Institutions and Economic Outcomes: A Dominance-Based Analysis*

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Abstract

An important issue in both welfare and development economics is the interaction between institutions and economic outcomes. While welfarists are typically concerned with how these variables contribute to overall wellbeing, empirical assessments of their joint contribution are limited. Development economists, on the other hand, have focused extensively on whether institutions cause or are caused by growth yet the relevant literature is still rife with debate. In this paper, we use a notion of distributional dominance to tackle both the measurement of multivariate welfare and the evaluation of inter-temporal dependence without hindrance from the mix of discrete (political) and continuous (economic) variables in our data set. On the causality front, our results support the view that institutions promote growth more than growth promotes institutions. On the welfare front, we find that economic growth had a positive impact from 1960 to 2000 but declines in institutional quality over the earlier part of this period were sufficient to produce a decline in overall wellbeing until the mid-1970s. Subsequent improvements in institutions then reversed the trend and, ultimately, wellbeing in 2000 was higher than that in 1960.

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1 Introduction

The interaction between institutions (polity) and economic outcomes is a key issue in both welfare and development economics. While welfarists are concerned with how these variables contribute to overall wellbeing, development economists have taken a more inter-temporal approach and focused on issues of causality.[1] Neither of these questions, however, has been fully settled. On the welfare front, it is generally agreed that polity and growth jointly promote wellbeing yet empirical assessments of the effects are limited. On the causality front, the problem is almost reversed. Theory suggests that causality can run in both directions and, despite much empirical work to disentangle these channels, a consensus has not emerged. In this paper, we analyze both multivariate welfare and inter-temporal dependence using a notion of distributional dominance. Our approach provides a powerful tool for addressing the issues discussed above, especially when the data set contains discrete (polity) and continuous (growth) variables.

While our reason for studying welfare is to fill a gap in the literature, our reason for studying dependence is to tackle a long-standing debate using new techniques. As such, it will be useful to review some of the scholarship that underlies this debate. On one hand, prolonged economic failure may compel agents to demand better institutions and any growth that makes them richer or more educated may also provide extra bargaining power to make these demands credibly. On the other hand though, better institutions (for example, property rights, political freedoms, and government accountability) may provide better investment incentives and thus encourage economic activity.[2] A key empirical study that finds causality from institutions to economic outcomes is Acemoglu et al (2001). The authors argue that institutions introduced by European colonizers varied according to settlement objectives and show that the persistence of these institutions to the present day has had important income per capita implications for the ex-colonies.

[1] As will be discussed later, we interpret this as an evaluation of dependence rather than pure causality.

[2] Additional theoretical linkages are discussed in Sen (1999) and Friedman (2005).

Using a growth accounting framework, Hall and Jones (1999) also argue for the primacy of institutions, finding that differences in social infrastructure help explain the large differences in capital accumulation and productivity observed across countries. More recent work by Gwartney et al (2006) confirms the importance of such an institutions-investment channel while Dawson (2003) identifies freedoms related to international finance as those which affect growth through investment and freedoms related to political, civil, and economic liberties as those which affect growth directly. Consistent with Calderon and Chong (2000) and Kaufmann and Kraay (2002), however, both Dawson (2003) and Gwartney et al (2006) also find evidence of reverse causality when certain institutional measures are used. The importance of disaggregating institutions is further established by the Heckelman (2000) result that an average measure of freedom along with its monetary, capital, and property rights components precedes growth but that growth likely precedes the extent of government intervention. A consistent conclusion is reached by Alvarez and Vega (2003) who find clear evidence of causality from institutions to growth when institutions are measured as economic freedoms but confounded evidence when they are measured as political freedoms.[3]

That the debate is far from settled is also reflected in several papers which have raised questions about the econometric methods used to investigate the relationship between growth and institutions. Levine and Renelt (1992), for example, demonstrate that slight changes in the list of explanatory variables can overturn the results of many empirical growth studies while De Haan et al (2006) also criticize the specification of certain growth models used in the literature. Perhaps the most searing criticism though is provided by Glaeser et al (2004) who argue that traditional methods for testing the relationship between institutions and economic outcomes are flawed and, once proper measures and valid instruments are employed, institutions only have a second order effect on economic

[3]Empirical tests of causality have also been debated in the financial development literature. See, for example, Beck et al (2000), King and Levine (1993), Rajan and Zingales (1998), Morris et al (2001), and Calderon and Liu (2003).

performance.

In light of the preceding discussion, we abstract from conventional regression methods and analyze the relationship between institutions and economic outcomes in the context of inter-temporal dependence instead of just inter-temporal correlation. We stress that what is being considered here is dependence rather than pure causality. Indeed, the development literature's use of the term causality is much in the spirit of Granger (1969) and thus has more to do with dependence than causality as we currently understand it. Moreover, even without the appropriate counterfactuals for a causal analysis, we can measure degrees of dependence. Given theoretical support for both the "polity causes growth" and "growth causes polity" hypotheses, we argue that they should not be treated as alternatives and instead focus on identifying the dominant hypothesis by adapting the overlap index proposed by Anderson et al (2009, 2010) for use with a mixture of discrete and continuous variables. The basic premise is that the joint density of two independent variables overlaps the product of their marginal densities at every point of support so, if institutions do indeed determine economic outcomes more than economic outcomes determine institutions, the joint density of earlier institutions and later outcomes should be systematically further away from independence than that of earlier outcomes and later institutions. Using this approach, we can admit non-linear relationships non-parametrically and bypass the error-term constraints that plague regression methods.

