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Inequalities in Self-Reported Health: A Meta-Regression Analysis

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Abstract

There is a growing health economics literature in Europe using standardised cross-country health inequality indexes. Yet limited efforts has been put forward to examine the extent to which such evidence is subject to any specific methodological and publication biases despite studies rely on different samples , heterogeneous health system institutions and use different empirical strategies and data manipulation procedures. We draw upon appropriate statistical methods to examine the presence of publication bias in the health economics literature measuring health inequalities of self-reported health. In addition, we test for other biases including the effect of precision estimates based on meta-regression analysis (MRA). We account for a set of biases in estimates of income-related health inequalities that rely on centration index-related methods and self-reported health measures. Our findings suggest evidence of publication bias that primarily depends on the cardinalisation of self-reported health and study-specific precision. However, no robust evidence of other publication biases has been identified.

*Keywords***:** health inequalities, concentration index, self-reported health, and publication bias

1. Introduction

Health inequalities are generally regarded as a key outcome measure to evaluate health systems performance (WHO, 2000). In response to such as policy need, health economics research has focused on developing sound methodologies to undertake such measurements, primarily drawing from index measures that meet some ideal properties, and more specifically concentration indices .

The wealth of evidence on heterogeneity in existing estimates suggests that there are reasons to believe that publication bias exists. Often studies rely on different datasets of similar European countries, use different inferences and often carry out adjustments to adequate the measure of self-reported health employed to ideal requirements (Van Doorslaer et al, 1997, 2004). However, limited meta-analysis, or metaregression studies have been undertaken to account for the numerous study biases that are generally present in the empirical literature. The health economics literature is prone area for biased estimates (Costa-Font et al, 2013 for a review). One of the areas where it appears biased estimates can emerge is in the measuring of health inequalities due to the large difficulties in measuring health, accounting for study and institutional constraints as well as study year and data alongside other potential explanations for publication bus such as precision.

This paper attempts to examine the extent to which inequalities in health are affected by precision and publication biases: namely, to investigate whether health inequality estimates are indeed biased by some precision effects, the sort of publication outlets they get published on alongside other study characteristics that could potentially shape the empirical estimates in some direction. In doing so, it is then possible to use the meta-regression analysis (MRA) a set of techniques developed to integrate and correct estimated regression coefficients. Thus, allows filtering the sort of biases, and hence coming up with an unbiased estimate for each country. A second objective lies in explaining the determinants of health inequality taking advantage of MRA. Indeed, MRA produces estimates after correcting for precision effects (generally proxied by the standard error of the estimates). In addition, , such regression can incorporate institutional determinants of the countries where the studies refer to such as whether certain health systems are more prone to

exhibit health inequalities than others. More specifically, we test for the existence of different biases that explain inequality estimates when study characteristics and methodologies or empirical strategies are controlled for.

Given the heterogeneity in inequality measurement methodologies in social science, and in the health status measures, we restrict our analysis to studies that employed homogeneous inequality indexes (generally representing the methods health economists rely on), and more specifically concentration indexes. Furthermore, given the distinct meaning of health status measures, we in addition restricted our sample our sample to studies that employ measured of self –reported health. The empirical strategy followed is to first graphically examine funnel graphs, which plot estimates against a measure of precision[2]. The latter is informative of the distribution of the sample of studies examined. Next, we undertake multivariate MRA to explain the typically large systematic variation among reported effects and to estimate the size of potential biases. With sufficient data, we can sensibly estimate the effects that various methodological choices have upon the magnitude of the reported empirical results.

To summarise, this paper aims at examining the following issues:

a) The country-specific determinants of health and health care inequalities;
b) While controlling for system specific effects, to isolate the effect of precision from health inequality measurement
c) To identify the causes of the heterogeneity in health equity studies.

The structure of the paper is as follows. In Section 2 we present the methods and data used for this analysis. In Section 3 we offer a discussion of the results and section 4 is devoted to conclusions and implications.

[2] A funnel graph is a scatter diagram of a reported empirical estimate (e_i) and its precision ($1/SE_i$).

2. Methods and Data

2.1 Methods and empirical strategy

Measuring inequalities in health

Inequality is in itself a measure of relative dispersion that can be identified visually by comparing extremes on a distribution. However, the measure encounters severe difficulties when it comes to finding ways to compare two country distributions over time and space. One way to summarise such information is by using inequality indices. Inequalities indices include ranking, Lorenz curves and Gini coefficients and Concentration Curves and Concentration Indices.

