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The Ricardian Vice:

Why Sala-i-Martin's calculations of world income inequality are wrong[1]

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ABSTRACT

The paper discusses recent world income inequality calculations by Sala-i-Martin. It shows that the two main problems with which the author had to grapple (too few data to derive countries' income distributions, and sparseness of such data in time) are not solved in a satisfactory fashion. They, and several other simplifying assumptions, make Sala-i-Martin results very dubious. We argue that Sala-i-Martin has ended up by producing a population-weighted inter-national distribution of income augmented by a constant shift parameter and not a distribution of income among world citizens.

[1] The two papers discussed here are: "The disturbing 'rise' in global income inequality" (version March 12, 2001) published as NBER Working paper No. 8904 (April 2002) and called here Paper No. 1; and "The world distribution of income (estimated from individual country distributions" (version May 1, 2002) published as NBER Working Paper No. 8905 (May 2002) and called here Paper No. 2. Both papers can be downloaded from http://www.columbia.edu/~xs23/home.html and www.nber.org.

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1. Different types of inter-national inequality

It has been well known for some time that inter-national inequality displays two contradictory features depending on whether we use population-weighted data or nor. As Figure 1 shows, if we use GDPs per capita with weights being the same for each country (Concept 1 inequality), there is a clear divergence in world incomes during the last twenty years. That divergence has been noticed by many researchers, and some like Mukand and Rodrik (2002) have wondered how to reconcile this divergence in outcomes with an apparent convergence in economic policy. But if we use another concept of inter-national inequality (Concept 2 inequality) where GDPs per capita are weighted by population sizes, inter-national inequality is displaying an exactly opposite pattern: it has been decreasing during the last twenty years. This too has been noticed by researchers including myself (Milanovic, 2002a), but prior to that by Melchior, Telle and Wiig (2000), Schultz (1998) etc.

Two points have not been widely appreciated though. First, that the decline in Concept 2 inequality over the last 20 years in entirely explained by China. As Figure 2 shows, once China is excluded, there is no decline—rather a mild increase. [3] Second, that this concept is only an approximation to what we would ideally like to measure, namely inequality across all individuals in the world. In concept 2 inequality, we, of course, assign to each Chinese the mean income of China, and to each American the mean income of the US. The ranking criterion in both Concept 1 and Concept 2 is GDP per capita: *nations* (not individuals!) are ranked by their GDP per capita. It is only seemingly that we include the 1.2 billion Chinese and the 300 million Americans. The within-country inequality is entirely ignored.

[3] Figures 1 and 2 are from Milanovic (2002a).

Figure 1. Inter-national inequality: unweighted (Concept 1)
and population weighted (Concept 2)

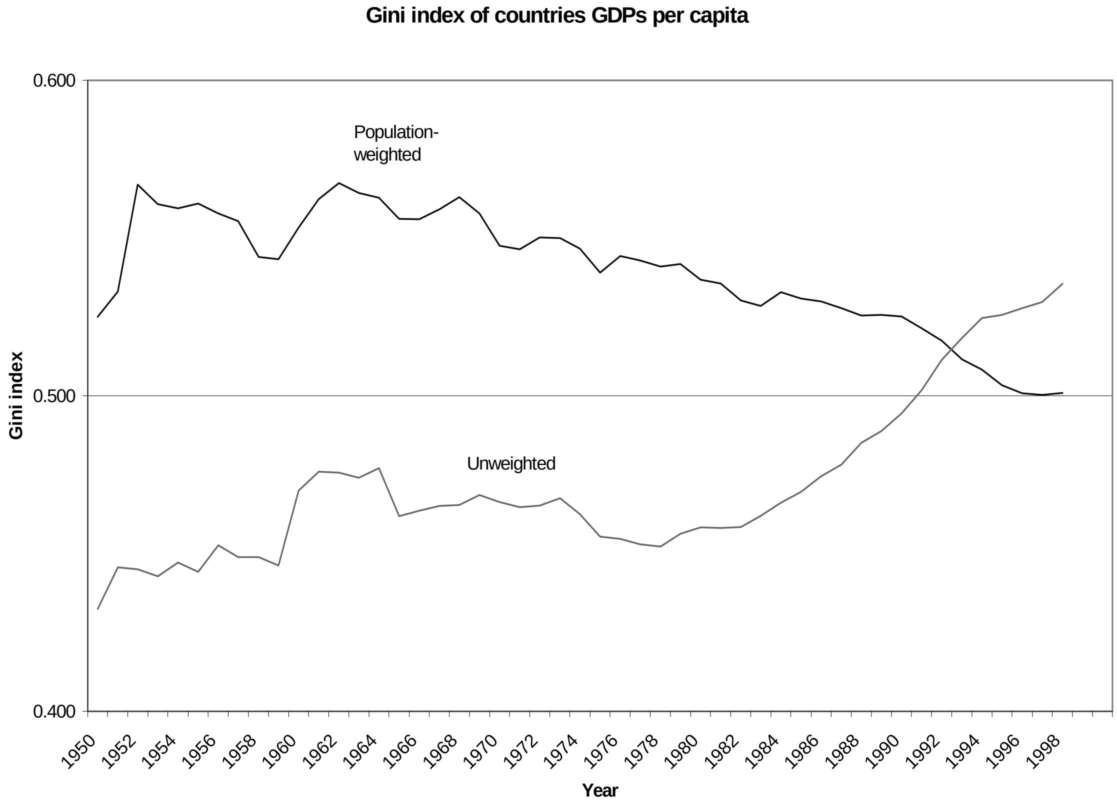
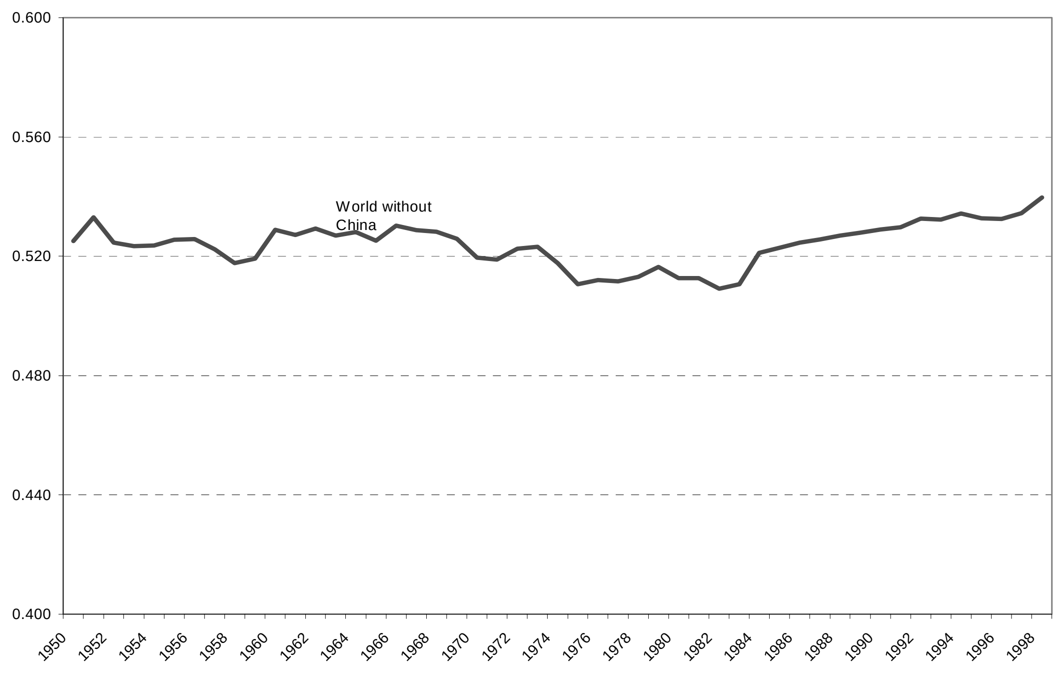


Figure 2. Inter-national population weighted inequality without China



So why was Concept 3 inequality (inequality across individuals of the world) not measured until very recently? The reason is that in order to measure it, one needs to have detailed households survey data from most of the countries of the world, hoping to cover at least 90 percent of world population and even more of world income. Moreover, one would need to actually have access to micro (individual-level) data for most of the countries in order to be able to check whether the welfare indicator (income or expenditure) is correctly defined, to create income or expenditure per capita values, to use survey-provided weights which are supposed to control for differences in response rates, and most importantly, to be able to "slice" the distribution into a lot of income classes—into ten deciles, or even better into ventiles (20 classes), or more.