Dominance-based techniques are also germane because they are what we use to examine the other important aspect of the polity-growth interaction: the effect on overall welfare. Changes in economic and political variables have not always been in the same direction, making their net impact on wellbeing difficult to ascertain. Drawing from the multivariate stochastic dominance literature, however, we can compare the current distribution over growth-polity pairs to past distributions over these pairs and make qualitative statements about the progress of wellbeing.

The next section presents our methodology in more detail. Section 3 then discusses the data used while Section 4 reports our results. We find that economic growth had a positive impact on wellbeing from 1960 to 2000 yet declines in polity over the earlier part of this period were sufficient to produce a decline in overall welfare until the mid-1970s. Subsequent increases in polity then reversed the trend and, ultimately, welfare in 2000 was higher than that in 1960. We also find evidence that the causal effects of polity on growth dominate those of growth on polity, particularly when the data are population weighted.

2 Methodology

2.1 Multivariate Wellbeing

With some modification, the multivariate stochastic dominance techniques presented in Anderson (2008) and Duclos, Sahn, and Younger (2006) can be used to assess changes in overall wellbeing. Although these techniques do not provide a complete ordering of states, when they do provide a ranking, the ordering is unambiguous. Suppose societal wellbeing in period t can be written as $U(y_t, x_t)$: a monotonic, non-decreasing function of the continuous variable economic wellbeing (y_t) and the discrete variable political freedoms (x_t). Further, let y_t and x_t be jointly distributed with potentially time-varying PDF $g_t(y,x)$ and corresponding CDF $G_t(y,x)$. Suppose $\partial^2 U/\partial x \partial y$ is negative and define $D \equiv G_t(y,x) - G_{t-i}(y,x)$. If $\partial^2 U/\partial x \partial y$ is positive, then D is defined in terms of the counter cumulative densities (see Anderson (2008)).[4] When $D \leq 0$ for all pairs (y,x) with strict inequality for at least some, then $E(U(y_t, x_t)) \geq E(U(y_{t-i}, x_{t-i}))$. Moreover, based on Atkinson and Bourguignon (1982), the society at t can be considered a welfare improvement over the society at $t-i$ for all wellbeing functions in the monotonic non-decreasing family. In fact, as long as D is significantly negative for some pairs (y,x) and

[4] The signs of the cross-partials reflect the substitutability (-ve) or complementarity (+ve) of x and y in the wellbeing calculus.

not significantly positive for all other pairs, $E\left(U\left(y_t, x_t\right)\right) \geq E\left(U\left(y_{t-i}, x_{t-i}\right)\right)$ can be established and an approximately first order welfare improvement obtains. When dominance is ascertained for a family of wellbeing indicators, there is no need to choose composite indicators from those families since all those choices become ordinally equivalent.

In order to make quantitative statements about D, we use the Kolmogorov-Smirnov statistic for differences between distributions. The statistic is based on the maximum value of D over the support of the two distributions being compared and an estimate of this value can be obtained from sample-based estimates of the joint densities in two periods.[5] The formula used for $P\left(\sqrt{n}D < \lambda\right)$ is $1 - e^{-2\lambda^2}$ which is Rayleigh's formula for the univariate statistic ($K = 1$, where K is the number of variables the distribution describes). Although Kiefer and Wolfowitz (1958) establish the existence of a distribution function for D when $K > 1$, they find that it generally depends on G. Later work by Kiefer (1961), however, suggests that the formula for the univariate case provides a conservative (i.e. larger) estimate of the true value when $K > 1$.

2.2 Dependence Dominance

The literature abounds with types of dependence. Lehmann (1966) outlines three: positive (negative) quadrant dependence, positive (negative) regression dependence, and positive (negative) likelihood ratio dependence.[6] The problem for our analysis is that all of these notions deal with monotone relationships yet there should be no presumption that the polity-growth nexus is characterized by such monotonicity.[7] Therefore, we employ a more general concept of "distance from independence" which admits both monotone and non-monotone relationships. Letting z be an n-dimensional vector and $f_a\left(z\right)$ and $f_b\left(z\right)$ be

[5] Although the joint distribution of polity and growth describes a mixture of discrete and continuous variables, this does not pose a problem since sample cumulants are easily calculated.

[6] See also Bartolucci et al (2001), Pandit and Shetty (2003), and Denuit and Scaillet (2004)

[7] While the case for positive dependence can be gleaned from some of the development literature discussed in Section 1, the argument that negative dependence cannot be ignored is supported by the post-WWII literature on wage moderation. Maier (1987), for instance, argues that the limited freedoms of labour unions in Germany, Italy, and Japan after the war helped foster growth-promoting compromise during this period.

two continuous multivariate distributions, the extent to which $f_a(z)$ and $f_b(z)$ overlap can be measured as:

$$OV = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \min\{f_a(z), f_b(z)\}\, dz_1 \cdots dz_n$$

