NONLINEARITIES IN THE BECKER-TOMES-SOLON MODEL

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Abstract. The aim of this paper is to explore nonlinearities in the relationship between parents and children earnings. We first discuss a simple extension of the Becker-Tomes-Solon model accounting for nonlinearity. We then test the linearity of intergenerational transmission employing a set of 141 intergenerational mobility tables in 35 different countries at different time periods, and find that linearity is rejected in 89 tables. We finally explore the correlation between the "strength of concavity" and income inequality. Our findings suggest that more unequal societies tend to have a more concave intergenerational transmission process.

JEL Classification Numbers: D31; J62.

Keywords: Intergenerational earnings elasticity; Becker-Tomes-Solon model, Nonlinearity, Income inequality.

1. Introduction

The seminal Becker and Tomes ([3], [4]) model is indisputably the main theoretical framework used by economists to understand the determinants of intergenerational mobility. Becker and Tomes suggest a theory of family behavior that unifies the economic and sociological approaches, and gives a rational choice interpretation to Galton's regression to the mean model of intergenerational transmission (Galton [20]). Recently, Solon [34] extends and clarifies the main features of the Becker-Tomes model, and provides a very useful decomposition of the intergenerational earnings elasticity in terms of the underlying structural parameters. The Becker-Tomes-Solon (BTS henceforth) model defines a simple rational choice framework that underlies intergenerational income regressions. It is fair to say

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that the BTS model is by now the main theoretical framework used in applied economics for interpreting intergenerational earnings elasticity estimates.

There is by now is a large set of estimates of the intergenerational earnings elasticity (henceforth IGE) using data from different countries and time periods.[1] However, estimates of IGE have typically assumed the (log)-linearity of the intergenerational income transmission process. Comparatively less attention has been paid to the existence of *nonlinearities* in the intergenerational transmission process within the BTS model. Becker and Tomes [4] originally conjectured that credit constraints imply the *concavity* of intergenerational transmission. Grawe [22] argued that the absence of credit constraints does not necessarily imply linearity in the relationship between child and parent earnings as nonlinearities depend on the nature of the earnings function. Mazumder [27] and Couch and Lillard [15] find a concave relationship between offspring's and parent's earnings for the US. Bratsberg *et al.* [11] find that the patterns of intergenerational earnings is linear for the US and UK, but *convex* for Nordic countries. They conjecture that convexity is related to the strong public education system in the Nordic countries.

This paper has two main purposes. The first is to complete Solon's description of the BTS model by incorporating nonlinearities in a simple and self consistent way. The second is to empirically address the nonlinearity issue. We employ a rich data set of occupational mobility tables provided in Ganzeboom, Luijk, and Treiman [21], which allows comprehensive cross-country comparative mobility analysis for many countries and time periods. This data set has the distinctive advantage of

[1]A partial list, including only published articles, includes Aaronson and Mazumder [1], Andrews and Leigh, [2], Bhattacharya and Mazumder [5], Bjorklund and Jantti [6], Blanden [7], Blanden *et al.* [8], Blanden *et al.* [9], Bratberg *et al.* [10], Bratsberg *et al.* [11], Corak [12], Corak *et al.* [13], Couch and Dunn [14], Dearden *et al.* [17], Dunn [19], Grawe [22], Ferreira and Veloso [23], Lefranc and Trannoy [24], Lefranc *et al.* [25], Leigh [26], Mazumder [27], Mocetti [28], Ng *et al.* [30], Ng [29], Piraino [31], Raaum *et al.* [32], and Solon [33].

employing a consistent and well defined classification of social status. However, since social status in the data set is an ordinal variable, it does not allow a direct testing of nonlinearity. We circumvent this problem making some assumptions on the structure of the occupational classes. Our main finding is that Nordic and Eastern bloc countries tend to have a convex intergenerational transmission, while developing countries tend to display a concave process. In general, we find that more unequal societies tend to have a more concave intergenerational transmission process.

The paper is organized as follows: the second section recalls the essential ingredients of the BTS model; the third section discusses the theoretical motivations for the existence of nonlinearities; the fourth section summarizes the empirical findings and the fifth section reports concluding remarks. Most tables and figures are collected in the Appendix.

2. The BTS model

The BTS model is very well known, and clearly described in Solon [34]. We recall here its essential ingredients.

