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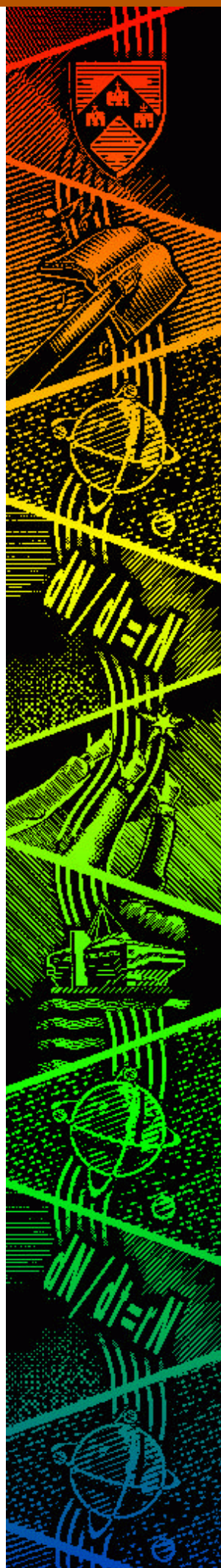
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Income, Income Inequality and Health:
What can we Learn from Aggregate Data?

by

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Income, income inequality and health: what can we learn from aggregate data?

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Abstract

It has been suggested that, especially in countries with high per capita income, there is an independent effect of income distribution on the health of individuals. One source of evidence in support of this relative income hypothesis are analyses of aggregate cross section data on population health, per capita income and income inequality. We examine the empirical robustness of cross-section analyses by using a new data set to replicate and extend the approach in a frequently cited paper. We find that the estimated relationship between income inequality and life expectancy is dependent on the data set used, the functional form estimated and the way in which the epidemiological transition is specified. The association is never significant in any of our models. We argue there are serious methodological difficulties in using aggregate cross sections as means of testing hypotheses about the effect of income, and its distribution, on the health of individuals.

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1 Introduction

There is a long tradition of empirical investigation of the relationship between income and health using cross section country or area level data (Adelman, 1963; Judge, Mulligan and Benzeval, 1998). The studies suggest that population health (whether measured positively by life expectancy or negatively by mortality) improves with average income but at a decreasing rate. This is the *absolute income* hypothesis.

The more recent *relative income* hypothesis is that the health of individuals in a society also depends on the degree of income inequality in that society. It is also suggested that the beneficial effect of absolute income becomes less important at higher income levels (the *epidemiological transition*), so that the distribution of income becomes more important the greater the average income of society. Proponents of the relative income hypothesis suggest that it is supported *inter alia* by a large number of aggregate cross-section evidence which shows that population health declines with measures of income inequality, after allowing for the effect of per capita income (Wilkinson, 1996).

In this paper we suggest that there are empirical and methodological grounds for being doubtful of the usefulness of using aggregate level evidence to test hypotheses about the effect of income and income inequality on the health of individuals.

In section 2 we empirically investigate the usefulness of aggregate level studies by replicating and extending a seminal paper (Rodgers 1979) which has been extensively cited as support for the relative income effect.¹ We find that our results with respect to income distribution differ markedly: income distribution is never significantly associated with life expectancy. The data we use is more recent than that in Rodgers (1979) so that it could be argued that the form of the relationship between health, income and income distribution has changed over time. Accordingly section 3 examines a variety of functional forms. An alternative explanation for the difference between our results and those of Rodgers (1979) is that because of the passage of time our countries are on average richer and we need to take account of possibility that the effect of income and income distribution is different at high and low incomes. Section 4 considers alternative methods of modelling this epidemiological transition.

None of the empirical results in sections 2 to 4 provide support for the relative income hypothesis. We discuss in section 5 the circumstances in which aggregate population level data can be used to test the relative income

¹According to BIDS, Rodgers (1979) was cited 14 times to 1990 and 31 times since 1990.

effect. We argue that if the individual level relationship between health and individual income is non-linear there is an *aggregation problem*. Aggregate cross section studies should not be used to test the relative income hypothesis and should be interpreted with caution when used to investigate the absolute income hypothesis.

The aggregation problem and its implications for aggregate cross section empirical work on the relationship between health, income and income inequality have been known for some time, both by those investigating the absolute income hypothesis (Adelman, 1963; Preston, 1975; Rodgers, 1979) and by the leading proponents of the relative deprivation hypothesis (Wilkinson 1996). Our justification for presenting them again is two fold. First, despite a recent reminder (Gravelle, 1998) of the problems in interpreting observed correlations between population health and income inequality, investigators continue to use aggregate cross section data to investigate hypotheses about individual health (Chiang, 1999; Ross et al, 2000; Walberg et al., 1998). Second, it has been less widely appreciated that aggregation issues also have implications for the interpretation of the estimated relationships between population health and per capita income.

2 Robustness to data

2.1 The data

Our income inequality data for 75 countries are from the Deininger and Squire (1996) World Tables and relate to 1980-82 and 1989-90, periods in which there were a reasonably large number of observations. Only countries with data described as high quality by Deininger and Squire (1996) were selected. Data on GDP per capita was taken from the Penn World Tables Mark 5 (<http://cansim.epas.utoronto.ca:5680/pwt/pwt.html>; see Summers and Heston, 1996) which give income data from 1950 to 1992 at purchasing power parity rates. The health measure is male life expectancy at birth and the data are from the US census international database (<http://www.census.gov/ftp/pub/ipc/www/idbnew.html>).

Summary statistics are in Table 1 and scatter plots in Figures 1 to 3. Figure 1 shows the scatter plot of life expectancy against per capita income. It is apparent from the data that there is non-linear association between life expectancy and per capita income. Figure 2 plots life expectancy against the Gini coefficient which is our measure of income inequality. There is little sign of association and the correlation coefficient for the variables is -0.20 . Figure 3 is a scatter plot of Gini against per capita income and shows a weak

but significant negative correlation of -0.33 .

2.2 Replications

After experimentation with a number of alternatives Rodgers (1979) favoured specification was:

$$L_k = \beta_0 + \beta_1 \frac{1}{y_k} + \beta_2 \frac{1}{y_k^2} + \beta_3 G_k + \epsilon_k, \quad (1)$$

where L_k is life expectancy in country k , y_k is per capita income, y_k^2 is the square of per capita income, G_k is the Gini coefficient, and ϵ_k is an error term. Life expectancy is thus hypothesised to increase at a decreasing rate with income and to tend to a maximum value.

