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Corruption Clubs: Empirical Evidence from Kernel Density Estimates

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Abstract

A common finding of many analytical models is the existence of multiple equilibria of corruption. Countries characterised by the same economic, social and cultural background do not necessarily experience the same levels of corruption. In this article, we use Kernel Density Estimation techniques to analyse the cross-country distribution of corruption. Particular emphasis will be given to the question whether the distribution of corruption shows more than one peak. We find that most of the estimated densities exhibit twin peaks. We also provide some evidence on the intra-distribution dynamics and the persistence of corruption. We find the group of countries classified within the two ‘clubs’ to be very stable. Corruption is highly persistent phenomenon. Substantial changes in the economic, political and cultural environment of countries within the ‘corruption club’ are required before a significant decline of corruption is to be expected.

Keywords: Corruption; Kernel Density Estimation; Multiple Equilibria

JEL classification: K42; H10

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Corruption Clubs: Empirical Evidence from Kernel Density Estimates

I. Introduction

Since Rose-Ackerman's seminal 1978 analysis, the study of corruption ranks high on the research agenda of economists. However, lack of reliable and systematic adaptability has kept corruption out of the research agenda of empirical economists. The last decades have seen a rapidly growing number of theoretical and empirical papers on the causes and consequences of corruption.

Empirical studies typically regress an index of 'perceived corruption' for a cross-section of countries on various economic and institutional factors, such as the level of income, the openness of the economy, the level of wages in the public sector, and the existence and efficiency of institutional controls. These empirical studies clearly provide a number of important insights. However, a severe shortcoming of this regression framework is the implicit assumption that the estimated model is common to all economies. If this is not the case – and a number of theoretical models cast severe doubts on this assumption – an analysis which examines the overall distribution of corruption provides us with more information than the analysis of the conditional mean. More specifically, a common finding of many analytical models is the (possible) existence of multiple equilibria of corruption. Countries characterised by the same economic, social and cultural background not necessarily experience the same level of corruption. This would not be the predicted outcome of studies assuming one regression model to fit all countries.

In this article, we use Kernel Density Estimation techniques to analyse the cross-country distribution of corruption in more detail. Particular emphasis will be given to the question whether the distribution of corruption shows more than one peak. We find that most of the estimated densities exhibit twin peaks, which gives empirical support to models predicting multiple equilibria. We also provide some evidence on the intra-distribution dynamics and the persistence of corruption. We find the group of countries classified within the two 'clubs' to be very stable.

The rest of the article is organised as follows. Section II surveys theoretical models on corruption and focuses on arguments supporting the existence of multiple equilibria. Section III describes the data. Section IV reviews nonparametric techniques for the estimation of the corruption distribution across countries, reports the results of the empirical analysis and concludes.

II. Theoretical Background

Corruption is a many-faced phenomenon and it would be far beyond the scope of this article to give a comprehensive overview of the existing economic literature.¹ Instead, we will confine ourselves to those analytical approaches that offer some implications for the question of multiple equilibria in corruption.

In an overlapping generation framework, Lui (1986) shows, that when corruption becomes more prevalent in an economy, it is harder to audit a corrupt official effectively. Hence the economy will remain highly corrupt. If, on the other hand, most officials do not accept bribes, it will be easier to discover those who do and the corruption equilibrium will be lower. The existence of two stable stationary equilibria (one with a high level of corruption and the other with less corruption) is also highlighted in Cadot (1987) as well as Andvig and Moene (1990). In a two-period model, Andvig and Moene argue that the relative attractiveness of corruption for bureaucrats depends on the probability of being detected and being punished. For punishment, it matters if the corrupt bureaucrat is being caught by a non-corrupt or a corrupt colleague. Whereas the first scenario would result in punishment, the second would allow the bureaucrat to bribe his colleague for not reporting the case and thereby preventing punishment. The profitability of corruption therefore appears to be related to its established frequency.