The Lorenz Curve and Gini coefficient measure the absolute level of inequality in health (LeGrand, 1989; Wagstaff, Paci and van Doorslaer, 1991) and the expression is given by:

$$G = \left(\frac{2}{\mu}\right) Cov(y, R_h) \qquad (1)$$

where R_h is the relative rank in the health distribution, with individuals ordered from the lowest to the highest level of health.

Similarly, concentration curves can be used to evaluate to what extent certain characteristics are unequally distributed according to health, not income, and to calculate the concentration indices.

There are three basic requirements of an inequity index: i) to reflect the socioeconomic dimension of inequalities in health, ii) to reflect the experiences of the population as a whole, and iii) to be sensitive to changes in the distribution of the population among socioeconomic groups. Many indices, such as the Gini coefficient, do not satisfy the first requirement. Others, such as ranking, do not take into account the other two: they only focus on the experience of the groups at the extreme of the distribution and they do not reflect the distribution of the population in several groups.

The main advantages of Concentration Indices are that they meet the basic requirements and they are an easy way to compare inequalities among countries. In addition, they are useful for several reasons: to check whether the relative magnitude in some country is important and to evaluate which health care systems contribute more to widening levels of inequality.

The Gini coefficient and the Concentration index are directly related through the following expression:

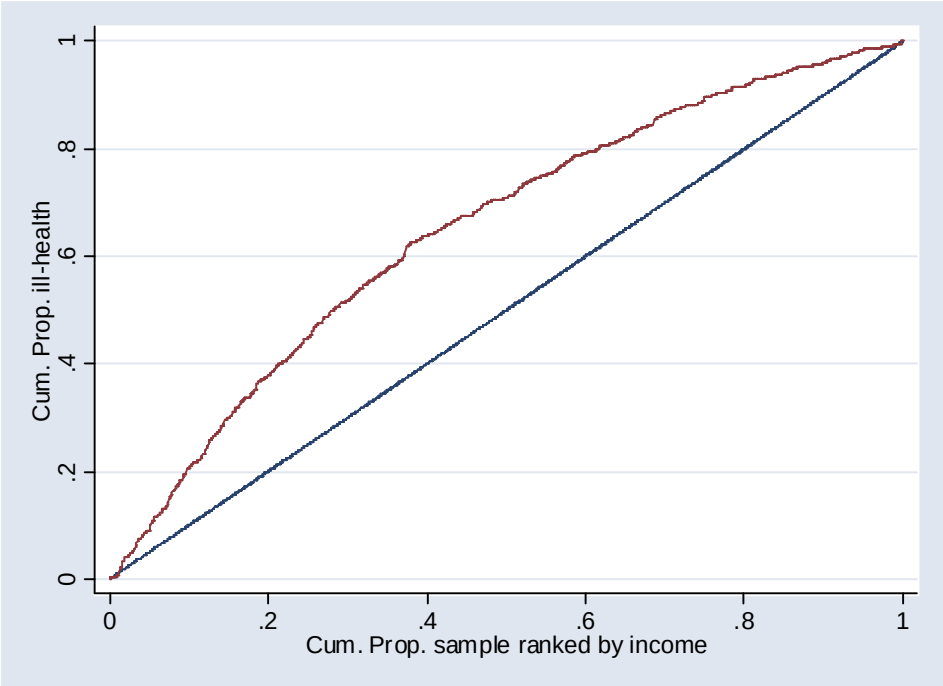
$$C = \{\rho(y,R)/\rho(y,Rh)\}G \qquad (2)$$

Policy makers may also be concerned about other sources of inequality that are captured in a measure of total health inequality. This can be analysed using health Lorenz curves and inequality can be measured using the Gini coefficient of health inequality (Le Grand, 1989; Wagstaff, Paci and van Doorslaer, 1991). The attraction of this approach is that there is a direct relationship between the concentration index and the Gini coefficient for health: the concentration index is proportional to the Gini coefficient, where the factor of proportionality is given by the ratio between the correlation coefficient for health and income rank and the correlation coefficient between health and health rank (Kakwani, 1980; van Doorslaer and Jones, 2003). This means that it is easy to move between these particular measures of socioeconomic and pure health inequality.

