefficients

Period	Constant	Time	Eastern Europe dummy	Adjusted R^2	Number of observations
Unweighted					
1950–2000	39.4	–0.075 (–3.8)	0.316 (7.0)	0.86	526
1950–79	52.0	–0.076 (–1.6)	–0.069 (–0.5)	0.92	168
1980–2000	13.7	0.118 (2.0)	0.426 (5.7)	0.87	358
Weighted					
1950–2000	45.8	–0.013 (–11.9)	0.394 (53.5)	0.79	[126,609]
1950–79	31.5	–0.181 (–103.9)	–0.049 (–1.8)	0.94	[38,609]
1980–2000	19.7	0.467 (189.8)	0.266 (35.8)	0.83	[88,000]

Note: *t*-statistics are in parentheses. Individual country dummy variables are not shown.

example, during the 20 years, a country starting with a Gini coefficient of 40.0 (percent) would be expected to experience a rise to 42.36. The upper panel also confirms the impression that the transition process for socialist economies was unequalizing. In the period 1980–2000, these economies had a large positive coefficient on the time variable.[28] The regressions achieve a high degree of explanation (R^2), although likely primarily due to the country dummy variables, which capture the large and typically persistent differences among countries in inequality levels.

The lower panel of table 1.7 reports results for weighted regressions, in which each country's weight is proportional to its population and inversely proportional to its number of observations.[29] These population-weighted results find an even more dramatic reversal from equalizing trends through 1979 to unequalizing trends thereafter (the b coefficient is a larger negative value in the first period and a larger positive value in the second period than in the unweighted regressions). The coefficient for the period 1980–2000 implies a rise of a remarkable 9 points on the Gini coefficient over the 20-year span (e.g., from 40.0 to 49.3).[30]

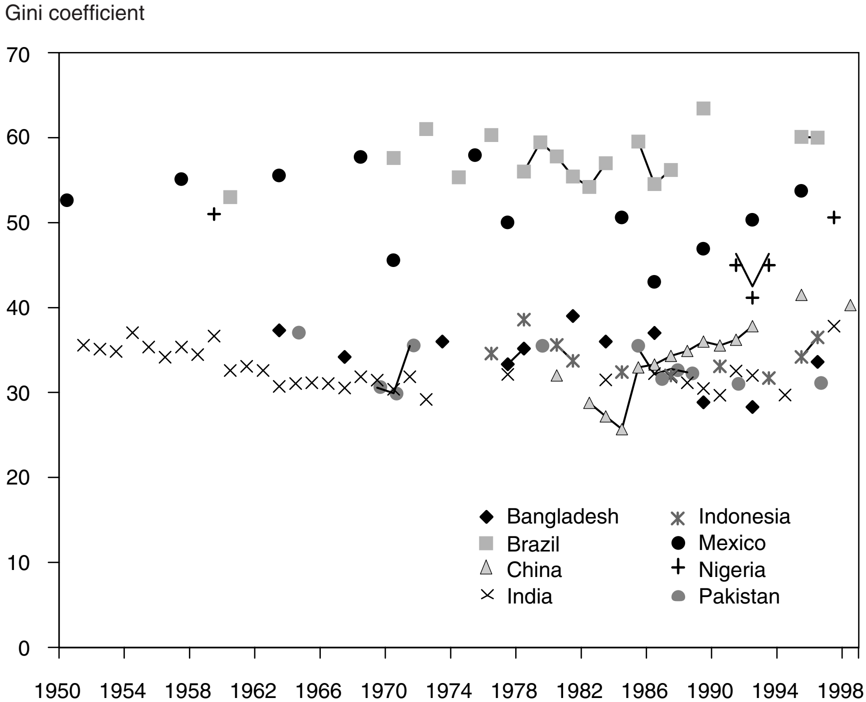
Figure 1.1 displays the time trends for the Gini coefficients of eight major developing countries with large poor populations. The figure shows

28. In the regression equation, an Eastern European economy has a time coefficient equal to $b + d$.

29. The latter weight adjusts for the fact that for some countries sample survey data are available for nearly every year, whereas for others only a few years are available; the absence of the weights would tend to overstate the experience of the country with more observations, which might be useful for some purposes but not for the purpose of a population-weighted result seeking overall representativeness.

30. Note that the *t*-statistics for the weighted regressions are not reliable indicators of statistical significance. Because each observation is multiplied by the ratio of the country's population to the population of the smallest country, there is an artificial ballooning of the "number" of observations (hence the brackets on the number of observations in this panel of the table), overstating the usual *t*-statistic measure.

Figure 1.1 Time path of the Gini coefficient for selected economies, 1950–98



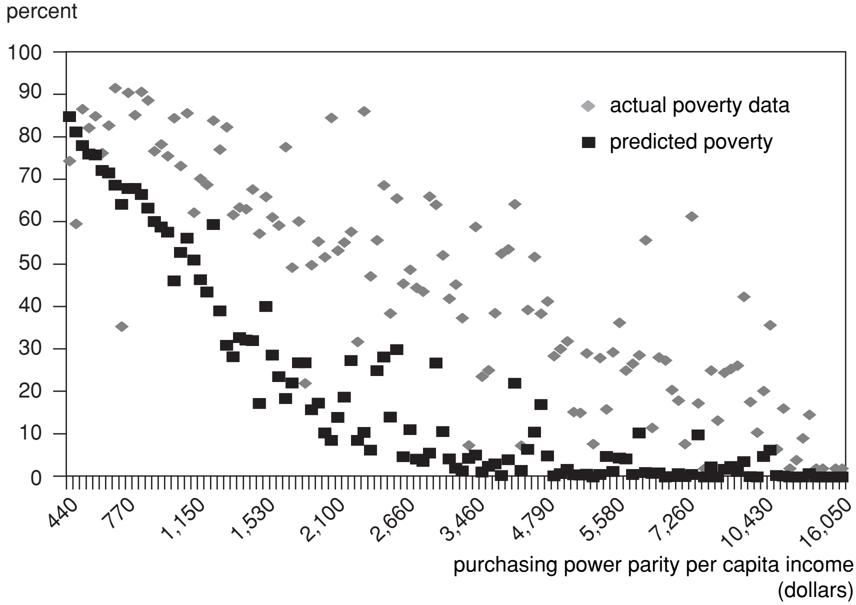
Source: WIDER (2000).

that each country's Gini tends to remain relatively close to its particular plateau. It also shows important increases in the Gini coefficient in recent years for a number of key economies, however, including Brazil, China, Indonesia, Mexico, and Nigeria. These countries bulk large enough in the global poverty totals for their rising inequality to have played a substantial role in explaining the time-series paradox of persistent poverty despite the achievement of global growth.

Cross-Section Paradox

Even if the time-series paradox can be partly or fully explained by trend bias in the measured poverty data and/or a trend of rising within-country inequality after 1980, there remains a strong cross-section paradox of persistent poverty as well. As developed in appendix 1B, the incidence of poverty in many middle-income countries seems to be persistently higher than one might expect from certain standard distributional analytics. In particular, if it is assumed that the underlying income distribution is normal in terms of the logarithm of income (the "lognormal" distribution),

Figure 1.2 Actual versus lognormal-predicted poverty (percent)



Source: Author's calculations.

the poverty incidence fraction can be predicted from the average per capita income, poverty threshold, and Gini coefficient (see appendix 1B). The predicted headcount poverty fraction will be lower as the average per capita income rises (for a constant global poverty threshold, in this case the $730 annual PPP income international line), but will be higher if the Gini coefficient is higher.

Figure 1.2 displays the actual and predicted poverty percentages for those countries in appendix table 1A.1 for which World Bank estimates are available on both poverty and Gini coefficients. In the figure, the actual poverty data are indicated by a diamond. In comparison, for each country, the corresponding predicted poverty percentage is shown by a square. As the figure shows, in the range of PPP per capita incomes of about $400 to $750, predicted poverty tends to be in the same range as actual poverty. The average ratio of predicted to actual is 1.01 in this range. Above this level of income, predicted poverty falls increasingly below actual poverty. The average ratios of predicted to actual are as follows. For PPP per capita of $750–$1,000, the average ratio is 0.71; $1,000–$2,000: 0.47; $2,000–$4,000: 0.21; $4,000–$6,000: 0.10; $6,000–$10,000: 0.08. The underprediction is acute for the countries with greater equality.[31]

31. Underprediction is substantial even at intermediate inequality. Thus, the high ratio of average per capita income to the poverty threshold in China (about fivefold), combined with

Table 1.8 Actual and predicted poverty rates for selected countries

Country	PPP per capita income (1990 dollars)	Gini coefficient (ratio)	Actual poverty incidence (percent)	Lognormal predicted poverty (percent)
Tanzania	500	0.38	59.7	81.3
Ethiopia	620	0.40	76.4	72.3
Nigeria	770	0.51	90.8	66.8
Senegal	1,400	0.41	67.8	31.8
India	2,230	0.38	86.2	10.7
China	3,550	0.40	53.7	3.9
Colombia	5,580	0.57	28.7	10.3
Brazil	6,840	0.60	17.4	9.9
Mexico	8,070	0.54	42.5	3.8

PPP = purchasing power parity

Sources: Tables 1A.1 and 1B.1 in the appendices.