In a dynamic optimisation framework, Dawid and Feichtinger (1996) show that rational agents may generate multiple equilibria of corruption within the same kind of socio-economic environment. Acemoglu (1995) considers individual's choices between two activities: productive entrepreneurship and unproductive rent-seeking (corruption). A higher proportion of corrupt individuals reduces the return both to entrepreneurship and corruption. If the relative return to entrepreneurship falls faster, a multiplicity of equilibrium allocations may arise: as the number of individuals choosing to be corrupt increases (declines), the relative returns to entrepreneurship will decline (increase) and corruption becomes even more (less) attractive.

A similar strategic complement also is the basic source of multiple equilibria in Tirole (1996). Agents can choose to be honest or corrupt and whether they are honest is imperfectly observable. The author argues that the incentive for an individual to be corrupt depends on the collective reputation of the group to which he/she belongs. The appearance of a large number of corrupt individuals destroys the collective reputation of the group and for this reason it is in

¹ Surveys of this literature include Bardhan (1997), Tanzi (1998) and more recently Jain (2001) and Aidt (2003).

the best interest of an individual to be corrupt too. Similarly, when agents have a good collective reputation, it pays for each agent to be honest as well.²

Acemoglu's and Tirole's contribution also point at an additional mechanism for corruption to be reinforced. They argue that a society that is in the high rent-seeking (corruption) equilibrium will tend to have a social consensus that gives relatively more respect to these activities as opposed to societies in the low rent-seeking (corruption) equilibrium. Since political reforms are initiated by politicians, societies with high levels of corruption would not be likely to introduce effective measures to reduce corruption. High (low) levels of corruption are then reinforced due to the political or jurisdictional channel.³

Each of these mechanisms described above has the potential to make corruption self-enforcing and to generate multiple equilibria in the distribution of corruption. Despite the strong arguments in favour of multiple equilibria, this issue has not been investigated empirically so far.

III. Data

We use data on corruption from four different sources. The first set of corruption indices is published by the Institute of Management Development (IMD) in the World Competitiveness Yearbook. Managers are asked if 'improper practices like bribing and corruption exist/ exist not in public sphere?' The index is scaled from 0 to 10, with lower values indicating a higher level of corruption, and covers up to 53 countries for the period 1990-2002. The second indicator is published by the World Economic Forum (WEF) since 1996. Business People are asked if 'irregular, additional payments connected with import and export permits, business licenses, exchange controls, tax assessments, police protection or loan applications are not common?' in their country of operation and is scaled from 1 to 7. In contrast to the original data source, we rescaled this index to a scale from 0 to 10. The index covers up to 82 countries between 1996 and 2002.

² Adrianova (2001) extends this model by considering collective as well as individual reputation.

³ In a recent survey, Jain (2001) illustrates the complexity of the relationship between corruption and the effectiveness of a country's legal system by means of a simple example: 'The level of corruption in a country with an ineffective legal system may begin to rise in response to, say, an external shock. The political elite may find the increased income from corruption irresistible. Once corrupted, the elite will attempt to reduce the effectiveness of the legal and juridical systems through manipulation of resource allocation and appointments to key positions. Reduced resources will make it difficult for the legal system to combat corruption, thus allowing corruption to spread even more' (p. 72). This inter-relation is also stressed for Russia by Levin and Satarov (2000). In the context of transitional Russia, they propose that various forms of corruption are created due to an underdeveloped body of legislation that makes manifest itself in poor awareness of the law, ill-defined legislative procedures and inconsistencies among legislative acts. At the same time, Levin and Satarov stress that 'corruption infiltrates courts' (p. 123). Lawyers can use bribes as an effective tool for the defense of their clients. More systematic evidence for the interrelationship between corruption and rule of law is provided in Herzfeld and Weiss (2003).

