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Regression-Based Inequality Decomposition: A Critical Review and Application to Farm-Household Income Data

by

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Regression-Based Inequality Decomposition: A Critical Review and Application to Farm-Household Income Data*

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Abstract

The purpose of this paper is to critically review and discuss several interpretations of inequality decomposition methods offered in the literature. In particular, I claim that the "property of uniform additions" is not necessarily a desired property of inequality decomposition methods. This applies to decomposition of inequality by income sources as well as to regression-based decomposition by determinants of income. Thus, relying on this property (or lack thereof) to judge against decompositions based on the Gini index of inequality may be misleading. The Gini decomposition rule is more intuitively interpretable than alternative rules, and allows the derivation of the marginal effect on inequality of a uniform increase in an income source or a determinant of income. The results of several competing decomposition rules are compared using simulations and a case study of farm household income in Georgia.

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Introduction

Income inequality can be decomposed in various dimensions. The most common decomposition is perhaps by population subgroups (e.g., households headed by males and by females). This paper considers the less common decomposition, by income sources, offered by Shorrocks (1982, 1983), which was subsequently extended by Morduch and Sicular (2002) and Fields (2003) to regression-based decomposition by determinants of income. The purpose of this paper is to critically discuss several interpretations of these inequality decomposition methods that have been offered in the literature. In particular, several authors concluded, based on theoretical arguments and empirical examples, that the natural decomposition rule based on the Gini index of inequality does not produce meaningful results. This paper shows that the Gini-based decomposition rule offers advantages over alternative decomposition rules, and that some of the interpretations made in the literature in support of the alternative rules do not hold ground. This argument is supported by simulations and by an empirical analysis.

A description of these decomposition methods is provided in the next section. After that, some existing interpretations of these methods are critically discussed. This is followed by an empirical example based on a survey of farm households in Georgia. The last section contains a summary and some concluding comments.

Inequality decomposition methods

Shorrocks (1982,1983) suggested focusing on inequality measures that can be written as a weighted sum of incomes:

$$(1) \qquad I(\mathbf{y}) = \Sigma_i a_i(\mathbf{y}) y_i,$$

where a_i are the weights, y_i is the income of household i, and $\mathbf{y}$ is the vector of household incomes. If income is observed as the sum of incomes from k different sources, $y_i = \Sigma_k y_i^k$, the inequality measure (1) can be written as the sum of source-specific components S^k:

$$(2) \qquad I(\mathbf{y}) = \Sigma_i a_i(\mathbf{y}) \Sigma_k y_i^k = \Sigma_k[\Sigma_i a_i(\mathbf{y}) y_i^k] \equiv \Sigma_k S^k.$$

Dividing (2) through by $I(\mathbf{y})$, one obtains the proportional contribution of income source k to overall inequality as:

(3) $\quad s^k = \Sigma_i a_i(\mathbf{y}) y_i^k / I(\mathbf{y})$.

Shorrocks (1982) noted that the decomposition procedure (3) yields an infinite number of potential decomposition rules for each inequality index, because in principle, the weights $a_i(\mathbf{y})$ can be chosen in numerous ways, so that the proportional contribution assigned to any income source can be made to take any value between minus and plus infinity. In particular, three measures of inequality that are commonly used in empirical applications are: (a) the Gini index, with $a_i(\mathbf{y})=2(i-(n+1)/2)/(\mu n^2)$, where i is the index of observation after sorting the observations from lowest to highest income, n is the number of observations and μ is mean income; (b) the squared coefficient of variation with $a_i(\mathbf{y})=(y_i - \mu)/(n \mu^2)$; and (c) Theil's T index with $a_i(\mathbf{y})=\ln(y_i/\mu)/n$.

Shorrocks (1982) further showed how additional restrictions on the choice of weights can reduce the number of potential decomposition rules. In particular, two restrictions are sufficient to derive a unique decomposition rule. The restrictions are (a) that an equally-distributed income source has a zero contribution to overall inequality; and (b) that if total income is divided into two components whose factor distributions are permutations of each other, their inequality contributions are equal. The unique decomposition rule obtained by imposing these restrictions is:

(4) $\quad s^k = \mathrm{cov}(\mathbf{y}^k,\mathbf{y})/\mathrm{var}(\mathbf{y})$.