The number of household surveys, for many countries in the world, is quite limited. Even more limited is access to individual-level data because many countries are loath to release the detailed data to researchers. And, until fairly recently there were no surveys at all, or no reliable surveys, for many parts of the world. For example, no survey for China was available before 1982; there were no published survey results (much less access to individual-level data) for the former Soviet Union, and almost all of Africa had been "uncovered" by surveys until some 10 to 15 years ago. So, even if theoretically, one had access to all household surveys conducted in the world, she could not have been able to do much calculations before the mid- or late 1980's. The is the reason why the only study so far to have used only household surveys (3/4 of which were available at the individual level) to calculate directly Concept 3 inequality (Milanovic, 2002) does this for three benchmark years, 1988, 1993 and 1998.[4]

Several authors have, however, made some very broad approximations (Bourguignon, 1999; Chotikapanich, Valenzuela and Rao, 1997) without claiming too much precision for their estimates. Chotikapanich et al. explicitly treat theirs as a *pis-aller*, an approximation that is far from ideal and that is necessary only because much better data are unavailable. Not only were many important countries not represented in the data (household surveys being

[4] The data can be downloaded from www.worldbank.org/research/inequality.

non-existent or not available), but for those that had surveys, neither individual nor decile data were in many cases available. Thus researchers like Chotikapanich, Valenzuela and Rao (1997) and Quah (1999 and 2002) had the following idea: why not use the information on Gini coefficient and mean income (or country's GDP) and impose lognormal distribution (the most common distribution of income) or Pareto distribution (less common) and get an estimate of income levels at different percentiles (10^{th}, 20^{th} and so forth). This is essentially what Sala-i-Martin—with whose recent two papers we are concerned here—has done as well except that instead of ''imposing'' a lognormal (or any other distribution) on a few data points, he made a non-parametric (kernel) estimate of each distribution based on quintile shares obtained from the Deininger-Squire (DS) data base for the period 1970-96,[5] and from World Bank World Development Indicators (WDI) for the other two years (up to 1998).[6] In Paper No. 1 the kernel function was applied to all data points (quintiles) of all countries taken together, that is, the data were all lined together as in a string, and then a density function was estimated across all of them. In Paper No. 2, Sala-i-Martin improves on this approach by estimating a kernel function for each distribution separately—across the five quintile data for each country/year. The former is the estimation of "kernel of quintiles" (Paper No. 1); the latter is "kernel of kernels" (Paper No. 2), and the differences are found to be negligible (Paper No. 2, p. 16).

[5] Deininger and Squire do give in their much-used data base, information not only on Gini coefficients but on quintile shares—although the country coverage of the latter statistics is less.

[6] Sala-i-Martin writes that he is using both Deininger-Squire and World Development Indicators (WDI) quintile shares (Paper No.1, p. 10). He does not give the source for the latter (it must be various issues of WDI). These data are also relatively few in number (compared to the Deininger-Squire compilation), and not as well documented. Thus, the entire discussion here will be based on the Deininger-Squire database version 2 which is also available on the Internet at http://www.worldbank.org/research/growth/dddeisqu.htm. The issue of documentation (in particular whether we deal with distribution of household income across households, or distribution of per capita income across individuals) is extremely important and is not adequately addressed in WDI.

2. Enter Sala-i-Martin

One may wonder why Sala-i-Martin's work would justify critical scrutiny more than the other mentioned papers. There are two reasons for this. First, unlike other authors quoted above who explicitly acknowledge the limits of their data and estimations, Sala-i-Martin makes a bold claim to have derived a distribution of income across world individuals and to have done this for the period of the last thirty years (and for each year). Second, his estimates are widely quoted in professional and popular press. As of November 2003, Sala-i-Martin's Website provides to its readers more than 30 newspaper references—in several languages—to the two papers. Some of those who quote his results are individuals of very high authority in economics.[7] They may be unaware or unfamiliar with different methodological and empirical choices made by Sala-i-Martin in his calculations. Because of the sheer ambition of the claims made, and the publicity received, his work therefore requires careful scrutiny. As I hope to show here, his claims are unsound, both on methodological and empirical grounds.

Selection of countries. Let us consider first he list of countries included in Sala-i-Martin's estimations. Here it is as given by the author (Paper No.1, p.10).

"Group A. Countries for which we have a time series of income shares by quintiles (by time series we mean that we have a number of observations over time, although we may not have observations for every year between 1970 and 1998).

Group B: countries for which we have only one observation between 1970 and 1998.

Group C. Countries for which we have NO observations of income shares."

There are 68 countries in the Group A accounting for 4.7 billion people. Then, "although shares estimated by Deininger and Squire and the World Bank, are not constant, they do not seem to experience large movements. If anything they seem to have small time trends. Using this information, we regress income shares to get a linear trend for ach country." (Paper No. 1, p. 10).

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[7] Paul Samuelson, Alan Greenspan and Robert Barro, according to the information provided on Sala-i-Martin's Website (http://www.columbia.edu/~xs23/home.html).

So, for group A for which there are observations, although, as it is delicately put, "we may not have observations for every year"—we shall see below, that there is only *one* country which has observations for all the years—missing country/years are approximated by linear extrapolation.

For group B of countries (29 countries, 315 million people), income shares are assumed constant for the entire period (that is, from one data point, information is extrapolated back and forth to all the years).

For group C countries (28 countries, 232 million people) all citizens are supposed to have GDP per capita of the country—that is, inequality is nil, and we are back to calculating Concept 2 inequality.[8]

There are some strange omission in the country coverage (given in the Appendix 2, Paper No.2) Thus, Russia is not included at all despite the fact that Deininger-Squire data base provides two observations and that the country is also included in WDI. Moreover, *none* of the former Soviet republics is included although most of them are in the DS database. Table 1 shows, for example, that there are 12 former Soviet republics in the Deininger-Squire data base with a total of 26 observations (not counting the observations from WDI). It is very odd to leave them out. It is even stranger—and not without an effect on the results—if one realizes that these countries are precisely the ones characterized by significant increases in income inequality: the Russian Gini, for example, jumps from 24 to 48, Ukrainian from 23 to 47, and very much the same for all the others. We shall show below that Sala-i-Martin's calculations boil down to assuming within-country inequality to be fixed throughout the entire period, and if so, the inclusion of countries with large increases in inequality might have pushed overall inequality up, and invalidated his claim of decreasing world inequality.

[8] The number of people included in each Group differs somewhat between the two papers (cf. Paper No. 1, p. 10 and Paper No. 2, Appendix, p. 65).

Sala-i-Martin discusses the non-inclusion of the former Soviet republics in a footnote in Paper No.2 (page 5), and claims (i) that these countries were not included because they did not exist prior to 1992, and (ii) that their omission does not bias world inequality. In his correspondence with me, Sala-i-Martin adduces yet another reason: these countries were not included because Penn World Tables (which Sala-i-Martin uses to get GDP per capita numbers) do not include Russia, Ukraine etc. We shall address each of these explanations.

The first explanation is rather lame, as Estonia with 4, Latvia and Russia with 3, or Ukraine with 2 observations have greater or equal number of observations as (say) Egypt and Morocco which are both included. The same rules as applied elsewhere—extrapolate from two or three observations to all the years—could have been applied to them. The fact that they are "new" countries is totally irrelevant. Here comes, however, Sala-i-Martin's point that even if quintiles for these countries exist, GDPs per capita do not. A glance at Penn World Tables 5.5 and 5.6 (PWT) reveals however that the USSR is included from 1960 to 1989 with GDP per capita expressed in 1980 international dollars. Then, simply taking a ratio between Russia's current roubles or dollar GDP per capita in (say) 1980 and Soviet GDP per capita in 1985 would have given Sala-i-Martin Russia's GDP per capita in international dollars of 1980—the exact information that he needs. Once the benchmark value is available, one simply needs to apply Russian real growth rates available from any Russian Statistical Yearbook (or many international sources). The same holds for all other republics—15 of them. An alternative, and well-known, source would have been Maddison (1995, 2001) which gives the GDP per capita for the USSR for the entire 1950-98 period (see Table C1-c in Maddison, 2001). [9]

There is another strange omission: that of Bulgaria. Now, Bulgaria is not a new country, and it is included in PWT for the entire period 1960-1992. Yet it is not included in Sala-i-Martin's calculations. Incidentally, it is also a country with one of the largest number

[9] Moreover, Maddison (1995, p. 142) gives Russia's 1990 GDP per capita in 1990 international dollars. Conversion from Maddison's numbers expressed in 1990 international Geary-Khamis dollars to Penn World Tables 5.6 values expressed in 1980 international dollars, or PWT 6.1 expressed in 1996 international dollars, is a fairly simple exercise.

of quintile data in the Deininger-Squire data base, so it cannot be a shortage of inequality measures that is to blame.

The second explanation (the omissions do not bias the results) is wrong. Adding the Soviet republics, Bulgaria, and (former) Yugoslavia[10] together is adding about 350 million people or more than 6% of world population and some 7% of world PPP income in the late 1980's. And as Milanovic (2002) shows, the transition countries (mostly former Soviet Union) account for about a half of the 2.8 Gini point increase of "true" (Concept 3) world inequality between 1988 and 1993. Thus Sala-i-Martin's omission of these observations certainly biases overall inequality down. The reader can simply refer to Sala-i-Martin's Gini values shown in Figure 8 below, and add for all the years after 1990, about 1½ Gini points. Instead of a clear downward trend, she would observe a stable Gini.[11]

[10] Yugoslavia (and its successor republics) is excluded despite having 9 observations. There are also a few other mysterious exclusions: Iran (4 observations), the Bahamas (11 observations), Surinam (5 observations) and Vietnam (2 observations). Iran and Vietnam alone would have added more than 150 million people to Sala-i-Martin's sample. In PWT 6.1, the GDP per capita data for Iran are available from 1955, for Vietnam from 1983 (see PWT 6.1, available at http://pwt.econ.upenn.edu/).