If $f_a(z)$ is the unrestricted joint PDF of z and $f_b(z)$ is the joint distribution when the z's are independent, then $OV \in [0, 1]$ is an index of independence and $1 - OV$ is a general index of dependence, be it monotone or not. Another attractive feature of OV is that, if used in a testing environment, it will evade the objection of test inconsistency (see Cox and Hinkley (1974)) that beleaguers statistics based only on pairwise comparisons at a fixed number of arbitrarily chosen points. In recent work, Anderson, Linton, and Whang (2009) show that the kernel estimator of $\theta = \int \min\{f_a(z), f_b(z)\}\, dz$ is distributed as follows:

$$\sqrt{n}\left(\widehat{\theta} - \theta\right) - \alpha_n \longrightarrow N(0, v)$$

$$where$$

$$v = p_0\sigma_0^2 + p_a(1 - p_a) + p_b(1 - p_b)$$

$$p_0 = P(Z \in C_{ab});\ C_{ab} = \{z \in \mathbb{R}^n : f_a(z) = f_b(z) > 0\}$$

$$p_a = P(Z \in C_a);\ C_a = \{z \in \mathbb{R}^n : f_a(z) < f_b(z)\}$$

$$p_b = P(Z \in C_b);\ C_b = \{z \in \mathbb{R}^n : f_a(z) > f_b(z)\}$$

Note that α_n and σ_0^2 are bias correction factors in the mean and variance calculations respectively, details of which are also available in Anderson et al (2009). In the polity-growth application, the slight wrinkle for OV is that z is a mixture of discrete and continuous variables. Denoting the discrete variables by z_d and the continuous ones by z_c so that $z = (z_d, z_c)$, the appropriate overlap measure is:

$$OV_{mix} = \int_{-\infty}^{\infty} \sum_{z_d} \min\left\{f_a(z), f_b(z)\right\} dz_c$$

The discrete version of OV has been developed in Anderson, Ge, and Leo (2010) so the properties of OV_{mix} can be derived as a mixture of the two cases. Moreover, OV_{mix} lends itself quite naturally to a test of dependence dominance. To see how, let y_t be a vector of economic variables in period t with joint distribution $f(y_t)$ and let x_t be a vector of institutional indices in period t with joint density $p(x_t)$. The joint distribution of economic outcomes in period j and institutions in period k is denoted by $g(y_j, x_k)$. Under independence, $g(y_j, x_k) = f(y_j)\, p(x_k)$ and the following measure of their dependence can be constructed:

$$d(y_j, x_k) = 1 - \int_{y_j} \sum_{x_k} \min\left\{g(y_j, x_k), f(y_j)\, p(x_k)\right\} dy_j \in (0, 1)$$

A greater degree of dependence between y_j and x_k implies less overlap between $g(y_j, x_k)$ and $f(y_j)\, p(x_k)$, leading to higher values of $d(y_j, x_k)$. Unlike univariate overlap measures based on two distinct distributions, the lower bound of OV (upper bound of d) in this application is greater than zero (less than one) since $g(y_j, x_k)$ and $f(y_j)\, p(x_k)$ will never fail to have points of common support.[8] To test for dependence dominance, we focus on $d(y_{t-i}, x_t) - d(y_t, x_{t-i})$ for $i = 1, \ldots, l$. Consistently negative differences support the hypothesis that institutions promote growth more than growth promotes institutions while consistently positive differences support the reverse. Essentially, conditions like $d(y_{t-i}, x_t) - d(y_t, x_{t-i}) \geq 0$ for all i or $d(y_{t-i}, x_t) - d(y_t, x_{t-i}) \leq 0$ for all i (with strict inequality holding somewhere) are forms of dominance relationships and establishing them empirically would lend considerable support to one view or the other. Since these inequalities need to hold simultaneously, the simultaneous comparison techniques in Wolak (1989) and Stoline and Ury (1979) are appropriate.

[8] This is a matter of further research by the authors.

3 Data

We consider a sample of 84 developed and developing countries over the period 1960 to 2000, drawing data on economic outcomes and institutional quality at 5 year intervals.[9]

Economic outcomes are measured using real GDP per capita from the World Bank Development Indicators database. For institutions, Glaeser et al (2004) suggest that constraints on the executive is the most defensible of all the standard measures so we use the corresponding variable from the frequently cited Polity IV project.[10] The Polity project was initiated in the late 1960s by Ted Robert Gurr, then of Princeton University. The first wave of data was collected by a single coder who, for each country in the sample, used historical records to ordinally score the country's authority traits (i.e., executive constraints, political participation, etc.). The data was eventually expanded into an annual format and vetted on several occasions to ensure consistency.[11] Polity IV, currently maintained by the Center for Systemic Peace, tracks six main political traits for over 160 countries. The executive constraints indicator we use here captures the extent to which decision-makers are limited by accountability groups (i.e., democratic legislatures, independent judiciaries and, in coup-prone states, the military). The bindingness of such constraints is measured on a seven-point scale. Higher values reflect better institutions, with 1 representing unlimited authority and 7 representing executive parity. Most parliamentary democracies are coded as 7's while countries where the executive controls the

[9] Dictated largely by data availability, our sample includes the following countries: Algeria, Argentina, Australia, Austria, Belgium, Benin, Bolivia, Brazil, Burkina Faso, Cameroon, Canada, Central African Rep, Chad, Chile, China, Colombia, Congo Brazzaville, Congo Kinshasa, Costa Rica, Denmark, Dominican Rep, Ecuador, Egypt, El Salvador, Finland, France, Gabon, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Ivory Coast, Japan, Kenya, Liberia, Madagascar, Malawi, Malaysia, Mauritania, Mexico, Morocco, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Rwanda, Senegal, Sierra Leone, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syria, Thailand, Togo, Trinidad, Tunisia, United Kingdom, United States, Uruguay, Venezuela, Zambia.