This is the decomposition rule that is based on the squared coefficient of variation inequality index. Fields (2003) reaches the same conclusion in a different way. However, Shorrocks (1983) still suggests not to rely solely on this decomposition rule. In his empirical application, he compares the three different decomposition rules presented above. We will return to this comparison in the next section.

Morduch and Sicular (2002) and Fields (2003) extended the decomposition procedure (3) to a regression-based decomposition by determinants of income. They express household income (or log-income) as:

(5) $\mathbf{y}=\mathbf{X}\boldsymbol{\beta}+\boldsymbol{\varepsilon}$,

where $\mathbf{X}$ is a matrix of explanatory variables, $\boldsymbol{\beta}$ is a vector of coefficients, and $\boldsymbol{\varepsilon}$ is a vector of residuals. Given a vector of consistently estimated coefficients $\mathbf{b}$, income can be expressed as a sum of predicted income and a prediction error according to:

(6) $\mathbf{y} = \mathbf{X}\mathbf{b}+\mathbf{e}$.

Substituting (6) into (1) and dividing through by $I(\mathbf{y})$, the share of inequality attributed to explanatory variable m is obtained as:

(7) $s^m = b_m \Sigma_i a_i(\mathbf{y}) x_i^m / I(\mathbf{y})$.[1]

Interpreting and comparing inequality decomposition rules

Shorrocks (1983), while preaching for the unique decomposition rule (4), suggested judging alternative rules by confronting empirical results with "intuitive feelings for what is reasonable." Both Shorrocks (1983) and Morduch and Sicular (2002) compare the decomposition results of (4) and two additional decomposition rules: one based on the Gini index of inequality,

(8) $\mathrm{G}(\mathbf{y}) = \Sigma_k\{2\Sigma_i[i\text{-}(n+1)/2]y_i^k/n^2/\mu\}$,

and another is an entropy measure proposed by Theil:

[1] Wan (2004) extended this method to account for the contribution of the intercept of the income regression to inequality. Wan and Zhou (2005) presented an alternative method. It should be added that Morduch and Sicular (2002) suggested a simple procedure to compute standard errors of s^m, but the procedure turns out to be incorrect. They claim that since the components are linear in the regression coefficients, i.e. $s^m=b_m\Sigma_i a_i(\mathbf{y})x_i^m/I(\mathbf{y})$, standard errors are simply $\sigma(s^m)= \sigma(b_m)\Sigma_i a_i(\mathbf{y})x_i^m/I(\mathbf{y})$. This ignores the fact that $\Sigma_i a_i(\mathbf{y})x_i^m/I(\mathbf{y})$ is a random variable that is not independent of b_m (through the dependence of b_m on $\mathbf{y}$). Hence the true standard errors cannot be computed in such a simple way (which, in fact, results in t-statistics that are identical to those of the regression coefficients). At least for the Gini index of inequality, it is not straightforward to compute standard error of the index itself (See Modarres and Gastwirth 2006 and references therein), so it is reasonable to expect that computing standard errors of *components* of that index would not be straightforward either. We use bootstrapping to obtain standard errors in the empirical application below.

(9) $\quad T(\mathbf{y}) = \Sigma_k\Sigma_i \log(y_i/\mu)y_i^k/n/\mu.$

Shorrocks (1983) used income data from the United States, disaggregated into ten different sources of income, and decomposed income inequality by income source. The three decomposition rules gave qualitatively similar results, except with respect to the contribution of direct taxes of female-headed households, which was negative by (4) and (9) and positive by (8). Shorrocks (1983) used this to recommend against using the decomposition rule (8) corresponding to the Gini index of inequality. Morduch and Sicular (2002) applied these same decomposition rules to income data from rural China, using the regression-based procedure (7). They also concluded that the decomposition based on the Gini inequality index produced several counter-intuitive results.