[11] Another curious fact is that not all of the transition countries are omitted: Czechoslovakia, despite the fact that it no longer exists (no more than the USSR) is duly in the sample. One is unable to say how the two new countries are treated, where *their* GDP per capita data come from (PWT 5.6 gives the data for the *whole* of Czechoslovakia up to 1992; PWT 6.1 gives the data for the two republics from 1990 onwards). None of these things is explained. Included are also Hungary and Poland. Now, it is precisely these three (or four) countries, the only ones among the transition countries, that have experienced but mild increases in inequality. In the Deininger-Squire database, the Gini for Poland goes up from 27 in 1989 to 28 in 1993, the Gini for Hungary increases from 23 to 32 and then drops back to 23, and the Czech Gini goes from 25 to 28. Compare this with Russian and Ukrainian increases of more than 20 Gini points.

3. The Ricardian vice: fragmentary and sparse data overcome by making heroic and unwarranted assumptions

The description of the estimation approach used by Sala-i-Martin already highlights the problems. The first problem has to do with very few data (quintiles) available to derive a distribution. We call this *fragmentary* data. The second problem has to do with the absence of even such fragmentary data for most of the years. These missing years then have to be filled in by extrapolations. We call this the problem of *sparse* data.

We shall discuss, first, how entire distributions are derived from only five data points, and second, how these sparse data are combined in order to produce a semblance of a dense distribution in time, or in simple terms how Sala-i-Martin moves from having two or three observations for Egypt, Switzerland or Greece over the 29 year period to "pretending" that he has all of them. [12]

Fragmentary data. First, we should note that that the Deininger-Squire quintiles used to derive distributions are often not calculated from primary household-level observations, but from grouped data and were estimated by fitting the Lorenz curves. Thus, quintiles which are themselves estimates are used to estimate the entire distributions. [13]

Then, notice that once a researcher has decided to either impose a distribution using a few data points, or to do a non-parametric estimation also using a few data points, there is nothing stopping him/her from estimating income levels at any point in income distribution: one does not need to stop at deciles or even centiles, one author went all the way to *millesimes*, estimating the distribution for each one-tenth of a percentile.[14] But notice too that these are still very much *estimates*, rather guesses, and, as we shall show below, once they are made from very few data points, they are very rough and quite likely very inaccurate

[12] In terms of the actual steps made by Sala-i-Martin, first comes the estimation of quintile shares for all the years and then the derivation of kernel density functions. But for discussion, it is easier to reverse the order.

[13] This was drawn to my attention by Martin Ravallion.

[14] The paper, which I was asked to referee, belongs to an anonymous author. I do not know if it was published.

estimates as well. Actually, before Sala-i-Martin no-one has done what he has, for no-one was as wiling and eager to push the art of approximation so far. The reason was not that the data were not there (the Deininger-Squire data base has been available since 1995) nor that the methodology, as we have just mentioned, was unknown. It is simply that no one thought that the heroic assumption that ought to be made were defensible or justified—or in other words, that the results based on such heroic assumptions would make much sense.

A *differencia specifica* of Sala-i-Martin's is the use of non-parametric estimates of the density functions. At first this seems to be an improvement: one does not impose an a priori function on the data. On the data…But how many data points there are? Five in all cases. Normally, we use non-parametric estimates in order to create some sense out of a plethora of data points—to derive regularities from the many "noisy" observations. It is for example common to use non-parametric estimates of food-ratios from household survey data: we want to "extract" an Engel curve from thousands of recalcitrant and often "noisy" data. But here we deal with the exactly the opposite problem: we have *five* observations and we need to "stretch" them into producing literally a hundred observations. How is this miracle performed? I have used the individual-level Malaysian data for the year 1997. Figure 3 shows income density function estimated from such micro data by applying a non-parametric kernel estimate. The shape is a familiar one: (log) normal. I have then created five quintiles from the individual data, and applied to these five quintiles Sala-i-Martin's Gaussian kernel with the suggested bandwidth of 0.35.[15] Figure 4 shows Sala-i-Martin's approximation. Picture is worth a thousand words…[16]

[15] In Paper No. 2, Sala-i-Martin approximates a density function for each country/year separately, and so the optimal bandwidth should, in principle, vary between the countries. He settles though on a common bandwidth of 0.35.

[16] I have performed the same calculation for three other countries (Brazil 1998, Italy 1998, Pakistan 1997). Not surprisingly, the results are the same. (They are available on request.)

Figure 3. Kernel estimate of income density function based on individual-level data (Malaysia 1997)

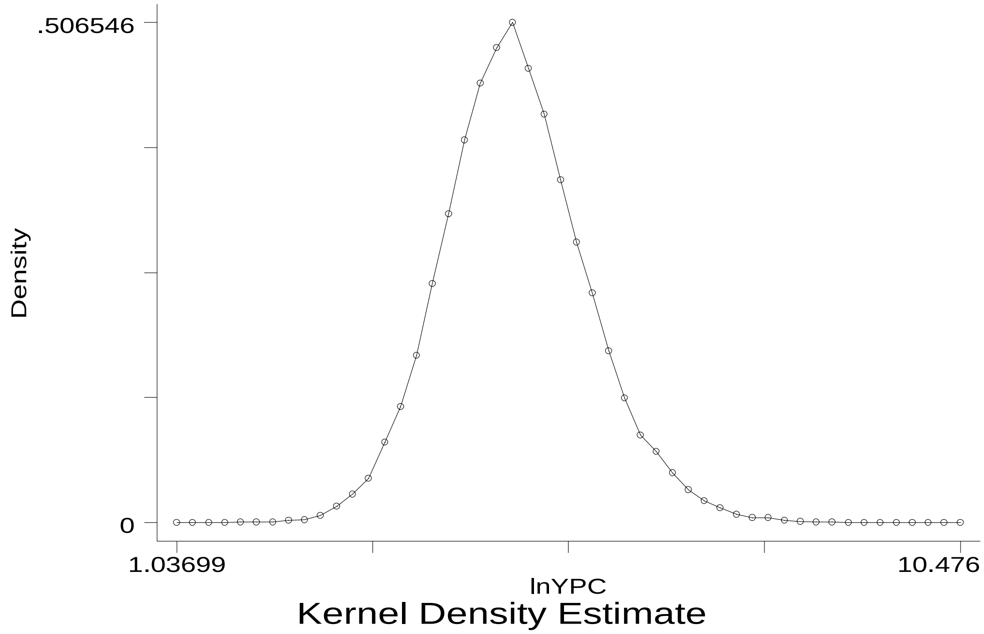
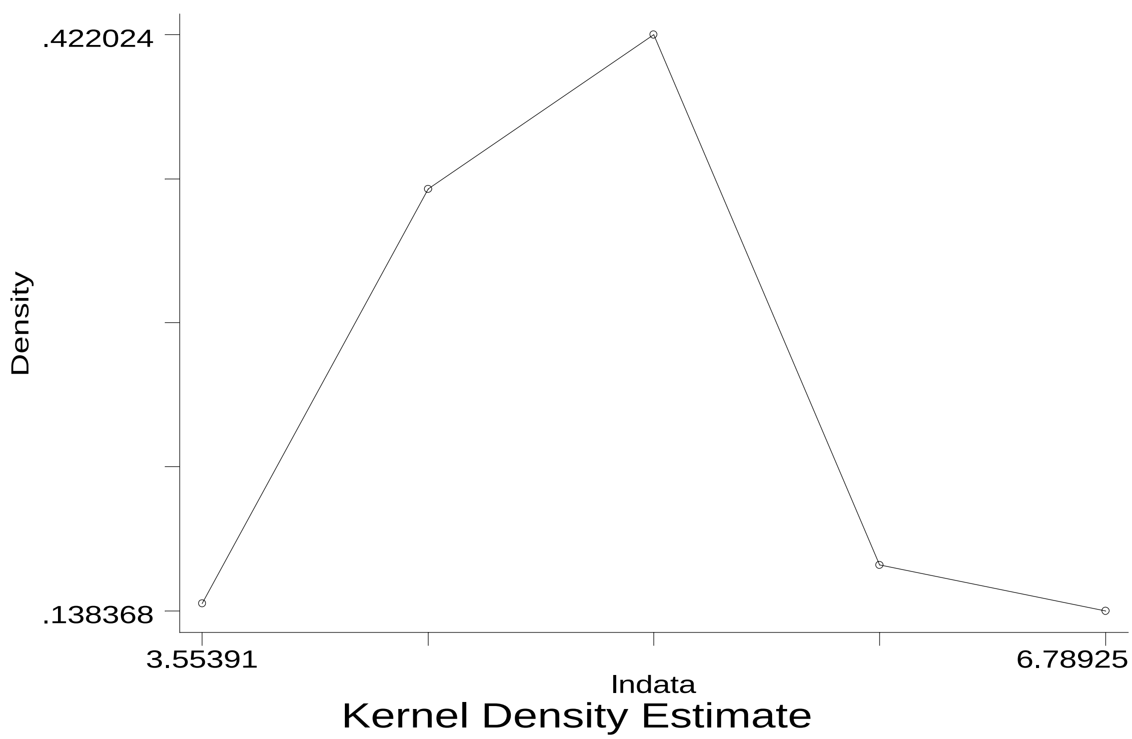