A third measure of corruption is the Graft index published by the World Bank (Kaufmann, Kraay and Mastruzzi, 2003). Several indices from different sources are assembled using a unobserved components model. The authors argue that the observed level of corruption of a country j is a linear function of the unobserved ‘true’ corruption level and an error term. The Graft index is published in 1996, 1998, 2000 and 2002 and covers up to 195 countries. For ease of comparison with the others indices we rescaled this index from the original scale, -2.5 to $+2.5$, to a scale from 0 to 10. The last set of indices is the well known Corruption Perception Index (CPI) assembled and published by Transparency International. It is a ‘poll of polls’ and consists of several corruption measures from up to 15 different sources.⁴ It differs from the Graft index in the methodology of construction and a CPI-value of a country is published if it is covered by at least three different sources. This indicator is scaled from 0 to 10 with lower values indicating a higher level of perceived corruption and is published annually since 1995. We used a period until 2002 for up to 109 countries.

IV. Method and Results

A kernel density estimate of a univariate density f based on a random sample $x_i, i = 1, \dots, n$ is⁵

$$\hat{f}_h(x) = (nh)^{-1} \sum_{i=1}^n K\left(\frac{X - x_i}{h}\right)$$

where $h > 0$ is the bandwidth (or window-width) and K denotes the kernel function. The bandwidth h determines the smoothness of the estimated density with a small h leading to an estimate with a high variability and a large h to a smoother density estimate. In our application x_i refers to the level of corruption in country i in a particular time period.

The choice of bandwidth is critical to determine the shape of the density and is the basis for the modality test. Two criteria, ‘Silverman’s rule of thumb’ (Silverman, 1981) and ‘Sheather and Jones plug-in’ (Sheather and Jones, 1991) are frequently used to find the ‘optimal’ bandwidth. We first apply Sheather and Jones plug-in method to determine optimal window-width for the average corruption levels over time.⁶ If the kernel density of the distribution of corruption is found to be bimodal with this window-width, then the actual distribution is likely to be bimodal.

⁴ For more details see Lambsdorff (2002).

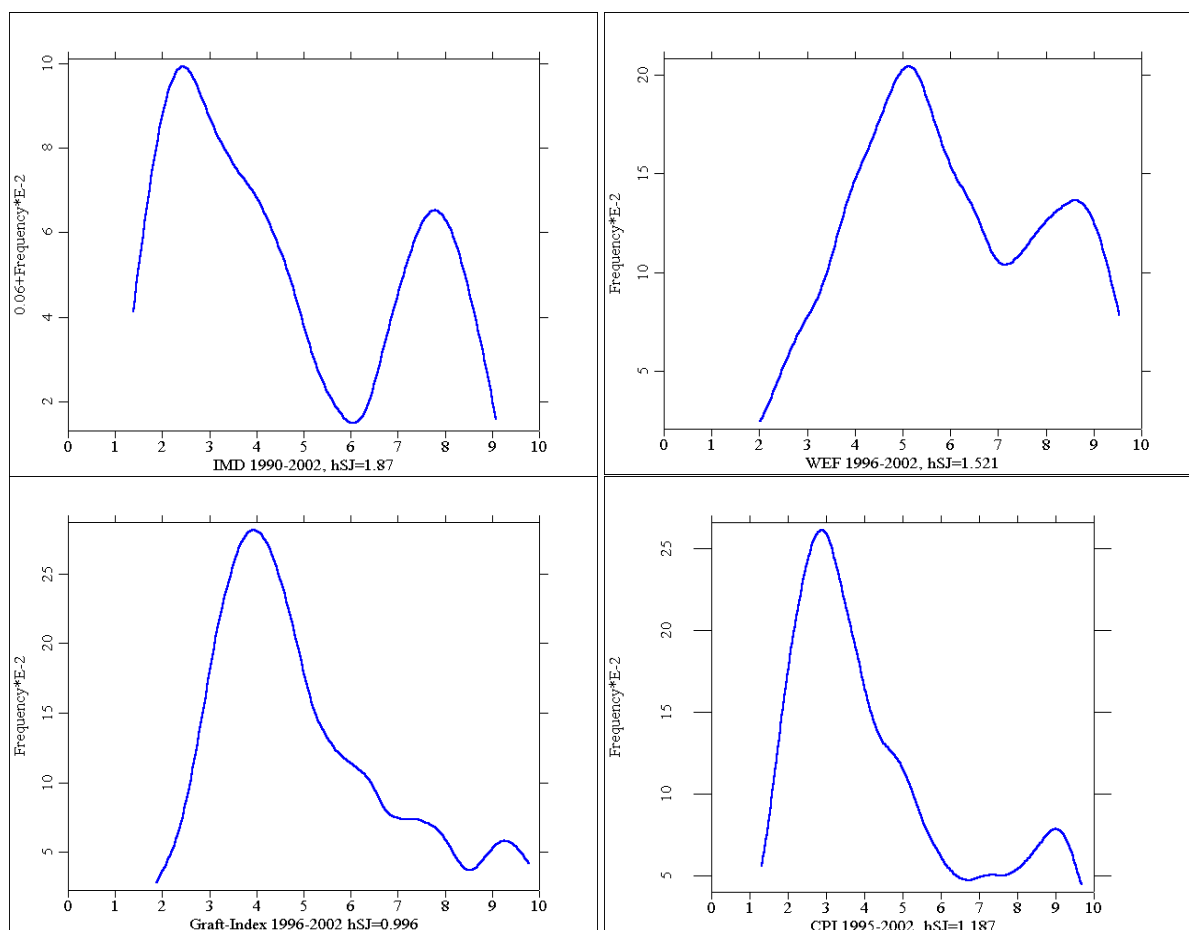
⁵ The methodological background of the Kernel Density Estimation is described in detail in Silverman (1986) and Wand and Jones (1995).