Morduch and Sicular (2002) defined the *property of uniform additions* of an inequality index in the following way. An inequality index is said to satisfy this property if adding a fixed amount of income across the entire population decreases inequality. They further adopted this definition to inequality decomposition methods, so that the property is satisfied if the contribution to inequality of a positive equally-distributed income component is negative. They showed that the Theil decomposition rule (9) satisfies this property, while with the Gini rule (8) and the squared coefficient of variation rule (4), equally-distributed income components have zero contributions to inequality. Morduch and Sicular (2002) used this result as an argument against using the Gini decomposition rule (8).

In fact, the *property of uniform additions* is not necessarily a desired property of inequality decomposition rules. On the contrary, it makes much sense that a uniformly equal source of income contributes zero to inequality. In particular, both the Gini and the squared coefficient of variation decomposition rules tell us how much the *variability* in each source of income contributes to overall inequality. It is perfectly natural, then, that an income source with zero variability will contribute zero to income inequality. These decomposition rules do not tell us the impact on inequality of a *uniform increase* in any income source, including equally-distributed income components, as implied by the interpretation of Morduch and Sicular (2002). Expressions such as “education strongly reduces inequality (page 104)” are meaningless unless one clearly specifies whether this relates to an overall increase in educational attainment, to a reduction of inequality of educational attainment, or some combination of those.

In their conclusions, Morduch and Sicular (2002) note that "the aggregate Gini coefficient falls if an income source is increased by a constant amount for all members of the population, but none of the components of the standard decomposition of the Gini are affected (page 104)" and thus conclude that "it is of limited use in describing causes of inequality (page 105)." In fact, increasing an income source by a constant amount is equivalent to increasing *any* income source by this constant amount, and in the regression framework this amounts to an increase in the intercept without affecting the other coefficients. Therefore, it is perfectly reasonable that the *relative* contributions of the explanatory variables remain the same.

This discussion raises the point that it is not always clear what the inequality contributions of the different income sources or the different explanatory variables actually mean. Most authors have been pretty vague about this. The exception is Shorrocks (1982), who shows that the inequality contribution of an income source derived using the squared coefficient of variation decomposition rule are equal to the average of two quantities: the inequality that would be observed if this income source was the only source of inequality, and the amount by which inequality would fall if inequality in this income source was eliminated. In addition, Lerman and Yitzhaki (1985) have shown that in the case of the Gini decomposition rule, the contribution of each income component is related to the variability in that component.

In order to inspect further the association between the variances of income components and the inequality contributions of these components, I have conducted a simulation exercise, in which income vectors from three different sources are drawn randomly, and then a mean-preserving random vector is added to each of the income sources in turn. The results of this exercise are shown in table 1. First, one can observe that the inequality contributions according to the Gini and squared CV decomposition rules are very similar. On the other hand, the inequality contributions according to Theil's T decomposition rule are different. In particular, the inequality contribution of Y_3 is negative. When the variance of each income source is increased by one standard deviation, each of the inequality measures increases, as expected, and the increases are qualitatively ranked similarly to the rankings of the inequality contributions. Hence, this exercise implies that the relative rankings of inequality contributions of different income sources is qualitatively related to the sensitivity of overall inequality to increases in the variances of those income sources. Quantitatively, however, at least for the Theil's T decomposition rule, the decomposition results could be misleading, as in the case of Y_3, whose variance contributes positively to overall income inequality but has a negative contribution to inequality. The conclusion is that one should be cautious when interpreting the inequality contributions according to Theil's T decomposition rule.

This conclusion and the logic behind it is in sharp contrast to the interpretation of Morduch and Sicular (2002), who imply that the inequality contributions are related to changes in *levels* rather than in the *variances* of income components. In order to find the impact on inequality of a uniform increase in a particular income source, one can use the results of Lerman and Yitzhaki (1985), who have shown that the relative change in the Gini inequality index following a uniform percentage change in $\mathbf{y}^k$ is $(s^k\text{-}\alpha^k)G(\mathbf{y})$, where α^k is the share of income from source k in total income. For the general case, Shorrocks (1983) has noted that comparing s^k and α^k is useful for knowing whether the k^{th} income source is equalizing or disequalizing. In the case of the Gini decomposition rule, $s^k=0$ if k stands for an equally-distributed income component. Hence, it follows that the effect of a uniform increase in this income component on the Gini index is unambiguously negative. This shows that the property of uniform additions, as adopted by Morduch and Sicular (2002) for inequality decompositions, is not intuitively appealing. It also implies an advantage for using the Gini decomposition rule (8) rather than the Theil decomposition rule (9). As a result, the conclusion of Morduch and Sicular (2002) that "information provided by the decomposition of the Theil-T index is thus potentially of greater use to researchers (page 105)" is not necessarily correct.