Methods based on concentration curves and concentration indices have been extensively used for measuring inequalities and inequities (Wagstaff and van Doorslaer, 2000). The health concentration curve (CC) and concentration index (CI) provide measures of relative income-related health inequality (Wagstaff, Van Doorslaer and Paci, 1989). Wagstaff, Paci and van Doorslaer (1991) have reviewed and compared the properties of the concentration curves and indices with alternative measures of health inequality. They argue that the main advantages are the following: they capture the socioeconomic dimension of health inequalities; they use information from the whole income distribution rather than just the extremes; they provide the possibility to represent results visually through the concentration curve; and finally, they allow checks for dominance relationships.

The concentration index (CI) is derived from the concentration curve (CC). This is illustrated in Figure 1 for a measure of ill-health. The sample of interest is ranked by socioeconomic status. If income is used as the relevant ranking variable, the horizontal axis begins with the poorest individual and progresses through the income distribution up to the richest individual. This relative income rank is then plotted against the cumulative proportion of illness on the vertical axis. This assumes that a cardinal measure of illness is available that can be compared and aggregated across individuals. The 45-degree line shows the line of perfect equality, along which the population shares of illness are proportional to income, such that the poorest 20% of individuals experience 20% of the illness in the population. "Pro-poor" inequality is illustrated by the concave curve in the figure which corresponds to the concentration curve. In the example shown, the poorest 20% of income earners experience more than 20% of illnesses. The size of inequality can be summarised by the health concentration index, which is given by twice the area between the concentration curve and the 45-degree line.

Figure 1: Concentration curve for ill-health



Source: Authors' elaboration

There are various ways of expressing the CI algebraically. The one that is mostly used in the literature for its convenience is:

$$C = \frac{2}{\mu}\sum_{i=1}^{N}\ \left(y_i - \mu\right)\left(R_i - \tfrac{1}{2}\right) = \frac{2}{\mu}\mathrm{cov}(y_i, R_i) \qquad (3)$$

This shows that the value of the concentration index is equal to the covariance between individual health (h_i) and the individual's relative rank (R_i), scaled by the mean of health in the population (μ). Then the whole expression is multiplied by 2 to ensure the concentration index ranges between -1 and +1. Equation (1) indicates that the CI is a measure of the degree of association between an individual's level of health and their relative position in the income distribution. It is important to highlight that a value of CI = 0 does not mean an absence of inequality, but an absence of the socioeconomic gradient in the distribution; this is, an absence of inequality associated with socioeconomic characteristics.

2.2 Metaregression analysis

The standard MRA model used in the vast majority of economic applications is:

$$e_j = \ \beta\ +\ \sum\alpha_k Z_{jk} + \ \varepsilon_j \quad (j=1, 2, \ldots L) \qquad (4)$$

Where e_j is the empirical effect in question, and Z_{jk} are moderator variables used to explain the large study-to-study heterogeneity routinely found in economics research (Stanley and Jarrell, 1989). Moderator variables might include:

1. Dummy variables which reflect whether potentially relevant independent variables have been omitted from (or included in) the primary study.
2. Specification variables that account for differences in functional forms, types of regression, and data definitions or sources, etc.
3. Sample size (Stanley and Jarrell, 1989, p.165).[3]

[3] As discussed in the next section, one of these moderator variables should be the estimate's standard error if we are to identify and control for publication selection bias.

The conventional model of publication selection in both economics and medical research is a simple MRA between a study's estimated effect and its standard error.

$$CI_i = \beta_1 + \beta_0 SE_i + \varepsilon_i \quad (5)$$

(Egger et al., 1997; Stanley, 2005; Stanley, 2008).

An obvious statistical problem is that estimated effects in equation (5) will have different variances (*i.e.*, heteroschedasticity). Weighted least squares (WLS) are the conventional correction for heteroschedasticity. The WLS version of (5) may be obtained by weighting the squared errors by the inverse of the estimates' individual variances (*i.e.*, $1/SE^2_i$), or by dividing equation (5) by SE_i.[4] Doing so, the resulting model is given by (6):

$$t_i = CI_i/SE_i = \beta_0 + \beta_1 (1/SE_i) + \beta_2 X_i + v_i \quad (6)$$

Note that the dependent variable becomes the study's reported t-value, and the independent variable is precision, $1/SE_i$. As SE_i approaches zero in equation (5), the expected effect will approach β_1, regardless of publication selection bias. For this reason, medical researchers use the estimate of β_1 in equation (5) or (6) as the corrected empirical effect.[5] X_i refers to the set of other covariates that are study specific and are thought to influence the empirical estimates. Both the funnel graph and this MRA model of publication selection reveal the central importance of precision in evaluating research. Testing precision's coefficient (H_0: β_1=0) serves as a powerful statistical test—precision-effect test (PET) — for a genuine empirical effect beyond publication selection (Stanley, 2008). PET's validity has been confirmed in simulations and in several economic applications (Stanley, 2008; Doucouliagos and Stanley, 2009).

