Thoughts on the inequality of opportunities: new evidence

Wallace Patrick Santos de Farias Souza, Ana Cláudia Annegues and Victor Rodrigues de Oliveira

Abstract

This article evaluates the effects of a set of variables on the inequality of opportunities in Brazil, using the method developed by Li, Chen and Gao (2011) and combining data from the National Household Survey (PNAD) and Finanças do Brasil (FINBRA) on the Brazilian states for 1995-2012. The results show that economic growth has become less important in that debate than other conditioning factors over the last few years. The current pattern of education spending contributes to the maintenance of social vulnerability, thereby making it harder for individuals to participate fully in society. In contrast, increases in formal education and formalization have made opportunities less unequal.

Keywords

Macroeconomics, economic growth, equality of opportunities, measurement, econometric models, Brazil

JEL classification

D63, C14, C23

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I. Introduction

The freedom to choose the quantity of one's working hours automatically entails that differential earnings will follow from choices for which one is personally responsible. Responsibility is a necessary consequence of any substantial amount of freedom and is therefore part and parcel of any free society.

Fleurbaey (2008, p. 1)

Inequality can have many dimensions. In general, economists focus specifically on its monetary dimension, measuring the inequality of individual or family incomes. Nonetheless, inequality can also be understood more broadly as the outcome of unequal access to opportunities for work, education, happiness, health, a longer life expectancy, assets and social mobility, among other things. Modern inequality theory, as expressed in the key texts of Rawls (1971) and Roemer (1998), includes those dimensions in its analysis.[1]

This approach focuses less on the final distribution of resources than on the intermediate process by which they are allocated, since this will depend on the factors that determine individual economic gains. Those factors are: individual effort, measured by variables that agents can control; and circumstances, such as race or colour, socioeconomic origin, and others, which they cannot control. According to the concept of equality of opportunities, the inequality of total income comprises inequality originating in differential effort, and inequality stemming from circumstantial factors beyond individual control. Only the latter would be considered objectively unfair and should therefore be the target of public policies.[2]

Equality of opportunities and its measurement are relevant not only from the normative standpoint. Firstly, a growing body of empirical evidence shows that preferences in terms of redistribution and policy orientation are tempered by equity concerns. For example, Alesina and Angeletos (2005) showed that, in the United States, individuals who believe that personal economic success is related more to effort than luck have weaker preferences for redistribution. Moreover, based on data obtained from the World Values Survey, Alesina and La Ferrara (2005) found that perceptions of justice are related to individuals' political orientation: when people believe that effort is the key determinant of economic advantages, redistribution and taxes are low; whereas in societies where people believe that the initial conditions (birth and connections established from then on) are the main determinants of economic success, taxes and redistribution will be higher. Secondly, as the determinants of economic inequality (circumstances and effort) influence individual incentives, those determinants are related to aggregate economic outcomes such as economic growth. In *World Development Report 2006*, the World Bank argues that income inequality owing to circumstances can produce a suboptimal accumulation of human capital and, therefore, a lower rate of economic growth; whereas income inequality owing

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1 The theoretical literature indicates that the notion of equality of opportunities incorporates two basic principles: the principle of compensation, which requires the elimination of inequalities arising from circumstances; and the principle of reward, which refers to the way in which efforts between individuals with identical circumstances are rewarded. The compensation principle allows for an ex post or an ex ante perspective. The first analyses the real income of the individual and relates to the differences in income between individuals with the same responsibility characteristics and different circumstances. The ex ante approach, in contrast, focuses on prospects, for there to be equality of opportunities if individuals face different opportunity sets (or different value sets) owing to their circumstances. In the case of the principle of reward, the literature distinguishes between liberal reward and utilitarian reward. In the first case, it is argued that the government should not redistribute income between those that share the same characteristics of circumstance, because their income differences are exclusively due to differences in effort. In the second case, it is argued that one should not worry about what only arises from differences in effort. For a more detailed analysis of these points, see Ramos and Van De Gaer (2012).

2 Schokkaert and Devooght (2003), Gaertner and Schwettmann (2007) and Cappelen, Sorenson and Tungodden (2010) provided solid evidence that, judging by the income distribution, individuals clearly distinguish circumstances and effort, as suggested by the theories of equality of opportunities. For example, Cappelen, Sorenson and Tungodden (2010) proposed an exercise to evaluate the elements for which individuals feel responsible. The authors noted that the vast majority of participants did not attribute individual responsibility for the price determined on a random basis, an impersonal factor that is beyond the control of the individual; but they did hold them responsible for their choice of work time.

to individual responsibility variables can encourage people to invest in human capital and make the greatest possible effort (World Bank, 2005).

Over the last few decades, inequality indices in Brazil have fallen steadily, although it is still on the list of the most unequal countries in the world (Barros and others, 2007).[3] In the social sphere, programmes to combat poverty and misery were adopted in a modest way in 1995, but with greater emphasis as from 2003.[4] Public policies on universal access to education[5] and basic health care also play a key role in reducing Brazilian disparities.[6] Apart from growth and closer targeting of social programmes, the macroeconomic reforms implemented in the country as from the first half of the 1990s, such as monetary stabilization and trade liberalization, may also have helped reduce income inequality in Brazil. Since the introduction of the Real Plan, there has been a steady rise in the minimum wage, which has a direct effect on family welfare, particularly among the poorest. Albeit to a limited extent, the combination of those factors shows that Brazil has high rates of income concentration and wide regional disparities; and economic growth has had varied effects on reducing income inequality, poverty and the inequality of opportunities in different historical periods.

Although the macroeconomic environment plays a major role from the social standpoint, studies on Brazil have paid little attention to that topic, preferring to focus more on the impact of social programmes such as the *Bolsa Família* family subsidy scheme.[7] That debate has been ongoing in the international literature for some time, with an increasing number of studies investigating the effects of macroeconomic factors on social indicators. The most widely studied macroeconomic variables are economic growth and inflation.