Application to Georgian farm-household income data

To demonstrate the usefulness and compare the performance of the regression-based inequality decomposition method based on the different inequality measures, I continue with an empirical application, using farm-household income data from Georgia. A sample of farm households was chosen because they are known to derive income from multiple sources, most notably farm income and off-farm income, and this has been documented in numerous studies in both developed and developing countries. Moreover, the diversification of income sources is known to have implications for inequality (see for example Adams 2001, Zhu and Luo 2006).

The data were obtained from a farm-household survey conducted in 2003 in four districts surrounding the capital city of Tbilisi: Dusheti, Mtskheta, Sagarejo, and Gardabani. The survey included a total of 2,520 individual farms. In each district, ten villages (Sakrebulos) were selected randomly, and sixty-three households were surveyed in each village using the "random walking" procedure.[2] The survey questionnaires were designed to collect information about the demographic profile of the household, household income and its sources, land resources and other farm assets, farming activity and related activities (finances, investments), and social aspects (Gogodze et al. forthcoming).

Income was divided into three main components. Farm income was the largest component, consisting of 44% of total income on average. Non-farm income was the second largest component (35%), about a quarter of which was derived from non-farm businesses and the remaining three quarters from off-farm paid work. Other income (21%) consisted of social assistance payments (about two thirds) and private remittances (about a third). The computation of inequality and its decomposition was performed over per-capita annual income, which had a sample mean of 1,161 Lari, equivalent to $531 at the time of the survey.

Table 2 shows the results of inequality decomposition by income sources. It is easy to see that farm income, the main single source of income of these households, contributes more than half of the total income inequality, proportionately more than its income share. On the other hand, non-farm income contributes to inequality less than its income share, and the same is true for other income. These results are consistent across the three decomposition rules. According to the intuition of Shorrocks (1983), this implies that non-farm income is an equalizing source of income. This can be verified by obtaining the marginal effects on inequality of uniform increases in each of the income sources. In the case of the Gini inequality index, the Lerman and Yitzhaki (1985) formula was used to derive the marginal effects. Since no such formula exists for the other two inequality indices, simulations were used instead. The results are in the bottom part of table 2. The three inequality indices give qualitatively similar results, confirming the intuitive prediction, that a uniform increase in either non-farm income or other income reduces inequality.

[2] In principle, the first house in the village is chosen randomly, then the interviewer walks to the end of the street, turns right or left at a toss of a coin, and picks the first house on that street.

Off-farm income was found as an equalizing income source in other countries as well, including the U.S. (see El-Osta et al., 1995, and references therein), China (Zhu and Luo, 2006), the Republic of Georgia (Kalakashvili, 2005), Egypt (Adams, 2001), Taiwan (Chinn, 1979), and the Philippines (Leones and Feldman, 1998). Gallup (2002), on the other hand, found that income other than farming contributed positively to inequality in Vietnam, and similar results were obtained by Elbers and Lanjouw (2001) for Ecuador. de Janvri and Sadoulet (2001) found that in Mexico, non-farm income as a whole reduced household income inequality, but not-agricultural wages in particular increased inequality. On the contrary, Canagarajah et al. (2001) found that in Ghana and Uganda, non-farm self-employment income was much more disequalizing than non-farm wages. Estudillo et al. (2001) found that nonfarm income changed from an equalizing to a disequalizing source as it became a major income source in Philippine rice villages.

We now move to the regression-based decomposition exercise using (5)-(7). The variables used to explain per-capita income and their descriptive statistics can be seen in table 3. I include age of the head of household and its squared value, to account for life-cycle effects. Years of schooling are also included, as well as family size. The economic resources of the household are represented by the log of landholdings, the number of plots of land, a dummy for households who raise livestock, and the log of the value of fixed farm assets. A dummy variable for Gardabani region is also included. Other regional dummies, as well as several other explanatory variable, did not come out significant in preliminary regressions are were removed. For a larger set of explanatory variables, see the regressions in Gogodze et al. (forthcoming).

