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Measuring Inequality: On the Correlation Between Indices

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MEASURING INEQUALITY:

ON THE CORRELATION BETWEEN INDICES

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Abstract:

A preliminary step in the measurement of inequality regards the choice of the index to use. Several indices exist, each one responding to a built-in *aversion to inequality*, and the choice affects conclusions. But how much? And in which way? We test the ranking correlation between inequality indices, by drawing a distinction between cases involving non-intersecting and intersecting Lorenz curves.

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1. Introduction

A vast literature has flourished over the last thirty years in order to present more refined and complete indices of inequality, but a general consensus on the *best* index to use has not been reached. In this paper, the focus is on a particular aspect of this problem, the robustness of inequality comparisons to the use of alternative indices.

In this section we introduce the issue under investigation by briefly discussing the problem of the index choice[1] while in the next section we attempt to evaluate the impact of this issue in empirical studies: how much do inequality comparisons rely on the indices that are used? How much correlation is there between inequality indices? How important is the problem of Lorenz intersection when real world distributions are investigated? Finally, Section 3 concludes.

Income distributions are usually represented through Lorenz curves *L(p)* which plot the relationship between the cumulative percentage of recipient units *p,* arranged in ascending order of income, and the cumulative percentage of income they earn. It is well known that a first comparison between distributions is possible through the *Lorenz Dominance Criterion (LDC):*

> *Given two distributions X and Y, if* $L(p)X \geq L(p)Y$ *for each* $0 \leq p \leq 1$*, and* $L(p)X > L(p)Y$ *for some p, then distribution X is more equal than distribution Y.*

This statement can be justified in two different ways, through a *positive* approach, which builds upon a series of axioms implicitly assumed when the LDC is applied, and through a *normative* approach, which starts from the representation of social values through a Social Welfare Function (SWF).[2]

Whatever is the approach, the core of the problem lies in the incompletness of LDC to judge intersecting Lorenz curves, and therefore in the need to use sinthetic indices to complete the ranking. It seems reasonable to evaluate inequality indices on the basis of their ability to order distributions as the LDC does when Lorenz curves do not intersect. Lorenz consistent (LC) indices are the class of *General Entropy Measures* (and the indices ordinally equivalent to them, as the Coefficient of variation, Herfindal and Theil), the Gini coefficient, the Kakwani index and the Atkinson index.

If Lorenz curves did not intersect, LDC would be a complete criterion and, if one were only interested in the ordering of distributions, any Lorenz Consistent index would provide sufficient information. *Unfortunately*, intersection can occur and, *unfortunately*, LC indices do

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[1] We refer to the existing literature for a complete description of the indices and approaches used in inequality studies (for example Cowell 1995, Sen 1973, Kakwani 1980).

[2] For a comprehensive analysis of the axioms underlying Lorenz consistency and of the properties of SWFs., see for example Cowell (1995) and Fields and Fei (1978).

not necessarily provide the same information: the ranking of distributions depends upon the index chosen. In other words, any distributive change that implies an intersection of Lorenz curves might lead to an increase in inequality as measured by one LC index and to a decrease in inequality as measured by another LC index. To understand this point, it might be useful to think that a distribution can be transformed into another one by a sequence of transfers; indices are not ordinally equivalent because of the different way they weight transfers. Clearly, two interscting Lorenz curves can be transformed one into each other by, for sake of simplicity, two transfers: one progressive transfer at the bottom of the distribution and one regressive transfer at the top, the first one implying more equality, the second one more inequality. If an index gives more emphasis at the bottom of the distribution, the equalising effect appears stronger than the disequalising effect and less inequality is measured. The opposite happens if the index weights more heavily the transfer at the top of the distribution. In other words, two or more LC indices, depending on their own sensitivity to transfers, can capture in opposite ways the same change in the distribution of income.

2. Correlation between inequality indices using LIS data

As the previous overview has recalled, alternative indices can order distributions differently. However, what is the real extent of the disagreement between indices? How important is the problem of Lorenz crossing? How much correlation is there between inequality indices?