Rodgers (1979) used data on 56 developed and developing countries from 1951-1969 including income distribution data from Paukert (1973). The first three columns in Table 2 are the results reported in Rodgers (1979) when (1) was estimated with and without the second and third terms. All variables are significant. The fact that the Gini has large significant coefficients (as it has in nearly all of the models reported in Rodgers (1979) has frequently been cited as support of the relative income hypothesis (Duleep, 1995; Wilkinson, 1996; Kennedy et al (1996). Kawachi, I. et al.(1997)

In comparing our results with those in Rodgers (1979) we do not wish to cast aspersions on the quality of the work. It is thorough and careful to recognise the implications of aggregation. The aim in Rodgers (1979) is to investigate the relationship between income and health. It is not suggested that income inequality had any effect on individual health. The Gini inequality measure in (1) is introduced solely as a means of dealing with the aggregation problem (see section 5), not to test the relative income hypothesis.

We re-estimated the three equations in the first three columns of Table 2 using our data set. All regressions were performed in STATA 6. The results are in columns 4 to 6. The RESET test indicates that regression 5 is misspecified.² Comparing columns 4 to 6 with those for the original study in columns 1 to 3 we see that the income coefficients have the same pattern and are significant. The coefficient on the Gini is again negative but is not significant.

Since we have taken data from two separate periods we also estimated the full Rodgers (1979) reciprocal model using a dummy to distinguish between the 1980-82 and 1988-90 observations. None of the terms including

²For the RESET test the regression is re-estimated including powers of the estimated value of the dependent variable from the original equation. If the coefficients on the power terms are jointly significant the original equation is misspecified (Maddala 1992)

the period dummy are significant and the dummy terms are also jointly insignificant, suggesting that pooling the observations from the two periods is acceptable. The Gini is still insignificant and the estimated effect of the income variables does not change greatly.

3 Alternative Functional Forms

The absolute and relative income hypotheses place qualitative rather than quantitative restrictions on the relationship between life expectancy, average income and income distribution. Given that the periods covered by the two data sets differ by around 20 to 30 years, it may be that our failure to find a significant association between life expectancy and income inequality is due to changes in the underlying relationship. We therefore experimented with a variety of specifications to test how robust the qualitative results are to the functions used to estimate the relationships.

3.1 Parametric estimation

The Box-Cox transformation $x(\lambda)$ applied to a variable x is a general transformation which yields a number of interesting special cases at particular values of the transformation parameter λ :

$$x(\lambda) = \frac{x^\lambda - 1}{\lambda} \quad \lambda \neq 0 \quad (2)$$

$$= \ln x \quad \lambda = 0 \quad (3)$$

$$= x - 1 \quad \lambda = 1 \quad (4)$$

$$= -\frac{1}{x} - 1 \quad \lambda = -1 \quad (5)$$

The Box-Cox procedure is to estimate a regression equation using Box-Cox transformed explanatory variables. The procedure yields coefficients on the transformed variables and an estimated value of the transformation parameter λ . Standard statistical tests can then be applied to estimated coefficients and to the estimated transformation parameter. Thus it is possible to test, say, whether the estimated λ is significantly different from zero and whether the logarithmic form is a sensible specification.

The Box-Cox method suffers from the limitation that the same transformation parameter is applied to all the transformed right hand side variables. An additional difficulty is that λ is estimated so that the standard errors will be inflated (Greene 1997). An alternative approach is to estimate a particular functional form and then apply the RESET test to determine whether

the form is well specified (Godfrey et al, 1988). To compare non-nested functional forms against each other we use the J-test (Maddala, 1992).

Table 3 presents the results for a set of alternative functional forms. The first three columns reports regressions with various Box-Cox transformed variables. For model 1 life expectancy was regressed on the Box-Cox transformed values of income, income squared and the untransformed Gini. In model 2 the Box-Cox transformation has been applied to the Gini as well as to the income variables. In model 3 life expectancy and the explanatory variables have all been transformed. In no case is the Gini significant, though mean income is significant in two of the cases. In model 1 we cannot reject the null hypothesis that $\lambda = -1$ which would be the same form as the original reciprocal model of Rodgers (1979).

Model 4 has life expectancy as a quadratic function of income and the Gini. Only income (positively) and income squared (negatively) are significantly associated with life expectancy. For model 5 we used the translog form which is quadratic in the logarithms of the explanatory variables and is a good approximation to general functions (Kennedy, 1998). None of the coefficients involving the Gini were significant in either model 4 or model 5. Further, we could not reject the null joint hypothesis that all three of the coefficients involving the Gini were zero in the quadratic ($F=0.9572$) and translog ($F=0.2701$) models

The Reset tests suggest that the quadratic form (column 4) is misspecified so that the trans-log (column 5) is our preferred specification from the non Box-Cox forms. Since the Box-Cox results are consistent with the original Rodgers (1979) reciprocal form we tested the translog against the reciprocal form reported in column 6 of Table 2. To compare the translog model with the Rodgers (1979) reciprocal specification we perform a non-nested J-test. Taking the predicted values from the Rodgers specification, \hat{y}_R and the translog model, \hat{y}_T we estimate $y - \hat{y}_R = \alpha (\hat{y}_T - \hat{y}_R) + v$. The estimated value of α is 0.70 with a t-statistic of 1.46 and so is not significantly different from zero. We conclude that the translog model does not provide any further explanation of life expectancy over Rodgers (1979) reciprocal specification and in neither model is there a significant effect of income distribution.

3.2 Non parametric estimation

The above methods of estimating the functional form determining life expectancy are parametric in the sense that they assume that the relationship to be estimated is known apart from the value of a small number of crucial parameters. Non-parametric estimation (Pagan and Ullah, 1999) allows the shape of the relationship to be determined by the data with very few

restrictive assumptions

We want to estimate a model of the form

$$L_k = F(y_k) + \beta G_k + \varepsilon_k$$

without specifying the form of the income life expectancy relationship $F(y_k)$ in advance. By allowing F to be determined by the data we can hope to isolate the relationship between the Gini and life expectancy. To do so we use a three stage procedure (Robinson, 1988). We first run a non-parametric regression of life expectancy on income, yielding the predicted value of life expectancy given income: $P(L_k | y_k)$.