The debate on the relation between inequality and economic growth begins with the theoretical formulation of the Kuznets curve (1955), which postulated a non-linear relation between the two variables, described by an inverted “U” shaped curve. The idea is that the income distribution is likely to worsen in the initial stages of development; but, later, productivity increases can be expected to spread domestically and, thus, inequality would tend to diminish. Since then, the literature has failed to reach a conclusion on the true nature of that relation. Alesina and Rodrik (1994) regressed the annual average growth rate against initial inequality measured by the Gini coefficient, based on cross-sectional data for different countries. The results show that income inequality is inversely related to subsequent economic growth. Li and Zou (1998) and Forbes (2000) used panel data with fixed effects to find that income inequality was positively related to economic growth. Other approaches highlight the positive effects of growth through economic agents’ access to the labour market (Nolan, 1987); and, more recently, Ravallion (2012) has shown that initial poverty levels are likely to be associated with low rates of economic growth.

In the case of inflation, the argument is that its adverse effect on income inequality is due to price rises, which have a major effect on the poorest population groups. Some theoretical studies attempt to systemize this argument by developing general-equilibrium models, such as in Erosa and Ventura (2002) and Cysne, Maldonado and Monteiro (2005). Some results are inconclusive and depend on the origin of the inflationary process: if price rises reflect supply-side pressures, inequality is likely to

[3] The list of factors that contribute to variations in income inequality include education, race, social programmes, region and spatial demographics (Neri, 2011).

[4] A detailed analysis of current poverty reduction programmes and future strategies can be found in Rocha (2007).

[5] The main changes in Brazilian public education include the decentralization of educational resources and the expansion of enrolment as from 1996, which culminated in the creation of the Fund for the Maintenance and Development of Basic Education and the Upgrading of Teaching Staff (FUNDEF).

[6] Menezes-Filho, Fernandes and Picchetti (2007) argued that, as from 1997, with a rapid increase in the proportion of young people in secondary education, the composition effect and the compression effect (wage differential) started to reduce income inequality.

[7] Avila, Bagolin and Comim (2012, p. 461) question the validity of transfer programmes, showing that, at least in segments with a certain (low) level of income, monetary increases do not necessarily lead to an improvement in individuals’ multidimensional conditions; in other words, monetary incomes alone are insufficient to characterize human deprivations.

decline; but if inflation is being driven by demand, inequality will worsen (Blinder and Esaki, 1978; Buse, 1982).

This study adds a set of variables to the list of determinants of inequality generated by circumstances, some of which are based on the empirical analysis performed by Marrero and Rodríguez (2010). Although social programmes attract greater attention when inequality reduction policies are discussed, the economic environment plays a major role (even determining the viability or otherwise of the social policy measures), so it is advisable to empirically measure the impact of the variables comprising it.

Unfair inequality is measured by estimating a model in which income depends on circumstance and effort variables. The logarithm of real wages is used as the dependent variable (as a proxy for individual income), along with a set of explanatory variables that represent specific characteristics of individuals, including the decision to migrate. As the migratory process is self-selective, the method proposed by Nelsen (2006)[8] is used to avoid biased wage estimates. The components of total inequality are then calculated on the basis of the model's adjusted incomes, holding constant variables of circumstance (inequality of effort) and effort (inequality of circumstance). In this stage, indices of the inequality of opportunities are calculated using the Gini coefficient.

The indices thus calculated are used to construct a data panel spanning 1996-2012, with state-level information. Then, a set of variables is used to verify the impact on inequality of circumstances constructed as described above, which is considered the only part of inequality that is socially undesirable.

The variables used follow the approaches previously discussed in the literature: real per capita gross domestic product (GDP) as an indicator of growth; per capita health and education expenditure; the average number of years of schooling among men and women; and the degree of informality of the economy. The method proposed by Li, Chen and Gao (2011) is used to estimate the impact of those variables on the level of inequality. This method makes it possible to deal with the problem, because it involves a nonparametric approach, which does not impose any specific functional form to describe the behaviour of the data. It is also appropriate for using panel data, because it eliminates the fixed effects without the need to express the variables in first-difference form.

This article is divided into four sections in addition to the Introduction. Section II presents the empirical procedures adopted, and section III describes the databases. Section IV provides justification for the variables used and discusses the results of the estimations. Section V concludes the study with some final thoughts.

II. Empirical strategy

To evaluate how the variables defined above are related to the inequality of opportunities, the method proposed by Li, Chen and Gao (2011) is used. Although the literature on panel data is wide-ranging, the parametric specifications can result in under- specified models and, consequently, inconsistent estimators. Various studies have been made to overcome that problem (Ullah and Roy, 1998; Fan and Li, 2004; Henderson, Carroll and Li, 2008; Zhang, Fan and Sun, 2009). At the same time, a line of research has emerged in the last few years that aims to model non-stationary time series. Gao and Hawthorne (2006) showed that the models in which the linear trend is obtained through a parametric specification do not display good fit. One of the main characteristics of the nonparametric models is that the data "speak for themselves." In this connection, Gao and Hawthorne (2006) and Atak, Linton

8 For applications to the international and national cases, respectively, see Meng (2001) and Ramalho and Queiroz (2011).

and Xiao (2011) used that strategy to determine the functional form of the trend in a context of panel data and time series models. Nonetheless, little attention has been paid to nonparametric time series with time-varying coefficients,[9] and still less for panel models. One of the first studies to incorporate these aspects was Robinson (2012). Nonetheless, Li, Chen and Gao (2011) developed a method to estimate the non-linear trend and the coefficients of the explanatory variables, without using first differences to eliminate the fixed effects.