The issue of correlation between indices can be addressed in two different ways: As Champernowne (1974) did, a family of theoretical distributions (lognormal distributions with different values of parameters α, β, γ, representing respectively inequality among high, middle and low incomes) can be derived. He therefore studies a series of distributions which differ for variance, skewness and Kurtosis, he computes inequality according to some well-known indices of inequality and computes the ranking correlation between them. These coefficients of correlation are presented in the top-right part of Table 1. The correlation is very high among all the LC indices. The less correlated is the coefficient of variation (*CV)*, particularly when correlated to Atkinson with ε=1 (*A(1.0*) in Table 1 - coefficient of 0.802).[3] Yet, Champernowne himself underlines that, by using real data, the correlation is likely to be lower because real distributions are much closer one to each other than theoretical ones, thus implying that Lorenz intersection is more likely to appear in real world.

[3] The Spearman coefficient of correlation, used to test ranking correlation, is computed using, instead of inequality values, values representing the position of each distribution into the ranking (1, 2, ...N).

One could extend the study of Champernowne by testing different functional forms of income distribution, i.e., choosing the functional form that best fits the data. However, in this paper, an alternative empirical approach is taken. Using the Luxembourg Income Study (LIS) database, a consistent and comprehensive source of inequality data, the correlation between indices has been calculated[4]. Inequality is computed on equivalent income Y, where total household disposable income is adjusted with respect to household size according to the formula:

$$Y=DPI/S^{0.5} \qquad \textbf{(1)}$$

Where *DPI* is total disposable income in the household, *S* is household size and 0.5 is the scale relativity with respect to size. The sample data are weighted by the number of individuals, not by the number of households, leading to the equivalent income distribution of the population of individuals.

The correlation between indices is represented in the bottom-left part of Table 1. The correlation coefficients are slightly lower than the theoretical values (from Champernowne, 1974) presented in the top-right part of the same table: as suggested, this could be partially due to the fact that real distributions are much closer one to each other than theoretical distributions. Therefore, Lorenz intersection (and contrasting rankings) are more likely to happen with real data.

The correlation is particularly low with *CV* (coefficient of variation) and with *A2.5* (Atkinson, with $\varepsilon=2.5$) that definitely show the most peculiar behaviour among all LC indices. These two indices are ordinally equivalent to indices of the *GEM* family in which extreme values of the parameter θ (2 for *CV* and -1.5 for *A2.5*) are applied, thus confirming that extreme sensitivities to transfers strongly affect the overall measure of inequality and the ranking of distributions. In contrast, the most common measures (Gini - *G*, Theil - *T*, Atkinson with $\varepsilon=0.5$ - *A0.5*) present very high correlation coefficients: for example, *G* has a correlation of 0.955 with *A0.5* and of 0.979 with *T*. Also Kakwani (*K*) and Herfindal (*H*) indices have correlation coefficients very close to 1 (*K* has a correlation of 0.978 with *A0.5* and 0.991 with *G*). These findings do not mean that there exists a core of indices that are more precise in measuring inequality; on the contrary, in these indices, differences in their sensitivities to transfers are not as important such to determine relevant changes in the ranking.

An interesting implication of this exercise, however, refers to the relationship between LC and non-LC indices. This separation is theoretically important, since non-LC measures of inequality

[4] At present, microdata of more than 70 datasets representing 25 countries are present in LIS, available and comparable to a very good degree. Technical information is available at the LIS web page http://lissy.ceps.lu/.

are often rejected on the ground that they do not satisfy the basic axioms underlying the LDC[5]. However, from a ranking perspective, we find that these theoretical setbacks are relatively unimportant and that the ranking of Lorenz inconsistent indices is not *qualitatively* different from the ranking of LC indices[6]. For example, the Spearman coefficient between *PC40* and *G* is 0.973, between the difference of the income shares of the top 20% and the bottom 20% of the population (*E*) and *H* is 0.993 and between *T* and is 0.978. Only *MM* (the relative difference between the mean and the median income, often used in growth and inequality studies) has lower correlation (often below 0.8) with the other indices.

Before speculating on such findings, it might be worthy to separate cases of Lorenz dominance and cases of Lorenz intersection, in order to shed further light on the relationship between alternative indices.