Finally, as an extension, a Heckman-like correction called *Precision effect estimate with standard error (PEESE)* is provided, which refers to the precision effect estimate

[4] Rather than actually dividing all the observations of each variable by SE_i, many meta-analysts choose to use a canned statistical routine for WLS using $1/SE^2_i$ as the weights. Estimating equation (6) using OLS gives the same results as standard statistical routines for WLS on equation (5).

[5] Unfortunately, this estimate is known to be biased downward when there is a genuine nonzero effect (Stanley, 2008). To reduce this bias, Stanley and Doucouliagos (2007) offer an alternative MRA estimator. Also see Moreno *et al.* (2009).

with standard error model, and can be used to obtain an estimate that is robust to publication selection bias so that (6) can be extended to:

$$t_i = CI_i/SE_i = \beta_0 SE_i + \beta_1 (1/SE_i) + \beta_2 X_i (1/SE_i) + v_i \quad (7)$$

2.3 Data

The data used in this study has been built by carefully reading and coding published studies[6], selecting those that used a homogeneous measure of health that appears to be more prevalent, namely self-reported health status. When some of the information was not present in the study, we have inferred it from other paper estimates or asked authors to provide it so that a full database could be constructed. In some cases, we identified some errors in the original paper and we have corrected them in our estimate. From each study, we selected a set of relevant variables including: sample size, number of variables, method employed, institutional variables, precision and other relevant characteristics.

Table 1 reports the summary statistics of the main variables employed in the study. Specifically, our dependent variable is an estimate of the concentration index of self-reported health for a set of different countries (**CI**). Consistently, given that we focus on a measure of ill health estimated using the conventional scales, a negative concentration index is suggestive of ill health concentrated among the less affluent. However, we take the absolute value of significant estimates to ease the interpretation of the results. The average value of the concentration index is roughly 0.05, which exhibits a significant standard error (**SE**), suggesting the existence of significant heterogeneity in concentration index estimates, as exhibited in the Funnel plot. Furthermore, conventionally, MRA estimates include as covariates the standard error of each CI estimate (which proxies for the precision of each estimate) and exhibit a mean value of 0.015. Given that most studies supply European data, we have classified estimates based on some identifiable features of the health system, namely whether the data refers to a country where the health system is organised as an public national health service (NHS) (around 46% in our sample) or not. The latter is

[6] The list of studies included in the MRA can be provided by the authors upon request.

important so long as national health services tend to prioritise equity as a system goal under the mission of 'equal access for equal need'. **NHS** is a dummy variable taking the value of 1 if an estimates refers to a set of countries in Northern Europe as well as a few in southern Europe as well as Britain and Ireland, whilst countries organised as social insurance schemes would take that value of zero. Then our study incorporates variables proxying the year of the study (**Year**), which arguably will influence both the magnitude and the precision of the inequality estimates given that inequality indexes often have been improved over time. In addition, other controls that were deemed relevant were the number of observations (**N**) - the larger the number of estimates, the more reliable they are. Finally, given the complexity in measuring health, we examine whether health status as a variable was cardinalised (**Cardinal**) which refers to 88% of the cases included in the analysis, or instead whether health was measured in an ordinal or categorical format.

[Insert Table 1 about here]

3. Results

After extracting estimates for all the studies identified in the sample, we were left with 301 observations, which constitute a sample of homogeneous observations very much in line with other metaregression studies. Although new studies are being produced every year, the number of studies already meeting publication standards is sufficient to perform a metaregression analysis, given that the draw upon methods developed about two decades ago.