To understand the method used in this article, the dependent variable, Y_{it}, is modelled as follows:

$$Y_{it} = f_t + \sum_{j=1}^{d} \beta_{t,j} X_{it,j} + \alpha_i + \varepsilon_{it}$$

$$Y_{it} = f_t + \sum_{j=1}^{d} X_{it}^T \beta_t + \alpha_i + \varepsilon_{it}, \; i = 1, \dots, N, \; t = 1, \dots, T \tag{1}$$

where $X_{it} = \left(X_{1t,1}, \dots, X_{1y,d}\right)^T$, $\beta_t = \left(\beta_{t,1}, \dots, \beta_{t,d}\right)^T$, f_t and β_t are unknown functions, $\{\alpha_i\}$ is the unobserved individual effect, and $\{\varepsilon_i\}$ is a weakly dependent and stationary process for each observation i and independent of $\{X_{it}\}$ and $\{\alpha_i\}$, with $E\left[\varepsilon_{it}\right] = 0$ and $E\left[\varepsilon_{it}^2\right] = \sigma_\varepsilon^2$.[10] It is assumed that $\{\alpha_i\}$ is correlated with $\{X_{it}\}$; in other words, a model with fixed effects. The fixed effect is assumed to satisfy the following condition:[11]

$$\sum_{i=1}^{N} \alpha_i = 0 \tag{2}$$

The function f_t and the coefficient of vectors β_t are assumed to satisfy the following conditions:

$$f_t = f\left(\frac{t}{T}\right) \text{y} \; \beta_{t,j} = \beta_j\left(\frac{t}{T}\right) \; t = 1, \dots, T \tag{3}$$

In which $f(\cdot)$ and $\beta_j(\cdot)$ are unknown continuous functions. Two estimators will thus be analysed that eliminate the fixed effect differently.

1. Averaged local linear estimation

This estimate is introduced by defining:

$$Y_{.t} = \frac{1}{N}\sum_{i=1}^{N} Y_{it}, \; X_{.t} = \frac{1}{N}\sum_{i=1}^{N} X_{it} \; \text{y} \; \varepsilon_{.t} = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_{it}$$

Taking the mean in i and using $\sum_{i=1}^{N} \alpha_i = 0$ gives:

$$Y_{.t} = f_t + X_{.t}^T \beta_t + \varepsilon_{.t}, \qquad t = 1, \dots, T \tag{4}$$

9 In many research areas that need a broad set of statistics there are several models that are traditionally used. Nonetheless, these often ignore the underlying dynamic of the dataset, even though the study of that characteristic can sometimes be very attractive. To examine that dynamic characteristic and improve the model’s fit, the parameters are allowed to evolve through time. These models were introduced by Cleveland, Grosse and Shyu (1991).

10 Although the model imposes homoscedasticity, it is also possible to incorporate heteroscedasticity. For details see Li, Chen and Gao (2011).

11 This condition is identical to that assumed by Sun, Carroll and Li (2009).

In which the individual effects α_i's, are eliminated. Defining the following notations: $Y_{.t} = \left(Y_{.1}, \ldots, Y_{.T}\right)^T$, $f = \left(f_1, \ldots, f_T\right)^T$, $B\left(X, \beta\right) = \left(X_{.1}^T \beta_1, \ldots, X_{.T}^T \beta_T\right)^T$ and $\varepsilon = \left(\varepsilon_{.1}, \ldots, \varepsilon_{.T}\right)^T$, model (4) can be rewritten as follows:

$$Y = f + B\left(X, \beta\right) + \varepsilon \tag{5}$$

The formulation of the local linear estimator proposed by Fan and Gijbels (1996) is used to estimate $\beta_*\left(\,.\,\right) = \left(f\left(\,.\,\right), \beta_1\left(\,.\,\right), \ldots, \beta_d\left(\,.\,\right)\right)^T$.

For a $0<\tau<1$ given,

$$M\left(\tau\right) = \begin{pmatrix} 1 & X_{.1}^T & \frac{1-\tau T}{Th} & \frac{1-\tau T}{Th} & X_{.1}^T \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{.T}^T & \frac{T-\tau T}{Th} & \frac{T-\tau T}{Th} & X_{.T}^T \end{pmatrix} \tag{6}$$

and

$$W\left(\tau\right) = diag\left[K\left(\frac{1-\tau T}{Th}\right), \ldots, K\left(\frac{T-\tau T}{Th}\right)\right] \tag{7}$$

where K is the Kernel function and h is the bandwidth.

Assuming $\beta_*(\cdot)$ has continuous derivatives up to the second order, the Taylor expansion gives:

$$\beta_*\left(\frac{t}{T}\right) = \beta_*\left(\tau\right) + \beta_*'\left(\tau\right)\left(\frac{t}{T} - \tau\right) + O\left[\left(\frac{t}{T} - \tau\right)^2\right] \tag{8}$$

where $0<\tau<1$, and $\beta_*'\left(\,.\,\right)$ is the derivative of $\beta_*(\cdot)$. Based on the approximation established by (8), the local linear estimator of $\beta_*^T\left(\,.\,\right)$ is

$$\hat{\beta}_*\left(\tau\right) = \left[I_{d+1}, O_{d+1}\right]\left[M^T\left(\tau\right) W\left(\tau\right) M\left(\tau\right)\right]^{-1} M^{-1}\left(\tau\right) W\left(\tau\right) Y \tag{9}$$

in which I_{d+1} is a identity matrix, $(d+1)$x$(d+1)$ and 0_{d+1} is a null matrix $(d+1)$x$(d+1)$. The bandwidth is selected by cross validation.

2. Local linear dummy variable approach

Li, Chen and Gao (2011) defined an alternative estimator that displays a faster rate of convergence. For that purpose, model (1) is rewritten as follows:

$$\tilde{Y} = \tilde{f} + \tilde{B}\left(X, \beta\right) + \tilde{D}\alpha + \tilde{\varepsilon} \tag{10}$$

where

$$\tilde{Y} = \left(Y_1^T, \ldots, Y_N^T\right)^T,\ Y_i = \left(Y_{i1}, \ldots, Y_{iT}\right)^T,$$

$$\tilde{f} = \bar{I}_N \otimes \left(f_1, \ldots, f_T\right)^T = \bar{I}_N \otimes \bar{I}_T,$$

$$\tilde{B}\left(X,\beta\right)=\left(X_{11}^T\beta_1,\ldots,X_{1T}^T\beta_T,X_{21}^T\beta_1,\ldots,X_{NT}^T\beta_T\right)^T$$

$$\tilde{D}=I_N\otimes\bar{I}_T,$$

$$\alpha=\left(\alpha_1,\ldots,\alpha_N\right)^T,$$

$$\tilde{\varepsilon}=\left(\varepsilon_1^T,\ldots,\varepsilon_N^T\right)^T,\varepsilon_i=\left(\varepsilon_{i1},\ldots,\varepsilon_{iT}\right)^T,$$

$\otimes$ is the Kronecker operator, I_k is a k-dimensional vector of ones, and f is defined as in (4).