2.1 Correlation when Lorenz curves intersect

All the possible comparisons between Lorenz curves are herein considered. From the sample of 69 distributions of the Luxembourg Income Study database, 2346 combinations between couples of Lorenz curves are attainable. These couples are divided into two groups: the couples of intersecting curves (1512) and the couples of not intersecting curves (834).[7] This disaggregation partially changes the overall picture described in the previous section. First, Lorenz intersection is quite likely to happen (35.55% of the total comparisons) thus emphasising the importance of the issue under consideration. This percentage is higher than a previous study (Bishop et al., 1991) in which 9 distributions and 36 comparisons were considered. In their paper, Bishop et al. found intersection in only 25% of the cases, when drawing Lorenz curves with 10 points corresponding to deciles of the population. Since the frequency of intersections also depends upon the number of points used to draw the Lorenz curves (Buhmann et al. (1988), find intersections in 80% of the cases when Lorenz curves are built using 100 points), we have replicated the disaggregation of our sample by using 10 points only. However, also in this case we find intersections in 31% of the combinations. We keep analysing Lorenz curves built using 20 points in the difficult exercise to balance the risk of giving up information (if we reduce the number of points) and the risk of emphasising the importance of intersection among extreme incomes (the reliability of these incomes is arguable, as often they are the result of procedures of top and bottom recoding).

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[5] For example, the share of income accruing to the bottom 40% of the population, (*PC40*) is indifferent to the distribution of income (and consequently to transfers) among the top 60%.

[6] Throughout the paper we keep considering Lorenz consistency in the strong sense. In fact, some of the Lorenz inconsistent indices are in fact weakly Lorenz consistent.

[7] 20 points have been used to derive the Lorenz curve, each representing the cumulative income of successive 5% of the population. The sample of 69 distribution is comprehensive of both cross-country (25 countries are analysed) and time-series comparisons (up to 6 observations for the same country).

Second, in the case of non intersection, all LC indices agree (as expected) but also Lorenz inconsistent indices as *E* and *PC40* have the same ordering of LC indices (in fact they are consistent in the weak sense): in only 5 cases, *PC40* ranks the distribution whose Lorenz curve lies above, as unequal as the second one. These are the cases in which the two distributions are equal in the bottom 40% (the value of *PC40* is the same) but one curve lies above the other one in the following 60% (*PC40* fails to represent this difference). There are not such cases for *E*: Range orders distributions exactly as LC indices do. Other non-LC indices (inconsistent also in the weak sense), as the standard deviation of logarithms and *MM*, present Lorenz inconsistency in 19.7% and 12% of the comparisons respectively.

Third, a much higher disagreement appears when only cases of Lorenz intersection are analysed. In this occurrence, ranking correlation between indices is much lower (Table 2). However, for this type of analysis, a more powerful indicator is provided in Table 3: the percentage of agreement between indices in ordering distributions. For each inequality index we have computed the direction of inequality change in each one of the 834 couples of intersecting distributions. Then, we have computed the number of cases in which indices agree on the direction of the change and finally, we have expressed the frequency of this agreement in percentage terms.

From Table 3 it can be stressed that, when Lorenz curves intersect, the choice of the index used to measure inequality appears much more relevant than what inferred in the previous section. The most popular indices show a percentage of agreement around 80% (e.g., 84.77% between *T* and *G*; 82.61% between *T* and *A0.5*; 89.76% between *H* and *G*, 78.54% between *A0.5* and *G*) but this percentage is much lower for other couples of indices: for example, between *CV* and *A2.5* there is only 40.05% of agreement. Our conclusions are therefore not in line with Bishop et al. (1991), who under-evaluated the frequency of Lorenz intersection and the rate of disagreement between indices, and with Atkinson (1970) who, in contrast, over-evaluated Lorenz intersections. Their results were probably driven by the small size of their sample (9 countries in Bishop et al. and 12 countries in Atkinson).

Fourth, as in the overall analysis previously carried out, there is not a *qualitative* difference between the behaviour of LC and non-LC indices. For example, *T* is more likely to agree with a non-LC index as *E* (83.45%) than with *A0.5* (82.61%). Moreover, *G, T* and *A0.5* are more likely to agree with non-LC indices as *E* and *PC40* than with *extreme* LC indices as *CV* and *A2.5*.