To illustrate these points, table 1.8 reports actual and predicted poverty rates for selected economies. The illustrative cases in table 1.8 show the strong influence of the degree of inequality (Gini coefficient) in determining whether the lognormal distribution increasingly overpredicts poverty incidence as real per capita income rises. Brazil, which has the highest Gini (0.60), has the highest predicted relative to actual poverty incidence, but the predicted rate is still well below the actual. For Mexico and Colombia, which both have relatively high income concentration but not as high as that of Brazil, the predicted poverty level is considerably lower relative to the actual level. For Mexico, which has a substantially higher per capita income than Colombia, the underprediction is severe.

In short, the cross-section paradox of persistent poverty poses a caveat to the reliance on growth to reduce poverty. Poverty incidence remains stubbornly higher, as per capita income rises, than would be expected under at least one of the main theoretical distributional functions (the lognormal), except for countries with very high inequality. If this pattern is combined with the proposition that there is no systematic rise in inequality as per capita income rises (i.e., no Kuznets curve), in other words the stylized facts as of the late 1990s, an implication would seem to be that as

an intermediate inequality (Gini = 0.4), gives a lognormal-predicted poverty incidence of only 3.9 percent, far below the actual 53.7 percent. In contrast, for Brazil, where per capita income is even higher relative to the poverty threshold (ninefold), the high degree of inequality (Gini = 0.6) yields a predicted poverty rate of 9.9 percent, considerably closer to the actual 17.4 percent, suggesting high sensitivity to the Gini coefficient.

per capita income rises, the contribution of low-percentile components of the distribution to overall inequality rises while that of high-percentile components decreases, relative to the composition that would be expected from the lognormal distribution. In this way, overall inequality might not be rising, but that associated with the poverty group could be.[32] Some such effect would also seem likely to be required to harmonize the cross-section paradox even with the most recent stylized fact of rising inequality after 1980, simply because for most countries the most recent Gini coefficient levels are still far too low to generate lognormal-predicted poverty incidence anywhere near as high as actual poverty incidence (except for the lowest-income economies).

Population Growth Offset

Finally, there is one much more obvious reason why economic growth may reduce poverty only slowly over time: Even without any rise in within-country inequality, the *absolute number* of the poor globally can remain stubbornly high despite a falling poverty incidence because of a rise in total population and hence in the absolute number of the poor for any given headcount poverty ratio.

Suppose within-country distribution remained constant, the developing (and transition) economies grew at 2 percent per capita annually, and the poverty elasticity is 2. Suppose population growth continues at 1.6 percent. Then the absolute number of the poor would decline at only 2.4 percent a year, composed of a 4 percent annual decline from growth (2 percent $\times$ poverty elasticity of 2) minus the 1.6 percent population growth rate. At this rate—which is optimistic in light of the experience of at least 1980–2000—*it would take 29 years to cut the absolute number of people in extreme poverty in half*, or about twice as long as the 15-year target set forth in the United Nations Millennium Development Goals adopted in 2000 (United Nations 2002).[33] The influence of population growth in boosting the absolute number of the poor and hence slowing its reduction from economic growth is no great surprise, nor does it pose a paradox, but it is important to keep in mind in thinking realistically about the scope

32. Consider an example. The poor 60 percent of the population receive 20 percent of income, the middle-class 30 percent receive 25 percent, and the rich 10 percent receive 55 percent of income. The Gini coefficient is 0.55. After, say, two decades, per capita income doubles, but the poor 60 percent have no increase in income at all. Their share of income drops to 10 percent. Say the middle class share rises to 50 percent, and the rich share eases to 40 percent. The Gini coefficient remains unchanged at 0.55, but the composition of inequality has been redistributed, with a greater share of total inequality at the bottom of the distribution and a lesser share in the middle and upper classes. The second Lorenz curve lies below the first to the left (the poor 60 percent) and above it to the right (the top 40 percent).

33. That is, $1/(1.024)^{29} = 0.5$. For the United Nations Millennium Development Goals, see www.un.org/millenn:ungoals.

of the challenge involved in reducing by half the absolute number of those in severe poverty globally.

The Issue of Convergence

Despite the caveats, the central principle remains valid that the most certain way to reduce poverty is to achieve sustained growth. The question then becomes whether growth can be expected in the developing countries. This question in turn is related to the issue of whether there has been convergence or divergence in income levels between industrial and developing countries.

Much of the recent rhetoric in the policy and even research arenas seems to maintain that in economic terms the populations of poor countries have fallen farther behind the rich during the past several decades. Thus, in September 2000, World Bank president James D. Wolfensohn stated in a speech: "Something is wrong when the average income for the richest 20 countries is 37 times the average for the poorest 20—a gap that has more than doubled in the past 40 years." Similarly, the economist Paul Romer (1994) has developed "endogenous growth" theory to explain why diminishing returns to capital do not cause growth in industrial countries to slow down and why poor countries did not grow faster than rich countries in the decades after 1960.

The problem with this "nonconvergence" analysis is that it is built on an optical illusion that gives a misleading diagnosis. It focuses on "countries" instead of "people." It is true that many small countries have had slow growth, but it turns out that they are not representative of the experience of the majority of people who live in poor countries.

As shown in appendix 1C, when attention is focused on 75 countries with a population of 1 million or more, accounting for 83 percent of global population, it turns out that there was significant convergence in income levels in the period 1960–2000. The average real per capita growth rates for those countries that at the beginning of the period accounted for the bottom 60 percent of global population in PPP per capita income rankings amounted to 4 percent annually. In contrast, the corresponding rate for the initial fourth quintile was 2.34 percent, and for the top quintile, 2.23 percent. By 1999, the (population-weighted) per capita income of countries accounting for the poorest 60 percent in 1960 had doubled relative to that for the world's richest 20 percent in 1960.

The principal meaningful area of nonconvergence has been in the growth experience of sub-Saharan Africa. A statistical test in appendix 1C finds that per capita growth in this region in the past four decades has been 3 percent lower than in other developing regions, after taking account of the starting per capita income level. This result, however, suggests the need for special approaches toward this region, rather than blanket pessimism about developing countries' growth potential.

The more general pattern of convergence is not surprising, given the well-known growth successes of such economies as China, India, and South Korea, all of which were in the bottom 60 percent in 1960. What is surprising is that much of the convergence debate seems to have lost track of the forest by focusing on the individual trees, without considering the appropriate weight of each one. In short, the concern about nonconvergence is largely a red herring when it comes to its applicability to the question of whether global growth can or cannot be expected to help lift the world's poor out of poverty. Growth has been doing just that in a number of key countries that account for the bulk of the world's poor.

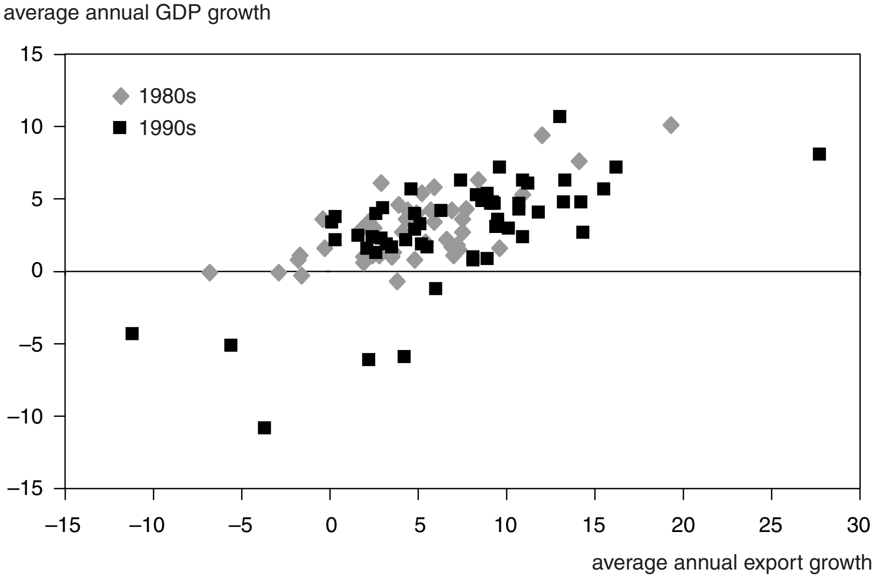
Does Trade Increase Growth?

If we accept that growth is instrumental to reducing poverty, and that despite concerns about nonconvergence the postwar growth record for the bulk of the population in developing countries has been relatively favorable, a central issue for this study then becomes: How can trade policy affect growth? This question in turn has two components: How does a developing country's own trade policy affect its growth? And how do industrial countries' trade policies affect developing countries' growth?