Figure 4. Kernel estimate of income density function based on five quintiles (Malaysia 1997)



But the problem of too few data to derive a distribution does not end here. Consider the example of China where Sala-i-Martin has the following five (cumulative) quintile shares for 1992: (0.062, 0.1672, 0.3253, 0.5835 and 1). Based on these five values (and GDP per capita) Sala-i-Martin estimates a kernel density function. But to derive a distribution based on five data points is to subject oneself to a very large degree of error (as illustrated by Figures 3 and 4). It is not only that "stretching" the five data points to represent a hundred is wrong, or that, depending on the smoothing techniques (bandwidth) and the assumption one makes (what type of kernel density function), vastly different results can be obtained—all compatible with the five numbers we have. It is that even if different kernels yield similar results, it still does not guarantee that we have "guessed" right—simply because income density function is an empirical function where, with five numbers we have, we cannot at all be sure to have approximated it correctly. We know that the bottom 20% of people of China receive 6.2% of total income. But this value is consistent with the bottom decile receiving 2% of total income, or 2.5%, or even only 1%. For the top, it is even worse, and that is where most of the mistake (and bias) lies. We know that the top quintile gets 41.65% of income. But how about the top decile? Do they get only 23% percent—which should be consistent with a relatively equal distribution—or perhaps 28 percent. [17] On per capita basis, the difference amounts to about 20 percent of income for about 120 million people or 2 percent of world population. And how about the top ventile (5 percent)? The margin of error is even greater there.

Or, take the United States, where the top quintile in 1996 receives 48.9 percent of total income, and the fourth quintile gets 27.8 percent. Applying the same logic: does the top decile get 25 percent of total income (just minimally more than the ninth decile), or a little under 35 percent? The difference in the top decile average income estimate is 40 percent, and per capita income of the top decile may range between $PPP 69,700 and $PPP 97,580 per capita per

[17] We know that they cannot get more. The average income of the fourth quintile is (0.5853-0.3253)/0.2=1.29 times greater than the mean. The ninth decile thus must receive more than 1.29*10=12.9 percent of total income, which limits the top decile to less than 28.7 percent (41.65-12.9).

year. [18] Whether we choose one or another income for these 30 million people, probably the most affluent in the world, will make a difference to our inequality calculations. For the difference is far from negligible: it amounts to 1.8 percent of total world income![19]

Sparse data. Let us now move to the sparseness of the data which is an even more serious problem. Table 1 shows the list of countries and number of observations available in the D-S database. There are 630 observations. After eliminating countries not included in Sala-i-Martin's calculations, we are left with 532 observations.[20] The average number of observations for Groups A and B is 5.5 out of 27 (years), which means that—for the countries for which the data *are* available—only about 20 percent of country/years are filled. (This is graphically shown in Table 2 where a black box indicates that an observation is available.) If we require, not unreasonably for a study that claims to have derived income inequality statistics for each year over the period, that a country should have observations for at least two-thirds of the time (that is, to have more than 18 observations), we are left with a total of six countries: USA, Bulgaria, Taiwan, Great Britain, Canada and Japan. [21] Only one country—the US—has observations for all the years.

Sala-i-Martin presents to the reader his results as if there we *no blanks* at all in the data. As we already know, he gets round blank spots by extrapolating forward and backward in time the results obtained from the years for which he has the data. Thus the Chilean black

[18] Calculated by taking the 1996 GDP per capita (27,880 in 1995 international dollars) and multiplying by factors or 2.5 and 3.5. (If the top decile gets between 25 and 35 percent of total US income, then average per capita income of its members is between 2.5 and 3.5 times the US average.)

[19] Calculated as follows. The US per capita GDP in 1996 was 3.72 times higher than the world GDP per capita. Then, the mean income of the top US decile is anything between 9.3 and 13 times mean world income. Since US top decile comprises about ½ of a percent of world population, their share in world income ranges between 4.7 and 6.5 percent.

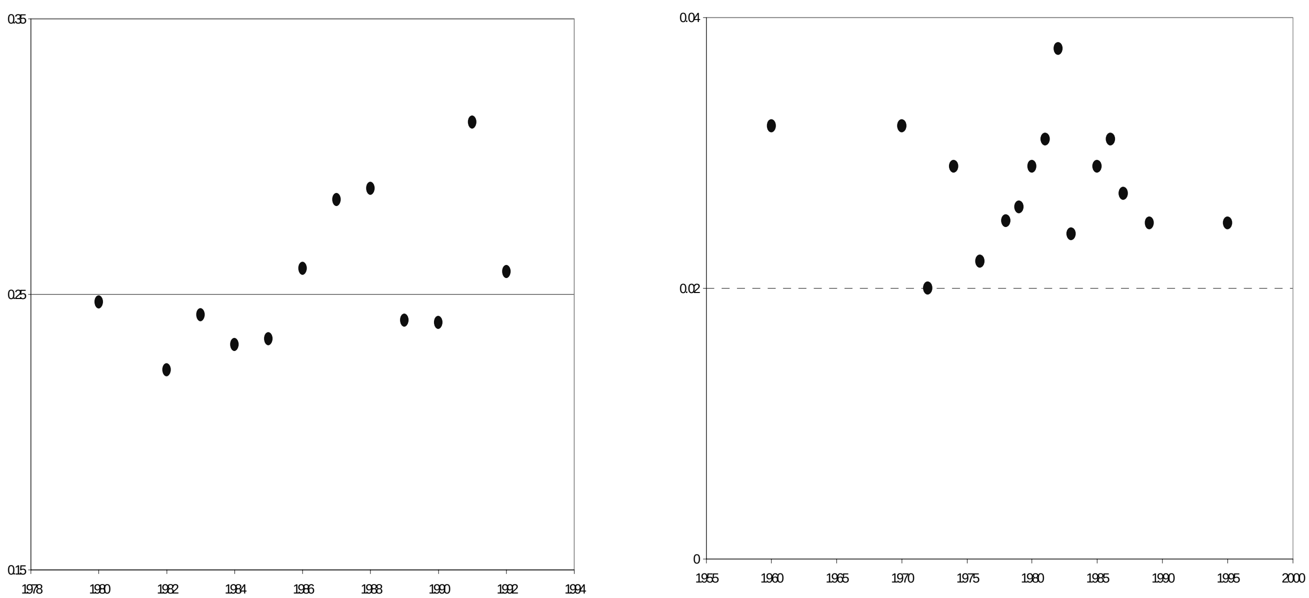
[20] The period covered by the Deininger-Squire database runs up to 1996. Sala-i-Martin's data (thanks to WDIs) extend into 1998. The difference cannot but be minor.

[21] And to complicate matters further, the Japanese surveys from which these data are derived are not nationally representative because they leave out farmers and one-person households, that is, ten percent of the population (see Tachibanaki and Yagi, 1997). And Bulgaria is, as we have seen, not included.

boxes for the years 1981, 1989 and 1994 are used to fill the blank spots for all earlier and later years (24 in total) assuming that quintile shares follow a linear trend. [22]

But the extrapolations are not at all obvious. Consider the data for China's fourth quintile (used here because of China's obvious importance) over the period 1980-92 (Figure 5, left panel). There seems to be an increasing tendency—but, on the other hand, isn't it driven by the value for 1991 when after the Tian-An Men massacre, there was a tightening of government policies and a reduction of inequalities, and didn't the value in 1992 already go back to where it was in 1986? Sala-i-Martin chooses to draw a straight line: the fourth quintile in all years, shown here as well as all the way back to 1970 (when the first national survey was 10 years into future!) will have a share of 25 percent of China's income. Voilà! Thus,

Figure 5. Income share of the fourth quintile in China (left) and first quintile in Brazil (right)



Source: Deininger-Squire data base Version 2.

[22] Sala-i-Martin must have felt, one would surmise, vaguely uncomfortable about these extrapolation as nowhere in the two papers does he give the number of observations available by country. And few things would have been easier (and more useful) to the reader than such essential information which could have been readily added to the Appendix table (in Paper No.2) where all countries and their populations (sic!) are listed. Equally revealing is the fact that in Paper No.1, Appendix Table 1 lists all the countries and Groups to which they belong but again fails to provide the number of observations.

Table 2 get filled with black dots. For many countries quintile shares exhibit a large variability: rather than moving in predictable ways, or being stable, they "jump" all around (see Sala-i-Martin Appendix Figures, Paper No.2, or Brazil in Figure 3 here). One is reminded of Samuelson's quip: "yes, you can draw them as straight lines, but only with a very thick chalk."

So, after being treated to an estimate of the entire distributions from five data points, we are now led for another leap into the unknown. These very dubious annual estimates are now extrapolated to years vastly apart to get estimates of quintile shares throughout the entire period. Here is the enormity of the assumptions. Data on income of the top 20% of (say) Chileans in the year 1994 are used not only to infer the income of the top decile, or of the top ventile in *that* year. They are also used to infer income of the bottom quintile and of the bottom decile and of the bottom 15% or whatever (that is, of the entire distribution) in *all other years*. [23] And thus for every country.