Fifth, such an investigation highlights the links between inequality and relative poverty. Measures of relative poverty[8] are often criticised on the grounds that they are closer to the concept of inequality rather than poverty. Running a test of ranking correlation in our sample,

[8] Measures in which the poverty line is defined as a certain percentage of the mean or the median income, contrary to measures of absolute poverty in which the poverty line is defined with respect to the cost of a certain bundle of goods.

we find that relative poverty measures are highly correlated to inequality measures (Table 4), particularly for measures of poverty built upon the line of the 50% of the mean income. It is therefore clear that inequality is positively correlated to relative poverty, that is, unequal countries also have high relative poverty rates. Whether this high correlation is a symptom of an economic relationship between inequality and poverty or rather an indicator of bad measurement of poverty is still a matter of debate and fuel for further research.

3. Some conclusions

While on the theoretical side different rankings of Lorenz intersecting distributions coexist, the lack of a unique ordering is also a relevant issue empirically. Whether it is important enough to care is a matter of debate. A test on LIS data shows that, when curves intersect, there is a relatively high percentage of cases in which the indices are not ordinally equivalent. There is not any qualitative difference between Lorenz consistent and Lorenz inconsistent indices in the way they rank distributions. Empirically, the sensitivity to transfers implicitly assumed by indices is a more relevant factor in determining the direction of the change in inequality than the theoretical distinction between their Lorenz consistency or otherwise.

To conclude, an empirical suggestion of this study would be to measure inequality using several indices, with different sensitivities to transfers. This would reveal what kind of inequality is prevalent in a country and how it changes. Table 5 shows how a composite use of different indices enlightens different aspects of inequality. Indices for 23 selected countries from LIS in the period 1986-1992 are computed, together with the relative ranking of each country. Belgium, Denmark and Hungary show a relatively high level of inequality among low incomes (their ranking for *A1.0* are relatively high). Czech Republic, Taiwan and Italy have inequality more concentrated among high incomes (the ranking for *CV* is higher than the ranking for other indices). The Netherlands and France have higher rankings for both *A1.0* and *CV*, thus implying that inequality is concentrated in both the tails of the distribution. Therefore, important characteristics of each distribution can be highlighted by studying inequality with indices that sketch alternative aversions to inequality.

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Table 1 - Ranking correlation: Champernowne results compared to LIS database

	$A^{0.5}$	$A^{1.0}$	$A^{2.5}$	CV	Gini	Herfindal	Kakwani	MM	PC40	Range	Theil	Logstdev
$A^{0.5}$	1	0.94		0.95	0.993						0.982	0.946
$A^{1.0}$	0.9157	1		0.802	0.901						0.866	0.998
$A^{2.5}$	0.6892	0.5246	1									
CV	0.845	0.6741	0.9533	1	0.974						0.985	0.811
Gini	0.9554	0.8008	0.722	0.8719	1						0.966	0.908
Herfindal	0.9447	0.7718	0.7731	0.9124	0.9879	1						
Kakwani	0.9781	0.8358	0.7066	0.8592	0.9909	0.9787	1					
MM	0.6866	0.4609	0.7717	0.8452	0.7766	0.8433	0.7404	1				
PC40	0.9406	0.812	0.6244	0.7922	0.973	0.9386	0.975	0.6742	1			
Range	0.9442	0.7756	0.736	0.8846	0.9954	0.9933	0.9856	0.8087	0.9668	1		
Theil	0.9741	0.8302	0.7868	0.9217	0.9791	0.9862	0.9852	0.782	0.939	0.9778	1	0.873
Logstdev	0.618	0.8552	0.2343	0.3245	0.4333	0.3951	0.4877	0.0861	0.4603	0.3958	0.4813	1

Notes: Champernowne coefficients in the top-right side of the table. Empirical coefficients using LIS database in the bottom-left side. The Spearman coefficient of ranking correlation is computed throughout the paper. $A^{0.5}$, $A^{1.0}$ and $A^{2.5}$ are the Atkinson indices with the parameter □ respectively equal to 0.5, 1.0 and 2.5.

Table 2 - Ranking correlation in the cases where Lorenz curves intersect.