Using the identification condition, equation (10) can be rewritten as follows:

$$\tilde{Y}=\tilde{f}+\tilde{B}\left(X,\beta\right)+\tilde{D}^*\alpha^*+\tilde{\varepsilon} \tag{11}$$

with $\alpha^*=\left(\alpha_2,\ldots,\alpha_N\right)^T$ and $\tilde{D}^*=\left(-\bar{I}_{N-1},I_{N-1}\right)^T\otimes\bar{I}_T$. The Taylor expansion established in equation (8) gives:

$$\tilde{f}+\tilde{B}\left(X,\beta\right)\approx\tilde{M}\left(\tau\right)\left\{B_*^T\left(\tau\right),h\left[\beta_*^{'}\left(\tau\right)\right]^T\right\}^T \tag{12}$$

in which $\beta_*\left(\cdot\right)=\left[f\left(\cdot\right),\beta_1\left(\cdot\right),\ldots,\beta_d\left(\cdot\right)\right]^T$ and $\bar{M}^T\left(\tau\right)=\left[M_1^T\left(\tau\right),\ldots,M_N^T\left(\tau\right)\right]$, with

$$M_I\left(\tau\right)=\begin{pmatrix}1 & X_{i1}^T & \frac{1-\tau T}{Th} & \frac{1-\tau T}{Th} & X_{i1}^T\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ 1 & X_{iT}^T & \frac{T-\tau T}{Th} & \frac{T-\tau T}{Th} & X_{iT}^T\end{pmatrix} \tag{13}$$

The estimator of $\beta_*(\tau)$ is

$$\tilde{\beta}_*\left(\tau\right)=\left[I_{d+1}\,O_{d+1}\right]\left[\tilde{M}^T\left(\tau\right)\tilde{W}^*\left(\tau\right)\right]^{-1}\tilde{M}^{-1}\left(\tau\right)\tilde{W}^*\,\tilde{Y} \tag{14}$$

where $\tilde{W}^*\left(\tau\right)=I_N\otimes W\left(\tau\right)$.

The bandwidth is selected by modified cross-validation as proposed by Sun, Carroll and Li (2009), unlike its standard form for the model proposed in the previous section, namely,

$$\hat{h}^{opt}=arg_h min\left[Y-B\left(X,\tilde{\beta}_{(-1)}\right)\right]^T M_D^T M_D\left[Y-B\left(X,\tilde{\beta}_{(-1)}\right)\right] \tag{15}$$

in which $M_D=I_{N\times T}-\frac{1}{T}I_N\otimes\left(\varepsilon_T\varepsilon_T^T\right)$ satisfies $M_D I_N\otimes\varepsilon_T=0$[12].

[12] This condition eliminates the fixed effect which is unknown.

III. Data

Two data sources were used to achieve the proposed objective: the National Household Survey (PNAD) and Finanças do Brasil (Finbra) of the National Treasury.

The National Household Survey is conducted by the Brazilian Geographical and Statistical Institute (IBGE) throughout national territory, using a probabilistic household sample. The survey has been held since the late 1960s, and includes permanent questions on the characteristics of the household and individuals, such as family size, household income and the education level of its members, among others. In some years, complementary socioeconomic and demographic characteristics are also investigated, such as migration, health, food security and others. The study led to the sample being adjusted to respect its original sampling plan.[13]

The study used data spanning 1995-2012,[14] with wages being deflated using the national consumer price index (INPC) for 2012.[15] It considered individuals aged between 25 and 65 years, and those who were heads of family, to mitigate the heterogeneity of the sample used.

Firstly, workers' wages were estimated as a function of a set of variables, namely gender, colour, labour market experience, years of schooling, migration, family status (married without children, married with children under 14 years of age, and mother with children under 14 years of age), labour market status (without a formal employment contract, self-employed, employer, civil servant, and own-account worker), and dummy geographic variables (urban or rural region, metropolitan region and states).[16]

Nonetheless, the theoretical model proposed by Borjas and Bratsberg (1996) establishes that the migration process is self-selective, because the decision depends on relative wage income, conditional on the skill set. Thus, the strategy used involved joint parameterization of the determinants of migration and wages. It is assumed that the individual can choose whether or not to migrate. A structural random utility model is used in which the net benefit of choosing alternative is represented by:

$$U_m = \delta_m \, ln\, G_m + k_m Z_m + v_m \tag{16}$$

where $\ln G_m$ is the expected wage for option (expressed in natural logarithmic form), Zm is a set of characteristics, k_m and δ_m are vectors to be estimated, and v_m is a random error term.

In addition, for each option available to individual i, there is a Mincer equation such as:

$$ln\, G_m = \mu_m R_m + u_m \tag{17}$$

Substituting (17) in (16), gives:

$$U_m^* = \mu_m \delta_m X_m + k_m Z_m + \delta_m u_m + v_m \tag{18}$$

[13] The PNAD sampling plan (design) incorporates all aspects that define a "complex sampling plan:" stratification of the sampling units, conglomeration (selection of the sample in various stages, with compound sampling units), unequal selection probabilities in one or more stages, and adjustments of the sample weights to calibrate with known population totals. For that reason, the data obtained through the PNAD samples generally cannot be treated as if they were independent and identically distributed observations (in other words, as if they had been generated by simple random samples with replacement). For details see Nascimento Silva, Pessoa and Lila (2002).

[14] Data for 2000 and 2010 were not used in this study, because the PNAD survey was not carried out in those census years.

[15] For details of the deflator, see Corseuil and Foguel (2002).