Second, we estimate the non-parametric relationship between the Gini and income, yielding the predicted value of G given income: $P(G_k | y_k)$. Finally, we estimate the regression

$$L_k - P(L_k | y_k) = b [G_k - P(G_k | y_k)]$$

using ordinary least squares.³

The coefficient on the Gini coefficient is -4.35 , with a bootstrapped standard error (500 replications) of 6.65. The result suggests that even when the relationship between income and life expectancy is not imposed but determined by the data, there is no significant association between the Gini and life expectancy after the effect of income has been allowed for.

The light line in Figure 1 shows predicted life expectancy from the first stage of this process, without allowing for the effect of the Gini. The heavy line is life expectancy predicted from income after allowing for the effect of the Gini. The Gini has a negative association with life expectancy and is, in our data, negatively correlated with income. Hence the heavy line, showing the true partial relationship between income and life expectancy, lies below the light line which also picks up the effect of the Gini and its correlation with income. The difference between the two lines is very small, reflecting the weak associations between the Gini and income (shown in Figure 3) and between the Gini and life expectancy (as shown by the regression analysis).

4 The epidemiological transition

Wilkinson (1996) suggests that the effects of relative deprivation may only arise in relatively rich countries. At a certain income level countries pass through an epidemiological transition where patterns of disease change from

³The predicted values were obtained using the KSM command in STATA 6. This applies locally weighted linear regressions to the data. The bandwidth was set at 0.8.

infectious diseases to degenerative diseases such as cancer and heart disease. The relationship between income and health changes. The marginal effect of increases in income falls and so that more of variations in health are explained by differences in income inequality. Hence, as the level of per capita income increases the effect of income inequality on population health becomes greater. This is not an implausible argument⁴ about the determinants of individual health and it suggests that if two data sets differ in the mix of rich and poor countries it would be sensible to allow for the underlying relationship between health, income and income distribution being different in rich and poor countries.

We tested for evidence of a changing relationship between health and income inequality in a variety of ways. First, we allow for interactions between the Gini and income. If there is an epidemiological transition an increase in the Gini at higher income should be associated with a larger decrease in life expectancy. The coefficient on the Gini-income interaction term in the quadratic form in column 4 of Table 3 is indeed negative but it is insignificant, as is the coefficient on the log Gini-log income interaction in the translog form of column 5. Column 1 of Table 4 reports the reciprocal form with a Gini-income interaction term and the coefficient on the interaction is positive and insignificant.

Next we tested for the epidemiological transition by introducing a dummy variable for countries with average incomes of over \$5000. Column 2 has the reciprocal form with slope and intercept dummies on all the explanatory variables. None of the terms involving the income level dummy are significant and we cannot reject the joint hypothesis that they are all zero. Column 3 has the reciprocal form but with the high level income dummy interacting only with the Gini. The coefficient on the $D*Gini$ term in column 2 is negative but insignificant.

Adding a high income dummy introduces a discontinuity in the estimated life expectancy-income relationship: it implies that life expectancy could jump up or down at an income level of \$5000. This seems implausible. In column 4 we include a high income dummy variable DS but use spline estimation (Greene, 1997) so that the life expectancy-income relationship is not discontinuous at the critical \$5000 point. A joint test of the significance of the terms including DS fails to reject the null hypothesis that they are all

⁴The same predictions can be made from a model of individual health in which income distribution has no effect. Equation (7) in section 5 shows that the effect of income inequality on population health depends on the second derivative of the individual mortality equation at the average level of income. If an increase in income increases the second derivative ($m'''(\bar{y}) > 0$) then differences in income inequality will have greater effects when average income is higher.

zero (Prob 0.76).

Finally, in column 6 we include an interaction term between the Gini, the high income dummy and the excess of income over \$5000. A positive sign on the coefficient on this variable indicates that the effect of the Gini increases with income in rich countries only. The estimated coefficient is indeed positive but not nearly significant.

Overall, our tests do not suggest that the relationship between life expectancy, per capita income and income distribution is different in high and low income countries.

5 Aggregation problems

5.1 The general issue

Whenever hypotheses about individual level relationships are tested with data which sums or averages individual level data the aggregation problem may arise (Deaton and Muellbauer, 1980). Suppose that an individual's health depends only on their income and that increases in income improve health but at a decreasing rate. The increase in health from giving £1000 to a rich individual is less than the increase in income from giving £1000 to a poor individual. A transfer of income from poor to rich does not affect average income but does increase income inequality. The transfer also reduces the average health of the population since the improvement in the health of the rich is more than offset by the decline in the health of the poor. If we only have data on the average health, average income and degree of income inequality across a set of populations we could observe a negative relationship between population health and income inequality, even though income inequality has no causal effect on the health of any individual. Thus we could, incorrectly, conclude that comparisons of average health, average income and income inequality across populations supports the relative income hypothesis.

Let the mortality risk of an individual with income y depend only on her income: $m(y)$.^{5,6} Those individuals with higher incomes have lower mortality risk: $dm/dy = m'(y) < 0$. Taking a second order approximation, we can express the mortality risk of an individual in terms of the individual's income

⁵This sub section is based on the appendix to Gravelle (1998).

⁶We can allow for the dependence of mortality risk on age and sex by interpreting $m(y)$ as the mortality risk of a given age and sex group in the population. The population mortality rate is then a weighted average of the mortality risks of the age and sex groups. The conclusions below are unaffected.

y and the mean income \bar{y} of the population:

$$m(y) \approx m(\bar{y}) + m'(\bar{y})(y - \bar{y}) + \frac{1}{2}m''(\bar{y})(y - \bar{y})^2 \quad (6)$$

where $m''(y) = d^2m/dy^2$ is second derivative of $m(y)$. The population mortality rate is the expected value of $m(y)$. Taking expectations of both side of (6), and remembering that, by definition, the average deviation of incomes from the mean income is zero, so that the second term disappears, gives

$$\begin{aligned} Em(y) &\approx m(\bar{y}) + m'(\bar{y})E(y - \bar{y}) + \frac{1}{2}m''(\bar{y})E(y - \bar{y})^2 \\ &= m(\bar{y}) + \frac{1}{2}m''(\bar{y})V(y) \end{aligned} \quad (7)$$

$Em(y)$ is the population mortality rate and $V(y)$ is the variance of incomes across the population. Increases in the average income of the population reduce population mortality since $m(\bar{y})$ falls with \bar{y} . If $m'' > 0$, so that the protective effect of an increase in income is smaller at high incomes the population mortality rate will increase if the variance of incomes increases. This suggests that increases in income inequality, with average income held constant, lead to increases in population mortality even if there is no direct effect of income inequality on the mortality risk of any individual.