We have seen that for Group A and B countries (97 countries), observations are available for, on average, only 5.5 out of 27 years. For 28 countries in Group C, there are no data at all. This means that the overall time coverage is 15.8 percent—leaving aside the former Soviet republics, Bulgaria, Yugoslavia, Vietnam, Iran etc. which are not included at all.[24] If in addition, we assume that for a distribution to be reasonably well described, we need ten data points (ten deciles), the desirable number of data-points becomes 27 times 125 times 10 = 33750. Instead, Sala-i-Martin has 2667 data points,[25] or 7.9 percent.

Here is the deep-rooted problem with Sala-i-Martin's calculations. He tries to overcome the problem of fragmentary data by imposing a distribution on them. Given the very few data points—some of which may themselves be fitted approximations—it is a dramatic oversimplification with an unknown bias. But in addition, he faces the problem of

[23] This is because *n*-th quintile share in year *t*, influences our linear approximation of that and all other quintile shares (since the five shares have to add up to 1) in all the years for which one does the extrapolations.

[24] Out of total maximum number of country/years, 27 times 125 = 3375, there are only 97 times 5.5 = 532 observations.

[25] 97 x 5.5 x 5.

data sparseness. He overcomes it by extending in time these largely arbitrary estimations obtained from the country/years for which he had the data! "He then piled one simplifying assumption upon another until, having really settled everything by these assumptions, he was left with only a few aggregate variables between which, given these assumptions, he set up simpler one-way relations so that, in the end, the desired results emerged almost as tautologies." Thus Schumpeter (1980 [1954], p. 472-3) defined the Ricardian vice.

In conclusion, to calculate true world inequality there is no shortcut from using the individual-level data complemented (when individual data are unavailable) with grouped data with at least decile shares. To do anything else, introduces a large and unknown degree of arbitrariness in the results. This, combined with other problems (discussed below) and the general issues that plague such calculations *even* if one had access to all individual-level data (unequal reliability of surveys, differences in the definitions of welfare aggregates and the like) makes the noise element dominate, by far, the signal.

4. Other problems

We are not at the end of the problems yet. There are three more.

The first is the use of GDP per capita rather then survey means. This was done by other authors as well (Chotikapanich, Valenzuela and Rao, 1997; Schultz 1998; Bhalla, 2002). There are two problems with this approach. First, it introduces an inconsistency: we use and trust household survey data for the distributions, but we do not believe their means. In other words, surveys are good in guessing distributions, but they miss the means (income levels). Some authors like Surjit Bhalla (2002) have insisted on this issue by claiming that survey means (as is apparently the case in India) underestimate true income, and have erected the negative difference between the survey means and GDP per capita from an issue that may (or may not: the extensive debate on this in India is not conclusive) hold for India, into a general proposition for all countries and all time. Second, the use of GDP per capita means that we implicitly believe that over- or under-estimation of income by surveys is proportional to reported income. If GDP per capita is 20 percent higher than the survey mean, by raising all survey incomes by 20 percent we are claiming that under-reporting is proportional to reported income. But, from the literature (see Ravallion, 2001 p. 1805; Ravallion, 2000, pp. 3250-1 in the context of India, or Wagner and Grabka, 1999 for Germany) we know that this is not the case. If there is a misstatement of survey incomes, it is most at low ends (where people are missed by surveys) and top ends (where people hide their incomes, or where income types associated with rich people are imperfectly reported). [26] As Ravallion (2000) writes, there is an internal inconsistency in use of national accounts data instead of household survey means. As the two have diverged in time in India, the adjustment factor by which survey means have been raised, has also increased. But at the same time, the authors persist in increasing income of all recipients by the same percentage for any given year. Thus, they need to argue that "the rate underestimation is roughly constant between people at one date, but…it has risen over

[26] There are several ways in which this underreporting takes place. First, there is "top-coding" (maximum acceptable value) for some income components like capital gains in the US Census Survey (top coded at $99,999 per household). Other countries (Germany) do the same. Second, there is a consistent underestimation of income sources associated with the rich. Property income is underestimated by 60 percent in France (Concialdi, 1997, p. 261) and by more than 40 percent in Germany (Wagner and Grabka, 1999).

time with growth in mean consumption (Ravallion, 2000, p. 3250). In conclusion, if we do not believe survey levels, and want to correct them, adjusting them by the same percentage across the board is very crude and almost surely wrong.

The second problem is mixing of income and expenditure data. This is the problem present in Milanovic (2002) as well. It is made unavoidable by the fact that countries "specialize" in having either income or expenditure surveys, and then the coverage of the whole world by either income or expenditure surveys alone becomes impossible. Sala-i-Martin, as well as the Deininger-Squire database, also mixes the two sources: the quintiles are in some cases derived from expenditure (or consumption) shares, and in some from income shares.

The third, and a very serious issue, is the mixing of quintile shares obtained from distributions of households with quintile shares derived from distributions of individuals. One is the distribution of households by household income, denoted D(H|Yh), and another is distribution of persons by household per capita income, denoted D(p|Yp). [27] The latter is, of course, the one that we want to use. Sala-i-Martin does not mention explicitly that he is combining the two sources. However, by comparing the total number of observations used by Sala-i-Martin from the Deininger-Squire data base (about 540) with the total number of both household- and individual-based quintile shares available in the D-S base for the period after 1970 (about 600), and taking into account that about 50 observations (Bulgaria, Russia, Iran etc.) have not been used, it becomes clear that Sala-i-Martin must have combined D(p|Yp) and D(H|Yh) distributions. The D(H|Yh) distributions account for about 40 percent of the D-S database. Thus, had they not been used, Sala-i-Martin's number of observations would have been significantly smaller (about 350). The use of the wrong distribution D(H|Yh) makes a total mess of world inequality calculations as now the issues of family size (vastly different between countries) and inconsistency in the recipient units entirely vitiate the calculations, making them simply meaningless. The five data points representing a distribution of *households* by total *household* income in a country X in a year *t* are now interpreted to be the

[27] To complicate matters further, there are also distributions of households by household per capita income D(H|Yp) but they are few in numbers.

same as (i) the distribution of *people* by their per capita income, and is used to guess (ii) the entire income distribution of *people* for year *t*, and (iii) for many years forward and backward. [28]

Moreover, even here, and rather surprisingly, lurks an additional source of bias. For some unknown reason, the Deininger-Squire data uses much more of household-based D(H|Yh) information for the period up to the 1990's. Table 3 gives the share of household- vs. individual-based quintiles for each decade used by the Deininger-Squire. Since D(H|Yh) distributions are generally more unequal than D(p|Yp) distributions, the overall (or average) level of inequality in the 1990's will tend to be relatively low. As a result, the actual increase in inequality which took place in the decades of the 1980's and 1990's, and which is plain to see when we control for the type of recipient—that is, if we include only observations based on distributions of persons—will fail to show in the data when D(H|Yh) and D(p|Yp) are mixed together. This is illustrated in Figure 6.

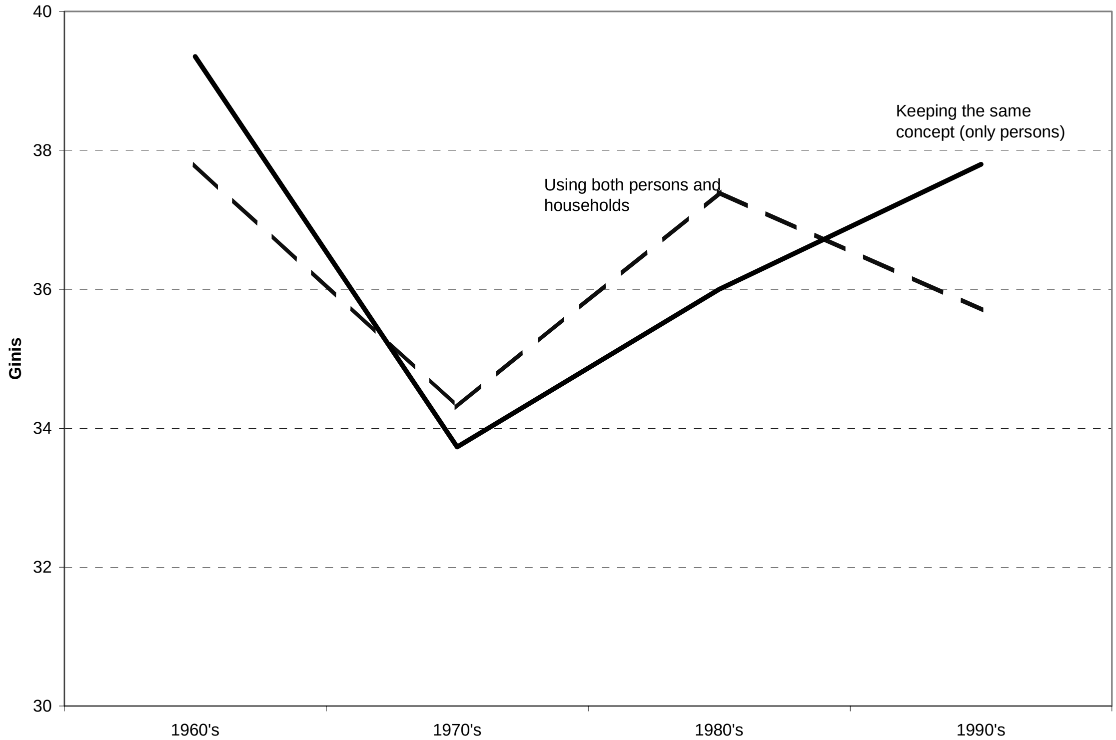
Table 3. The two types of distributions used in the Deininger-Squire database

Decade	Observations based on D(p|Yp)	Observations based on D(H|Yh)	Share of D(H|Yh) observations in total
1960's	32	43	0.57
1970's	60	93	0.61
1980's	123	105	0.46
1990's	146	17	0.10

Source: Calculated from the Deininger-Squire database version 2.