	$A^{0.5}$	$A^{1.0}$	$A^{2.5}$	CV	Gini	Herfindal	Kakwani	PC40	Range	Theil	Logstdev
$A^{0.5}$	1										
$A^{1.0}$	0.4863	1									
$A^{2.5}$	0.2186	0.1243	1								
C	0.3345	0.167	0.826	1							
Gini	0.6297	0.2615	0.1035	0.2571	1						
Herfindal	0.6001	0.2455	0.216	0.3808	0.7842	1					
Kakwani	0.7113	0.3002	0.1344	0.2834	0.8645	0.7709	1				
PC40	0.49	0.1793	0.1276	0.0144	0.6749	0.4949	0.6715	1			
Range	0.5968	0.2393	0.0856	0.2469	0.8929	0.8302	0.8114	0.6466	1		
Theil	0.6969	0.3095	0.3747	0.5214	0.6847	0.7906	0.7533	0.4482	0.6599	1	
Logstdev	0.1762	0.5579	0.0718	0.0604	-0.005	0.0383	0.0297	-0.1138	-0.0192	0.0823	1

Notes: The Spearman coefficient of correlation is computed. $A^{0.5}$, $A^{1.0}$ and $A^{2.5}$ are the Atkinson indices with the parameter □ respectively equal to 0.5, 1.0 and 2.5.

Table 3 - Percentage of agreement between indices where Lorenz curves intersect

	$A^{0.5}$	$A^{1.0}$	$A^{2.5}$	CV	Gini	Herfindal	Kakwani	MM	PC 40	Range	Theil	Logstdev
$A^{0.5}$	1											
$A^{1.0}$	73.86	1	x									
$A^{2.5}$	54.39	54.39	1									
C	60.01	40.75	93.73	1								
Gini	78.54	53.96	60.37	66.51	1							
Herfindal	75.37	49.57	67.44	73.8	89.76	1						
Kakwani	83.9	58.54	58.66	64.94	93.05	88.05	1					
MM	55.63	33.25	78.53	79.45	69.74	77.09	65.58	1				
PC 40	73.74	54.79	47.44	53.33	83.69	75.12	84.15	60.73	1			
Range	75.66	50.24	61.71	67.84	94.84	92.32	90.12	72.91	82.49	1		
Theil	82.61	57.43	69.88	76.18	84.77	89.51	87.8	69.11	73.14	83.45	1	
Logstdev	70.23	86.05	31.71	32.84	41.82	39.11	46.49	25.65	43.05	38.01	46.62	1

Notes: $A^{0.5}$, $A^{1.0}$ and $A^{2.5}$ are the Atkinson indices with the parameter □ respectively equal to 0.5, 1.0 and 2.5.

Table 4 - Ranking correlation between inequality and relative poverty indices

	$A^{0.5}$	Gap40	Gap50	Head40	Head50	Gini	Sen40	Sen50	Theil
$A^{0.5}$	1								
Gap40	.7262	1							
Gap50	.8265	.9126	1						
Head40	.7440	.8711	.9044	1					
Head50	.7646	.7363	.8781	.9245	1				
Gini	.9554	.6360	.7665	.7745	.8333	1			
Sen40	.7281	.9980	.9159	.8722	.7446	.6402	1		
Sen50	.8257	.9168	.9981	.8944	.8757	.7646	.9209	1	
Theil	.9741	.6388	.7550	.7312	.7793	.9791	.6421	.7533	1

Notes: Gap40 (Gap50) = $\frac{\sum_i (z - y_i)}{q\,z}$ where z is the 40% (50%) of the mean income, y_i is the income of the poor and q is the number of the poor.

Head40 (Head50) = % of units below the 40% (50%) of the mean income.

Sen40 (Sen50) = $Head\left[Gap + (1 - Gap)G_p\right]$ where Head is Head40 (Head50) above defined, Gap is Gap40 (Gap50) above defined and G_p is the Gini coefficient among the poor.