[16] The sample used does not include the Federal District, because the Finbra data were not available for several years.

in which U_m^* is a latent variable that measures the net benefit of option m. To correct for selection bias, Nelsen (2006) proposes to estimate (18) by using copulas.[17] For that purpose, the following is the selection equation:

$$S_i = \begin{cases} 0, si\ S_i^* = z_i\gamma' + \varepsilon_{si} \leq 0, \\ 1, si\ S_i^* = z_i\gamma' + \varepsilon_{si} > 0. \end{cases}$$

where S_i is an indicator of selection and z_i is a vector of co-variables.

The result variable follows the following structure:

$$y_i = x_i^{'}\beta + \varepsilon_{1i} \tag{19}$$

As ε_{is} and ε_{1i} are not independent, ordinary least squares (OLS) regression would produce biased estimations of β. Based on this structure, the log-likelihood function is:

$$L = \prod_{i=1}^{N} \left\{ \int_{-\infty}^{-z_i^{'}\gamma} f_s(\varepsilon_s) d\varepsilon s \right\}^{S_i = 0} \left\{ \int_{-z_i^{'}\gamma}^{\infty} f_{s1}(\varepsilon_s, \varepsilon_{1i}) d\varepsilon s \right\}^{S_i = 1} \tag{20}$$

in which f_{sj} is the probability density function of ε_s and ε_j for j = 0,1. From equation (20), it can be deduced that:

$$\int_{-\infty}^{-z_i^{'}\gamma} f_s(\varepsilon_s) d\varepsilon s = F_s\left(-z_i^{'}\gamma\right)$$

$$\int_{-z_i^{'}\gamma}^{\infty} f_{s1}(\varepsilon_s, \varepsilon_{1i}) d\varepsilon s = \frac{\partial}{\partial \varepsilon_1}\left\{F_1(\varepsilon_1) - F_{s1}\left(-z_i^{'}, \varepsilon_1\right)\right\}\Big|_{\varepsilon_1 = \varepsilon_{1i}}$$

To implement this structure through copulas, let ω_1 and ω_2 be two random variables. It is assumed that $u_i = F_i(\omega_i)$ is the marginal density function of ω_i for i = 1, 2 and $F(\omega_1, \omega_2)$ is the joint distribution function. The copula, $C(\cdot)$ makes it possible to obtain $F(\omega_1, \omega_2)$ through the marginal densities, in other words

$$F(\omega_1, \omega_2) = C\left\{F_1(\omega_1), F_2(\omega_2); \theta\right\} = C\left\{u_1, u_2; \theta\right\} \tag{21}$$

where θ measures the degree of dependence.

To implement this strategy, the partial derivative of the joint distribution function is required, namely,

$$\frac{\partial}{\partial \omega_1} F(\omega_1, \omega_2) = \frac{\partial}{\partial u_1} C\left\{u_1, u_2; \theta\right\} \times \frac{\partial F_1(\omega_1)}{\partial \omega_1}$$

[17] In statistical sciences, particularly in probability theory, the copula concept is defined as a multivariate distribution function with uniformly distributed marginal densities.

Thus, the likelihood function, equation (20), is rewritten as follows:

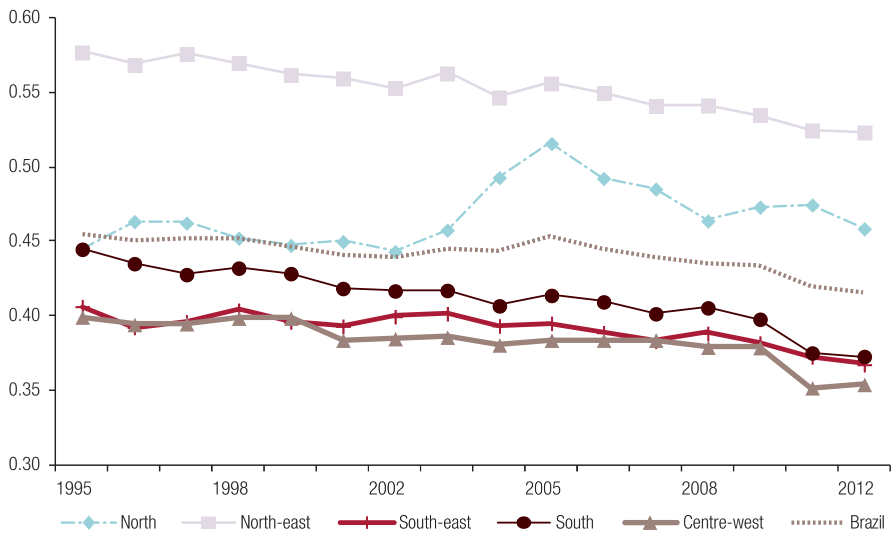
$$L = \prod_{i=1}^{N} \left[F_s\left(-z_i'\gamma\right) \right]^{S_i=0} \left[\left\{ 1 - \frac{\partial}{\partial u_1} C\left\{u_{1i}, u_{si}; \theta_1\right\} \right\} \times f_1\left(\varepsilon_{1i}\right) \right]^{S_i=1} \qquad (22)$$

As there are many copulas that can be used, equation (22) will be estimated for different copulas, and the final model will be chosen on the basis of information criteria.

The Gini coefficient of unfair inequality is calculated based on the wages adjusted by those variables. Once the inequality measures for each state and year have been obtained, the method described in the previous section is employed. In this stage, which aims to evaluate the determinants of the inequality of opportunities, the following explanatory variables are used, following the work of Marrero and Rodríguez (2010):[18] the logarithms of per capita GDP, per capita education spending, per capita health spending, average years of schooling among men and women, and the informality rate of the economy (defined as the percentage of individuals who do not have a formal employment contract).[19]

Table A1.2 of the annex reports the measurement of inequality of opportunities for all states in 1995-2012. Inequality levels were maintained in the north region, except in the State of Tocantins (where there was an 11.82% reduction). In the north-east region, the opposite occurred, with a substantial reduction in the indices in the States of Pernambuco, Piauí and Ceará. The indices also declined in all of the states of the south-east, south and centre-west regions. Figure 1 shows the trend of inequality in the Brazilian regions between 1995 and 2012. Although there was a declining trend in all regions, the index rose in the north-east at the end of the period of analysis.