Much has been written on the first of these two questions. It is probably fair to say that there is a weak consensus that open trade policies, including low protection on imports, help foster growth. Although there is a recognition that industrialization in such economies as South Korea and Brazil developed with the aid of infant-industry protection, there is also a recognition that the highly inward-oriented development strategies of the Latin American economies in the 1960s and 1970s eventually led to serious inefficiencies and weak export bases, especially as these strategies entered their later phases of expansion into the production of capital goods. The alternative strategy of a strong emphasis on export expansion and participation in world markets in Korea is usually seen as having proved to be superior.

As discussed in chapter 5, there is nonetheless division among economists on the extent to which open strategies, and especially simple import liberalization, have contributed to growth. This has been the dominant conceptual framework in the international official organizations since at least the 1980s, premised in part on important empirical work on major country case studies (Little, Scitovsky, and Scott 1970; Balassa 1971; Krueger 1978). More recent work finding similarly that "trade is good for growth" includes in particular that by Edwards (1993) and Dollar and Kraay (2001b). This work, however, is not without critics. In particular, Rodriguez and Rodrik (2000) have questioned the results of the statistical work relating growth to open trade policies, on such grounds as the absence of good measures of the extent of protection. Similarly, Birdsall and

Figure 1.3 Average GDP and export growth, 1980s and 1990s



Source: World Bank, World Development Indicators CD-ROM, 2001.

Hamoudi (2002) have shown that the "increase in openness" variable used by Dollar and Kraay (2001b) is subject to bias from capturing primarily the erosion of world prices for raw materials exports rather than any failure to open trade.

There is far more consensus, in contrast, that open trade policies for *industrial* countries are favorable to the growth prospects of developing countries. There has been little if any empirical work on this issue, probably because it would be difficult to formulate a conceptual basis for arguing the contrary (whereas the infant-industry and other arguments can be marshaled to question the free trade position for developing countries' own policies). At the very least, the elimination of import barriers in industrial countries to exports from developing countries should raise the terms of trade for the latter. In practice, the more important dynamics probably have to do with the growing integration of production in developing countries with more open industrial-country markets, which is often coordinated by multinational firms. The explosion of Mexico's exports to the United States during the past decade thanks to free trade under the North American Free Trade Agreement is a prime example.

The evidence does show that higher export growth is associated with higher GDP growth. Thus, figure 1.3 displays, for 64 developing countries with populations over 10 million in 1999, the rate of real growth of GDP on the y-axis and that of exports of goods and services on the x-axis. The diamonds refer to the period 1980–90; the squares, to 1990–99. There is a clear positive relationship between export growth and GDP growth in both periods.[34] A simple (ordinary-least-squares) regression of GDP growth on export growth for this set of data yields the following results:

$$g_Y = \underset{(6.8)}{1.58} + \underset{(6.1)}{0.153}\, g_X \text{; Adj. } R^2 = 0.13 \tag{1.2}$$

where growth rates are in real annual average percentage terms, and the *t*-statistics are shown in parentheses. The export growth term is highly significant, and its coefficient indicates that each percentage point of additional export growth has been associated with a rise of 0.15 percentage point in GDP growth.

Even after taking account of such considerations as ambiguity in causality because exports are part of the national accounts identity for GDP, it seems highly likely that the inference would remain valid that faster export growth spurs economic growth in developing countries. One reason is that exports provide financing for imports of key intermediate inputs, capital goods, and technologies not available domestically. Another is that export orientation tends to impose the discipline of international competitiveness on domestic production.

It should be recognized, moreover, that a strong correlation between export growth and GDP growth implies, other things being equal, that lower protection in developing countries is likely to help rather than hinder growth. The reason is that high protection tends to act as a tax on exports, by creating a distorted incentive for producing for the domestic rather than the international market. Indeed, there is a formal proposition (the Lerner symmetry theorem; Lerner 1936) that maintains that an import tariff has an effect equivalent to an export tax.

In turn, through the successive removal of trade barriers, industrial countries should be able to help spur the exports of developing countries by increasing their export opportunities. Although it is difficult to quantify how much faster developing countries' exports can be expected to grow under alternative scenarios of industrial-country import liberalization, increasing market access would seem to be a central way in which industrial countries contribute to growth and hence poverty reduction in the developing world.

Conclusion

The task of reducing global poverty is enormous: Fully half of the world's population lives in poverty at the $2 per day threshold. Because trade is

34. The data are from the World Bank's World Development Indicators CD-ROM for 2001.

the most natural economic relationship between industrial and developing countries, it is important to consider how changes in trade policy could serve as a means by which industrial countries could help reduce global poverty.

Special market access for poor countries has so far been the main policy oriented toward this end. These regimes are potentially important and relatively efficient at reaching the poor. The reason is that the "poverty intensity of trade" with these countries is higher than that for imports from developing countries more generally, especially when considering the share of the poor in national income rather than in number of households. This chapter develops this concept and finds that whereas industrial-country imports from developing countries overall have a poverty intensity of 32 percent weighting by headcount and only 8 percent by income share, imports from the LDCs, HIPCs, and SSA have a poverty intensity of 60 to 70 percent on a headcount basis and about 50 percent on an income-share basis. Chapter 2 examines the experience with special-access regimes.

The poverty-intensity concept can also be used to highlight the products most important for reducing poverty. These include the well-known cases of apparel and textiles, toys, and footwear; and certain agricultural goods (e.g., cocoa and cotton); but also less immediately obvious products such as precious stones and, arguably, the key case of petroleum (where the large weight of such suppliers as Nigeria, Angola, Algeria, and Venezuela means relatively high poverty intensity). By implication, high protection on poverty-intensive products is more onerous for global poverty than that on other goods such as semiconductors and motor vehicles.

Although the poverty-intensity focus suggests that trade and other general economic instruments may reach the global poor more efficiently if they are concentrated on the LDCs, HIPCs, and SSA, it turns out that these recognized groupings account for only one-fourth of the global poor. Only two of the countries with poverty populations in excess of 100 million (Bangladesh and Nigeria) are in one of these groupings. Trade policy will thus have to provide new opportunities for a much wider range of developing countries if it is to help address the other three-fourths of the global poor. These include the two largest national concentrations of poverty: India (with 860 million poor) and China (670 million). Two other countries with more than 100 million poor people each (Indonesia and Pakistan) are also outside the normal poor-country groupings, as are numerous countries with 30 to 50 million poor people each, comprising middle-population poor countries (e.g., Ethiopia, Vietnam, and Egypt) as well as large-population middle-income countries with substantial inequality (e.g., Mexico, Russia, and Brazil). As developed in chapters 4 and 5, global trade liberalization could provide major inroads in reducing poverty in these countries as well. In short, the strategy for using trade policy to help reduce global poverty should involve both an "intensive" track of prompt free access for the special regime candidates and an "extensive" track of general multilateral liberalization for the other developing countries where in aggregate many more of the world's poor are to be found.

The analysis of this chapter suggests that growth reduces poverty, but that the pace of decline has been below what might have been expected, and higher poverty persists than might be expected in many middle-income countries. Appendix 1B sets forth the analytics relating poverty incidence to per capita income and the degree of inequality using the log-normal income distribution. Where income inequality is moderate, the "poverty elasticity" is 2 to 3 or higher, meaning that a 1 percent rise in per capita income reduces the number in poverty by 2 to 3 percent. Where income is highly unequally distributed, or where per capita income is very low, this elasticity is closer to unity.

Given the expected range for this elasticity, however, the pace of poverty reduction has been disappointing. World Bank estimates indicate that extreme poverty ($1 per day) fell only from 28 percent of global population in 1987 to 24 percent in 1998, whereas the application of a central poverty elasticity of 2 to the rise in per capita income should have reduced this incidence to about 18 percent during this period. An intense debate has developed between Bhalla (2002) and World Bank experts, in which Bhalla has argued that the survey data used by the World Bank have increasingly understated the incomes of the poor, as demonstrated by the shortfall of survey averages from those national accounts data. After considering the analysis and data brought to bear on this issue by Deaton (2003), this chapter suggests that although World Bank estimates may understate the pace of poverty reduction, Bhalla likely overstates it considerably.

Even so, the central judgment remains valid that growth should reduce poverty, even if the pace has been slower than might have been expected. The more recent data suggest that the discrepancy may partly be explained by rising within-country inequality in the past two decades, a new pattern following the previous "stylized fact" that within-country distributions have remained constant over long periods. New regression estimates in this chapter show that whereas there was virtually no statistical time trend for Gini coefficients in the period 1950–80, in the period 1980–2000 there was a statistically significant if moderate increase (and the size is much larger weighting by population).

Whether growth reduces poverty also depends on whether developing countries achieve growth. Appendix 1C examines the "convergence" controversy. It finds that the popular notion that there has been a failure of convergence between rich and poor countries in global growth experience is based on a statistical illusion because it fails to take account of the importance of each country in global population. When this is done, it is demonstrated that for the period 1960–2000, global growth showed convergence rather than divergence. Moreover, this was not a "China only" story. The list of major economies that started out in the bottom 80 percent of world population arrayed by per capita income in 1960 and achieved faster per capita growth than the top 20 percent includes not only China but also India, Indonesia, Pakistan, Thailand, Egypt, Sri Lanka, Korea, Turkey, Malaysia, Brazil, Hong Kong, Chile, and several other developing economies, as well as now-developed Portugal, Japan, Greece, and Spain.