[28] Facing the same problem of mixing household- and person-based data (and also using the D-S database), Schultz (1999) decides not to do the mixing: "Without a theory or a reliable procedure for relating the processes generating household and person income distributions…I am reluctant to mix the data on households and persons, because ot could conceal important regularities" (p. 324).

Figure 6. Mean Ginis in each decade (1960's to 1990's)

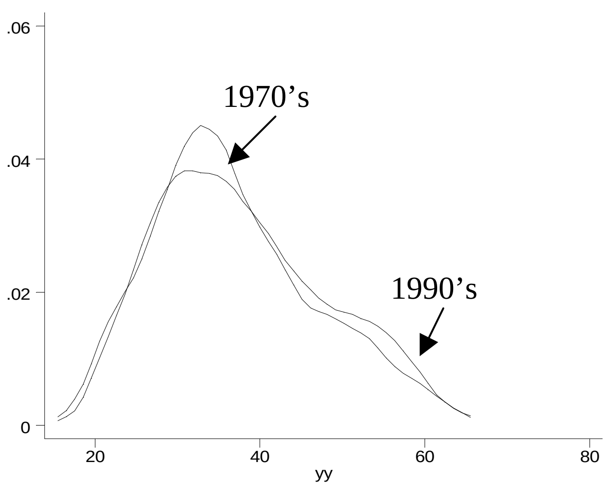


Source: calculated from the Deininger-Squire database version 2

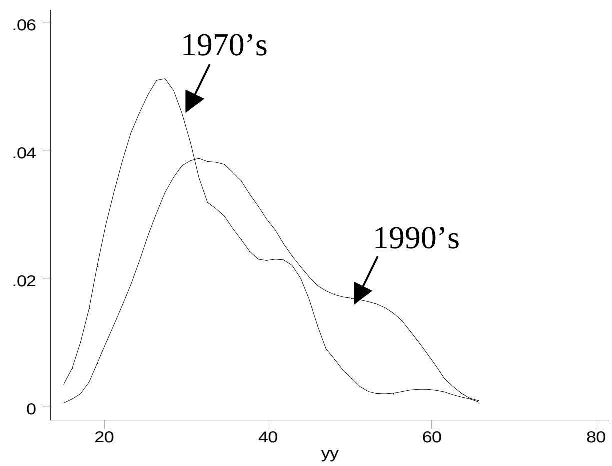
And it is not that the results in Figure 6 are driven by some odd high-Gini outliers in the 1990's. Figure 7 (left panel) shows the distribution of the Ginis in the 1970's and 1990's when persons and households are mixed up: the two distributions are practically the same. Figure 7 (right panel) shows the distribution of countries' Ginis when the concept (income per capita across persons) is held constant. Now, it is not only that the mean and the median Gini are higher in the 1990's—the entire distribution of the Ginis has shifted rightward. This is hardly surprising since we know that in the 1990's there was another bout of increases in inequality, this time in transition countries, China, India and parts of Latin America. The use of the mixed household- and individual- data will then additionally bias Sala-i-Martin's calculations downward. It is important to note, however, that this effect is accidental: it just so happened that the D-S database includes less of household-based observations in the 1990's. Yet, the problem highlights the more general issue of careless combination of the data where, driven by the need to stretch the number of observations way beyond what the data allow, one commits biases whose very direction cannot be gauged.

Figure 7. Distribution of Gini coefficients from the Deininger-Squire data base

Mixing households and persons
as recipient units



Holding the recipient unit (person) constant



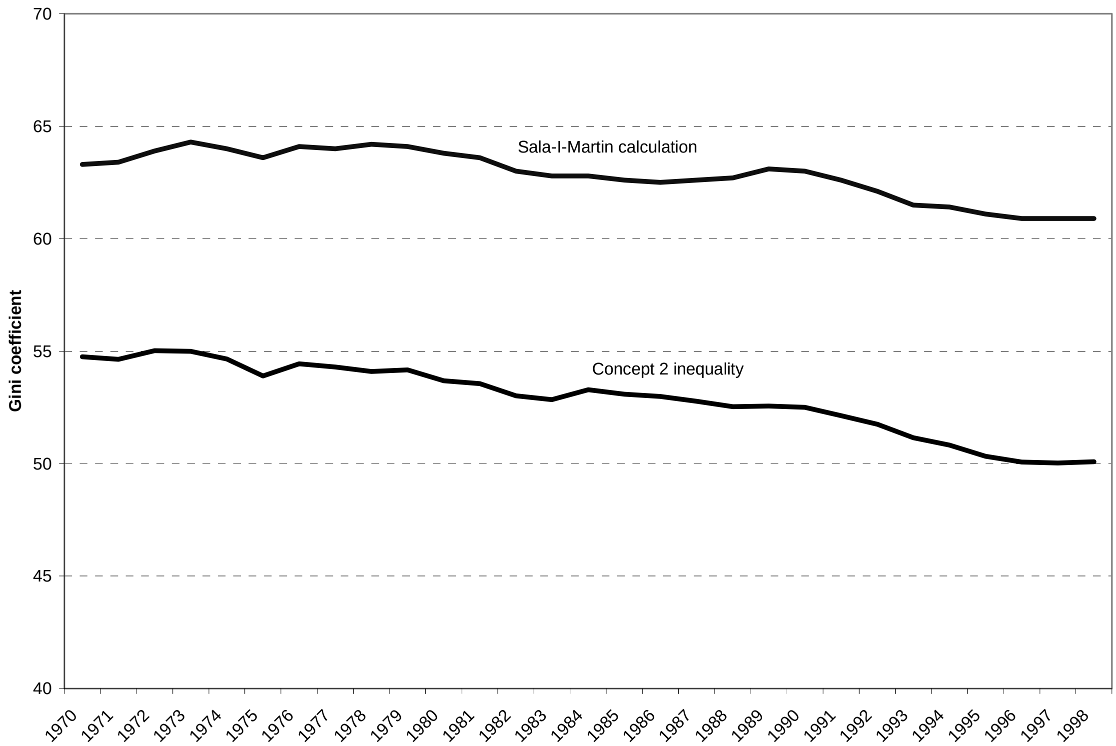
5. The bottom line

The bottom line is that it is not surprising the purported Concept 3 inequality as calculated by Sala-i-Martin behaves almost identically as the Concept 2 inequality (see Figure 8) . This is because the “fitting” of distributions based on very fragmentary data, plus the extrapolations in time, had emptied out almost all variability from the within-country component. Basically, within-country inequality is fixed—by the elimination of “troublesome” (high inequality) countries, by the minimization of distributions’ variability through the use of very few data points and linear extrapolations, by the assumption that all countries whose distributions are unavailable exhibit perfect equality, and by the mixing of household- and person-based distributions. It is the within-country inequality, which superimposed onto Concept 2 inequality, yields inequality among world’s individuals. If within-country inequality is fixed (and countries’ relative positions do not change much),[29] then what is superimposed on the Concept 2 inequality is simply a shift parameter.

It is not surprising then that the evolution through time of what is ostensibly a Concept 3 inequality will be the same as the evolution in time of the Concept 2 inequality—as indeed we see in Figure 8. One might conclude that what Sala-i-Martin has ended up by producing is inequality between population-weighted GDPs per capita which simply masquerades as inequality between individuals, or more exactly, a Concept 2 inequality with a constant shift parameter.