[10] Citations include Hanson (2004), Hausmann, Pritchett, and Rodrik (2005), and Klomp and De Haan (2009). Acemoglu et al (2001) also use the Polity IV data in their robustness checks. For the project's user guide, see Gurr et al (2010).

[11] One caveat to the annual frequency is that measures of executive constraints are not reported for transition years. This affected a few of our observations so we used the closest available data point – usually within one or two years of the missing one – to circumvent it.

judiciary and/or routinely overrides the constitution are coded as 1's.

At this point, it is useful to address the often overlooked issue of population weighting. If the polity-growth nexus is viewed as a latent technological relationship, then each country should be interpreted as a particular draw from that technology and given equal weight. If, on the other hand, we take a representative agent view, then country-level observations should be population weighted so as to give each individual in the world sample equal weight. In what follows, we present the results of both approaches as well as a representative agent version that excludes the two most populous countries – China and India. Our population data also come from the World Bank database.

Summary statistics are reported in Tables 1(a) and 1(b). When unweighted, average GDP per capita exhibits sustained growth throughout the period. Average polity, in contrast, declined over the first 15 years of our sample, returning to its initial level in the mid-1980s and rising to unprecedented levels thereafter. The 1980s also saw a reversal in the plight of the poorest nation as minimum GDP per capita transitioned from consistent improvements to substantial losses late in the decade. With regard to dispersion, polity and GDP per capita seem to be driven by very different processes. Polity, in particular, appears to be a convergent measure whereas GDP per capita appears to be a divergent one. The population weighted statistics tell a similar story for polity but not for GDP per capita which, when weighted, is characterized by greater dispersion and substantially lower means and medians.

4 Results

4.1 Multivariate Wellbeing

Tables 2(a) to 2(f) report the Kolmogorov-Smirnov first order stochastic dominance comparisons for all possible pairs of years in the sample. The joint densities have been estimated using cumulants of the Epanechnikov kernel in the continuous dimension and straightforward cumulation in the discrete dimension.[12] An increase in overall wellbeing from year B to year A is declared if "H_0: Year A dominates Year B" is accepted and "H_0: Year B dominates Year A" is rejected. If both hypotheses are rejected or both hypotheses are accepted, then an indeterminate change in welfare is reported.

In this application, the unweighted results in Table 2(a) are the clearest. Under negative cross-partials, the unweighted sample yields only 5 indeterminacies out of the 36 possible year-to-year comparisons while the weighted samples with and without China and India yield 21 and 9 respectively. The unweighted results reflect the fact that declines in polity between 1960 and 1975 outweighed progress in incomes, leading to declines in overall wellbeing relative to initial conditions. By 1985, however, the drop in polity had been made up and further progress in such institutions meant that unambiguous increases in wellbeing were sustained through to 2000. The population weighted results in Tables 2(b) and 2(c) tell a consistent story, particularly when China and India are excluded from the sample. In the latter case, the main difference relative to Table 2(a) is that a swifter recovery in polity under population weighting pulls the welfare declines in the earlier part of the observation period up to indeterminacy. The results under positive cross-partials are similar in most respects, however the weighted calculation in Table 2(e) is now characterized by less indeterminacy than the unweighted one in Table 2(d).

4.2 Dependence Dominance

To avoid difficulties with joint density estimation at points with too few observations, we amalgamate polity categories 1 and 2 and polity categories 3 and 4 to form a new five-point polity scale. For all lags examined – 0 to 40 years in 5 year intervals – the dependence of GDP on past polity and the dependence of polity on past GDP are readily established. With causality in both directions, we now turn to the question of interest: does one direction dominate in the sense that the degree of dependence is always at least

[12] Per capita GDP is very close to log normally distributed, hence the use of the Epanechnikov kernel with the optimal bandwidth for normality following Silverman (1986).

as great in that direction at every lag? Tables 3(a), 3(b), and 3(c) report the dependence dominance results for the unweighted, population weighted, and population weighted excluding China and India samples. We have used a discrete-continuous specification for the joint densities, employing a Gaussian kernel for the continuous component and Silverman's rule of thumb for the window width.[13] Tables 4(a), 4(b), and 4(c) report the results when the joint densities are specified with smoothed estimates of the discrete component probabilities as per Li and Racine (2003) and Li et al (2006).[14]

With respect to the unweighted results in Table 3(a), there is some indication that the dependence of growth on polity dominates the dependence of polity on growth at longer lags but the differences are largely insignificant. The smoothed cell probability results in Table 4(a) are much stronger in this direction, with dominance at longer lags accepted under usual levels of significance. The weighted results in Tables 3(b) and 3(c) also exhibit a clearer pattern than those in 3(a). At all lags where $d\left(y_{t-i}, x_t\right) - d\left(y_t, x_{t-i}\right) < 0$, the hypothesis that polity promotes growth more than growth promotes polity is accepted under modest degrees of significance. In contrast, the reverse hypothesis is readily rejected at all lags where $d\left(y_{t-i}, x_t\right) - d\left(y_t, x_{t-i}\right) > 0$. Moreover, if we exclude China and India to avoid the extraordinary importance that population weighting assigns to their circumstances, the conclusion emerges more strongly in both the discrete-continuous and smoothed cell specifications.