⁶ We perform different robustness exercises to show that results do not change substantially with different smoothing parameters. Despite the fact that Silverman’s rule of thumb tends to over-smooth bimodal distributions (see Silverman, 1986; p. 47), the results when using other methods are very similar.

Modality of cross-country corruption distributions

Figure 1 displays the kernel densities for the four indices used, the corresponding optimal window-widths and the observable number of modes are displayed in Table A1 in the appendix.

Figure. 1: Kernel density estimation of corruption indicators



Notes: Optimal bandwidth computed when using the Sheather and Jones plug-in method. The bandwidth parameters h_{SJ} is reported for each corruption index. The Epanechnikov kernel function is used in all four cases.

Figure 1 suggests a bimodal distribution at least for three of the four indices. The bimodality is particularly pronounced for the IMD index, but very weak in the case of the Graft index.⁷ The first local maximum is at 2.4 for the IMD (5.1 for the WEF index and 3.9 for the Graft index) the second mode is at 7.8 for the IMD index (and around 9 for all other indices). The density shows that there are more countries in the club with high levels of corruption than there are in the group of low-corruption countries. The smaller number of low-corruption countries in panels (c) and (d) is due to the fact that the Graft index and the CPI typically cover poorer and smaller countries than the IMD and the WEF indices.

⁷ The CPI shows a third mode around 7.4 which is, however, very weakly distinct.

The use of these window-widths is illustrative for the purpose of Figure 1, but does not allow an appropriate statistical test of hypothesis about modality. For hypothesis testing and multimodality tests, the concept of critical bandwidth (Silverman, 1981) is used. A critical bandwidth h^{crit} is defined as the smallest window-width which shows at most k modes. In other words, every bandwidth $h < h^{crit}$ generates a density function with more than k modes. This suggests that h^{crit} can be used as a statistic to test the null hypothesis that $f(x)$ has at most k modes versus the alternative hypothesis that $f(x)$ has more than k modes. A ‘large’ value of h^{crit} indicates more than k modes and rejects the null hypothesis.

The significance of the critical window-width value is assessed using bootstrap methods. The achieved significance level (ASL, or p -value) is obtained by generating a large number of bootstrap samples under the null hypothesis and by counting the proportion of samples for which the density function has at most k modes ($ASL_k = \# \{h_k^* > h_k^{crit}\} / B$, where h^* is the optimal bandwidth from the bootstrap sample and B is the number of bootstrap samples). The null hypothesis of k modes will be rejected against the alternative hypothesis of more than k modes whenever ASL_k is smaller than standard levels of significance.