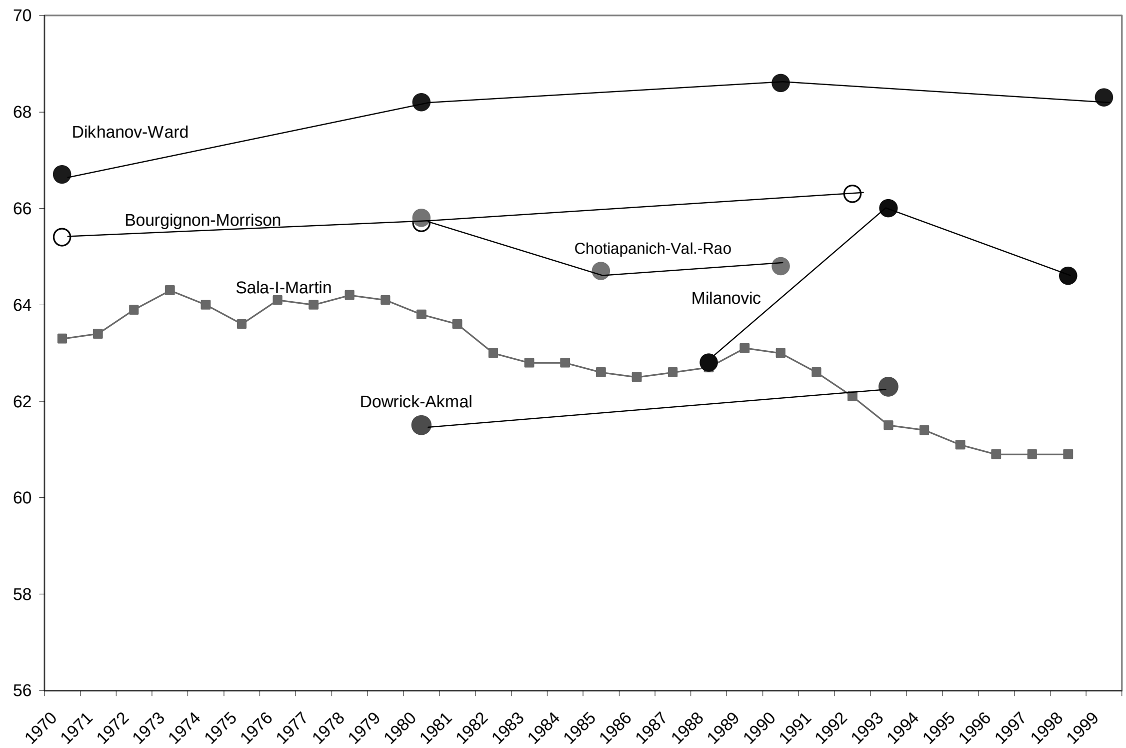
[29] Note that even if all within-country distributions are unchanged, but some countries grow faster (or slower) than others (so that their relative position changes), inequality between individuals of the world will change too.

Figure 8. Sala-i-Martin Concept 3 inequality and inter-national population weighted inequality



While Sala-i-Martin's results move in parallel with the Concept 2 inequality, they move out of step with all other calculations of *Concept 3* inequality. Figure 9 confronts Sala-i-Martin's results with other authors who have tried to calculate world inequality among individuals. Sala-i-Martin's is the only calculation that shows inequality steadily decreasing during the last 30 years. All others show inequality on the rise, or going up and down without an apparent trend. Sala-i-Martin results give also, by far, the lowest Gini of all other calculations. Around 1993, the median estimate of other calculations is Gini between 64-65. Sala-i-Martin's Gini is 61.

Figure 9. Sala-i-Martin's calculations confronted to others



Sources: Milanovic (2002 and for 1998 estimate from 2002a), Bourguignon and Morrisson (1999), Dikhonov and Ward (2001), Dowrick and Akmal (2001).

To conclude, Sala-i-Martin has succumbed to the temptation of piling one assumption upon another with the result that neither the author, nor the reader can any longer tell which is the part of each assumptions, individually or together, in deriving the final result. Here are, in summary, the Ricardian building blocks used by Sala-i-Martin in his calculations—with (*) signs indicating the assumptions imparting *unambiguous* downward bias to the results:

1. (*) A strange omission of countries with "disturbing rises" in inequality; then,

2. Use five data points to approximate entire distributions.

3. When these five data points are not available (84 percent of the time), extrapolate backward and forward in time. When only one observation is available; assume

distribution stays the same for 30 years; (*) when there is no observation at all, assume everybody in the country has the same income.

4. (*) Treat distributions of household income across households as if they were distributions of per capita income across individuals.

5. Mix National accounts data (GDP per capita) and household survey data.

6. Mix expenditure and income data.

and produce world income distribution across individuals of the world for the last thirty years. To paraphrase, “never was so much calculated with so little.” And, unfortunately, it shows.

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Table 1. List of countries and number of observations in
Deininger-Squire data base (version 2), period 1970-96

United States of America	27	Panama	5	Turkey	2
Bulgaria	24	Surinam	5	Tanzania	2
Taiwan	23	Czech Rep	4	Uganda	2
United Kingdom	22	Dominican Rep	4	Uzbekistan	2
Canada	18	Estonia	4	Vietnam	2
Japan	18	Ghana	4	Burkina Faso	1
Poland	17	Iran	4	Bolivia	1
Italy	16	Peru	4	Barbados	1
Brazil	15	Philippines	4	Botswana	1
Sweden	15	Portugal	4	Central African Rep	1
Finland	13	Tunisia	4	Chile	1
India	13	Zimbabwe	4	Cameroon	1
Netherland	13	Belgium	4	Djibouti	1
China	12	Chile	4	Ecuador	1
New Zealand	12	Greece	3	Ethopia	1
Australia	11	Guatemala	3	Fiji	1
Bahamas	11	Ireland	3	Guinea	1
Indonesia	10	Jordan	3	Gambia	1
Venezuela	10	Lithuania	3	Guinea Bissau	1
Costa Rica	9	Latvia	3	Guyana	1
Yugoslavia	9	Moldova	3	Israel	1
Bangladesh	8	Mauritius	3	Kenya	1
Colombia	8	Nigeria	3	Laos	1
Czechoslovakia	8	Romania	3	Lesotho	1
Spain	8	Slovakia	3	Madagascar	1
Jamaica	8	Slovenia	3	Mali	1
Norway	8	Trinidad & Tobago	3	Mongolia	1
Pakistan	8	Ukraine	3	Malawi	1
Germany	7	Belarus	2	Niger	1
Hong Kong	7	Algeria	2	Nicaragua	1
Honduras	7	Egypt	2	Nepal	1
Hungary	7	Gabon	2	Papua New Guinea	1
Korea, South	7	Kazakhstan	2	Paraguay	1
Sri Lanka	7	Kyrgyz	2	Rwanda	1
Denmark	6	Luxembourg	2	Senegal	1
France	6	Morocco	2	Sierra leone	1
Malaysia	6	Mauritania	2	Yemen	1
Singapore	6	Puerto Rico	2	South Africa	1
Thailand	6	Russia	2	Switzerland	1
Cote d'Ivoire	5	El Salvador	2	Armenia	1
Mexico	5	Seychelles	2	Austria	1
		Turkmenistan	2	**Total**	**630**

Table 2. Quintiles available in Deininger-Squire data base
(cases where recipients are persons) and used by Sala-i-Martin