(1) Parent's utility: Parents derive utility from their own lifetime consumption C_{t-1} and their child lifetime income y_t

$$U_{t-1} = (1-\alpha)\log\big(C_{t-1}\big) + \alpha\log\big(y_t\big) \tag{1}$$

where $0 < \alpha < 1$ denotes a coefficient of parent's altruism.

(2) Parent's budget constraint: Given tax rate τ, family net income is $(1-\tau)y_{t-1}$, and parent chooses family investment in child's human capital,

I_{t-1}, subject to the budget constraint

$$(1-\tau)y_{t-1} = C_{t-1} + I_{t-1}. \tag{2}$$

(3) HUMAN CAPITAL TECHNOLOGY: The technology translating private (I_{t-1}) and public (G_{t-1}) human capital investment into child's human capital h_t is

$$h_t = \theta \log\big(I_{t-1} + G_{t-1}\big) + e_t \tag{3}$$

where e_t denotes child's initial endowment, influenced by nature and nurture, but orthogonal to I_{t-1} and G_{t-1}.

(4) CHILD'S INCOME: Child's income depends on human capital:

$$\log y_t = \mu + p h_t. \tag{4}$$

(5) PUBLIC INVESTMENT: Public investment G_{t-1} is governed by:

$$\frac{G_{t-1}}{(1-\tau)y_t} = \varphi - \gamma \log y_{t-1} \tag{5}$$

where τ is the tax rate and γ captures the progressivity of public investment in children's human capital.

(6) INITIAL ENDOWMENT: e_t evolves through family generations according to a $AR(1)$ process

$$e_t = \delta + \lambda e_{t-1} + v_t. \tag{6}$$

Maximizing parent's utility (1) under the budget constraint (2) and using (3)–(4), gives the optimal level of parent's investment in child's human capital

$$I^*_{t-1} = \frac{\alpha\theta p}{1-\alpha(1-\theta p)}(1-\tau)Y_{t-1} - \frac{1-\alpha}{1-\alpha(1-\theta p)}G_{t-1} \tag{7}$$

so that I^*_{t-1} increases with parent's altruism, with the efficiency of human capital investment, and decreases with public investment.

Substituting (7) in (3) and (4) and using (5) gives (an approximation of) the log-linear intergenerational income transmission equation (see Solon [34] for details)

$$\log y_t = m + b \log y_{t-1} + pe_t \tag{8}$$

with $m = \mu + \varphi\theta p + \theta p \log \frac{\alpha\theta p(1-\tau)}{1-\alpha(1-\theta p}$ and $b = (1-\gamma)\theta p$.

Equation (8) takes exactly the form of the standard log-linear earnings equation which is typically used to estimate intergenerational earnings elasticities. However, seen as a regression equation, since e_t follows the $AR(1)$ process (4), the OLS estimate of the slope coefficient β in the linear regression of $\log y_t$ on $\log y_{t-1}$ is

$$plim\ \hat{\beta} = \frac{b+\lambda}{1+b\lambda} = \frac{\lambda + (1-\gamma)\theta p}{1+(1-\gamma)\theta p\lambda}. \tag{9}$$

Equation (9) helps understanding estimated IGE across countries and times in terms of the underlying structural parameters. In particular, the BTS model predicts that intergenerational elasticity is greater the higher the heritability coefficient λ, the productivity of the educational system θ, and the return to human capital p, and the lower the progressivity of public investment γ.

It is instructive to view equation (9) alternatively as the result of an omitted variable problem. In particular, subtracting λy_{t-1} from both sides of (8) and using (4) we have

$$\log y_t = m^* + (b+\lambda) \log y_{t-1} - \lambda b \log y_{t-2} + pu_t \tag{10}$$

where $m^* = (1-\lambda)m + \delta$. Using the standard formula for the omitted variable bias, it can be verified that under stationarity the OLS regression coefficient in the regression of $\log y_t$ on $\log y_{t-1}$, when (10) is the true model, is given by equation (9).

3. Nonlinearity

In this section, we discuss simple theoretical motivations for the possible nonlinearity in the parent-child log-income relationship in (8).