Table 4 shows the coefficients of the per-capita income generating function (6) and the resulting inequality contributions (7). All regression coefficients are statistically significant and most have the expected sign. Age has a nonlinear effect, first negative and subsequently positive, on income. This is not a common result, perhaps income from sources other than labor is increasing with the age of the head of household, or labor income of young household members dominates. Schooling has a positive effect, while family size has a negative effect. Per-capita income is increasing with landholdings, but decreasing with the number of plots, indicating than land fragmentation is costly at least in terms of expected income. Income is higher in households that raise livestock, and is increasing with the value of farm assets. Income is higher in Gardabani region than in the neighboring regions.

Turning to the decomposition results, we note that that Gini and squared CV decomposition rules give qualitatively similar results, while the Theil's T decomposition rule give very different results. For example, the number of plots has a negative inequality contribution under the Gini and squared CV decomposition rule and a positive inequality contribution under the Theil's T decomposition rule. On the other hand, the livestock dummy and the value of farm assets have positive inequality contributions under the Gini and squared CV decomposition rule and negative inequality contributions under the Theil's T decomposition rule. The regression residual contributes 65% of income inequality under the Gini decomposition rule and 79% of inequality under the squared CV decomposition rule. The decomposition results of the Theil's T decomposition rule are difficult to interpret: the intercept, which has a zero variance in the sample, has a large negative inequality contribution, while the residual has a positive contribution of more than 100%. Interestingly, the sum of the contributions of all explanatory variables under the squared CV decomposition rule amount to the R^2 of the income regression. Finally, under both Gini and squared CV decomposition rules, landholdings seem to have the largest contribution to inequality among the explanatory variables. This is consistent with the fact that landholdings is particularly important to farm income and that farm income was found to be an inequality-increasing income source.

It can be claimed that the decomposition results are not too informative because the explanatory variables account for only 21% to 35% of income inequality. However, this is similar to claiming that wage regressions are useless because age and schooling explain only 10% to 20% of wages. In fact, the results are useful in showing how the explained part of income inequality is attributed to the different explanatory variables. The empirical results of Morduch and Sicular (2002) showed a better fit. Cowell and Jenkins (1995) also found that explanatory variables explained a relatively small fraction of income inequality, using two different methodologies.

Using the regression coefficients, it is possible to compute the "income shares" of the explanatory variables as

(10) $\alpha^m = b_m \Sigma_i x_i^m / \Sigma_i y_i$,

and evaluate the impact on the Gini index of inequality of a uniform increase in an explanatory variable, as in Lerman and Yitzhaki (1985), by computing $(s^m\text{-}\alpha^m)G(\mathbf{y})$. The results are not always interpretable, though, and the logic is similar to the case of marginal effects in nonlinear models (i.e. probit). An obvious example is the case of age and age squared: one cannot increase one without increasing the other, hence marginal effects of age alone or age squared alone are meaningless, and one can only use a simulation exercise in which both age and age squared are increased. Another example is dummy explanatory variables such as livestock and Gardabani region. These variables can only be changed from zero to one, and hence marginal effects based on percentage changes are meaningless, and one has to resort to simulations in this case as well. The meaning of percentage changes in integer explanatory variables such as schooling, family size, and number of plots could also be challenged. The alternative is to use simulations and add one unit to each variable at a time. However, for the case of inequality decompositions this is not advised, because adding a unit changes not only the size of the variable but also its distribution (in most cases it would reduce the variance), and hence using percentage changes is the preferred method for these variables. Finally, simulation is also the only way to obtain marginal effects for the case of squared CV decomposition rule or Theil's T decomposition rule, for which the Lerman and Yitzhaki (1985) formula does not apply.