This result is more general than it appears and does not depend on the use of approximations. Most measures of income inequality are increased by a mean preserving spread in the distribution of y and mean preserving spreads increase the expected value of a convex function of y (Atkinson, 1970; Rothschild and Stiglitz, 1970). Hence, if individual mortality risk is a convex function of income ($m'' > 0$), an increase in income inequality, as indicated by most inequality measures, with average income held constant, will increase the population mortality rate even though income inequality has no effect on the mortality risk of any individual. The finding that there is a positive partial correlation between population mortality and a measure of income distribution may therefore not be evidence that individual health is adversely affected by income inequality; it may just reflect the shape of the relationship between individual mortality risk and individual income.

5.2 Interpretation of aggregate cross section studies

We now examine in more detail the implications of non-linearity of the individual mortality risk-income relationship for the interpretation of studies of the empirical relationship between population health, per capita income and

measures of income distribution. The basic issue is whether such aggregate studies can help us to identify the determinants of the health of individuals.

To provide a concrete illustration we use a specific but not implausible model of the determinants of individual mortality risk:

$$m_{jk} = \beta_0 + \beta_1 y_{jk} + \beta_2 y_{jk}^2 + \beta_3 R_{jk} + \beta_4 z_{jk} + e_{jk} \quad (8)$$

where m_{jk} is the mortality risk of individual j in country k , y_{jk} is her income, and e_{jk} is an error term. z_{jk} is another variable affecting health and might vary across individuals in country k (for example educational achievement) or it might be the same for all individuals in the country (for example public health measures or the quality of the environment). Examples in the aggregate cross section empirical literature include public and private health care expenditure, unemployment, ethnicity, and female employment (Judge, Mulligan and Benzeval, 1998). Strictly we should interpret z_{jk} as a vector of non income variables affecting health but we treat it as a single variable to keep the analysis reasonably simple.

The effect on mortality risk of an increase in income is

$$\frac{dm_{jk}}{dy_{jk}} = \beta_1 + 2\beta_2 y_{jk} < 0 \quad (9)$$

We assume that $\beta_1 < 0$, so that for small enough income levels, mortality risk declines with income. We also assume that $\beta_2 \geq 0$ which allows for the case in which mortality risk falls more slowly as income increases.⁷

R_{jk} is a variable which depends on the some characteristics of the distribution of income in country k and possibly also on individual j 's own income. Increases in R_{jk} may increase individual mortality risk ($\beta_3 \geq 0$). The inclusion of R_{jk} is intended to reflect the relative income hypothesis that an individual's health depends on the income of others as well as her own income.

R_{jk} may be the Gini coefficient (Cowell, 1995) for country k , in which case $R_{jk} = R_k$ for all individuals j in country k . Alternatively, we may hypothesise that the individual j 's mortality risk depends on the level of her income relative to that of other individuals in the country, in which case R_{jk} varies across individuals in country k (Hey and Lambert, 1980).

With individual level data we could test our hypotheses about the determinants of mortality risk directly. But suppose such data is not available and we are forced to use aggregate, country level, data. The true country

⁷When $\beta_2 > 0$ we assume $y_{jk} < -\beta_1/2\beta_2$ so that increases in income always reduce mortality risk.

level relationship implied by the individual level relationship (8) is found by taking expectations over the individuals in each country

$$m_k = \beta_0 + \beta_1 y_k + \beta_2 s_k + \beta_3 R_k + \beta_4 z_k + e_k \quad (10)$$

$m_k = E_j m_{jk}$ is population mortality in country k , $y_k = E_j y_{jk}$ is per capita income, $s_k = E_j y_{jk}^2$ is the average squared income, $R_k = E_j R_{jk}$, $z_k = E_j z_{jk}$ and $e_k = E_j e_{jk}$.

We may have data only on population mortality (m_k), per capita income (y_k) and some measure of income inequality G_k for each country. In the case where z_k is a vector we may be able to measure some of its components but not others. To capture the effect of missing variables in z_k vector simply we interpret it as a single unobserved variable with unknown effect on health: β_4 may be positive or negative.

Suppose we estimate the equation

$$m_k = b_0 + b_1 y_k + b_2 y_k^2 + b_3 G_k \quad (11)$$

The square of average income y_k^2 is included in an attempt to allow for the non-linearities in the individual level mortality-income relationship, and, we hope, enable us to test the relative income hypothesis by circumventing the aggregation problem..

There are three potential misspecifications in (11): the use of the squared average income y_k^2 instead of the average squared income s_k , the use of the inequality measure G_k instead of R_k and the omission of z_k . Each can lead to biased estimates of the true country level model (10) and vitiate attempts to estimate the effect of income and income inequality on health.

Table 5 gives the expected values of the estimated coefficients b_1 , b_2 and b_3 (Greene, 1997) in four cases, depending on whether the relationship between income and health is linear and on whether there is a relative income effect. In the table α_{io} is the regression coefficient obtained from regressing the omitted variable o on the included variable i . For example α_{yR} , α_{y^2R} , and α_{GR} are the coefficients on average income, squared average income and the inequality measure when the omitted variable R_k is regressed on all the included variables.

Relative income hypothesis

Suppose for the moment that there is no omitted z_k variable affecting health ($\beta_4 = 0$), or more, but not entirely, plausibly that such omitted variables are not correlated with the included income inequality variable ($\alpha_{Gz} = 0$). Can we then use the results of the regression (11) to test the relative income hypothesis? The coefficient b_3 on the income inequality variable G_k will be an unbiased estimate of the true effect of relative deprivation

(β_3) only if it is also true that $\alpha_{Gs}\beta_2 = 0$ and $\alpha_{GR} = 1$. If the income mortality risk relationship is linear (cases (a) and (b)) then $\beta_2 = 0$ so that the first requirement is satisfied. If the relationship is non-linear ($\beta_2 > 0$) we require that the included inequality measure G_k is uncorrelated with the average squared income: $\alpha_{Gs} = 0$. Any mean preserving spread in income will increase most of the standard income inequality measures and will also increase average squared income since squared income is a convex function of income. It is possible to find combinations of an income inequality measure and changes in income distribution for which G_k is uncorrelated with s_k but such combinations seem implausible empirically.⁸ It seems likely therefore that $\alpha_{Gs} > 0$. Hence if the individual mortality risk-health relationship is non-linear (cases (c) and (d)) so that $\beta_3 > 0$, the estimated coefficient on the inequality measure will overestimate the effect of income inequality on individual mortality risk, even if the actual inequality index used is a perfect measure ($\alpha_{GR} = 1$) of the conceptually correct inequality measure: $b_3 > \beta_3$. The estimated coefficient on the included inequality measure could be positive even if, as in case (d), there was no true individual level effect.