3.1. **Concavity: Perfect capital markets.** Becker and Tomes [4] argue that if parents can borrow against child's future incomes, parent's budget constraint (2) does not bind and private human capital investment I_{t-1} becomes independent on family income y_{t-1}. Thus, the direct effect of parent's income b in equation (8) is null, and the intergenerational earnings transmission (10) becomes

$$\log y_t = m^* + \lambda \log y_{t-1} + pu_t. \tag{11}$$

In this case the intergenerational earnings elasticity will be equal to the heritability coefficient λ. Thus, since $\beta > \lambda$, perfect capital markets imply a lower IGE (a more meritocratic society).

If we accept Becker and Tomes conjecture that borrowing constraints are more likely to impact on poorer parents (say when $\log y_{t-1}$ is lower than a given level $\bar{k}$), it follows that intergenerational earnings will be governed by a Threshold Auto Regression (TAR) model

$$\log y_t = m^* + (b + \lambda) \log y_{t-1} - \lambda b \log y_{t-2} + pu_t, \ \log y_{t-1} \le \bar{k} \tag{12}$$

$$\log y_t = m^* + \lambda \log y_{t-1} + pu_t, \ \log y_{t-1} > \bar{k}. \tag{13}$$

The question then becomes, in the TAR process (12)-(13), what is the conditional first order autocorrelation for the rich and poor families? In particular, how do they compare with the first order autocorrelation for the two separate processes (8) and (11)? Unfortunately, the econometrics of TAR models, without further assumptions, does not give a general answer to this question. However, simulations with a set of plausible values reveal that the conditional rich and poor autocorrelations are fairly close to the ones for the two separate processes (namely β for poor families and $\lambda < \beta$ for rich families) and, at any rate, the conditional first order autocorrelation is always greater for richer families compared to poorer ones. Thus, model (12)-(13) implies that the relationship between $\log y_t$ and $\log y_{t-1}$ will be *concave* as depicted in Figure 1 below.

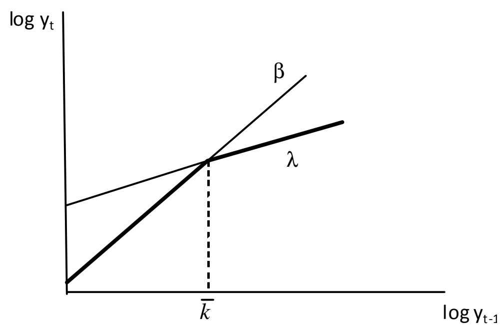

FIGURE 1. The Becker-Tomes conjecture (concavity)

3.2. **Convexity: Corner solution.** While most theoretical and empirical literature has followed the Becker and Tomes conjecture and tested for the concavity of intergenerational earnings transmission, the alternative convexity hypothesis has been much less investigated. An immediate consequence of the optimizing framework (1)–(5) is that equation (7) determines optimal parent's investment *under the assumption that the maximization problem has an interior solution.* This obvious observation gives a very simple explanation of the possible nonlinearity in intergenerational transmission without the need of further assumptions. Looking at equation (7), it emerges that for poor parents or when altruism is low (in particular, whenever y_{t-1} is lower than $\frac{1-\alpha}{\alpha\theta p(1-\tau)}G_{t-1}$), optimal investment in child's education is zero. Thus, letting $\log\left(\frac{1-\alpha}{\alpha\theta p(1-\tau)}\right)+\log G_{t-1}=\hat{k}$, say, intergenerational earnings transmission will be governed by a TAR model:

$$\log y_t = m^* + (b+\lambda)\log y_{t-1} - \lambda b \log y_{t-2} + pu_t,\ \log y_{t-1} > \hat{k} \tag{14}$$

$$\log y_t = m^* + \lambda \log y_{t-1} + pu_t,\ \log y_{t-1} \le \hat{k} \tag{15}$$

where, opposite to the Becker Tomes conjecture, poor parents are governed by process (11) while rich families by process (8). The relationship between $\log y_t$ and $\log y_{t-1}$ will now be *convex* as depicted in Figure 2 below.