If growth is ultimately the main source of reducing poverty, then the link to trade policy turns importantly on whether trade policy reforms can help achieve greater growth. Cross-country evidence shows a close correlation between export growth and GDP growth. Each 1 percentage point of additional export growth is associated with 0.15 percentage point of faster GDP growth, although more sophisticated econometric techniques would be required to take account of endogeneity (exports are part of GDP in national income accounting). The evidence over the past four decades is nonetheless suggestive enough to provide support for the idea that improved trade opportunities for developing countries resulting from global trade policy reform could make an important contribution to growth and hence poverty reduction over time. The trade-growth-poverty relationship is analyzed further, and quantitative estimates are summarized, in chapter 5.

Appendix 1A
Estimating Poverty Rates

The World Bank (2001) provides direct estimates for the percentage of the population of each country living under the \$2 per day poverty threshold, or the "headcount ratio" measure of poverty.[35] There are, however, numerous countries for which these estimates are not available. To obtain working estimates for these countries, it is possible to estimate a statistical regression of the poverty fraction on PPP per capita income and the Gini coefficient of income concentration using data on those countries for which poverty rates are available. A higher average income should reduce the fraction of the population below the international poverty line, whereas a higher income concentration should leave a larger fraction of the population in poverty than would otherwise be expected.

Figure 1A.1 shows the expected downward-sloping relationship for the percent of population in poverty (vertical axis) to the average PPP per capita income (horizontal axis). The concave relationship also suggests the logarithm of income, rather than absolute level, as the appropriate specification. As for the influence of income concentration, the expected effect would be for the slope of the poverty-income curve to be steeper for a more equal income distribution (lower Gini) and gentler for a less equal distribution (higher Gini). In effect, at very low average per capita income, the headcount poverty fraction will start out close to 100 percent, but otherwise the poverty-income curve will swivel upward or downward depending on the degree of concentration. The estimation form $\Phi_p = a + b \ln y^* + c\,(G \ln y^*)$ captures this relationship, where Φ_p is the percent of population below the poverty line, y^* is 1999 PPP per capita income, and G is the Gini coefficient (from 0 to 1, typically in the range 0.35–0.55). With b negative and c positive, the effect is to make the slope of the regression line equal to $-[b - cG]$, accomplishing the swivel of the curve associated with varying concentration.

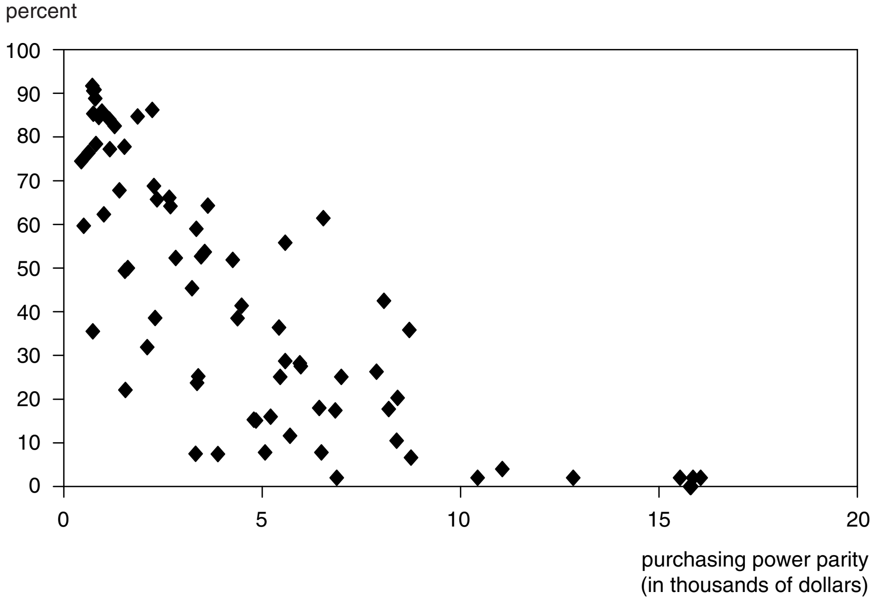
For a set of 69 countries with World Bank data available for both poverty incidence and the Gini coefficient (World Bank 2001, 280–83), an ordinary-least-squares regression yields (t-statistics in parentheses):

$$\underset{}{\Phi_p} = \underset{(15.1)}{245.0} - \underset{(-13.8)}{27.8} \ln y^* + \underset{(2.96)}{6.48}\,(G \ln y^*);\ \text{Adj. } R^2 = 0.74 \qquad \text{(A.1)}$$

For 14 countries with estimates available for y^* and G but not Φ_p, equation A.1 may be applied directly to estimate the percent of population below the international poverty line. For another 33 countries with y^*

35. This appendix uses the data available on the CD-ROM for *World Development Report 2001*.

Figure 1A.1 Poverty incidence and per capita income



Sources: World Bank (1982, 2001).

available but no available estimate of the Gini coefficient, applying the median Gini for the region in question also permits the use of equation A.1 to estimate the poverty headcount.[36] Finally, for 8 LDCs for which no estimate of per capita income is available, it is assumed that the poverty rate is equal to the average for 18 LDCs for which World Bank poverty estimates are available (72.8 percent). The resulting poverty estimates for 127 individual developing countries are reported in appendix table 1A.1. These countries have a total population of 5.0 billion and account for all but about 100 million of the population of developing countries (see table 1.2).

36. For 73 countries with Gini coefficients available from the World Bank, the regional median values are Africa, 0.408; Asia-Pacific, 0.367; Latin America, 0.503; Middle East, 0.38; and emerging Europe, 0.327.

Table 1A.1 Poverty in developing countries ($2 PPP per day definition)

Country	Population (millions)	Per capita income[a]	Number in poverty (millions)	Gini coefficient	Percent in poverty	Income share of poor	Least developed countries[c]	Heavily indebted poor countries[c]	Sub-Saharan Africa[c]
Afghanistan	26.55		19.33		72.8	1.000	1	0	0
Albania	3.38	3,240	1.26	0.327	37.5	0.084	0	0	0
Algeria	29.95	4,840	4.52	0.353	15.1	0.023	0	0	0
Angola	12.36	1,100	8.51	0.408	68.9	0.457	1	1	1
Argentina	36.58	11,940	5.37	0.503	14.7	0.009	0	0	0
Armenia	3.81	2,360	1.74	0.327	45.6	0.141	0	0	0
Azerbaijan	7.98	2,450	3.56	0.327	44.6	0.133	0	0	0
Bangladesh	127.67	1,530	99.33	0.336	77.8	0.371	1	0	0
Belarus	10.03	6,880	0.20	0.217	2.0	0.002	0	0	0
Benin	6.11	920	4.49	0.408	73.4	0.582	1	1	1
Bhutan	0.80	1,350	0.49	0.367	61.8	0.334	1	0	0
Bolivia	8.14	2,300	3.14	0.420	38.6	0.123	0	1	0
Botswana	1.59	6,540	0.98	0.408	61.4	0.069	0	0	1
Brazil	167.97	6,840	29.23	0.600	17.4	0.019	0	0	0
Bulgaria	8.21	5,070	0.64	0.283	7.8	0.011	0	0	0
Burkina Faso	11.00	960	9.43	0.482	85.8	0.652	1	1	1
Burundi	6.68	570	5.50	0.333	82.3	1.000	1	1	1
Cambodia	11.76	1,350	7.47	0.404	63.5	0.344	1	0	0
Cameroon	14.69	1,490	9.00	0.408	61.2	0.300	0	1	1
Cape Verde	0.44	4,680	0.13	0.367	30.2	0.047	1	0	1
Central African Republic	3.54	1,150	2.97	0.613	84.0	0.533	1	1	1
Chad	7.49	840	5.66	0.408	75.7	0.657	1	1	1
Chile	15.02	8,410	3.05	0.565	20.3	0.018	0	0	0
China	1,253.60	3,550	673.18	0.403	53.7	0.110	0	0	0
Colombia	41.54	5,580	11.92	0.571	28.7	0.038	0	0	0
Comoros	0.56	1,490	0.33	0.367	59.3	0.291	1	1	1
Congo, Democratic Republic of[b]	49.78	800	38.23	0.408	76.8	0.701	1	1	1
Congo, Republic of	2.86	540	2.48	0.408	86.8	1.000	0	1	1
Costa Rica	3.59	7,880	0.94	0.470	26.3	0.024	0	0	0
Côte d'Ivoire	15.55	1,540	7.68	0.367	49.4	0.234	0	1	1
Croatia	4.46	7,260	0.60	0.268	13.4	0.013	0	0	0
Czech Republic	10.28	12,840	0.21	0.254	2.0	0.001	0	0	0