5 Conclusion

There has been considerable debate over whether it is institutions that cause growth or growth that causes institutions and the discussion has been fomented, at least in part, by the fact that the two hypotheses are not mutually exclusive. In this paper, we argued

[13] Our dependence dominance analysis uses the multivariate overlap measure software of Anderson, Linton, and Whang (2009) which employs a multivariate Gaussian kernel. The window width suggested by Silverman (1986) is $1.06\sigma n^{-1/(4+k)}$.

[14] This approach to calculating the densities was suggested by a referee and, with it, we are able to use the original seven-point polity scale.

that the relevant question is not which hypothesis is correct but, rather, which hypothesis dominates. Since conventional regression techniques have difficulty capturing non-linear dependence, especially when one of the variables is an index with limited variation, we propose a dependence dominance test based on the overlap measure of Anderson et al (2009, 2010) to examine the polity-growth nexus. Taken together, our results suggest that institutions promote economic outcomes more than economic outcomes promote institutions. Another advantage of the dominance-based approach is its natural link to multivariate welfare comparisons. Our results on this front suggest that, while economic growth had a positive impact on wellbeing between 1960 and 2000, early declines in polity were sufficient to produce a decline in overall welfare until the mid-1970s. Subsequent increases in polity then reversed the trend and, ultimately, wellbeing in 2000 was higher than that in 1960.

Table 1: Summary Statistics

(a) Unweighted Sample

	Polity Index					GDP per Capita				
	Mean	Median	StDev	Max	Min	Mean	Median	StDev	Max	Min
1960	4.0595	3	2.3865	7	1	2.8340	0.9360	3.8138	18.7110	0.0990
1965	3.9048	3	2.4079	7	1	3.4042	1.0250	4.6036	21.8770	0.1000
1970	3.5476	3	2.3867	7	1	4.1108	1.2265	5.4884	25.1250	0.1220
1975	3.4881	3	2.4909	7	1	4.7011	1.4135	6.1152	25.5950	0.1400
1980	3.7024	3	2.4971	7	1	5.2871	1.5490	6.9372	28.2060	0.1400
1985	4.0238	3	2.4690	7	1	5.6276	1.4660	7.6299	29.6870	0.1530
1990	4.6071	5	2.3593	7	1	6.2496	1.5100	8.6665	33.3690	0.1320
1995	5.0238	6	2.1055	7	1	6.7504	1.6780	9.2308	35.4390	0.0560
2000	5.2381	6	1.8860	7	1	7.7052	2.0165	10.572	37.4720	0.0850

(b) Population Weighted Sample

	Polity Index			GDP per Capita		
	Mean	Median	StDev	Mean	Median	StDev
1960	4.3159	3	2.4045	2.6032	0.1880	4.3386
1965	4.1409	3	2.4693	3.0737	0.1930	5.1541
1970	3.9913	3	2.4946	3.6255	0.2280	6.0631
1975	3.7311	2	2.3118	3.9241	0.2200	6.6360
1980	4.3024	3	2.3210	4.3216	0.2500	7.4917
1985	4.5155	3	2.2116	4.6062	0.2820	8.1715
1990	4.6626	3	2.1532	5.0420	0.3730	9.2744
1995	4.8433	5	2.0778	5.3339	0.5960	9.6872
2000	5.1097	6	1.8967	5.8958	0.8440	10.6937

Table 2(a): Multivariate Dominance Tests (Negative Second Partials) Unweighted

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	↓	0.0261	0.1185
1960	1970	n/d	0.0979	0.5147
1960	1975	n/d	0.2087	0.6071
1960	1980	↓	0.0083	0.4770
1960	1985	↓	0.0237	0.1157
1960	1990	↑	0.5182	0.0199
1960	1995	↑	0.8237	0.0000
1960	2000	↑	0.9178	0.0059
1965	1970	↓	0.0315	0.2655
1965	1975	n/d	0.1238	0.4559
1965	1980	↓	0.0444	0.3183
1965	1985	↑	0.1060	0.0265
1965	1990	↑	0.6296	0.0062
1965	1995	↑	0.9156	0.0000
1965	2000	↑	0.9736	0.0006
1970	1975	↓	0.0480	0.1301
1970	1980	n/d	0.1196	0.0584
1970	1985	↑	0.3863	0.0180
1970	1990	↑	0.9027	0.0056
1970	1995	↑	0.9859	0.0000
1970	2000	↑	0.9968	0.0000
1975	1980	↑	0.1101	0.0000
1975	1985	↑	0.4667	0.0007
1975	1990	↑	0.8702	0.0001
1975	1995	↑	0.9810	0.0000
1975	2000	↑	0.9953	0.0000
1980	1985	↑	0.1930	0.0014
1980	1990	↑	0.7597	0.0001
1980	1995	↑	0.9562	0.0000
1980	2000	↑	0.9880	0.0001
1985	1990	↑	0.4457	0.0000
1985	1995	↑	0.8491	0.0000
1985	2000	↑	0.9435	0.0001
1990	1995	↑	0.3072	0.0000
1990	2000	↑	0.5581	0.0000
1995	2000	n/d	0.1617	0.0564