Figure 1
Brazil: trend of inequality of opportunities, 1995-2012
(Percentages)



Source: Prepared by the authors.

The results obtained in the analysis of the trend of inequality of opportunities are similar to those reported by Silva and others (2013) for the Brazilian municipalities. As those authors note, states in the north and north-east regions, known for their high levels of social vulnerability, displayed a level of

[18] The values corresponding to GDP, and to education and health expenditure, were deflated using the annual average of the extended national consumer price index (IPCA).

[19] See the descriptive statistics of the variables used in table A1.3 of the annex.

inequality of opportunities that was above the Brazilian average. Based on the methodology proposed in this paper, and according to the list of variables used by Marrero and Rodríguez (2010), high indices of unfair inequality were recorded in the north-east throughout the period analysed —a result that corroborates the evidence presented by Silva and others (2013). It was also found that the level of inequality that cannot be attributed to individual decisions is considerably higher than the estimates obtained in the study by Silva and others (2013).

The next section discusses the results for the determinants of the inequality of opportunities.[20]

IV. Results

In an initial stage, the self-selectivity of the migration process was corrected for. To that end, the copulas selected through the Akaike information criterion, based on equation (22), were as follows: FGM for 1997, Plackett for 2003, AMH for 2007, Gaussian for 2002 and 2005 and Frank for the other years (see table A1.1 of the annex). In the next stage, the effect of the selected variables on the inequality of opportunities was calculated using the estimator proposed by Li, Chen and Gao (2011). The following equation represents the model used to estimate the impact of each of the variables described on the inequality of opportunities.

$$\begin{aligned} Y_{it} = f\left(\frac{t}{T}\right) + \beta_1\left(\frac{t}{T}\right)X_{it,1} + \beta_2\left(\frac{t}{T}\right)X_{it,2} + \beta_3\left(\frac{t}{T}\right)X_{it,3} + \beta_4\left(\frac{t}{T}\right)X_{it,4} \\ + \beta_5\left(\frac{t}{T}\right)X_{it,5} + \beta_6\left(\frac{t}{T}\right)X_{it,6} + \alpha_i + \varepsilon_{it}, 1 \le i \le N, 1 \le t \le T \end{aligned} \tag{23}$$

in which Y_{it} is the measure of the inequality of opportunities, $X_{it,1}$ is the logarithm of per capita real GDP, $X_{it,2}$ is the logarithm of real per capita health spending, $X_{it,3}$ is the logarithm of real per capita education spending, $X_{it,4}$ is the average number of years' schooling among men, $X_{it,5}$ is the average number of years' schooling among women, and $X_{it,6}$ is the degree of informality of the economy.

Real per capita GDP is one of the variables commonly used in the literature to investigate the role of macroeconomic factors in determining inequality, because it affects individuals' economic conditions. Economic growth draws a larger number of workers into the labour market, which in turn causes a reduction in inequality of outcomes (Metcalf, 1969; Mirer, 1973; Powers, 1995). Also on the list of macroeconomic variables, per capita expenditure on health and education affects individuals' incomes, particularly among the underprivileged, because they help to raise their productivity. The empirical evidence presented by Marrero and Rodríguez (2010) showed that increasing these categories of expenditure had an impact in reducing inequality indices.

The average number of years' schooling among men and women gives an idea of each individual's productivity. As happens with per capita investments in education, an increase in a population's average years of schooling tends to have a positive effect on average worker productivity. Consequently, incomes rise and they become more fairly distributed.

The theoretical model of Chong and Gradstein (2007) suggests a positive relation between income inequality and the degree of informality of the economy. In an environment with low-quality institutions in which property rights are not respected, underprivileged individuals are unable to extract a large part of the resources produced, so they end up migrating to the informal sector, where they

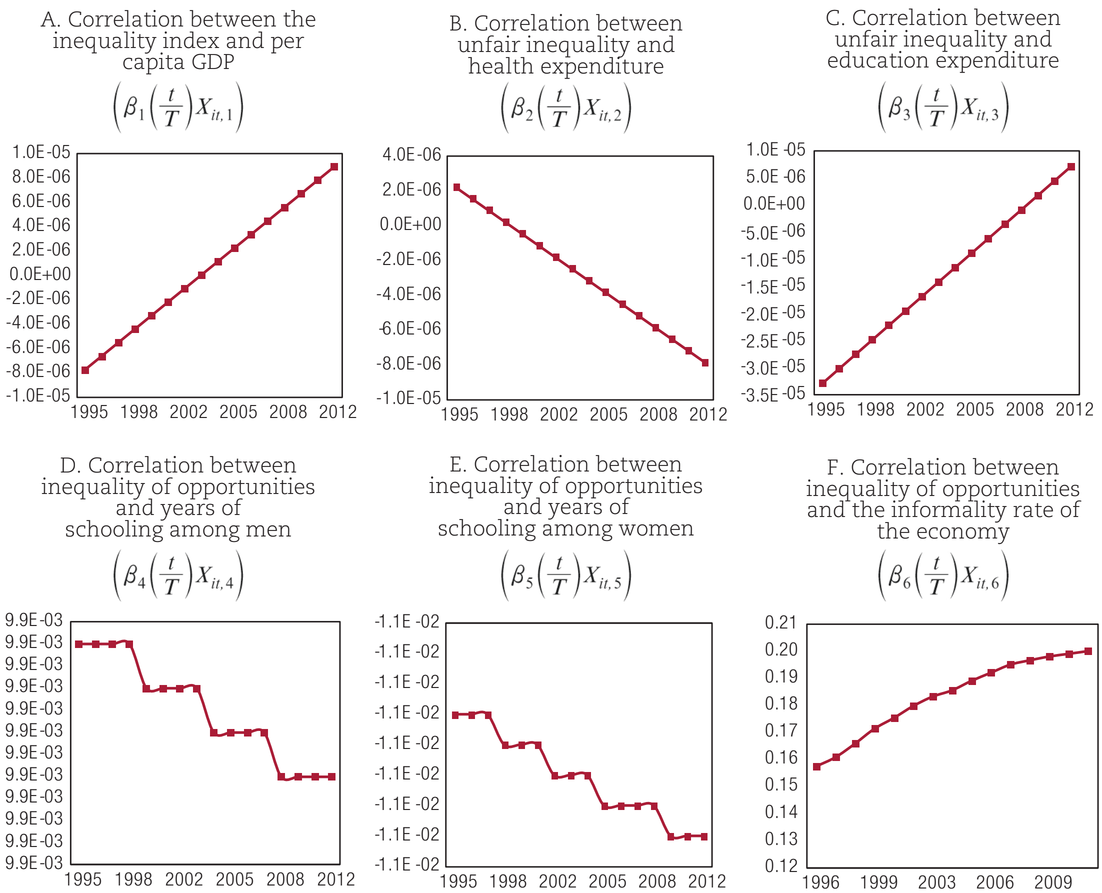
[20] As the results of the two estimators proposed by Li, Chen and Gao (2011) were very similar, it was decided only to present the results obtained through the local linear dummy variable, as in section II.2. The results of the other estimator can be obtained from the authors on request.