Table 5 - Inequality indices and their rankings in selected LIS countries

Country	$A^{1.0}$		$A^{0.5}$		Theil		Herfind.		CV		Gini		kakwani		MM		Range		PC40	
SV92	0.060	1	0.031	1	0.065	1	0.112	1	0.403	1	0.189	1	0.033	1	0.060	4	0.290	1	28.0	1
CZ92	0.072	2	0.038	2	0.083	2	0.115	2	0.482	7	0.208	2	0.040	2	0.079	8	0.530	2	27.2	2
FI91	0.089	4	0.042	3	0.085	3	0.116	3	0.433	4	0.223	3	0.046	3	0.058	3	0.690	3	25.7	3
OS87	0.084	3	0.042	3	0.087	4	0.117	4	0.432	3	0.227	4	0.049	4	0.062	6	0.740	4	25.3	4
BE92	0.137	9	0.049	7	0.090	5	0.117	4	0.430	2	0.230	5	0.049	4	0.060	4	0.780	6	25.0	7
LX85	0.101	5	0.046	5	0.092	6	0.118	7	0.449	5	0.238	8	0.051	8	0.084	10	0.920	9	24.8	8
SW92	0.116	8	0.048	6	0.093	7	0.117	4	0.449	5	0.230	5	0.050	6	0.054	2	0.760	5	25.2	5
NW91	0.114	7	0.049	7	0.100	8	0.118	7	0.498	8	0.233	7	0.050	6	0.062	6	0.810	7	25.2	5
DK92	0.161	15	0.056	10	0.110	9	0.118	7	0.549	9	0.240	9	0.054	9	0.039	1	0.880	8	24.3	10
GE89	0.112	6	0.055	9	0.114	10	0.121	10	0.554	10	0.249	10	0.057	10	0.083	9	1.030	10	24.4	9
CN91	0.155	13	0.069	11	0.138	11	0.126	12	0.566	11	0.285	12	0.073	12	0.097	11	1.470	12	21.8	14
NL91	0.211	19	0.073	13	0.145	12	0.125	11	0.652	18	0.272	11	0.068	11	0.099	12	1.290	11	23.1	11
PL92	0.141	10	0.070	12	0.146	13	0.129	13	0.605	12	0.291	14	0.076	13	0.128	17	1.570	15	22.0	13
HU91	0.214	21	0.077	16	0.154	14	0.129	13	0.625	14	0.290	13	0.076	13	0.111	14	1.530	13	22.1	12
IS92	0.144	12	0.075	14	0.157	15	0.131	17	0.626	15	0.306	17	0.082	17	0.148	21	1.770	18	20.8	18
AS89	0.174	16	0.079	17	0.158	16	0.130	16	0.607	13	0.306	17	0.083	18	0.118	15	1.740	17	20.5	20
FB89	0.259	23	0.082	20	0.158	16	0.129	13	0.640	17	0.293	15	0.079	15	0.107	13	1.560	14	21.8	14
RC91	0.142	11	0.075	14	0.162	18	0.131	17	0.737	22	0.302	16	0.081	16	0.138	19	1.730	16	21.1	16
SP90	0.174	16	0.080	18	0.168	19	0.132	19	0.692	19	0.308	19	0.084	19	0.137	18	1.790	19	20.9	17
IT86	0.155	13	0.080	18	0.173	20	0.133	20	0.729	21	0.310	20	0.085	20	0.140	20	1.810	20	20.7	19
US91	0.217	22	0.096	22	0.188	21	0.137	21	0.638	16	0.337	22	0.101	22	0.121	16	2.140	22	18.3	23
IR87	0.213	20	0.094	21	0.193	22	0.138	22	0.716	20	0.330	21	0.096	21	0.161	23	2.070	21	19.6	21
UK91	0.204	18	0.099	23	0.214	23	0.140	23	0.871	23	0.341	23	0.101	22	0.157	22	2.210	23	18.8	22

Notes: SV92 = Slovakia, 1992; CZ92 = Czech Republic, 1992; FI91 - Finland, 1991; OS87 = Austria, 1987; BE92 = Belgium, 1992; LX85 = Luxembourg, 1985; SW92 = Sweden, 1992; NW91 = Norway, 1991; DK92 = Denmark, 1992; GE89 = Germany (Fed. Republic), 1989; CN91 = Canada, 1991; NL91 = The Netherlands, 1991; PL92 = Poland, 1992; HU91 = Hungary, 1991; IS92 = Israel, 1992; AS89 = Australia, 1989; FB89 = France, 1989; RC91 = Taiwan, 1991; SP90 =Spain, 1990; IT86 = Italy, 1986; US91 = United States, 1991; IR87 = Ireland, 1987; UK91 = United Kingdom, 1991.