The second requirement for an unbiased estimate of the relative income effect ($\alpha_{GR} = 1$) is less demanding. One simple version of the relative income hypothesis which ensures that $\alpha_{GR} = 1$ is that the health of each individual is affected by the same inequality measure and that this measure is the one employed in the estimation: $R_{jk} = R_k = G_k$. This version seems a little implausible, since it implies that an increase in income inequality affects the health of the rich and the poor equally. A more interesting version of relative income hypothesis is that the relative deprivation of an individual depends on the number of individuals who have a greater income and by the differences between her income and theirs. Then we can show that average level of relative deprivation in a country R_k is measured precisely by the Gini coefficient (Hey and Lambert, 1980). Hence if we use the Gini coefficient as the income inequality measure G_k we have $\alpha_{GR} = 1$.

Even if the measure of national income inequality G_k is not perfectly correlated with R_k it is likely that it will be positively correlated ($\alpha_{GR} > 0$). Hence *if* the individual level mortality-income relationship is linear ($\beta_2 = 0$) the coefficient on the included inequality measure G_k will have the correct sign. But note again that if the individual mortality risk-income relationship is non-linear we cannot infer from $b_3 > 0$ that income inequality or relative deprivation affects individual mortality risk ($\beta_3 > 0$) because we cannot

⁸For example suppose G_k is the range of incomes (or less bizarrely the decile ratio (Atkinson, 1995)). Then transfers of income from those at the 3rd decile to those at the 7th decile will increase the average squared income but have no effect on G_k

distinguish between cases (c) and (d).

If we now drop the assumption that $\alpha_{Gz}\beta_4 = 0$ it is apparent that the estimated coefficient on the income distribution measure is further biased by picking up the effect of the omitted z_k . In general the estimated coefficient b_3 on the income distribution measure G_k could be positive or negative, irrespective of the true effect of income distribution on individual health.

Absolute income hypothesis

The main aim of authors such as Adelman (1963), Preston (1975) and Rodgers (1979) is to estimate the effect of income on health from country data. Does data enable us to test hypotheses about the shape of the individual level relationship between income and health? If it is possible to test for a linear individual level relationship using aggregate data then, if the evidence suggests that the relationship is linear, we could test for the existence of an effect of inequality on individual health and thus test the relative income hypothesis with aggregate data.

Assume that $\alpha_{yz}\beta_4 = 0$ and $\alpha_{y^2z}\beta_4 = 0$. Consider cases (a) and (c) in Table 1 (no relative income effect ($\beta_3 = 0$)). The average squared income s_k is likely to be positively correlated with average income, so that $\alpha_{ys} > 0$. Hence, the estimated coefficient on average income b_1 is an unbiased estimate of the true effect only if the relationship between individual mortality risk and income is linear ($\beta_2 = 0$). However, if $\beta_2 > 0$, the estimated effect of mean income on mortality risk will be underestimated. If there is a relative income effect ($\beta_3 > 0$), the estimate coefficient on average income will also pick up any correlation between average income and the relative income measure. There are no a priori grounds for suggesting the sign of α_{yR} but the aggregate cross-section data set we use in the empirical investigations has a small but significant negative correlation between the Gini coefficient and average income (see Figure 2). Hence if there is a relative income effect of the Gini on mortality risk the overall bias in the estimated effect of average income on mortality risk is indeterminate: b_1 may be smaller or larger than the true effect.

It is not plausible that $\alpha_{yz}\beta_4 = 0$, since many health affecting variables are likely to be correlated with income. For example richer countries may have better public health measures or better education systems. They may have better or worse environmental pollution. The omission of such variables is another reason why the coefficients on average income may give a biased estimate of the effect of income on individual health.

Wilkinson (Chapter 5, 1996) suggests that the apparent paradox that income is closely associated with health within countries but not between them is support for the relative income hypothesis. However, the arguments in the preceding two paragraphs show that it is perfectly possible to have

an individual level effect of income on health (which is picked up in within countries studies) but to have a weaker association between per capita income and population health.

Attempts to test for the non-linearity of the relationship between individual income and health by investigating whether b_2 is different from zero are also problematic. It is plausible that the average squared income and the square of average income are positively correlated: $\alpha_{y^2s} > 0$. There are also no *a priori* restrictions on the correlation between squared average income and the relative income R_k , though the correlation between the Gini coefficient and squared average income is small but negative in our data set. The estimated non-linear term b_2 may over or underestimate the true effect. Again, allowing for the omitted variable z_k will reinforce this conclusion.

To summarise: if the individual income-health relationship is linear and health does not depend on income distribution (case (b)) then aggregate regressions should find a linear relationship between health and average income and no relationship with inequality measures. The combined hypotheses of linearity and no relative income effect would be rejected by the data if aggregate level studies find a non-linear population health-mean income relationship or an association of population health and inequality. However, the rejection would not tell us which of the two hypotheses was incorrect: linearity or no relative deprivation effect and there would be no means of distinguishing between cases (a), (c) and (d).

5.3 Defences of aggregate studies

Two defences of aggregate level studies as tests of the relative income hypothesis can be put forward. The first is that the relationship between individual health and income is linear so that there is no aggregation bias and any observed relationship between population health and income inequality reflects a genuine rather than artefactual effect of income inequality on individual health.

A diminishing protective effect of income on health seems intuitively plausible. When health is interpreted, negatively, as mortality risk it is impossible for the mortality risk to be less than zero so that if income has any effect on mortality risk it must become smaller at high income levels. However it could be argued that the levels of income currently observed may not be high enough to induce diminishing returns. Nor is the non-linearity observed when population health is plotted against per capita income (as in Figure 1) conclusive evidence of non-linearity at the individual level in view of the problems with interpreting aggregate studies discussed above.