can retain all of the fruits of their production. As productivity in the informal market is lower than in the formal sector, this would generate a higher degree of income inequality in the economy.

Figure 2 shows the effects of the variables mentioned through the estimator of the local linear dummy variable. The figure consists of six graphs which show how each of the variables impacts on the inequality of opportunities. Figure 2A shows the correlation between per capita GDP and the inequality index. Although the graph seems to suggest a positive relation, the estimated coefficient is negative. This shows that, at the start of the period of analysis, income conditions have a significant weight in reducing inequality. But, after that period, and given the buoyancy of the Brazilian economy since 2003, other factors started to become more important in explaining the trend of the inequality of opportunities, and the primacy of economic growth declined. Using Markov transition matrices, Magalhães and Miranda (2009) showed that per capita income displays a severe process of divergence in Brazil, in which most municipalities fall into one or other of just two groups: the rich club —formed mainly by the municipalities of the south, centre west and south-east, with a per capita income of between 1.27 and 1.68 times above the average of all municipalities— and the poor club —consisting of the municipalities of the north and north-east, with a per capita income of up to 0.55 of that average. Boueri and others (2007) showed that the ergodic distribution in the following period starts to suggest a convergent trend. Lastly, in the most recent decade, the long-term results show a concentration of municipalities and population in the intermediate classes of the distribution.

Figure 2

Estimation of inequality by different variables and Gini coefficient, 1995-2012



Source: Prepared by the authors.

Note: The values shown on the vertical axis represent the impact of a variable with a much higher scale unit than that of the inequality of opportunities. GDP: Gross domestic product.

The relation between economic growth and the reduction of inequality of opportunities is both complex and important. For that reason, it is necessary to understand the channels through which economic growth acts on individuals. It should not be forgotten that progress in terms of welfare, ultimately depends on economic growth and the way individuals take advantage of its benefits. Nonetheless, the characteristics of the economic growth are important, because it can act neutrally, in favour of, or against individuals. Consequently, strategies to reduce the inequality of opportunities cannot be exclusively based on economic growth, but must be combined with income redistribution policies and adequate public expenditure.

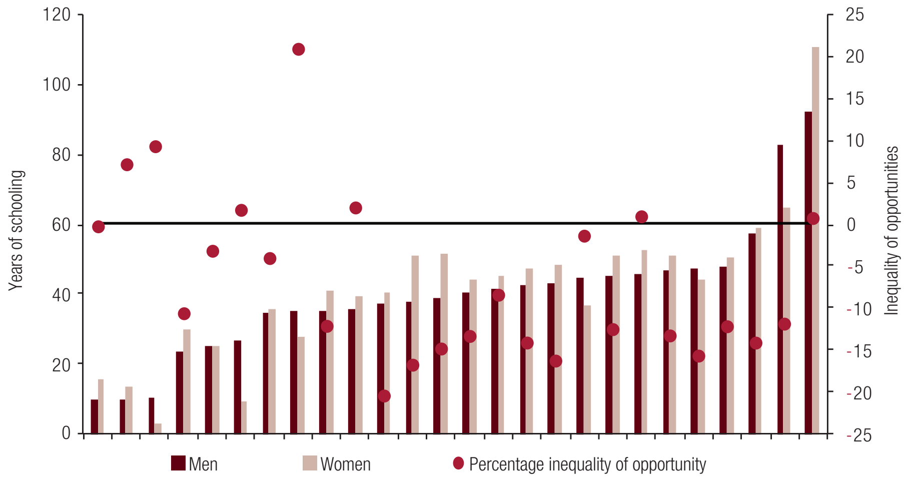
Figures 2B and 2C show the correlation between unfair inequality and expenditure on health and education, respectively.

The characteristics of the health sector and changes in the age structure and mortality and morbidity patterns in Brazil have consequences for the costs and use of medical and ambulatory services. In addition, transformations in health systems —the reorganization of care models— and the incorporation of new technologies, among other factors, have also changed the way those services are used. Those dynamics have modified the pattern of health expenditure in recent years. Changes in this sector can be analysed under a microeconomic approach. From the individual standpoint, the consumption of health goods and services directly affects welfare, insofar as health status determines the level of individual happiness. Similarly, from a macroeconomic point of view, the provision of health services affects economic growth, because it restores the human capital stock and determines the economy's productive capacity. Thus the relation between them can be seen both in the labour market, since it is a labour-intensive sector for low- and medium-complexity services, and in production, since it is also technology-intensive in the case of high-complexity services. Thus, the importance of investment in health, whatever its focus, can be seen in terms of social well-being. Accordingly, these changes have repercussions for resource allocation and for the organization of health service infrastructure, which shows the importance of providing these goods and services and their effects on individual opportunities. Figure 2B shows that the relation is negative throughout the period analysed, so investments in health play a major role in equalizing opportunities between individuals.