Djibouti	0.66		0.48		72.8	1.000	1	0	1
Dominican Republic	8.40	5,210	1.34	0.487	16.0	0.022	0	0	0
Ecuador	12.41	2,820	6.49	0.437	52.3	0.135	0	0	0
Egypt, Arab Republic	62.65	3,460	33.02	0.289	52.7	0.111	0	0	0
El Salvador	6.15	4,260	3.19	0.523	51.9	0.089	0	0	0
Equatorial Guinea	0.45	4,770	0.14	0.408	32.0	0.049	1	0	1
Eritrea	3.99	1,040	2.81	0.408	70.3	0.493	1	0	1
Estonia	1.44	8,190	0.26	0.354	17.7	0.016	0	0	0
Ethiopia	62.78	620	47.97	0.400	76.4	0.900	1	1	1
Gabon	1.21	5,280	0.36	0.408	29.4	0.041	0	0	1
Gambia, The	1.25	1,550	0.75	0.408	60.3	0.284	1	1	1
Georgia	5.45	2,540	2.38	0.327	43.7	0.126	0	0	0
Ghana	18.78	1,850	9.74	0.327	51.9	0.205	0	1	1
Greece	10.54	15,800	0.00	0.327	0.0	0.000	0	0	0
Guatemala	11.09	3,630	7.13	0.596	64.3	0.129	0	0	0
Guinea	7.25	1,870	4.01	0.403	55.3	0.216	1	1	1
Guinea-Bissau	1.18	630	0.98	0.408	82.9	0.960	1	1	1
Haiti	7.80	1,470	5.16	0.503	66.1	0.328	1	0	0
Honduras	6.32	2,270	4.35	0.537	68.8	0.221	0	1	0
Hungary	10.07	11,050	0.40	0.308	4.0	0.003	0	0	0
India	997.52	2,230	859.86	0.378	86.2	0.282	0	0	0
Indonesia	207.02	2,660	136.84	0.365	66.1	0.181	0	0	0
Iran, Islamic Republic	62.98	5,520	16.85	0.380	26.8	0.035	0	0	0
Jamaica	2.60	3,390	0.65	0.364	25.2	0.054	0	0	0
Jordan	4.74	3,880	0.35	0.364	7.4	0.014	0	0	0
Kazakhstan	14.93	4,790	2.28	0.354	15.3	0.023	0	0	0
Kenya	29.41	1,010	18.32	0.445	62.3	0.450	0	1	1
Kiribati	0.09		0.07		72.8	1.000	1	0	0
Korea, Republic of	46.86	15,530	0.94	0.316	2.0	0.001	0	0	0
Kyrgyz Republic	4.86	2,420	2.38	0.405	48.9	0.147	0	0	0
Laos	5.10	1,430	2.92	0.304	57.4	0.293	1	1	0
Latvia	2.43	6,220	0.50	0.324	20.6	0.024	0	0	0
Lesotho	2.11	2,350	1.38	0.560	65.7	0.204	1	0	1
Liberia	3.13		2.28		72.8	1.000	1	1	1
Lithuania	3.70	6,490	0.29	0.324	7.8	0.009	0	0	0
Macedonia	2.02	4,590	0.58	0.327	28.5	0.045	0	0	0

(table continues next page)

Table 1A.1 Poverty in developing countries ($2 PPP per day definition) *(continued)*

Country	Population (millions)	Per capita income[a]	Number in poverty (millions)	Gini coefficient	Percent in poverty	Income share of poor	Least developed countries[c]	Heavily indebted poor countries[c]	Sub-Saharan Africa[c]
Madagascar	15.05	790	13.36	0.460	88.8	0.821	1	1	1
Malawi	10.79	570	9.18	0.400	85.1	1.000	1	1	1
Malaysia	22.71	7,640	5.59	0.485	24.6	0.024	0	0	0
Maldives	0.28	4,880	0.08	0.367	29.2	0.044	1	0	0
Mali	10.58	740	9.59	0.505	90.6	0.894	1	1	1
Mauritania	2.60	1,550	0.57	0.408	22.1	0.104	1	1	1
Mauritius	1.17	8,950	0.19	0.408	16.2	0.013	0	0	1
Mexico	96.59	8,070	41.05	0.537	42.5	0.038	0	0	0
Moldova	4.28	2,100	1.37	0.344	31.9	0.111	0	0	0
Mongolia	2.38	1,610	1.19	0.332	50.0	0.227	0	0	0
Morocco	28.24	3,320	2.12	0.395	7.5	0.016	0	0	0
Mozambique	17.30	810	13.56	0.396	78.4	0.707	1	1	1
Myanmar	45.03		32.78		72.8	1.000	1	1	0
Namibia	1.70	5,580	0.95	0.408	55.8	0.073	0	0	1
Nepal	23.38	1,280	19.29	0.367	82.5	0.471	1	0	0
Nicaragua	4.92	2,060	2.84	0.503	57.8	0.205	0	1	0
Niger	10.50	740	8.95	0.505	85.3	0.841	1	1	1
Nigeria	123.90	770	112.50	0.506	90.8	0.861	0	0	1
Pakistan	134.79	1,860	114.17	0.312	84.7	0.332	0	0	0
Panama	2.81	5,450	0.71	0.485	25.1	0.034	0	0	0
Papua New Guinea	4.70	2,260	2.63	0.509	55.8	0.180	0	0	0
Paraguay	5.36	4,380	2.06	0.591	38.5	0.064	0	0	0
Peru	25.23	4,480	10.45	0.462	41.4	0.067	0	0	0
Philippines	74.26	3,990	29.24	0.462	39.4	0.072	0	0	0
Poland	38.65	8,390	4.06	0.329	10.5	0.009	0	0	0
Portugal	9.99	15,860	0.20	0.356	2.0	0.001	0	0	0
Romania	22.46	5,970	6.18	0.282	27.5	0.034	0	0	0
Russian Federation	146.20	6,990	36.70	0.487	25.1	0.026	0	0	0
Rwanda	8.31	880	7.03	0.289	84.6	0.702	1	1	1

Samoa	0.17	5,090	0.05	0.367	28.1	0.040	1	0	0
São Tomé and Príncipe	0.15		0.11		72.8	1.000	1	1	1
Saudi Arabia	20.20	11,050	1.85	0.38	9.2	0.006	0	0	0
Senegal	9.29	1,400	6.30	0.413	67.8	0.354	1	1	1
Sierra Leone	4.95	440	3.69	0.629	74.5	1.000	1	1	1
Slovak Republic	5.40	10,430	0.11	0.195	2.0	0.001	0	0	0
Slovenia	1.99	16,050	0.04	0.268	2.0	0.001	0	0	0
Solomon Islands	0.44	1,730	0.24	0.367	55.5	0.234	1	0	0
Somalia	9.71		7.07		72.8	1.000	1	1	1
South Africa	42.11	8,710	15.07	0.593	35.8	0.030	0	0	1
Sri Lanka	18.99	3,230	8.62	0.344	45.4	0.103	0	0	0
Sudan	28.99		21.11		72.8	1.000	1	1	1
Syrian Arab Republic	15.71	3,450	6.07	0.380	38.7	0.082	0	0	0
Tanzania	32.92	500	19.65	0.382	59.7	0.872	1	1	1
Thailand	60.25	5,950	16.99	0.414	28.2	0.035	0	0	0
Togo	4.57	1,380	2.88	0.408	63.2	0.334	1	1	1
Trinidad and Tobago	1.29	7,690	0.33	0.503	25.5	0.024	0	0	0
Tunisia	9.46	5,700	1.10	0.402	11.6	0.015	0	0	0
Turkey	64.39	6,440	11.59	0.415	18.0	0.020	0	0	0
Turkmenistan	4.78	3,340	2.82	0.408	59.0	0.129	0	0	0
Uganda	21.48	1,160	16.58	0.392	77.2	0.486	1	1	1
Ukraine	49.95	3,360	11.84	0.325	23.7	0.051	0	0	0
Uruguay	3.31	8,750	0.22	0.423	6.6	0.006	0	0	0
Uzbekistan	24.41	2,230	11.56	0.333	47.4	0.155	0	0	0
Vanuatu	0.20	2,940	0.08	0.367	42.0	0.104	1	0	0
Venezuela	23.71	5,420	8.63	0.488	36.4	0.049	0	0	0
Vietnam	77.52	1,860	41.37	0.361	53.4	0.209	0	1	0
Yemen, Republic of	17.05	730	6.05	0.395	35.5	0.355	1	1	0
Zambia	9.88	720	9.06	0.498	91.7	0.930	1	1	1
Zimbabwe	11.90	2,690	7.64	0.568	64.2	0.174	0	0	1

a. 1999 purchasing power parity dollars (World Bank 2001).
b. Per capita income from UNDP (2001).
c. 1 indicates applicable, 0 not applicable.