Although there is a considerable body of empirical investigation of indi-

vidual health using individual level data, relatively little of it looks at the effect of income on health. The balance of evidence from such studies suggests that the relationship is non-linear (Backlund, Sorlie and Johnson, 1996; Ecob and Davey Smith, 1999). A difficulty in investigating the income-health relationship is that health and income are likely to be simultaneously determined so that estimates of the effect of income need to allow for the effect of health on income. Ettner (1996) does allow for simultaneity and finds that the protective effect of income is smaller at high incomes.

The second route to rescuing aggregate level studies is to suggest that although there is non-linearity it does not explain all the association between population health and income inequality (Wolfson et al, 1999). Using US data on individual incomes, mortality risk and the distribution of income in the different states Wolfson et al (1999) suggest that after allowing for non-linearity the distribution of income is still associated with population mortality. It is difficult to judge the strength of their argument since no statistical tests of the association are reported and the study takes no account of other variables which may affect mortality risk.

Moreover, in the absence of any analytical or simulation studies, the proportion of the association between population health and income distribution which is due to non-linearity may be heavily dependent on the shape of the underlying individual health-income relationship and the distribution of income. Hence it is not possible to use a study from one country to argue about how much of population health and income inequality associations at aggregate area level in other countries or in cross country comparisons is an artefact of non-linearity and how much is reflecting a genuine effect of income distribution on individual health. If there is individual level data on income and health it seems a misdirection of effort to use it to attempt to determine how much of the aggregate level association between population health and income inequality is due to non linearity. The individual level data should be used to test the relative income hypothesis directly.

6 Conclusions

The relative deprivation hypothesis that the health of an individual depends on their income relative to the income of others, as well as on the absolute level of their income, is not *a priori* implausible. Drawing on concepts from psychology, politics and economics several authors have suggested pathways by which relative income could affect individual health (Kawachi and Kennedy, 1999; Wilkinson, 1999; Walberg et al., 1998;). Although some doubts have been raised about these pathways (Lynch et al., 2000), the rel-

ative deprivation hypothesis is worthy of serious consideration and testing. The bulk of efforts to test the hypothesis to date have relied on aggregate data and examined the relationship between population health, average income and measures of income distribution.

If individual level health-income relationships are non-linear attempts to test the relative income hypothesis on population level data are unlikely to be fruitful, even when investigators are aware of the aggregation problem and attempt to circumvent it. Estimates of the effect of income on health (the absolute income hypothesis) are likely to be biased. Tests of the relative income hypothesis are contaminated by the non-linearity of the individual health income relationship any association between income distribution and population health could be entirely due to it, rather than to any direct effect of relative income on individual health.

Such methodological cautions against using aggregate data to test individual level relationships are reinforced by our empirical experiments. Comparing the results of a much cited aggregate level study (Rodgers, 1979) with those from our more recent and larger data set we have found that estimated aggregate level relationships do not appear to be robust to the choice of data sets or to the specification of the functional form. Although the qualitative relationships between income and life expectancy were similar, the quantitative results were not. Given the difference in the periods examined in our study and Rodgers (1979) the changed quantitative estimates of the effect of income on life expectancy are not surprising, nor do they cast any serious doubt on the absolute income hypothesis.

However, whilst Rodgers (1979) found that income distribution had a significant negative association with life expectancy in almost all of his regression, we have found that the association is sometimes positive and sometimes negative and is never statistically significant.

Such results do not disprove the relative income hypothesis since, even in the absence of confounding by omitted variables, aggregate level studies are incapable of distinguishing between the direct effect of income inequality on individual health and non-linearity in the individual health-income relationship. The findings should however be a further warning against using aggregate level studies as evidence for the relative deprivation hypothesis.

Tests of hypotheses about the determinants of individual health require individual level data. There have been relatively few individual level tests of the relative income hypothesis to date and they have produced mixed results (Wagstaff and van Doorslaer, 2000). In part this is because statistical testing of hypotheses about the effect of income and income inequality on individual health must also be based on explicit models of the determinants of individual health which takes account of the other influences on health, the

reciprocal relationship between health and income, and the likelihood that relationships operate with considerable lags. Such modelling should also specify the pathways by which relative deprivation affects health and spell out clearly the implications for the appropriate measures of relative deprivation. Teasing out the relationship between individual health, individual characteristics and social circumstances using both individual and group level data will not be easy but the difficulties do not justify the analysis of purely aggregated data which is incapable in principle of answering these important questions.

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Table 1. Summary Statistics

Variable	Mean	Std Deviation	Minimum	Maximum
Gini	0.38	0.38	0.21	0.60
Male life expectancy (years)	66.19	7.97	41.10	75.99
GDP per capita (US \$000s)	6.27	6.27	0.55	18.06

TABLE 2. Replication with new data.

Variable	Rodgers (1979) ^a			Replication ^b			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1/Y	-4469 (-6.4)	-2236 (-12.11)	-3389 (-4.93)	-30.19 (-6.66)	-20.27 (-8.59)	-29.01 (-6.44)	-24.19 (-2.27)
1/Y ²	149900 (3.38)		76880 (1.74)	7.19 (2.77)		6.44 (2.45)	1.98 (0.23)
Gini		-43.87 (-4.94)	-36.47 (-3.76)		-8.41 (-1.48)	-5.39 (-0.97)	4.54 (-0.52)
D/Y							-6.08 (-0.51)
D/Y ²							4.99 (0.54)
D*Gini							-2.30 (-0.2)
D							2.71 (0.64)
Constant	72.9	73.7	75.1	74.59 (107.4)	76.1 (37.18)	76.44 (37.27)	74.92 (24.01)
R ² (adj)	0.712	0.76	0.773	0.72	0.71	0.72	0.71
Reset test (p value from F test)				0.14	0.002	0.34	0.45
N	56	56	56	75	75	75	75

^a Y is GDP per capita in \$

^b Y is GDP per capita in \$ 000's

G: Gini coefficient

D = 1 if data 1988-90, = 0 if 1980-82

Dependent variable: male life expectancy at birth

t-statistics are in brackets in columns (4) to (7) (Calculated using The Huber/White/sandwich adjusted std.errors).

Table 3. Alternative functional forms.