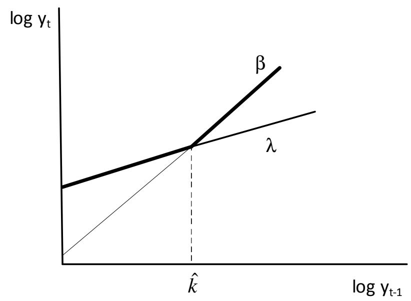

FIGURE 2. Corner solution (convexity)

4. An empirical investigation

As argued in the Introduction, there are some studies aimed to test the linearity of the intergenerational earnings transmission for a range of different countries. However, since estimation methods, variable definitions and sample selection rules often differ widely across studies, comparability of results may be tricky. Differing results may appear because of actual cross-country or time differences in intergenerational mobility, but also for the differences across studies in their earnings measures, age ranges or other sample selection rules.

To allow comparability of results, we use a sample of occupational mobility tables presented in Ganzeboom *et al.* [21]. This data set contains 149 intergenerational class mobility tables from 35 countries and different years, and is the most comprehensive and well structured data set on intergenerational occupational mobility to date, which allows a substantial degree of comparability among the different tables. Ganzeboom *et al.* [21] present the cross-classification of fathers occupation by sons current occupation for representative national samples of men aged 21-64, with the characteristic that the tables conform to a well specified six category scheme. The six social classes, in descending order of socio-economic status, are the following: 1) Large proprietors, higher and lower professionals and managers; 2) Routine non-manual workers; 3) Small proprietors with and without employees; 4) Lower grade technicians, manual supervisors and skilled manual workers; 5) Unskilled and semiskilled manual workers; 6) Self employed farmers and (unskilled) agricultural workers. In our application, we do not use 8 tables using inlaws status, so our data set is actually made of 141 tables.

For our purposes, the extensiveness and comparability of the data set does not come without a cost, mainly that these mobility tables report occupational status, rather than wages or income. On the one hand, since income in the BTS model must be interpreted as *lifetime* income, occupational class may actually be considered a more accurate proxy than current income which is mostly used in empirical applications. On the other hand, however, occupational class is an ordinal variable, and thus does not allow a direct testing nonlinearity. To circumvent this problem we make some assumptions on the structure of the occupational classes.

We first divide the original six sons' occupational classes into a binary variable (say Y_s), which takes value 1 if the son is in any of the first three social classes. Under this assumption, son's expected status is simply given by the probability that $Y_s = 1$. Next, we divide fathers' social classes into three categories, and we let Y_f denote a discrete random variable, which takes three possible values: *high* when father belongs to social class 1 or 2; *middle* when father belongs to social class 3 or 4; and *low* when father belongs to social class 5 or 6.

Under the assumption that the mobility process is *stochastically monotone*, the expected status of sons coming from a high class father will be greater than the expected status of sons coming from middle class father, which in turn will be greater than the expected status of sons coming from a low class father. This assumption is actually tested in Dardanoni *et al.* [16] using this data set, and is well supported by the data. Under the further assumption that the three father's social classes are equidistant in some real metric, it follows that intergenerational transmission will be:

$$\begin{aligned}
\mathit{Concave}:&\ E[Y_s \mid Y_f = \mathit{middle}] - E[Y_s \mid Y_f = \mathit{low}] > E[Y_s \mid Y_f = \mathit{high}] - E[Y_s \mid Y_f = \mathit{middle}] \\
\mathit{Linear}:&\ E[Y_s \mid Y_f = \mathit{middle}] - E[Y_s \mid Y_f = \mathit{low}] = E[Y_s \mid Y_f = \mathit{high}] - E[Y_s \mid Y_f = \mathit{middle}] \\
\mathit{Convex}:&\ E[Y_s \mid Y_f = \mathit{middle}] - E[Y_s \mid Y_f = \mathit{low}] < E[Y_s \mid Y_f = \mathit{high}] - E[Y_s \mid Y_f = \mathit{middle}]
\end{aligned}$$

Now, if we let $\mu = 2E[Y_s \mid Y_f = middle] - E[Y_s \mid Y_f = low] - E[Y_s \mid Y_f = high]$ and σ the standard deviation of μ (which is easily calculated using standard formulas for the distribution of binary variables) we can estimate the standardized score $\hat{z} = \frac{\hat{\mu}}{\hat{\sigma}}$ for each of the 141 tables, which is asymptotically normally distributed. Using the 95% upper and lower critical values of the standard normal, we can then infer that the relationship is linear when $\hat{z}$ lies inside the critical values, concave when $\hat{z}$ lies above the upper critical value and convex when it lies below the lower critical value.