Possibly the first and most natural way to examine the results is a simple graphical exploitation of the data. A resulting funnel plot reflects the distribution in **Figure 1**, which reports the absolute value of inequality of self-reported health studies plotted against a precision measure, which is the inverse of the standard error of the regression. Studies with less precision and hence, larger standard errors, are at the bottom of the graph and will produce estimates that are more spread out. **Figure 1** makes apparent that there are the large differences in the precision of inequality estimates, ranging from 0.2 to 0. Furthermore, it appears as though there were two

distributions in the analysis that superimpose each other, one with a concentration index that is very close to zero and another distribution cantered around 0.1. However, from simply observing a Funnel plot, it is not possible to ascertain the nature of such a distribution. The latter paves the way to pursuing a metaregression strategy to investigate the underlying difference in inequality estimates. MRA will allow us to control for potential variable that explain the distribution of average inequality estimates.

[Insert Figure 1 about here]

In a second step, we have run several meta-regression specification, and performed the conventional FAT–PET tests as in equation (6), which are reported in Table 2. These tests will allow us to identify early the presence of publication bias and whether robustness of the empirical estimates is an issue.

Results from Table 2 suggest that the coefficient of the intercept is significant and suggests that we can reject the null hypothesis of no publication bias. However, estimates differ depending on whether regression estimates have clustered the standard errors by belonging to the same study, alongside a battery of controls. The significance of the intercept coefficient is suggestive that the irrespectively of the controls we adjust the mean inequality estimate for there is still evidence of publication bias. Controls include the way in which health system is finance (i.e. whether estimates refer to an NHS country that does not exhibit a significant coefficient), the year of data of each estimate (suggesting the presence of inequalities increase over time), the number of observations (which importantly does not seem to influence the regression results), whether the health data was cardinally measured (which appears consistently significant), and finally, whether or not the data has both a panel format (which does not appear significant).

The coefficient for 1/SE reflects the precision of the MRA or the so –called PET (precision-effect test), suggesting that the concentration index ranges from 0.016 to 0 depending on the controls and the clustering of the standard errors. Unfortunately, this coefficient is known to be biased downwards when there is a genuine effect (Stanley, 2008), hence it contains important information but calls for further testing. . Only the

variable measuring the extent to which self-reported health was measured on a cardinal scale appears as significant the specifications reported in **Table 2**. These results are indicative that possibly some source of bias lies in how health is cardinalised, when it is cardinalised. Furthermore, the significance of the intercept suggests that we can reject the null hypothesis of no selection bias (according to the FAT - funnel-asymmetry test) even when more controls are taken into consideration.

[Insert Table 2 about here]

In order to further filtering the inequality estimates for potential precision effects, **Table 3** provides the estimates of the so-called precision *effect estimate with standard error model* (obtained as in the equation 7). The coefficient for precision effects (1/SE) refers to the precision-corrected concentration index coefficient; that is, the concentration index corrected by selection bias, which lies between 0.013 and 0.0 depending on the specific study controls that are introduced. However, the most important effect captured refers to the corrected concentration index after standard error clustering, suggesting that study-specific variability is more important than study characteristics such as the number of observations and other. One potential explanation of such results is the different degree of precision of different estimates given that they rely on different samples and empirical strategies

[Insert Table 3 about here]

4. Conclusions

This paper is to the best of our knowledge the first attempt to estimate the extent of publication bias of inequality estimates of the health economics literature. The results of the study are important given that there is no clear view on what is the current level of inequalities in health in European countries: alternative cross-country analyses provide different results. One might expect heterogeneity in inequality estimates to result from study and empirical methodologies followed country specific effects, as well as the reliance on different health variables, heterogeneous databases and health system specific designs. If measures of inequalities in self-reported health reported in

the literature were not corrected for methodological differences, comparisons of these measures across countries would not be appropriate, given that the data/methods used to obtain inequalities in health for each country will imply different types of measurement errors. The existing high heterogeneity and measurement error in the estimates shown in the literature on socioeconomic inequalities in health can be an issue in undertaking cross country comparisons, and potentially to estimate the effect of public policies on health inequalities.

This paper draws upon meta-regression analysis (MRA) to examine the influence of publication bias alongside precision and other study specific effects on estimates of income-related health inequalities. We rely on a sample of concentration index estimates and self-reported health measures, which is the common practice in the health economics literature. Our findings suggest evidence of publication bias that primarily depends on the cardinalisation of self-reported health. Furthermore, we find an effect from study-specific precision. We take advantage of an existing peer-reviewed literature on estimates of inequalities in health for different countries in Europe but these estimates have not been corrected and hence, comparisons across studies cannot be performed as they have different characteristics (including: year of the study, journal of publication, health variable used, inequality value, precision (standard error) of the estimated level of inequalities in health, among other factors). To date, there has been no analysis of this potential publication bias and subsequent correction of the measure of socioeconomic inequalities in health. By applying appropriate statistical methods, we are able to provide more comparable estimates of inequalities in health for each country. Once these corrected measures are provided, it is possible to make more valid comparisons of the ranking of countries according to the adjusted measures of health inequalities. It may also be possible to identify publication and other biases in research on health inequalities.