Table 2(b): Multivariate Dominance Tests (Negative Second Partials) Population Weighted

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	↓	0.0123	0.1048
1960	1970	↓	0.0162	0.3637
1960	1975	↓	0.0009	0.8672
1960	1980	n/d	0.0597	0.6918
1960	1985	n/d	0.0630	0.7953
1960	1990	n/d	0.1162	0.9598
1960	1995	n/d	0.6936	0.7642
1960	2000	n/d	0.5515	0.9597
1965	1970	↓	0.0355	0.2092
1965	1975	↓	0.0120	0.8335
1965	1980	↓	0.0414	0.4273
1965	1985	n/d	0.1160	0.6489
1965	1990	n/d	0.2459	0.9423
1965	1995	n/d	0.6834	0.7636
1965	2000	n/d	0.6728	0.9503
1970	1975	↓	0.0000	0.5539
1970	1980	n/d	0.0994	0.1521
1970	1985	n/d	0.3224	0.4893
1970	1990	n/d	0.4595	0.9020
1970	1995	n/d	0.9148	0.6193
1970	2000	n/d	0.8946	0.8931
1975	1980	↑	0.2234	0.0478
1975	1985	n/d	0.5106	0.3327
1975	1990	n/d	0.6637	0.8383
1975	1995	n/d	0.9763	0.4847
1975	2000	n/d	0.9688	0.8191
1980	1985	n/d	0.1334	0.1521
1980	1990	n/d	0.2621	0.3187
1980	1995	↑	0.6444	0.0000
1980	2000	↑	0.6859	0.0000
1985	1990	n/d	0.0304	0.0491
1985	1995	↑	0.5852	0.0000
1985	2000	↑	0.7567	0.0000
1990	1995	↑	0.3895	0.0000
1990	2000	↑	0.6973	0.0356
1995	2000	↑	0.3423	0.0017

Table 2(c): Multivariate Dominance Tests (Negative Second Partials) Weighted Excl. CHN and IND

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	n/d	0.0632	0.3941
1960	1970	n/d	0.2025	0.6304
1960	1975	n/d	0.2672	0.8181
1960	1980	↓	0.0074	0.7709
1960	1985	↓	0.0479	0.2634
1960	1990	n/d	0.5199	0.1390
1960	1995	↑	0.6931	0.0001
1960	2000	↑	0.8508	0.0392
1965	1970	n/d	0.1124	0.2601
1965	1975	n/d	0.0871	0.5083
1965	1980	n/d	0.0992	0.4365
1965	1985	n/d	0.3501	0.0965
1965	1990	↑	0.6268	0.0459
1965	1995	↑	0.8279	0.0001
1965	2000	↑	0.9633	0.0015
1970	1975	↓	0.0076	0.0856
1970	1980	↓	0.0109	0.0636
1970	1985	↑	0.4155	0.0413
1970	1990	↑	0.6813	0.0159
1970	1995	↑	0.8970	0.0002
1970	2000	↑	0.9875	0.0000
1975	1980	↑	0.0545	0.0015
1975	1985	↑	0.5862	0.0003
1975	1990	↑	0.7996	0.0349
1975	1995	↑	0.9592	0.0002
1975	2000	↑	0.9899	0.0000
1980	1985	↑	0.4081	0.0004
1980	1990	↑	0.6697	0.0000
1980	1995	↑	0.9125	0.0000
1980	2000	↑	0.9832	0.0001
1985	1990	↑	0.1052	0.0000
1985	1995	↑	0.5601	0.0000
1985	2000	↑	0.8763	0.0001
1990	1995	↑	0.2347	0.0001
1990	2000	↑	0.8086	0.0000
1995	2000	n/d	0.6192	0.0563

Table 2(d): Multivariate Dominance Tests (Positive Second Partials) Unweighted

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	↓	0.0057	0.0540
1960	1970	n/d	0.1361	0.1665
1960	1975	n/d	0.1469	0.3241
1960	1980	↑	0.0537	0.0103
1960	1985	↑	0.0522	0.0000
1960	1990	n/d	0.2431	0.5797
1960	1995	n/d	0.3072	0.7186
1960	2000	n/d	0.8489	0.6704
1965	1970	n/d	0.0900	0.0742
1965	1975	n/d	0.1086	0.2595
1965	1980	↑	0.0549	0.0000
1965	1985	↑	0.0805	0.0000
1965	1990	n/d	0.2424	0.5804
1965	1995	n/d	0.5032	0.7239
1965	2000	n/d	0.9240	0.6739
1970	1975	↓	0.0437	0.1446
1970	1980	↑	0.0859	0.0000
1970	1985	↑	0.2010	0.0004
1970	1990	n/d	0.4428	0.6960
1970	1995	n/d	0.6299	0.8321
1970	2000	n/d	0.9558	0.7811
1975	1980	n/d	0.0228	0.0027
1975	1985	↑	0.1074	0.0093
1975	1990	n/d	0.3169	0.6893
1975	1995	n/d	0.6258	0.8222
1975	2000	n/d	0.9437	0.7717
1980	1985	n/d	0.0439	0.0064
1980	1990	↑	0.1952	0.0024
1980	1995	↑	0.3858	0.0009
1980	2000	↑	0.8552	0.0004
1985	1990	↑	0.0920	0.0003
1985	1995	↑	0.2553	0.0000
1985	2000	↑	0.7823	0.0000
1990	1995	n/d	0.1885	0.1012
1990	2000	↑	0.6873	0.0234
1995	2000	↑	0.4619	0.0001