Table 1 in the Appendix summarizes the empirical evidence on nonlinearities in intergenerational earnings mobility in our sample. The linearity hypothesis cannot be rejected for 52 tables out of 141; in 63 intergenerational transmission is convex, and in 26 is concave. A glance at the table suggests that, similarly to Bratsberg *et al.* [11], Nordic countries in general tend to have a convex relationship. The same is true for Eastern bloc countries. On the other hand, in most developing countries intergenerational transmission seems to be concave.

These results are suggestive of a possible relationship between the concavity of the intergenerational transmission process and the degree of inequality. To test this hypothesis, we use the Gini coefficient as a measure of income inequality. We obtained data on the Gini coefficient of pre-tax income from the Luxembourg Income Study (LIS) and the Deininger and Squire [18] database, from which we select the highest quality estimate and the closest estimates to the year of the survey. Since for Belgium 1971 and Sweden 1950 there were no pre-tax Gini measures available in close years, we deleted them from the sample.

Table 2 cross-classifies intergenerational transmission for low, medium and high inequality for the 139 countries/years, and shows a positive association between concavity and income inequality. We finally regressed $\hat{z}$, which is our measure of the evidence on the "strength of concavity" of intergenerational transmission, on a constant and on the Gini coefficient. The relationship between inequality and concavity for all countries/years is depicted in figure 3. Table 3 shows that the estimated coefficient of the Gini is equal to 0.21, with a t-ratio of 4.9, which strongly confirms that more unequal societies tend to have a more concave intergenerational transmission process. Thus, it seems that when income inequality is high, the prospects of the sons of middle class families are closer to those of poor families, while when incomes are more equally distributed the prospects of the sons of middle class families are closer to those of rich ones.

5. Conclusions

The aim of this paper is twofold. First, we illustrate the conditions for the existence of nonlinearities in the BTS model; second we explore empirical evidence of nonlinearities in a large sample of comparable mobility tables across countries and times. Using a data set of 141 intergenerational class mobility tables from 35 countries at different years developed by Ganzeboom *et al.* [21], we reject linearities in 89 tables out of 141, and find that, on average, Nordic and Eastern bloc countries tend to have a convex intergenerational transmission process, while developing countries tend to have a concave one. We also investigate the relationship between concavity and income inequality, and find that there is a strong positive correlation between the degree of concavity of intergenerational transmission and the level of income inequality as measured by the Gini coefficient.

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Table 1. Nonlinearities in intergenerational transmission

Country	Year	Patterns	Country	Year	Patterns
Australia	1965, 1967, 1973	Convex	Japan	1969t	Linear
	1987	Linear		1955, 1965, 1971n,	Concave
Austria	1969n	Linear		1975	
	1974p, 1978	Concave	Maylasia	1967	Concave
Belgium	1971e, 1975, 1976	Concave	Netherlands	1970, 1979p	Convex
Brazil	1973	Concave		1958, 1971, 1974p,	Linear
Canada	1964, 1973	Convex		1976, 1977, 1977x,	
	1982w	Linear		1982, 1982u, 1985	
Czechoslovakia	1967	Linear		1967t, 1971e	Concave
Denmark	1971, 1972s	Linear	New Zealand	1976	Linear
England	1951, 1963, 1967t,	Convex	Nigeria	1971n	Concave
	1969, 1972, 1974,		Northern Ireland	1968, 1973	Convex
	1983, 1986		Norway	1965, 1973, 1982w	Convex
	1974p	Linear		1957, 1967t, 1972s	Linear
Finland	1972s, 1980	Convex	Philippines	1973	Linear
	1967t, 1975p	Linear		1968	Concave
	1982w	Concave	Poland	1972, 1982, 1987	Convex
France	1964, 1967	Convex	Puerto Rico	1954	Linear
	1958, 1970, 1971e	Concave	Quebec	1960, 1973, 1977	Convex
Germany	1959, 1969k, 1975p,	Convex	Scotland	1975	Convex
	1977z, 1978x, 1979z,			1974	Linear
	1980, 1980z, 1984a		Spain	1965, 1967t	Linear
	1969, 1976z, 1978,	Linear		1975	Concave
	1978z, 1980a, 1980p,		Sweden	1950, 1960, 1972s,	Convex
	1982a			1973, 1983w	
Hong Kong	1967	Linear	Switzerland	1976p	Linear
Hungary	1962, 1973, 1982,	Convex	Taiwan	1970	Concave
	1983, 1986		United States	1962o,1972g,1973o	Convex
India	1963c	Linear		1974g, 1975g, 1977g,	
	1962c, 1963, 1971n	Concave		1978g, 1981w, 1985g	
Ireland	1974	Linear		1959c, 1973g, 1974p	Linear
Israel	1962c, 1974	Linear		1976g, 1980g	
Italy	1963, 1974	Convex		1980g, 1982g, 1983g	
	1972, 1975p	Linear		1984g, 1986g	
	1968	Concave		1947	Concave
Japan	1967	Convex	Yugoslavia	1967t	Convex