We organise the literature by creating a database with all cross-country studies that provide estimates of socioeconomic inequalities in health, including details such as: the estimated level of inequalities in health, the precision of this estimate (standard error), the year of study's publication, the journal, the health variable used, the country analysed, the sample size used and several variables that will identify how those inequality measures were obtained. This information is analysed using

metaregression analysis (MRA). MRA entails a regression analysis of existing studies of socioeconomic inequalities in health, where the control variables are the type of study, the sample characteristics and the scope and precision of the estimate of socioeconomic inequalities in health, among others. MRA allows us to test the sensitivity of the estimate of inequalities in health to the study characteristics.

MRA is especially designed to allow correcting empirical estimates, in our case, measures of socioeconomic inequalities in health for potential biases. By creating a uniform structure for scrutinizing studies, our work attempts to make an important contribution to the literature on inequalities in health. Correcting for publication biases appear as particularly relevant when inequality estimates are employed in ranking health systems or simply when comparing estimates across countries, an issue that will be of interest to policymakers. Furthermore, once a corrected measure of inequalities in health has been attained, one can used such corrected estimates to contribute to research debates, such as those on the equity-efficiency trade-off, by providing corrected inequality values that can be used in any analysis. Finally, this methodology will offer some conclusions on the use of MRA for such purposes.

References

Costa-Font, J and McGuire, A and Stanley, T (2013) Publication selection in health policy research: the winner's curse hypothesis. *Health policy*, 109 (1) :78-87.

Doucouliagos, H and T. D. Stanley (2009). "Publication Selection Bias in Minimum-Wage Research? A Meta-Regression Analysis," *British Journal of Industrial Relations*, vol. 47(2), pages 406-428, 06.

Egger, M., Smith, G.D., Schneider, M., Minder, C., 1997. Bias in meta-analysis detected by a simple, graphical test. Lancet 350, 326-9.

Kamrul Islam M, Ulf-G Gerdtham, P Clarke and Kristina Burstrom (2010). Does income-related health inequality change as the population ages? Evidence from Swedish panel data. *Health Economics*, 19: 334 – 349

Stanley, TD (2005). Beyond publication bias. *Journal of Economic Surveys*, 19(3): 309-345

Stanley, TD (2008). Meta regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics*, 70(1): 103 - 127

Stanley, T and SB Jarrell (1989). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys*, 3: 161 – 170

Van Doorslaer E and X Koolman (2004). Explaining the differences in income-related health inequalities across European countries. *Health Economics*, 13: 609 – 62

Van Doorslaer E, A Wagstaff, H Bleichrodt, S Calonge, Ulf-G Gerdtham, M Gerfiin, J Geurts, L Gross, U Hakkinen, RE Leu, O O'Donnell, C Propper, F Puffer, M Rodriguez, G Sundberg, O Winkelhake (1997). Income-related inequalities in health: some international comparisons. *Journal of Health Economics* 16: 93 – 112

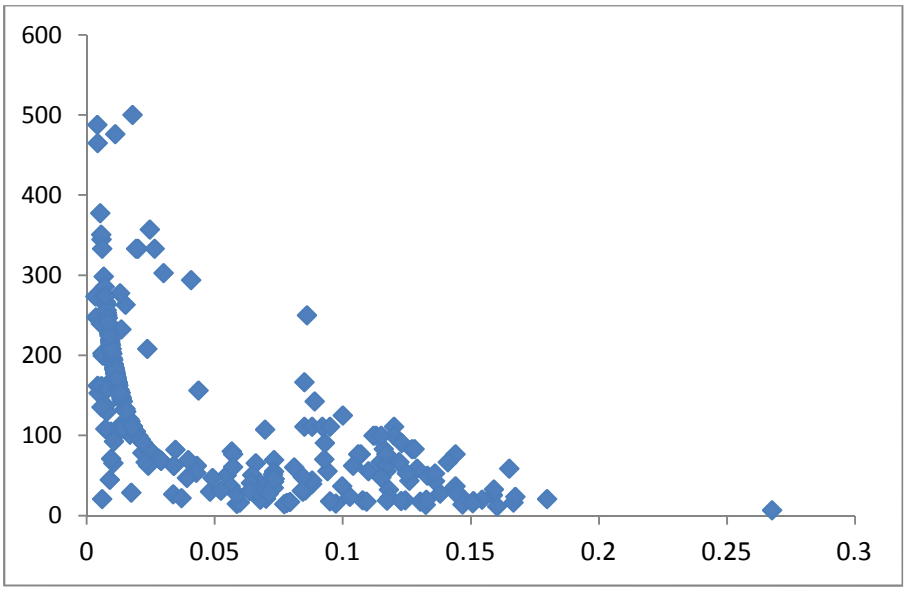
World Health Organisation. The world health report 2000 - Health systems: improving performance. World Health Organisation; 2000.