To test for multimodality in the distribution of corruption levels across countries (averages over time), we follow Silverman’s suggestion and test successively for an increasing number of modes until one finds a number that is not rejected. Table 1 shows the critical window-widths and significance levels for the tests of one, two and three modes. The unimodality hypothesis is rejected at a 10% or 5% level of significance for three out of four corruption indices. Out of 250 bootstrap samples, we observed 244 cases (234 cases) for the IMD and the CPI (for the WEF), for which $h_1^* < h_1^{crit}$ to obtain a distribution with more than one mode. The achieved significance level for the IMD and CPI thus is 0.024 (6 out of 250) and 0.064 for the WEF (16 out of 250). The null hypothesis of unimodality cannot be rejected for the Graft index. Here the bootstrap sample generated 46 cases, where $h_1^* > h_1^{crit}$ (a bandwidth h_1^* larger than the critical bandwidth of 1.46 to obtain a unimodal distribution).

Table 1: Bootstrap Multimodality Tests

	IMD 1990-2002		WEF 1996-2002		Graft 1996-2002		CPI 1995-2002	
	h_{crit}	ASL	h_{crit}	ASL	h_{crit}	ASL	h_{crit}	ASL
$k = 1$	3.63	0.024	2.33	0.064	1.46	0.184	2.78	0.024
$k = 2$	1.59	0.536	1.16	0.520	1.00	0.416	1.42	0.280
$k = 3$	1.38	0.248	1.04	0.328	0.86	0.312	0.99	0.556

Notes: 250 Bootstrap replications have been used to compute the ‘achieved significance level’ (ASL). k refers to the number of modes and h_{crit} is the critical bandwidth. Bold numbers indicate number of modes that could not be rejected at a significance level of 10% or below.

Replicating this procedure for the null hypothesis $k = 2$ indicates that this hypothesis cannot be rejected against the alternative hypothesis of $k > 2$ for all four indices. We conclude that corruption tends to have a bimodal distribution across countries. The fact that a bimodal distribution can not be found when using the Graft index might be related to the fact, that ‘rich’ countries are under-represented here.

Distributional changes over time and intra-distribution mobility

Studying corruption densities separately for different years does not change the results reported above significantly. In 28 out of 32 cases, the unimodality hypothesis is rejected at the 5% level of significance. The hypothesis of a bimodal distribution cannot be rejected in 25 cases.⁸ Cross-country corruption levels are characterised by a bimodal distribution in almost all years (see Tables A1, and A2). However, this exercise does not provide insights into the mobility of individual countries within the cross-sectional distribution. Do countries move frequently between the two corruption clubs?

In a first step, we allocate each country to one of the two clubs for every year on the basis of a discriminant analysis.⁹ Not surprisingly, we find that the high-corruption club contains nearly all developing countries of Africa, Asia and Latin America and the transition economies of

⁸ The only cases where a unimodal distribution is not rejected is the Graft index in the last two years, the IMD index in 1991, and the WEF index in 2002. The corruption data from the CPI in 1997 as well as the IMD in 1990 and 1992 suggest more than two modes. One could argue that bimodality is a result of sample selection since the largest sample (Graft index 2002) shows a unimodal distribution. But running the bootstrap test for a smaller sample for the years 2000 and 2002 reveals the same result; the unimodality hypothesis is not rejected at a 5% significance level.

⁹ The following simple rule is used for allocating countries: $i \in G_j$ if $x_i \in [c_j, c_{j+1}]$ for $j = 1, 2$, where c_j are the cut-points defined as the values of x at which the estimated density has a local minimum.

Europe and the former Soviet Union. The only EU-member state in this group is Greece. The second group of countries that are classified within the low-corruption club in every year consists of New Zealand, Australia, Singapore, Canada, the Scandinavian countries, Switzerland, the Netherlands and UK. Some other countries (most of the EU member states, Chile, Hong Kong, USA and other) are sometimes above and sometimes below the critical cut-points.