Appendix 1B
Poverty Incidence and Elasticity under the Lognormal Distribution

A functional form that has been found to be representative of income distributions is the lognormal distribution.[37] In this form (see Aitchison and Brown 1963, 8), the natural logarithm of income has a normal distribution. The probability distribution function of income y is[38]

$$f(y) = \frac{1}{\sqrt{2\pi}\sigma y} e^{-\frac{(\ln y - \delta)^2}{2\sigma^2}} \tag{B.1}$$

where the total integral of equation B.1 is unity, e is the base of the natural logarithm, δ is the mean of $\ln y$, and σ is the standard deviation of the logarithm of y. To normalize, divide income by the mean of income to get $x = y/\mu$. Following Bourguignon (2002), the lognormal distribution of this relative income may be expressed as a standard normal distribution ψ with mean 0 and standard deviation of unity, as follows:

$$f(x) = \frac{1}{\sigma x} \psi\left(\frac{1}{\sigma} \ln x + \frac{\sigma}{2}\right). \tag{B.2}$$

Correspondingly, the cumulative density function, or cumulative probability that relative income is less than or equal to a given level x, is the integral of equation B.2 up to the given relative income level. Again, this may be expressed in terms of the cumulative distribution function of the standard normal, yielding

$$F(x) = \Pi\left(\frac{1}{\sigma} \ln x + \frac{\sigma}{2}\right) \tag{B.3}$$

The headcount fraction of population in poverty is the integral of the probability distribution function up to (or value of the cumulative density function at) the poverty income threshold y_p, or

$$w_p = F(x_p) \tag{B.4}$$

37. This appendix is adapted and extended from Cline (2002a).

38. As Aitchison and Brown (1963) begin with the cumulative distribution function, which is normal in $\ln y$ rather than y, and obtain the probability distribution function as the derivative of the cumulative function, the term y in the denominator of B.1 results from taking the derivative of the logarithm of y. This term is absent from the more familiar normal probability distribution of y rather than $\ln y$.

Equation B.4 provides a basis for estimating the incidence of headcount poverty if we are given the average per capita income (μ), the poverty threshold income (y_p), and the distribution parameter of the lognormal function, σ. From Bourguignon (2003), the latter is

$$\sigma = \sqrt{2}\left\{\Pi^{-1}\left(\frac{G+1}{2}\right)\right\} \tag{B.5}$$

where Π^{-1} is the inverse function of the cumulative density function, and G is the Gini coefficient for the distribution.[39] Equations B.3 through B.5 can then be used to calculate the headcount poverty fraction given the ratio of the poverty income threshold to the average income.

For its part, the elasticity of the poverty headcount with respect to distributionally neutral growth is given by the percent change in the headcount for a 1 percent change in mean income, or

$$\varepsilon_p^g = -\frac{dF(x_p)/d\mu}{F(x_p)/\mu} \tag{B.6}$$

By definition, the derivative of the cumulative density function $F(x)$ is the probability distribution function $f(x)$. By the chain rule,

$$\varepsilon_p^g = \frac{-f(x_p)[dx_p/d\mu]}{F(x_p)/\mu} \tag{B.7}$$

Using the transform to the standard normal, we have

$$\varepsilon_p^g = \frac{-\frac{1}{\sigma x_p}\psi\left(\frac{1}{\sigma}\ln x_p + \frac{\sigma}{2}\right)\left[-\frac{y_p}{\mu^2}\right]}{\Pi\left(\frac{1}{\sigma}\ln x_p + \frac{\sigma}{2}\right)/\mu} = \frac{\frac{1}{\sigma}\psi\left(\frac{1}{\sigma}\ln x_p + \frac{\sigma}{2}\right)}{\Pi\left(\frac{1}{\sigma}\ln x_p + \frac{\sigma}{2}\right)} \tag{B.8}$$

Using the "hazard ratio," defined as the ratio of the probability density function to the cumulative density function or $\lambda(\ldots) \equiv \psi(\ldots)/\Pi(\ldots)$, rewriting equation B.8 confirms Bourguignon's (2003) result that the poverty elasticity with respect to growth is

$$\varepsilon_p^g = \frac{1}{\sigma}\lambda\left(\frac{1}{\sigma}\ln\frac{y_p}{\mu} + \frac{\sigma}{2}\right) \tag{B.9}$$

39. Bourguignon (2003) states that $G = 2\Pi(\sigma/[2^{1/2}]) - 1$. Rearranging and taking the inverse function yields equation B.5.

Table 1B.1 Lognormal poverty elasticity[a] as a function of Gini coefficient and ratio of mean income to poverty threshold income

		μ/y_p					
Gini	σ	**10**	**5**	**3.33**	**2.5**	**2**	**1.67**
0.3	0.54	7.7	5.5	4.2	3.4	2.8	2.3
0.35	0.64	5.5	4.0	3.1	2.5	2.1	1.8
0.4	0.74	4.1	3.0	2.3	1.9	1.6	1.4
0.45	0.85	3.1	2.3	1.8	1.5	1.3	1.1
0.5	0.95	2.4	1.8	1.4	1.2	1.0	0.9
0.55	1.07	1.9	1.4	1.1	1.0	0.8	0.7
0.6	1.19	1.5	1.1	0.9	0.8	0.7	0.6

a. Absolute value.

Equation B.9 shows that in the lognormal distribution, the poverty elasticity is a function of the ratio of average income to poverty threshold income (μ/y_p) and the degree of inequality (which, as noted, is a function of the parameter σ). Table 1B.1 reports the corresponding calculated poverty elasticity from the lognormal distribution for alternative combinations of the ratio of mean income to poverty-threshold income and the inequality parameter σ, along with the corresponding Gini coefficient.

As shown in the table, for a given degree of inequality, a higher ratio of mean income to poverty threshold income leads to a higher poverty elasticity. Conversely, for a given mean/poverty income ratio, a higher degree of inequality leads to a lower poverty elasticity. When using a global threshold for poverty (e.g., $2 per day), this means that the elasticity will tend to be high in areas such as East Asia, where mean income is relatively high and inequality relatively low, but low in regions such as sub-Saharan Africa, where mean income is low, or Latin America, where inequality is high.

Appendix 1C
Convergence Versus Divergence in International Income Levels

It has become something of a stylized fact that income levels in poor countries have failed to converge toward those of industrial countries during the past several decades. However, the impressive growth of such key economies as China, South Korea, and even Brazil (with its 1970s "miracle" growth) suggests that in at least some important dimensions convergence has been taking place. This appendix finds that although nonconvergence holds if the frame of reference is the unweighted number of countries, progress toward convergence has indeed taken place for a majority of the global population. For many purposes, the latter concept would seem the more relevant.

The World Bank's annual *World Development Report* provides data on real GDP growth over decadal periods (World Bank 1982, 110–11; 2001, 294–95). It also provides PPP income levels (most recently, for 1999, in World Bank 2001, 274–75). Given population (from World Bank 2001, 274–75, for 1999; and from IMF 2002b for 1960), it is possible to calculate per capita growth rates and income levels to examine the course of convergence during the period 1960–99.

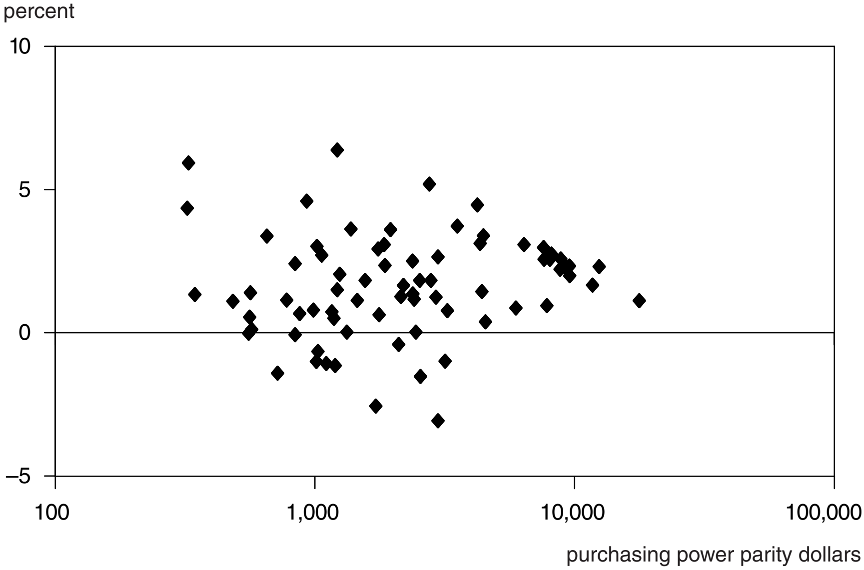
Unweighted Country Observations

Figure 1C.1 displays the average real per capita GDP growth rate for this period for 75 countries. This group includes all countries with population of 5 million or more in 1999 for which the full set of data (GDP growth, PPP income levels in 1999, and population) is available. The resulting coverage accounts for 82.8 percent of total world population in 1999.[40]

The horizontal axis shows the real PPP income per capita in 1960 imputed as follows. First, the country's own national accounts estimates of real GDP growth and the end-point population levels are used to determine the average annualized growth rate for real per capita income during this 39-year period. Second, the 1999 PPP per capita incomes are combined with these per capita growth rates to impute the 1960 level of PPP per capita income in 1999 dollar terms. The latter is displayed on the horizontal axis (logarithmic scale), while the average real per capita growth rate is shown on the vertical axis.