Table 2. Gini coefficient distribution

	Gini coefficient		
Pattern	< 30	30-35	> 35
Convex	24	21	17
Linear	19	15	18
Concave	3	10	12

Table 3. OLS regression results

Variable	Coefficient	Standard Error	t-ratio	P[|T|>t	Mean
Gini	0.21	0.043	4.9	0.0000	33.186
Constant	-7.899	1.453	-5.438	0.0000	
R-squared = 0.15		Number of observations = 139			

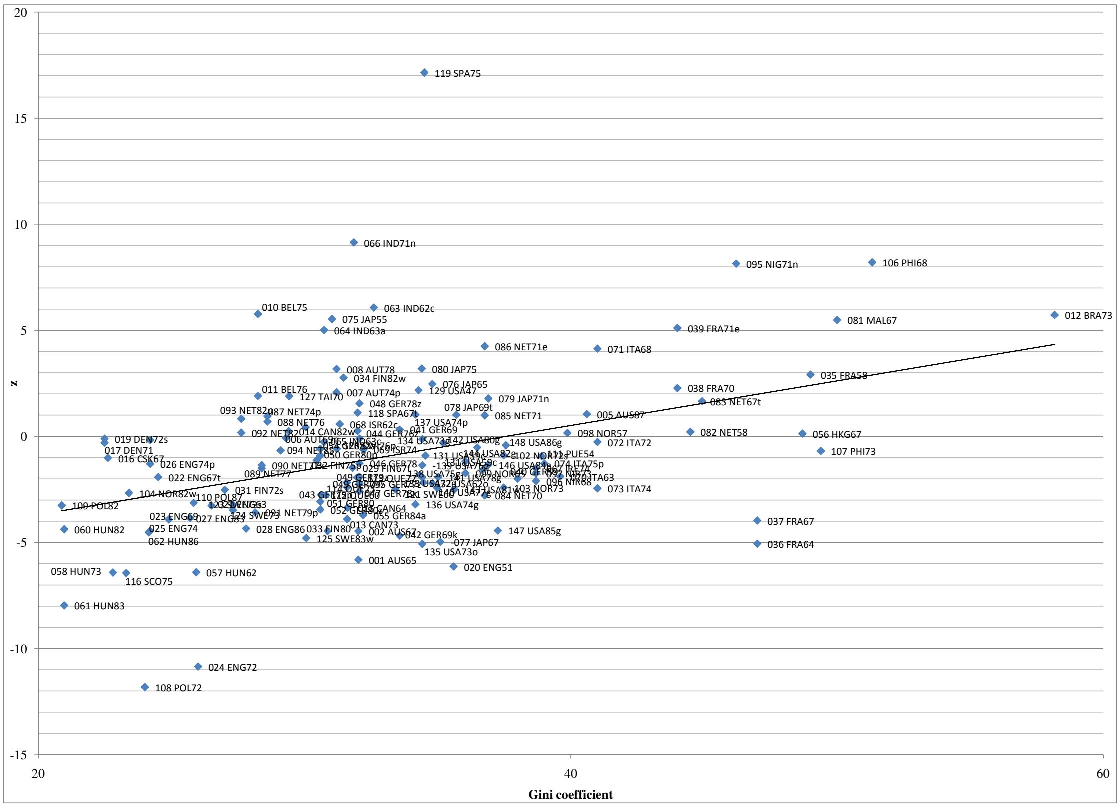

FIGURE 3. OLS regression