	Box-Cox transformations on ^{ab}			Quadratic ^{ac}	Translog ^{ac}
	Y, Y ²	Y, Y ² , G	L, Y, Y ² , G		
	(1)	(2)	(3)	(4)	(5)
Y	42.31 (0.04)	40.01 (0.09)	9.08e+09 (0.00)	3.84 (4.05)	
Y ²	-11.09 (0.04)	-10.69 (0.08)	-3.31e+08 (0.00)	-0.15 (-5.27)	
Gini	-7.48 (0.14)	-0.34 (0.48)	6.59e+08 (0.97)	26.40 (0.64)	
Gini ²				-26.50 (-0.41)	
Gini*GDP				-0.68 (-0.27)	
log Y					62.20 (4.82)
(log Y) ²					-3.36 (-4.92)
log Gini					-25.02 (0.64)
(log Gini) ²					-13.76 (-1.78)
log Y*log Gini					-0.54 (-0.13)
Constant	53.05	49.68	1.07e+10	47.12 (3.99)	-231.45 (-3.36)
R ² (adj)				0.57	0.72
RESET test (p value from F test)				0.00	0.18
Box-Cox lambda (std error)	-1.41 (.26)	-1.31 (0.26)	6.26 (0.93)		
N	75	75	75	75	75

GDP in \$ 000's.

^a Dependent variable: male life expectancy at birth

^b The p value from a chi squared tests with 1 degree of freedom are given in brackets for the independent variables.

^c t-statistics are in brackets (Calculated using The Huber/White/sandwich adjusted std.errors).

Table 4. Modelling the epidemiological transistion.

Variable	Gini & income Interaction	Slopes and Gini intercept dummies	Gini dummy	Spline dummy	Gini & high income interaction
	(1)	(2)	(3)	(4)	(5)
1/Y	-30.67 (-4.25)	-32.59 (-3.88)	-32.52 (-4.98)	-29.67 (-3.81)	-28.87 (-4.57)
1/Y ²	7.21 (1.99)	8.03 (1.93)	8.13 (2.44)	6.74 (1.69)	6.38 (1.87)
Gini	-5.42 (-0.86)	-8.39 (-0.97)	-5.83 (-1.05)	-5.65 (-0.93)	-5.37 (-0.95)
D*Y		83.85 (1.86)			
D*Y ²		-399.98 -0.29			
D*Gini		2.89 (-0.31)	-3.74 (-1.05)		
D		-6.44 (-1.15)			
DS*Y				36.12 (0.74)	
DS*Y ²				135.326 (0.68)	
Gini*Y	0.003 (0.41)				
Gini*D*(Y-5000)					0.02 (0.05)
Constant	77.06 (28.34)	79.22 (15.87)		76.83 (20.86)	76.38 (28.64)
R ² (adj)	0.72	0.72	0.72	0.72	0.72
Reset test (p value from F test)	0.29	0.04	0.38	0.12	0.32
N		75	75	75	75

GDP in \$ 000's.

Dependent variable = Male life expectancy at birth

t-statistics are in brackets (Calculated using The Huber/White/sandwich adjusted std.errors).

Expected value of estimated coefficients		
Relative income effect?		
	Yes: $\beta_3 > 0$	No: $\beta_3 = 0$
Non-linear income effect?	Case (a)	Case (b)
No: $\beta_2 = 0$	$b_1 \quad \beta_1 + \alpha_{yR}\beta_3 + \alpha_{yz}\beta_4 \geq \beta_1$ $b_2 \quad \alpha_{y^2R}\beta_3 + \alpha_{y^2z}\beta_4 \geq \beta_2$ $b_3 \quad \alpha_{GR}\beta_3 + \alpha_{Gz}\beta_4 \geq 0$	$\beta_1 + \alpha_{yz}\beta_4 \geq \beta_1 < 0$ $\beta_2 + \alpha_{y^2z}\beta_4 \geq \beta_2 > 0$ $\beta_3 + \alpha_{Gz}\beta_4 \geq \beta_3 = 0$
Yes: $\beta_2 > 0$	Case (c)	Case (d)
	$b_1 \quad \beta_1 + \alpha_{ys}\beta_2 + \alpha_{yR}\beta_3 + \alpha_{yz}\beta_4 \geq \beta_1$ $b_2 \quad \alpha_{y^2s}\beta_2 + \alpha_{y^2R}\beta_3 + \alpha_{y^2z}\beta_4 \leq 0$ $b_3 \quad \alpha_{Gs}\beta_2 + \alpha_{GR}\beta_3 + \alpha_{Gz}\beta_4 \leq 0$	$\beta_1 + \alpha_{ys}\beta_2 + \alpha_{yz}\beta_4 \geq \beta_1$ $\alpha_{y^2s}\beta_2 + \alpha_{y^2z}\beta_4 \geq 0$ $\alpha_{Gs}\beta_2 + \alpha_{Gz}\beta_4 \geq 0$

Table 5: Estimated coefficients b_i from regression $m_k = b_0 + b_1 y_k^2 + b_3 G_k$ when true model is $m_k = \beta_0 + \beta_1 y_k + \beta_2 s_k + \beta_3 R_k \beta_4 z_k + e_k$.