40. Countries excluded for lack of data include several large economies (former Soviet Union, Poland, Bangladesh, Saudi Arabia, Tanzania, and Vietnam) as well as countries under 5 million population in 1999.

Figure 1C.1 Per capita growth, 1960–99, and purchasing power parity per capita income, 1960



Sources: World Bank (1982, 2001).

This scatter diagram supports the notion that when a simple test is made across all countries without taking population size into account, there is an absence of convergence. For convergence to be present, there would need to be a downward-sloping relationship in the figure, with systematically higher per capita growth rates at lower initial real per capita income levels. Instead, the scatter is random (and a simple linear regression shows a positive but infinitesimal and statistically insignificant coefficient of per capita growth rate on income level).

Taking Population into Account

Once the actual countries behind the individual observations are taken into account, however, it turns out that there has been some significant convergence. Table 1C.1 examines the experience taking into account population size. It arrays the countries in ascending order of 1960 real per capita income (1999 PPP dollars per capita). It then separates the countries into three groups: those comprising the bottom 60 percent of total population in 1960, those in the next 20 percent, and those in the top 20 percent. Because of the large populations of China and India, the cutoff point for the bottom 60 percent of population is reached with the first 25 countries (cutoff: South Korea).[41] In contrast, the next quintile of 1960 population comprises 35 countries (cutoff: South Africa). The third and richest group comprises 15 countries, of which all are industrial economies except for Argentina (which just qualifies in the lower end of this income grouping in 1960).

The groupings in table 1C.1 are by base-period income position. There are important instances in which countries with rapid growth reach income levels that would classify them in higher groupings if arrayed by incomes at the end of the period. The most dramatic case is that of Japan, placed in the fourth quintile by the base-period ordering but with end-period per capita income right at the average for the fifth quintile. However, it is the base-period ordering that matters for the test of convergence, because the question is whether those countries starting out poor made relative progress.

The grouped data in table 1C.1 find that income levels did partially converge during the past four decades. This is evident, first, in the group average growth rates for real per capita income: 4 percent for the bottom 60 percent of world population, 2.34 percent for the quintile 60–80 percent, and 2.23 percent for the top 20 percent. (The individual country per capita growth rates are weighted by population to obtain the group weighted averages.) With higher growth rates in the poorest grouping, income levels must have been converging.[42]

This is borne out by comparing the ratios of group average per capita incomes at the beginning and end of the periods. Thus, at $567 in 1960, average per capita PPP income (in 1999 dollars) for the world's poorest 60 percent stood at 5.5 percent of the corresponding average income level for the top 20 percent. By 1999, in contrast, at $2,723, the average per capita income (PPP) had reached 10.9 percent of that for the top 20 percent

41. The actual cumulative population cutoffs for 1960 are 60.5 percent (at South Korea) and 80.6 percent (at South Africa).

42. I take it as self-evident that it is relative income levels, and hence higher per capita income growth rates for poorer countries, that define convergence, rather than absolute per capita income differences. This choice can be buttressed by, e.g., invoking logarithmic utility functions, but fundamentally reflects the intuition that, e.g., losing $100 in income is far more devastating to an urban slum dweller than to a millionaire. For its part, the absolute difference in per capita income will continue to diverge until the ratio of per capita income of rich to poor falls to no more than the ratio of per capita growth of poor to rich, at which point the absolute income levels will also begin to converge. Thus, e.g., the per capita growth differential between the poor 60 percent in table 1 and the upper 40 percent is about 2 percentage points. Considering that the median-country 1960 per capita income (in 1999 PPP dollars) was about $840 for the poorest 60 percent and $8,800 for the top 20 percent, the relative gap to be overcome is 10 to 1. If the 2-percentage-point growth differential were maintained, both the relative and absolute gap would be eliminated in about 150 years. Of this period, the absolute income gap would widen for the first 35 years before beginning to narrow.

Table 1C.1 Initial per capita income and per capita growth performance, 1960–99

Economy	y*60	y*99	gy*60–99	Pop60	Pop99
Pakistan	322	1,757	4.35	92.7	135
China	326	3,291	5.93	662.1	1,250
Malawi	345	581	1.34	3.4	11
Nigeria	484	744	1.10	51.6	124
Burundi	556	553	–0.01	2.9	7
Mali	561	693	0.54	4.1	11
Kenya	564	975	1.40	8.1	29
Ethiopia	572	599	0.12	20.7	63
Indonesia	653	2,439	3.38	92.7	207
Sierra Leone	718	414	–1.41	2.2	5
Nepal	780	1,219	1.15	9.2	23
Chad	839	816	–0.07	3.0	7
India	839	2,149	2.41	429.0	998
Uganda	874	1,136	0.67	7.6	21
Thailand	931	5,599	4.60	26.4	62
Togo	987	1,346	0.79	1.5	5
Zambia	1,013	686	–1.00	3.2	10
Egypt	1,019	3,303	3.02	25.9	62
Mozambique	1,027	797	–0.65	6.6	17
Sri Lanka	1,062	3,056	2.71	9.9	19
Niger	1,106	727	–1.08	3.1	10
Côte d'Ivoire	1,162	1,546	0.73	3.3	15
Cameroon	1,184	1,444	0.51	4.7	15
Madagascar	1,197	766	–1.15	5.4	15
South Korea	1,218	14,637	6.38	24.7	47
Bottom 60 percent, weighted average	**567**	**2,723**	**3.99**	**1,539.6**	**4,671.9**
Bolivia	1,219	2,193	1.50	3.8	8
Syria	1,246	2,761	2.04	4.6	16
Senegal	1,327	1,341	0.03	3.1	9
Romania	1,375	5,647	3.62	18.4	22
Papua New Guinea	1,456	2,263	1.13	1.9	5
Morocco	1,562	3,190	1.83	11.6	28
Angola	1,715	632	–2.56	4.8	12
Tunisia	1,752	5,478	2.92	4.2	9
Honduras	1,767	2,254	0.62	1.9	6
Turkey	1,847	6,126	3.07	27.5	64
Dominican Republic	1,862	4,653	2.35	3.0	8
Malaysia	1,954	7,963	3.60	8.1	23
Ghana	2,100	1,793	–0.41	6.8	19
Guatemala	2,146	3,517	1.27	3.8	11
Paraguay	2,196	4,193	1.66	1.8	5
Brazil	2,379	6,317	2.50	69.7	168
El Salvador	2,383	4,048	1.36	2.5	6
Philippines	2,412	3,815	1.18	27.4	77
Zimbabwe	2,452	2,470	0.02	3.8	12
Iran	2,531	5,163	1.83	21.5	63
Haiti	2,551	1,407	–1.53	3.6	8
Hong Kong	2,760	20,939	5.20	3.1	7
Colombia	2,794	5,709	1.83	15.4	42
Algeria	2,926	4,753	1.24	10.8	30
Congo, Democratic Republic of	2,977	897	–3.08	14.6	50

(table continues next page)

Table 1C.1 *(continued)*

Economy	y*60	y*99	gy*60–99	Pop60	Pop99
Chile	2,982	8,370	2.65	7.6	15
Nicaragua	3,172	2,154	–0.99	1.4	5
Peru	3,240	4,387	0.78	10.0	25
Portugal	3,538	15,147	3.73	8.8	10
Japan	4,220	24,041	4.46	94.1	127
Greece	4,329	14,595	3.12	8.3	11
Mexico	4,402	7,719	1.44	36.1	97
Spain	4,460	16,730	3.39	30.5	39
Venezuela	4,542	5,268	0.38	7.4	24
South Africa	5,944	8,318	0.86	17.1	42
Fourth quintile, weighted average	**3,145**	**8,053**	**2.34**	**499.0**	**1,103.0**
Finland	6,388	21,209	3.08	4.4	5
Denmark	7,604	24,280	2.98	4.6	5
Italy	7,627	20,751	2.57	49.6	58
Argentina	7,821	11,324	0.95	19.9	37
France	8,034	21,897	2.57	45.7	59
Austria	8,143	23,808	2.75	7.1	8
United Kingdom	8,790	20,883	2.22	52.4	59
Belgium	8,850	24,200	2.58	9.2	10
Netherlands	9,114	23,052	2.38	11.5	16
Australia	9,161	22,448	2.30	10.3	19
Canada	9,567	23,725	2.33	17.9	31
Sweden	9,588	20,824	1.99	7.5	9
Germany	11,728	22,404	1.66	55.4	82
United States	12,437	30,600	2.31	180.7	273
Switzerland	17,757	27,486	1.12	5.4	7
Top 20 percent, weighted average	**10,380**	**24,938**	**2.23**	**481.4**	**678.0**

y* = per capita purchasing power parity income in 1999 dollars

gy*60–99 = average annual growth rate of purchasing power parity per capita income, 1960–99

Pop60 = population, 1960 (millions)

Pop90 = population, 1990 (millions)

Sources: World Bank (1982, 2001); IMF (2002b).

grouping. Thus, *by 1999 the per capita income of countries accounting for the world's poorest 60 percent of population in 1960 had doubled relative to that for the countries accounting for the world's richest 20 percent in 1960.*

However, the intuition that convergence was dominated by some superperformers such as China and South Korea is borne out in table 1C.1 as well. Thus, of the 25 countries in the bottom 60 percent of world population, only four countries had average per capita income growth rates that exceeded the population-weighted group average: Pakistan, China, Thailand, and Korea. The lopsided nature of growth for the poor countries is underscored by the fact that seven countries in this grouping had negative per capita growth rates (Burundi, Sierra Leone, Chad, Zambia, Mozambique, Niger, and Madagascar). This subset also highlights the apparently accurate stylized fact that, as analyzed further below, it is the African countries that have lagged behind the most and been the most pronounced exceptions to convergence.