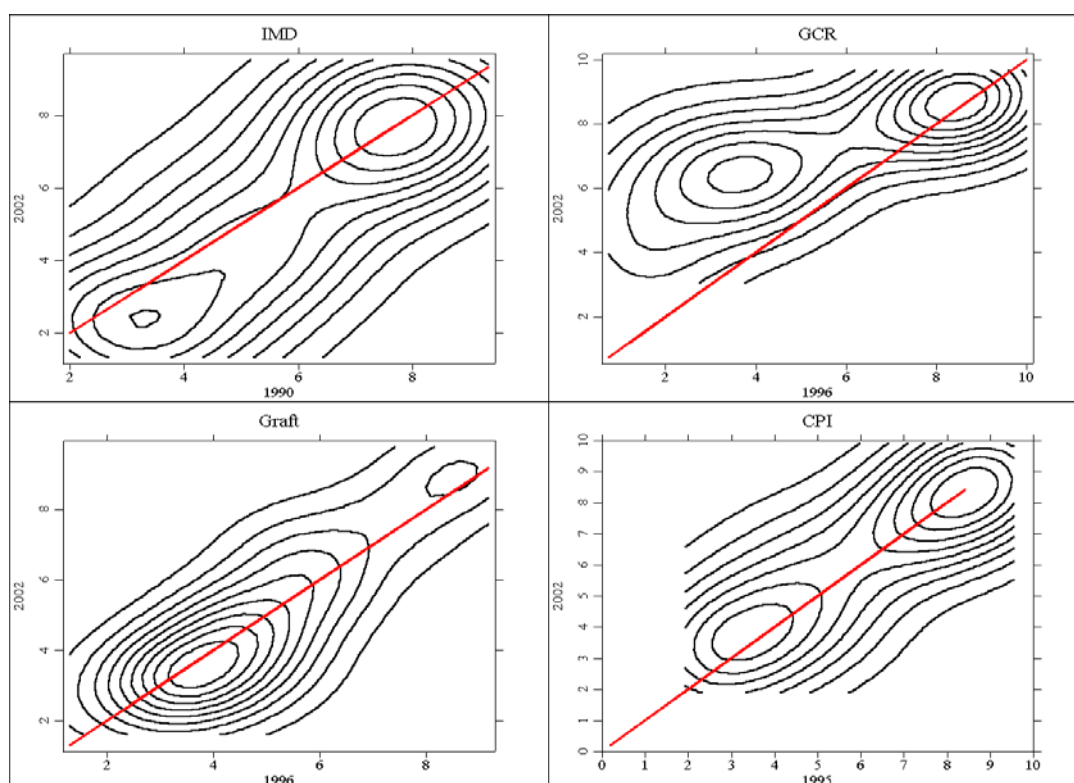
Additional evidence on intra-distribution mobility can be obtained by estimating bivariate kernel densities. The bivariate kernel density¹⁰ estimate for two variables x_{i1} and x_{i2} is

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_1 h_2} K\left(\frac{x_{i1} - x_1}{h_1}, \frac{x_{i2} - x_2}{h_2}\right).$$

K denotes a multivariate kernel function or a product of two univariate kernel functions, h_1 and h_2 are the bandwidth of the first and second variable, respectively. Here, the two variables x_1 and x_2 refer to the level of corruption at the beginning and the end of the time period. Using Silverman's rule of thumb for determining the optimal bandwidths we compute contour plots of bivariate density distributions for each corruption index (see Figure 2).

¹⁰ For details see Scott (1992) and Silverman (1986) chapter 4.

Figure 2: Stochastic kernel, contour plots of cross-country distribution of corruption



In all four cases, Figure 2 shows evidence for two peaks in the distribution (two ‘corruption clubs’). A further dominant characteristic in these kernels is a ridge along the main diagonal indicating persistence and immobility. Countries initially within the high-corruption club typically are classified within the same club at the end of the time period. Corruption is a highly persistent phenomenon. Substantial changes in the economic, political and cultural environment of countries within the ‘corruption club’ are required before a significant decline of corruption is to be expected.