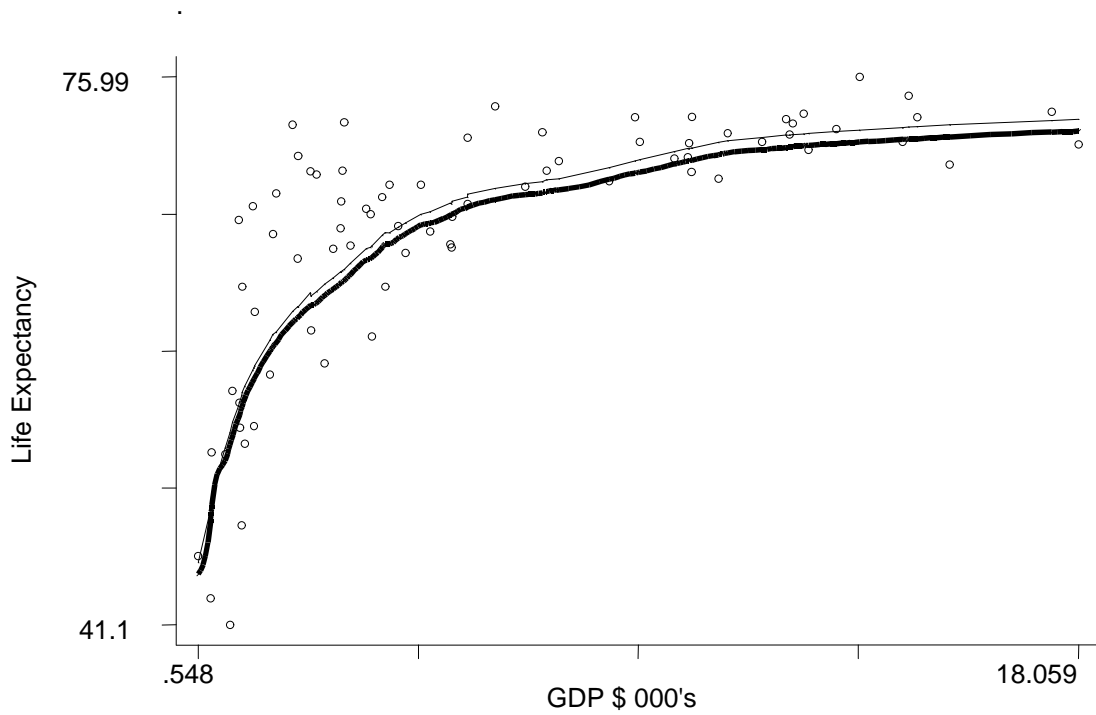


Figure 1: Life Expectancy and GDP per capita: — Nonparametric regression,
— Nonparametric regression, controlling for the Gini coefficient

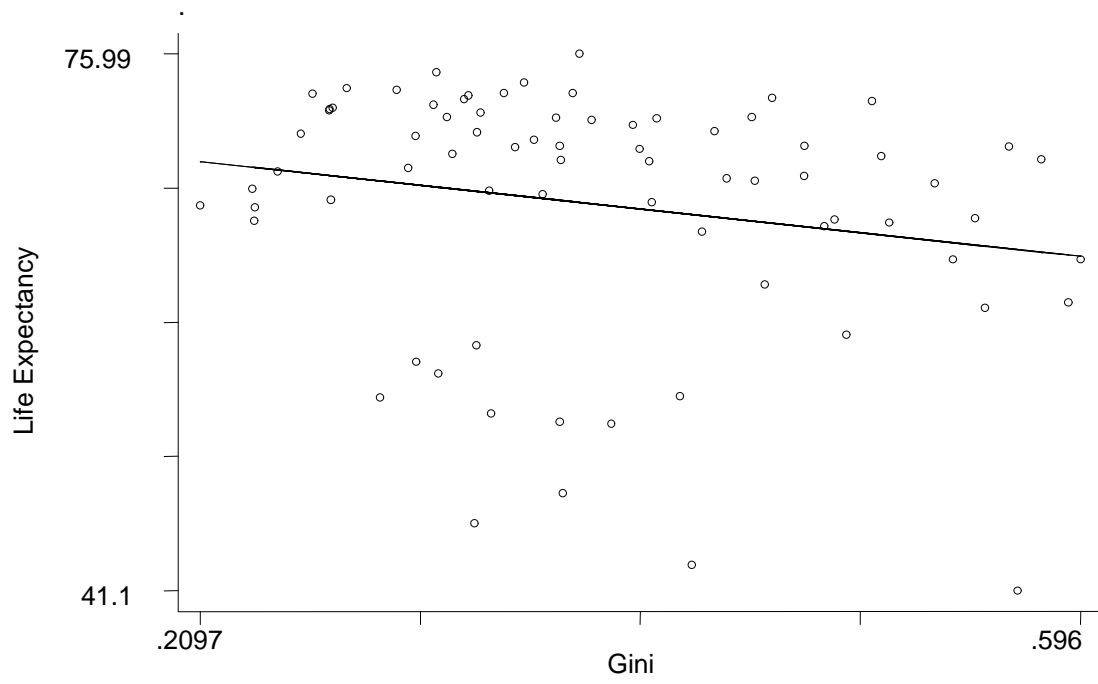


Figure 2: Life Expectancy and Gini coefficient (slope coefficient : -15.94 (t-stat. using robust std. error = -1.96); $R^2 = 0.03$)

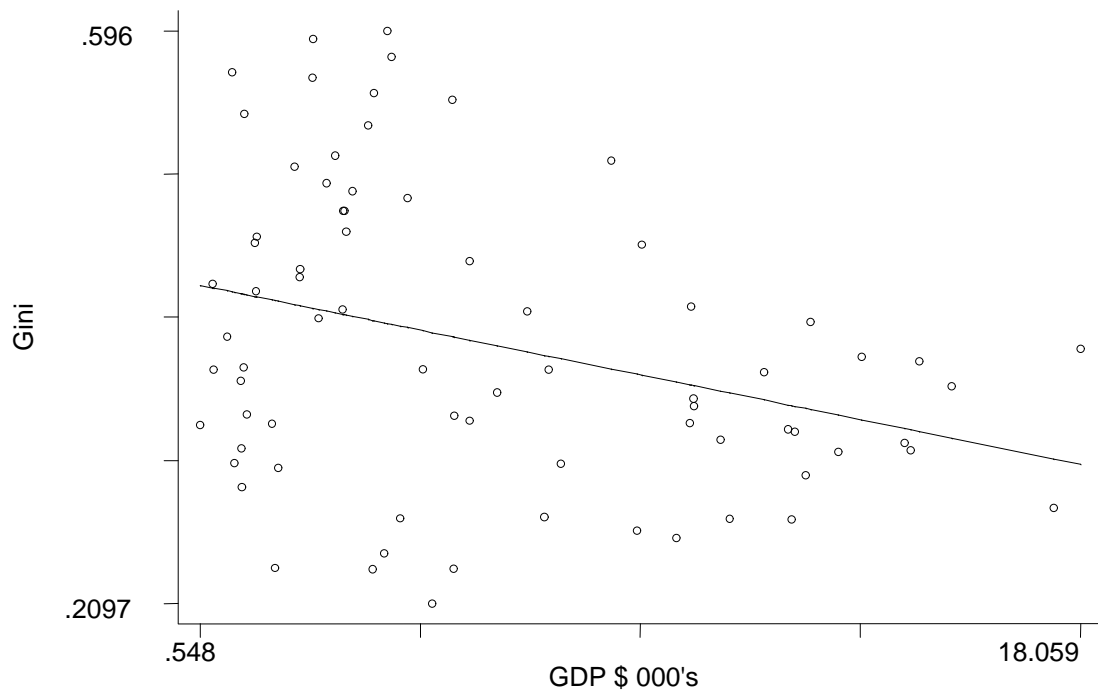


Figure 3: The Gini coefficient and income per capita (slope coefficient: -0.07 (t-stat. using robust std. error = -3.91); $R^2 = 0.10$)