Therefore, the following simulations are applied to the present empirical example: increasing age, schooling, family size, land, number of plots, and assets by 1%, and changing livestock and Gardabani region from zero to one.[3] The results are in table 5. The simulated marginal effects are mostly consistent in signs and levels of significance across the three inequality measures, although the absolute sizes are different. In particular, the results imply that a uniform increase in schooling, landholdings or farm assets reduces income inequality, while a uniform increase in family size or number of plots increases inequality (the effect of number of plots is slightly short of being statistically significant at 5%). The effect of a uniform increase in age on inequality is not statistically significant. The effects of changing livestock and Gardabani region from zero to one are negative and very large, implying that it is misleading to treat them as marginal effects.

[3] We have also computed marginal effects of adding one unit to the integer explanatory variables, and the results were of course quantitatively different, but did not affect signs and levels of significance. These results are available upon request.

It is interesting to note that there is no complete correspondence between the signs of inequality contributions (table 4) and marginal effects (table 5). In general, the sign of the marginal effect is opposite to that of the inequality contributions, but this does not hold in all cases.

These results have interesting policy implications. The negative marginal effect of schooling imply that enhancing schooling of the rural population in Georgia is likely to have an equalizing effect on income. The same is true for landholdings. In addition, since the inequality contribution of landholdings is positive, increasing landholdings through land reforms that equalizes landholdings distribution is likely to have an even stronger negative impact on income inequality. Similarly, enhancing farm assets through extension of credit to small farmers may also reduce inequality. Note that these last two results hold despite the fact that landholdings and farm assets operate mostly through farm income, which is inequality-increasing.

Summary and conclusions

This paper reviewed inequality decomposition methods by sources of income and the regression-based decomposition by determinants of income, and challenged several existing interpretations of these inequality decomposition methods. In particular, the paper showed that the property of uniform additions offered by Morduch and Sicular (2002) is not necessarily a desired property of inequality decomposition rules. It also challenged the conclusion of Shorrocks (1983) and Morduch and Sicular (2002), based on empirical examples, that the natural decomposition rule based on the Gini index of inequality does not produce meaningful results. On the contrary, the Gini decomposition rule offers several advantages over alternative decomposition rules, in particular by providing an intuitively appealing and easily interpretable result and by allowing one to derive the effects on inequality of a uniform increase in a certain income source or income determinant.

Farm household income data was used in order to demonstrate and compare the different decomposition rules. It was shown that simulations are necessary in order to adequately treat policy-relevant questions such as the changes in inequality that result from changes in policy-sensitive variables. In the case of this particular empirical application, it was found that the decomposition rules based Gini and squared CV inequality indices produce results that are qualitatively similar, while the decomposition rule based on Theil's T index are qualitatively different.

It was found that non-farm income is an equalizing source of income among farm household in Georgia. Landholdings seem to be the single most important determinant of income inequality. A uniform increase in schooling, landholdings, or farm assets is expected to reduce inequality, while a uniform increase in family size is expected to increase inequality.

Overall, this paper demonstrated the use of the different inequality decomposition methods in order to understand the sources and determinants of income inequality, and the caution that must be practiced when choosing the decomposition rule and interpreting the decomposition results.

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Table 1. Simulating the Impact of an Increase in the Variance of Income

	Gini	Squared CV	Theil's T
Inequality index	0.0403	0.0049	0.0025
Inequality contributions			
Y_1	0.7462	0.7382	1.1300
Y_2	0.1801	0.1845	0.0519
Y_3	0.0737	0.0773	-0.1821
Inequality changes due to a one standard deviation increase in the variance of income			
Y_1	0.01112	0.00328	0.00165
Y_2	0.00185	0.00049	0.00025
Y_3	0.00086	0.00023	0.00011

Notes:

* Income vectors were constructed in order to generate inequality contributions close to those obtained in the empirical application. First, U is constructed as a uniformly distributed random vector. Then, Y_1=20,000+16,000*U; Y_2=20,000+6,000*U+Y_1/11; and Y_3=20,000+4,000*U+Y_2/5.

** All inequality contributions and changes are strongly statistically significant. Tests of significance are based on bootstrapping.