Tables and Figures

Table 1. Summary Statistics

Variable	Definition	Number of Observations	Mean	(s.e)
CI	Concentration Index Estimate	301	0.0487	(0.002)
SE	Standard error of the concentration index	298	0.015	(0.001)
NHS	Estimate from a National Health Service	301	0.465	(0.028)
Year	Year of the estimate - 1978	195	16.4	(0.424)
N	Number of observations	139	6399	(424.5)
Cardinal	Some form of cardinal transformation is performed	301	0.887	(0.018)

Figure 1. Funnel Plot (CI on X – axis and 1/SE on Y -axis)



Source: own elaboration for study estimates

Table 2. Funnel Asymmetry Test (FAT) and Precision Effect Test (PET)

	coeff (s.e)	Coeff (s.e)	Coeff (s.e)
1/SE	0.013* (0.005)	0.007 (0.005)	0.006 (0.005)
NHS		-1.849 (1.491)	-1.641 (1.154)
Year of data		0.0379 (0.0383	0.008 (0.060)
N		-0.00011 (9.27E-4)	1.17E-05 (6.74E-05)
Cardinal		-5.624* (1.453)	-6.823* (1.369)
Panel			2.651 (2.416)
Intercept	2.155* (1.13)	8.1547* (2.888)	7.596* (2.542)
Study cluster	Yes	Yes	Yes
F- Test	6.55	17	194.2
Adjusted R^2	0.15	0.47	0.52

* Highlighted if significant at least at 5%.

Notes: 1/SE refers to a measure of precision of the inequality estimate reported in each study. NHS refers to a dummy variable taking the value of 1 if the estimate refers to a health system financed by taxes. Year of data refers to the year the estimate refers to. Cardinal refers to a dummy variable to account for the cardinalisation of an inequality estimate. Finally, Panel refers to a dummy variable to measure whether the estimate has been computed using longitudinal data, and hence, whether it filters potential unobserved heterogeneity.

Table 3. Precision Effect Estimate with Standard Error (PEESE)

	coeff	coeff	coeff	coeff
	(s.e)	(s.e)	(s.e)	(s.e)
SE	0.013*	0.013*	0.007*	0.007
	(0.004)	(0.006)	(0.002)	(0.006)
1/SE	11.42	11.4266	42.75	42.748
	(11.91)	(35.15)	(33.34)	(48.43)
nhs			-1.64*	-1.643
			(0.54)	(1.124)
yearofdata			0.014	0.0145
			(0.101)	(0.062)
N			1.59E-05	1.59E-05
			(6.4E-05)	(6.67E-05)
Cardinal			-6.76*	-6.767*
			(0.92)	(1.383)
Panel			2.694*	2.693
			(0.764)	(2.361)
Intercept	1.837*	1.837	6.835*	6.834
	(0.658)	(1.985)	(1.801)	(2.651)
Study cluster	No	Yes	No	Yes
F- Test	4.31	7.99	178.2	234.7
Adjusted R^2	0.15	0.3	0.42	0.52

Note: * Significant at least at 5%.

Notes: 1/SE refers to a measure of precision of the inequality estimate reported in each study. NHS refers to a dummy variable taking the value of 1 if the estimate refers to a health system financed by taxes. Year of data refers to the year the estimate refers to. Cardinal refers to a dummy variable to account for the cardinalisation of an inequality estimate. Finally, Panel refers to a dummy variable to measure whether the estimate has been computed using longitudinal data, and hence whether it filters potential unobserved heterogeneity.