Table 2(e): Multivariate Dominance Tests (Positive Second Partials) Population Weighted

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	↓	0.0030	0.1944
1960	1970	↓	0.0242	0.1749
1960	1975	n/d	0.8754	0.0861
1960	1980	n/d	0.0178	0.0320
1960	1985	n/d	0.0307	0.0000
1960	1990	↑	0.9536	0.0001
1960	1995	↑	0.9392	0.0265
1960	2000	↑	0.9891	0.0075
1965	1970	↓	0.0302	0.0785
1965	1975	↑	0.9183	0.0149
1965	1980	n/d	0.0176	0.0000
1965	1985	↑	0.1135	0.0000
1965	1990	↑	0.9734	0.0028
1965	1995	↑	0.9752	0.0332
1965	2000	↑	0.9944	0.0096
1970	1975	↑	0.8605	0.0000
1970	1980	n/d	0.0130	0.0000
1970	1985	↑	0.1147	0.0000
1970	1990	↑	0.9918	0.0151
1970	1995	n/d	0.9884	0.0921
1970	2000	↑	0.9986	0.0499
1975	1980	↓	0.0082	0.7330
1975	1985	n/d	0.0761	0.7245
1975	1990	n/d	0.7226	0.8607
1975	1995	n/d	0.8781	0.9218
1975	2000	n/d	0.9456	0.9002
1980	1985	↑	0.0600	0.0003
1980	1990	↑	0.0623	0.0002
1980	1995	↑	0.0706	0.0002
1980	2000	↑	0.5398	0.0002
1985	1990	↑	0.0566	0.0027
1985	1995	↑	0.0625	0.0023
1985	2000	↑	0.3449	0.0000
1990	1995	↑	0.3095	0.0377
1990	2000	↑	0.4747	0.0235
1995	2000	↑	0.3752	0.0004

Table 2(f): Multivariate Dominance Tests (Positive Second Partials) Weighted Excl. CHN and IND

Comparison Years B	Comparison Years A	Change in Wellbeing (↑=Increase, ↓=Decrease, n/d=Indeterminate)	P(A dominates B)	P(B dominates A)
1960	1965	↓	0.0137	0.2742
1960	1970	n/d	0.1029	0.4764
1960	1975	n/d	0.2126	0.6671
1960	1980	n/d	0.0640	0.1019
1960	1985	↑	0.1122	0.0000
1960	1990	↑	0.4249	0.0100
1960	1995	n/d	0.5035	0.0555
1960	2000	n/d	0.9000	0.0910
1965	1970	n/d	0.0719	0.2267
1965	1975	n/d	0.1817	0.4315
1965	1980	↑	0.0635	0.0000
1965	1985	↑	0.3610	0.0000
1965	1990	↑	0.5619	0.0259
1965	1995	n/d	0.7433	0.0826
1965	2000	n/d	0.9868	0.1246
1970	1975	↓	0.0297	0.0581
1970	1980	n/d	0.0474	0.0000
1970	1985	↑	0.3583	0.0001
1970	1990	n/d	0.5973	0.0711
1970	1995	n/d	0.8265	0.2144
1970	2000	n/d	0.9868	0.2245
1975	1980	n/d	0.0312	0.0058
1975	1985	↑	0.3109	0.0041
1975	1990	n/d	0.7060	0.1316
1975	1995	n/d	0.8444	0.2871
1975	2000	n/d	0.9844	0.2988
1980	1985	↑	0.2003	0.0011
1980	1990	↑	0.2088	0.0009
1980	1995	↑	0.2310	0.0007
1980	2000	↑	0.9373	0.0007
1985	1990	↑	0.1915	0.0093
1985	1995	↑	0.2080	0.0087
1985	2000	↑	0.7777	0.0001
1990	1995	n/d	0.1357	0.1003
1990	2000	n/d	0.8563	0.0543
1995	2000	↑	0.8126	0.0275

Table 3: Dependence Dominance Tests

(a) Unweighted

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.4242	0.4242	0.0000	0.5000	0.2819	0.2819	0.0000	0.5000
5	0.4169	0.4135	0.1730	0.5687	0.2671	0.2666	0.0126	0.5050
10	0.4254	0.4237	0.0766	0.5305	0.2674	0.2699	-0.0606	0.4758
15	0.4299	0.4203	0.3850	0.6499	0.2631	0.2597	0.0790	0.5315
20	0.4286	0.4145	0.5233	0.6996	0.2482	0.2486	-0.0066	0.4974
25	0.4200	0.4162	0.1251	0.5498	0.2260	0.2411	-0.2855	0.3876
30	0.4207	0.4216	-0.0235	0.4906	0.2043	0.2390	-0.5769	0.2820
35	0.4256	0.4342	-0.1943	0.4230	0.1754	0.2397	-0.8672	0.1929
40	0.4282	0.4291	-0.0139	0.4945	0.1485	0.2465	-0.9296	0.1763