Table 2. Income Inequality Decompositions for Farm Households in Georgia

	Gini	Squared CV	Theil's T
Inequality index	0.4906	1.982	0.4850
Inequality contributions			
Farm income	0.7660	0.8690	0.8833
Non-farm income	0.1757	0.1020	0.0793
Other income	0.0583	0.0290	0.0374
Inequality changes due to a one percent uniform increase in income			
Farm income	0.000352	0.008807	0.001057
Non-farm income	-0.000311	-0.006885	-0.000891
Other income	-0.000040	-0.001922	-0.000164

Notes:
All inequality contributions and changes are statistically significant at 1%. Tests of significance are based on bootstrapping.

Table 3. Explanatory Variables and Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Age	45.165	11.422	20	89
Schooling (years)	11.735	2.658	0	16
Family size	3.9377	1.5435	0	12
ln(land)	-0.428	1.0158	-4.6	5.95
Number of plots	2.4266	1.299	0	8
Livestock (dummy)	0.8024	0.3983	0	1
ln(farm assets)	8.0428	3.3806	0	13.6
Gardabani region (dummy)	0.25	0.4331	0	1

Table 4. Regression-Based Inequality Decomposition Results

Variable	Regression Coefficient	Inequality Contribution: Gini	Squared CV	Theil's T
Intercept	2134.6	0.0000	0.0000	-1.4130
	(4.02)**	(0.08)	(0.45)	(-3.74)**
Age	-69.683	-0.1547	-0.0307	1.8550
	(-3.37)**	(-2.98)**	(-2.23)*	(3.18)**
Age squared	0.742	0.1645	0.0361	-0.8333
	(3.55)**	(3.02)**	(2.15)*	(-3.37)**
Schooling	31.256	0.0022	0.0028	-0.2453
	(2.16)*	(1.04)	(1.80)	(-2.65)**
Family size	-187.8	0.0532	0.0113	0.5686
	(-6.90)**	(4.18)**	(1.73)	(5.08)**
ln(land)	773.1	0.2194	0.1169	0.5621
	(17.52)**	(6.20)**	(4.67)**	(7.17)**
Number of plots	-96.82	-0.0198	-0.0033	0.1378
	(-2.66)**	(-2.10)*	(-1.99)*	(2.04)*
Livestock	687.5	0.0729	0.0170	-0.2780
	(7.06)**	(6.04)**	(4.64)**	(-8.53)**
ln(farm assets)	85.36	0.0165	0.0116	-0.4380
	(14.01)**	(2.43)*	(3.26)**	(-8.32)**
Gardabani region	1291.6	-0.0053	0.0464	-0.1985
	(4.89)**	(-0.45)	(5.15)**	(-9.75)**
Residual		0.6511	0.7921	1.2830
		(22.45)**	(28.43)**	(23.36)**

Notes:
2,451 "clean" observations.
Asymptotic t-values in parentheses.
R^2=20.6%.
* Coefficient significant at 5%.
** Coefficient significant at 1%.

Table 5. Marginal Effects of Explanatory Variables on Inequality

Variable	Gini	Squared CV	Theil's T
Age	0.0006 (0.94)	-0.0008 (-0.12)	b
Schooling	-0.0015 (-3.09)**	-0.0153 (-2.86)**	-0.0031 (-3.01)**
Family size	0.0034 (5.82)**	0.0316 (5.56)**	b
ln(land)	-0.0032 (-6.57)**	-0.0325 (-4.13)**	-0.0066 (-5.55)**
Number of plots	0.0009 (1.84)	0.0098 (1.66)	0.0019 (1.78)
Livestock[a]	-0.4434 (-5.43)**	-6.5080 (-3.46)**	b
ln(farm assets)	-0.0004 (-5.85)**	-0.0036 (-3.92)**	-0.0007 (-5.05)**
Gardabani region[a]	-0.4227 (-9.57)**	-4.0300 (-4.86)**	b

Notes:
Asymptotic t-values in parentheses.
a Marginal effects of Livestock and Gardabani region were computed by the difference in inequality when changing all observations from zero to one. All other variables were increased by 1%.
b Theil's T marginal effects with respect to age, family size, livestock and Gardabani region could not be computed because for some observations the simulations resulted in negative incomes.
* Coefficient significant at 5%.
** Coefficient significant at 1%.

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