There has also been little convergence for the world's middle-income countries. The 35 countries in the 60–80 percent group of the distribution in 1960 had only minimally higher per capita growth rates (weighted average) than those in the top 20 percent (2.34 vs. 2.23 percent). Moreover, there was far more uniformity of growth performance among the top 20 percent grouping of industrial economies than among the 60–80 percent distributional group. In the latter (middle-income) grouping, strong performers such as Hong Kong, Japan (over the four decades as a whole), Malaysia, Turkey, Portugal, Spain, and Greece dominated the overall increase in group per capita income. In contrast, several major middle-income economies experienced per capita growth that was well under 1 percent annually (including South Africa, Venezuela, and Peru), or even negative growth (Angola, Ghana, Haiti, Congo, and Nicaragua).

Divergence: Sub-Saharan Africa

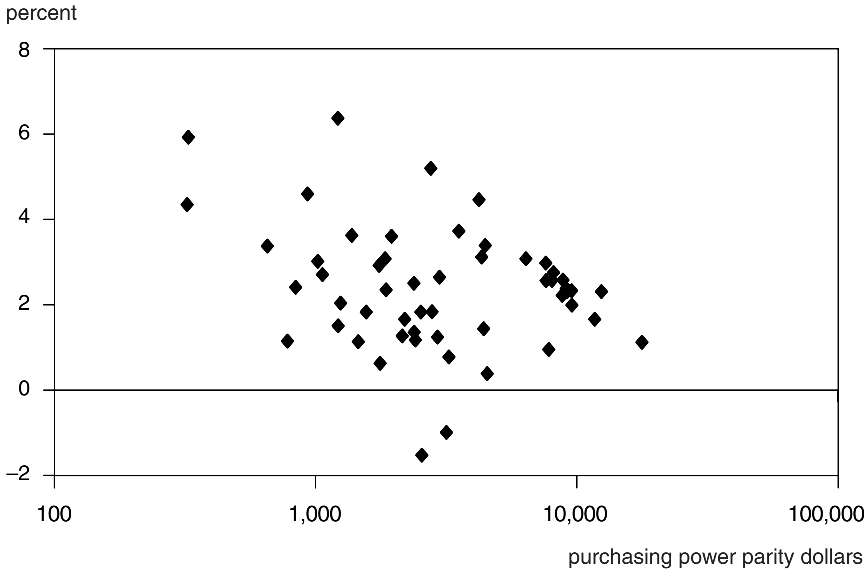
A casual inspection of table 1C.1 reveals that a number of countries with negative per capita growth in the period 1960–99 were in sub-Saharan Africa. There is the possibility, therefore, that even without taking population size into account, a simple relationship showing convergence can be found if the test is conducted excluding, or otherwise taking special account of, countries in this region. Figure 1C.2 does this by simply omitting country observations from SSA.

Figure 1C.2 shows a fairly clear pattern of lower growth per capita for countries that started the period with higher per capita incomes; in other words, convergence even before weighting for population. A statistical test using ordinary least squares confirms this result by isolating the influence of SSA using a dummy variable. Thus:

$$g_y = \underset{(4.3)}{6.23} - \underset{(-2.68)}{0.484} \ln(y) - \underset{(-7.84)}{3.01}D; \text{ adj. } R^2 = 0.45 \tag{C.1}$$

where g_y is average per capita growth in 1960–99, $\ln(y)$ is the natural logarithm of 1960 per capita income (PPP in 1999 dollars, as discussed above), D is a dummy variable with value 1 if the country is in SSA and 0 otherwise, and the t-statistic is reported in parentheses. This result shows a statistically significant negative relationship between per capita growth and the starting per capita income level. In other words, there is statistical confirmation of the convergence hypothesis even without applying population weights, so long as the experience of SSA economies is specially taken into account.

Figure 1C.2 Growth performance, excluding sub-Saharan Africa



Source: World Bank (1982, 2001).

In particular, from equation C.1 a country with a per capita income of $400 in 1960 (at 1999 PPP) would have typically grown at an average per capita rate of 3.33 percent during the next four decades, whereas a country with a per capita income of $10,000 would have grown at an average per capita rate of only 1.77 percent. In contrast, a typical SSA country with the same starting per capita income of $400 would have grown almost none at all (0.02 percent annually per capita).

It may be noted that the examples just given yield a lower growth rate for the poorest countries than suggested by the results in table 1C.1, which shows average growth of per capita income at 3.99 percent for the initially poorest 60 percent of world population total. The higher rate in the table reflects the other key influence: Taking population size into account further intensifies the convergence relationship because of the greater relative importance of China in particular and also Pakistan and South Korea, all three of which grew at rates considerably faster than the weighted poor-group average.

Accounting for Both Population Size and sub-Saharan Africa

Finally, the same regression test as presented in equation C.1 may be conducted using frequency weights that are proportional to country population. Thus, whereas Togo had a population of 1.4 million in 1960, China had a population of 662 million, so in the frequency-weighted test Togo is treated as one observation but China as 662/1.4 = 472 observations. This method balloons the "sample" size and hence the observed t-statistics, but the statistical significance of the convergence relationship has already been demonstrated without the weighting in equation C.1, and the focus of attention is now the change in the steepness of the slope relating per capita growth to starting income level. The weighted regression results are

$$g_y = 10.1 - 0.901 \ln(y) - 3.75D; \text{ adj. } R^2 = 0.597 \qquad \text{(C.2)}$$
$$(62.3) \quad (-40.5) \quad (-32.9)$$

where all variables are as before.

In the weighted regression results, the large weight of China (26.6 percent of the total sample by population) combined with its high per capita growth (5.9 percent annually) causes a steeper relationship of per capita growth to the logarithm of income level, with the constant term rising to 10 percent and the coefficient on the logarithm of per capita income growing from –0.48 in the unweighted test to almost twice as large, –0.9, in the weighted results. The downward shift for SSA from the overall relationship is somewhat larger in this test (3.75 percentage points below the general growth line, versus 3.01 percentage points in the unweighted results).

Conclusion

These results challenge the increasingly common view that the economic development record has been one of nonconvergence or even divergence between poor and rich countries. This impression may have arisen by a tendency to focus on the trees rather than the forest. Although it is true that if each country is treated as a single observation regardless of size, there is no relationship between per capita growth and the starting level of per capita income, once population size is taken into account, there is indeed a relationship of convergence. The countries accounting for the poorest 60 percent of global population in 1960 grew about twice as fast per capita in the period 1960–99 as the countries in the top 40 percent of global population. The finding of convergence is strengthened and verified statistically once the special experience of SSA is isolated and attention is focused on all other countries. Once the combined influences of population weighting and the special treatment of SSA are taken into account, the proconvergence finding is strengthened further.

Moreover, it is incorrect to characterize the growth experience as having shown convergence by "only China," as is sometimes suggested. Instead, there is a relatively long list of economies in the bottom 80 percent of global population in 1960 that achieved more rapid per capita growth during the next four decades than the average for the economies with the top 20 percent of population. This list includes (in order, from table 1C.1) Pakistan, China, Indonesia, India, Thailand, Egypt, Sri Lanka, South Korea, Romania, Tunisia, Turkey, the Dominican Republic, Malaysia, Brazil, Hong Kong, Chile, Portugal, Japan, Greece, and Spain.

The encouraging message in these results is that the development experience is far more successful at generating catch-up growth for the world's poor than much of the current international dialogue seems to recognize. The discouraging part of the findings, however, is the confirmation of another stylized fact: that SSA has been falling further and further behind. The statistical tests here suggest that with per capita growth about 3 percentage points below what has been the experience elsewhere over the past four decades, SSA has not even achieved nonconvergence (let alone convergence) but instead has followed a divergent growth path of falling relative income. An implication of these findings would seem to be that it is in Africa-specific causes and remedies (e.g., in the area of governance) that the specific problem of SSA's divergence must be addressed, rather than in global influences such as the international trade and monetary regimes.