(b) Population Weighted

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.4513	0.4513	0.0000	0.5000	0.3689	0.3689	0.0000	0.5000
5	0.4584	0.4542	0.2129	0.5843	0.3705	0.3708	-0.0101	0.4960
10	0.4636	0.4601	0.1601	0.5636	0.3702	0.3747	-0.1159	0.4539
15	0.4562	0.4757	-0.8129	0.2081	0.3533	0.3854	-0.7642	0.2224
20	0.4492	0.4709	-0.8188	0.2064	0.3343	0.3730	-0.8418	0.2000
25	0.4434	0.4640	-0.6857	0.2464	0.3125	0.3560	-0.8374	0.2012
30	0.4346	0.4682	-0.9411	0.1733	0.2890	0.3595	-1.1777	0.1195
35	0.4509	0.4582	-0.1665	0.4339	0.2983	0.3312	-0.4411	0.3296
40	0.4608	0.4443	0.2787	0.6098	0.2765	0.3087	-0.3026	0.3811

(c) Weighted Excl. CHN and IND

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.4655	0.4655	0.0000	0.5000	0.3879	0.3879	0.0000	0.5000
5	0.4663	0.4673	-0.0541	0.4784	0.3841	0.3888	-0.1271	0.4494
10	0.4713	0.4761	-0.2247	0.4111	0.3840	0.3940	-0.2550	0.3994
15	0.4629	0.4923	-1.2363	0.1082	0.3682	0.4058	-0.8906	0.1866
20	0.4546	0.4940	-1.4913	0.0679	0.3529	0.4053	-1.1296	0.1293
25	0.4454	0.4879	-1.4217	0.0776	0.3321	0.3961	-1.2303	0.1093
30	0.4436	0.4890	-1.2918	0.0982	0.3165	0.4005	-1.3924	0.0819
35	0.4554	0.4784	-0.5301	0.2980	0.3278	0.3798	-0.6922	0.2444
40	0.4748	0.4724	0.0410	0.5163	0.3364	0.3458	-0.0873	0.4652

Table 4: Dependence Dominance Tests (Smoothed Cell Probabilities)

(a) Unweighted

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.3408	0.3408	0.0000	0.5000	0.1616	0.1616	0.0000	0.5000
5	0.3496	0.3540	-0.1771	0.4297	0.1701	0.1743	-0.1133	0.4549
10	0.3600	0.3635	-0.1320	0.4475	0.1732	0.1768	-0.0902	0.4641
15	0.3444	0.3704	-0.8982	0.1845	0.1377	0.1878	-1.1624	0.1225
20	0.3469	0.3705	-0.7487	0.2270	0.1272	0.1641	-0.7860	0.2159
25	0.3419	0.3797	-1.0693	0.1425	0.1047	0.1501	-0.8610	0.1946
30	0.3393	0.3954	-1.3728	0.0849	0.0870	0.1420	-0.9058	0.1825
35	0.3229	0.4319	-2.1797	0.0146	0.0190	0.1721	-2.0474	0.0203
40	0.2882	0.4282	-1.9791	0.0239	0.0000*	0.0417	-0.3899	0.3483

(b) Population Weighted

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.3915	0.3915	0.0000	0.5000	0.2103	0.2103	0.0000	0.5000
5	0.3933	0.4093	-0.6384	0.2616	0.2040	0.2233	-0.5240	0.3001
10	0.3836	0.3861	-0.0926	0.4631	0.1795	0.1910	-0.2905	0.3857
15	0.3460	0.3943	-1.6739	0.0471	0.1222	0.2026	-1.8886	0.0295
20	0.3878	0.3763	0.3617	0.6412	0.1422	0.1658	-0.5075	0.3059
25	0.3953	0.3465	1.3791	0.9161	0.1415	0.1108	0.5935	0.7236
30	0.4181	0.3756	1.0418	0.8513	0.1539	0.1091	0.7540	0.7746
35	0.3889	0.4408	-1.0368	0.1499	0.0738	0.1812	-1.4911	0.0680
40	0.3479	0.3717	-0.3378	0.3678	0.0000*	0.0000*	0.0000	0.5000

(c) Weighted Excl. CHN and IND

Lag	No Bias Adjustment				Bias Adjusted			
(Years)	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value	$d(y_{t-i}, x_t)$	$d(y_t, x_{t-i})$	"t(diff)"	p-value
0	0.3855	0.3855	0.0000	0.5000	0.2069	0.2069	0.0000	0.5000
5	0.4028	0.4146	-0.4652	0.3209	0.2233	0.2443	-0.5491	0.2915
10	0.4178	0.4268	-0.3335	0.3694	0.2335	0.2510	-0.4315	0.3331
15	0.3902	0.4672	-2.6365	0.0042	0.1789	0.3063	-2.9342	0.0017
20	0.3883	0.4516	-1.9786	0.0239	0.1664	0.2743	-2.2512	0.0122
25	0.3864	0.4340	-1.3290	0.0919	0.1514	0.2344	-1.5571	0.0597
30	0.3953	0.4328	-0.9083	0.1819	0.1452	0.1987	-0.8876	0.1874
35	0.3704	0.4907	-2.3761	0.0087	0.0702	0.2365	-2.2239	0.0131
40	0.3120	0.4720	-2.2366	0.0127	0.0000*	0.0958	-0.8893	0.1869

*This value has been "winsorized" to zero since the bias adjustment, which is not capped, produced $d < 0$.

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