code	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96
AGO																											
ALB																											
ARG																											
ARM																				■							
AUS						■									■					■				■			
AUT																		■									
BEL																							■				
BEN																											
BFA																										■	
BGD																				■			■				
BGR	■	■	■	■	■	■	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■			
BHS																											
BLR																			■							■	
BOL																					■						
BRA			■						■	■				■		■				■						■	
BRB																											
BWA																											
CAF																							■				
CAN						■										■									■		
CHE													■														
CHL											■									■					■		
CHN											■		■	■	■	■	■	■	■	■	■	■	■				
CIV																■	■	■	■							■	
CMR														■													
COG																											
COL					■																	■				■	
CRI												■					■			■							■
CSK	■			■			■	■			■	■				■			■								
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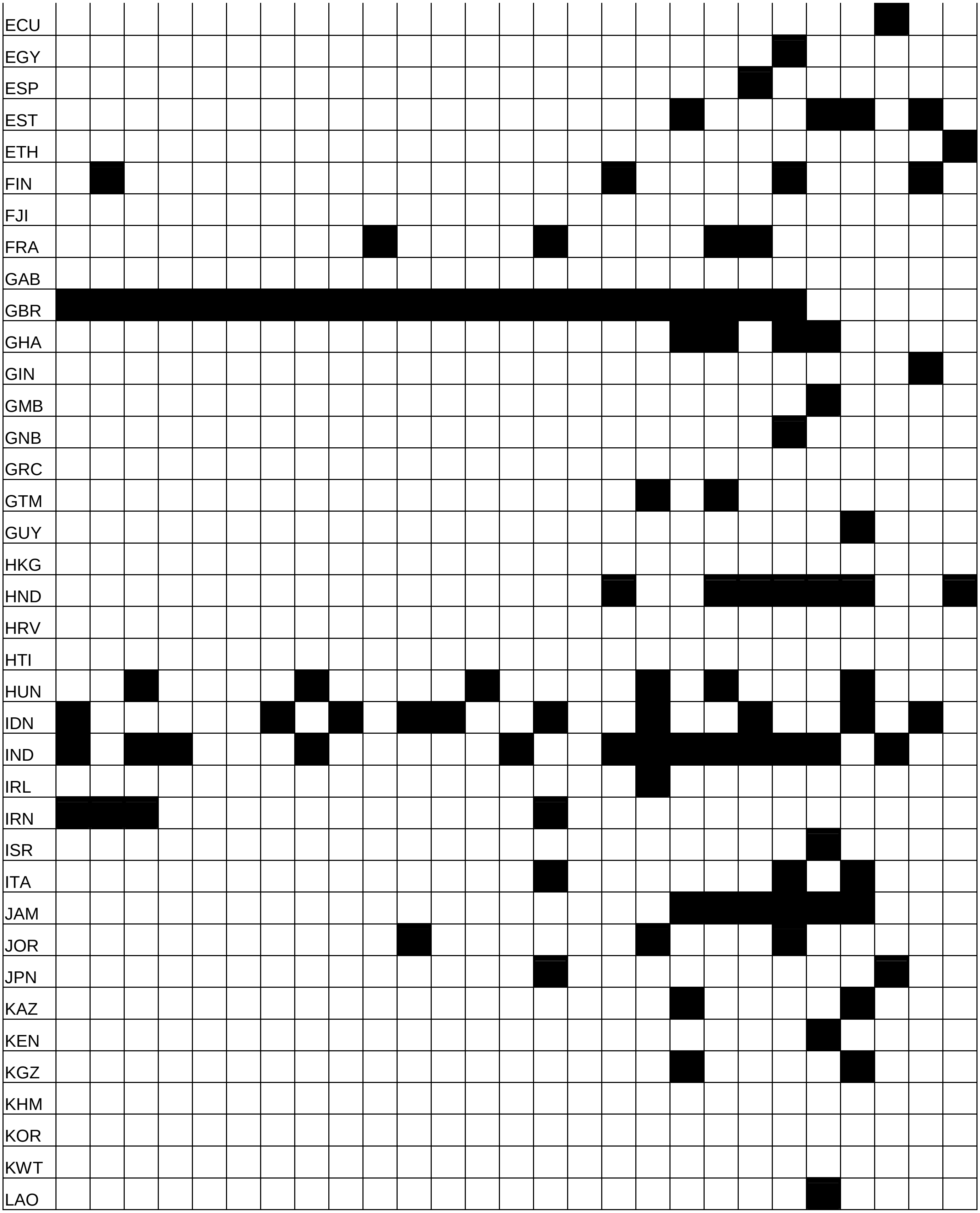
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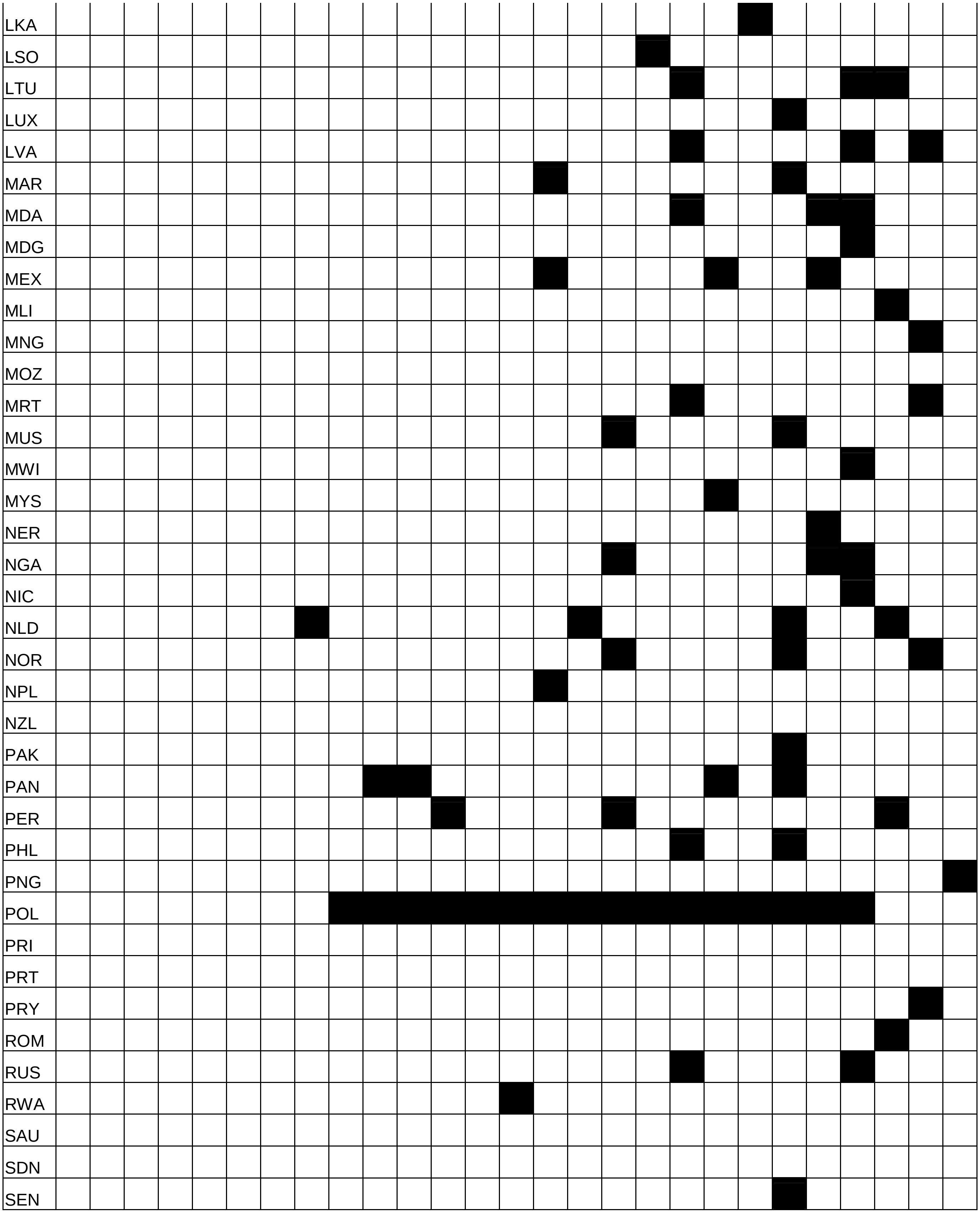
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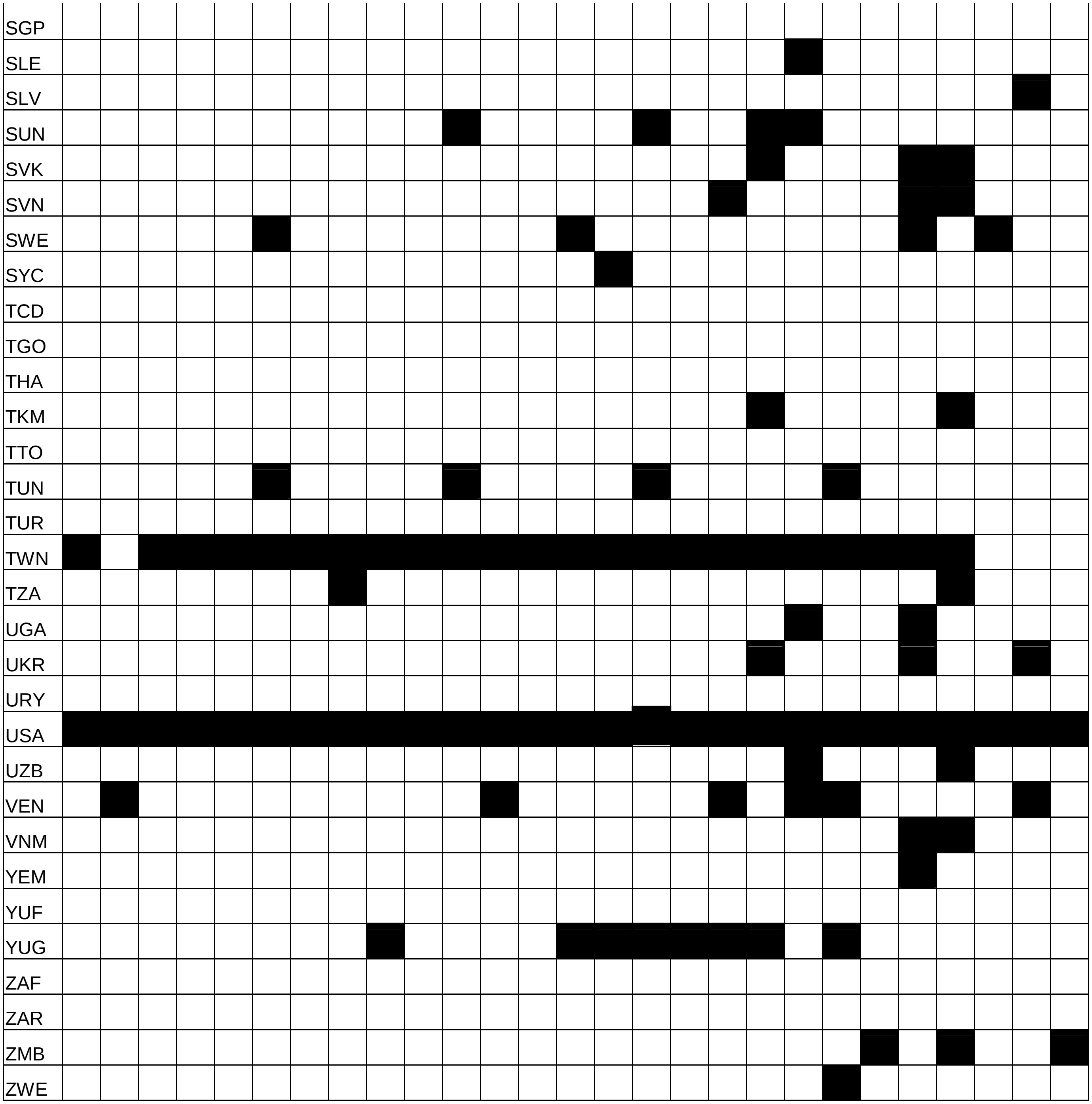
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