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Appendix

Table A1: Optimal bandwidths and observable modes

Year/Data	Graft index				CPI index				IMD index				WEF index			
	h_{SJ}	k	h_{Srt}	k	h_{SJ}	k	h_{Srt}	k	h_{SJ}	k	h_{Srt}	k	h_{SJ}	k	h_{Srt}	k
1990									2.307	2	2.151	3				
1991									1.140	1	0.942	1				
1992									2.786	2	2.616	3				
1993									2.343	2	2.681	2				
1994									1.806	2	2.610	2				
1995					1.93	2	2.418	2	1.796	2	2.455	2				
1996	1.101	2	1.295	2	1.645	3	2.333	3	2.145	2	2.568	2	1.835	2	2.649	2
1997					2.065	3	2.284	3	1.93	2	2.542	2	1.482	2	2.047	2
1998	0.827	3	1.172	2	1.411	2	1.969	2	1.783	2	2.513	2	1.431	2	2.239	2
1999					1.396	2	1.890	2	1.661	2	2.491	2	1.295	3	2.005	2
2000	1.145	2	1.299	2	1.557	2	1.946	2	1.792	3	2.458	2	1.167	2	1.929	2
2001					1.48	2	1.934	2	1.829	2	2.482	2	1.186	2	1.530	2
2002	1.096	2	1.388	1	1.307	3	1.875	2	2.152	2	2.453	2	1.943	1	1.517	2
Average	0.996	2	1.320	2	1.187	3	1.778	2	1.870	2	2.259	2	1.521	2	1.638	2

Notes: Epanechnikov Kernel; h_{SJ} – optimal bandwidth using Sheather und Jones plug-in; h_{Srt} – optimal bandwidth using Silverman’s rule of thumb; k – observable modes of the density.

Table A2: Bootstrap multimodality tests

Year	h_{crit}			ASL		
	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$
	IMD-Index					
1990	3.22	2.32	1.06	0.024	0.040	0.640
1991	0.87	0.64		0.588	0.592	
1992	3.79	2.75	1.44	0.036	0.024	0.472
1993	4.34	2.36		0.028	0.144	
1994	4.43	1.49		0.008	0.788	
1995	4.22	1.67		0.004	0.556	
1996	4.65	1.61		0.004	0.764	
1997	4.35	1.00		0.008	0.996	
1998	4.14	1.78		0.024	0.484	
1999	4.34	1.53		0.016	0.740	
2000	4.18	1.91		0.004	0.340	
2001	4.18	1.25		0.012	0.920	
2002	4.24	1.81		0.008	0.436	
	WEF index					
1996	4.92	1.71		0.012	0.680	
1997	3.86	1.20		0.008	0.856	
1998	3.94	0.92		0.016	0.984	
1999	3.58	1.41		0.012	0.572	
2000	3.56	0.79		0.012	0.992	
2001	2.22	1.05		0.040	0.692	
2002	1.73	1.10		0.204	0.584	
	Graft-Index					
1996	2.09	1.03		0.028	0.380	
1998	2.38	0.98		0.020	0.592	
2000	1.47	1.07		0.240	0.424	
2002	1.26	0.84		0.512	0.868	
	CPI					
1995	4.30	1.69		0.012	0.528	
1996	4.13	1.75		0.008	0.412	
1997	4.13	2.35	1.32	0.008	0.060	0.420
1998	2.94	1.31		0.036	0.584	
1999	2.81	1.13		0.028	0.840	
2000	2.68	1.43		0.040	0.384	
2001	2.73	1.16		0.028	0.836	
2002	2.94	1.55		0.020	0.248	

Notes: 250 Bootstrap replications are used to compute the achieved significance level (ASL). h_{crit} refers to the critical bandwidth. Bold numbers indicate the number of modes that could not be rejected at a significance level below 10%.