Figure 2C reports a positive relation between per capita education expenditure and the inequality of opportunities. This result stems largely from inefficient use of accountability policies. These have become important in the debate on the management of public expenditure, albeit on an incipient basis, but they did not attain the targets or bring equity to the education system. In that regard, the failure of Brazilian education, both in terms of direct investments and in the quality of teaching provided, contributes to that result. These factors serve to maintain a situation of social vulnerability that makes it harder for individuals to fully integrate into society.

Figures 2D and 2E show how the trend of years of formal schooling among men and women, respectively, affects individuals' opportunities. There is a clear and direct relation between those variables. Figure 3 shows that the states in which the inequality of opportunities has decreased by most were those that in general had the highest growth rates of formal education among men and women. That result shows that an increase in average years of schooling allowed for wage increases (directly), while a reduction in the rate of depreciation of the health stock (indirectly) also contributes positively to income in the labour market. The sum of those two factors affords individuals greater access to opportunities and, thus, the effect of circumstances is compensated through individual effort. It should be stressed that the monetary dimension of the inequality of opportunities, captured by the Gini coefficient, is a partial and limited approach. Although insufficient, the income-based approach to inequality of opportunities should not be rejected, however, because income deprivation is one of the main causes of reduced access to adequate education and health and security conditions, among other factors.

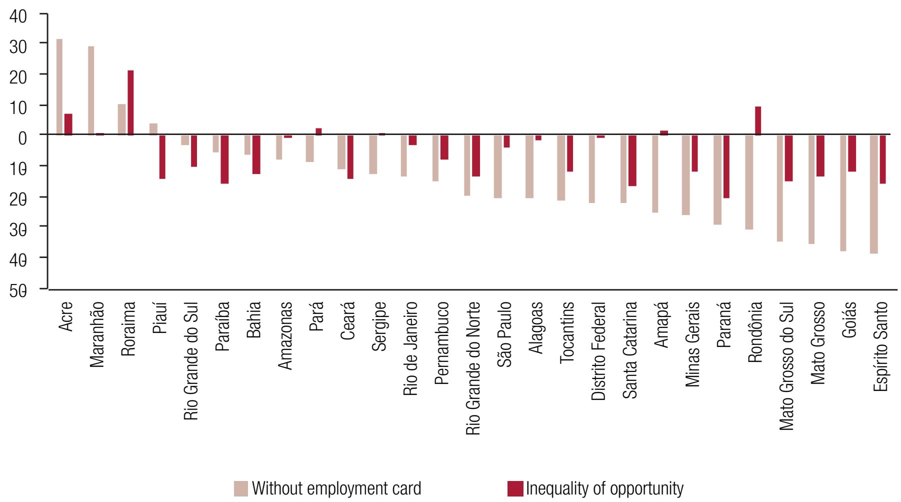
Figure 3
Brazil: rate of growth of years of schooling and inequality of opportunities, 1995-2012
(Percentage variations)



Source: Prepared by the authors.

In the 1990s, there was a steady reduction in the number of jobs considered as formal (employees with an employment contract) in Brazil. Nonetheless, from the following decade onwards, the proportion of workers with a formally registered as employed has increased. Figure 2F shows that the economy's informality rate (percentage of individuals without a formal employment contract) is positively related to the inequality of opportunities; so the recent increased formalization of the economy has led to a reduction in that inequality. The formality/informality variable has been gaining in importance, and the relation can also be seen in figure 4.

Figure 4
Brazil: trend of informality and inequality of opportunities, by state, 1995-2012
(Percentage variations)



Source: Prepared by the authors.

V. Conclusion

This article set out to evaluate the effects of certain macroeconomic variables on the inequality of opportunities. To that end, a two-stage empirical strategy was adopted. Firstly, a correction was made for the self-selectivity of migration, using the copulas method as proposed by Nelsen (2006). Secondly, after correcting the wage equation, the relation between a set of macroeconomic variables and inequality of opportunities resulting from the adjusted wages was estimated. This used the method developed by Li, Chen and Gao (2011), combining data from PNAD and Finbra on the Brazilian states for the period between 1995 and 2012.

The results show that, in the last few years, economic growth has lost ground in that debate with respect to the other macroeconomic conditioning factors. This result may reflect the difficulty of maintaining sustainable growth and the formation of groups of states that have grown apart in recent years, but which displayed a reversal of that trend. At the same time, health spending is negatively correlated with inequality of opportunities, but the same is not true of education expenditure. In that connection, strategies to reduce individual disparities should combine an increase in income with quality public expenditure. The current pattern of education spending contributes to the maintenance of a situation of social vulnerability that makes it harder for individuals to participate fully in society. On the other hand, the increase in formal education fosters a reduction in inequality of opportunities through a direct effect on the wage and an indirect effect on health status. Lastly, the growing formalization of the Brazilian economy, which has intensified since the decade of 2000, also contributes significantly to making opportunities more equal.

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Annex A1

Table A1.1
Results of the use of copulas to correct for the self-selectivity of migration, 1995-2012

Year	Akaike information criterion								Selected copula[a]	θ
	Gaussian	FGM	Plackett	AMH	Frank	Clayton	Gumbel	Joe		
1995	48 059.71	48 056.75	48 053.76	48 047.60	48 044.45	48 059.28	48 114.64	48 187.19	Frank	0.27
1996	47 520.12	47 502.70	47 523.15	47 521.48	47 490.60	47 513.63	47 508.93	47 647.91	Frank	0.33
1997	51 717.29	51 680.52	51 713.59	51 681.52	51 715.23	51 714.77	51 750.27	51 897.91	FGM	-0.89
1998	50 574.84	50 573.07	50 575.04	50 573.10	50 571.26	50 574.59	50 734.43	50 739.76	Frank	0.08
1999	51 681.11	51 672.20	51 647.59	51 639.06	51 615.59	51 676.01	51 715.85	51 893.31	Frank	0.41
2001	58 775.96	58 773.69	58 773.95	58 773.64	58 773.12	58 773.99	58 842.08	59 007.08	Frank	0.02
2002	62 605.30	62 606.21	62 606.21	62 606.20	62 608.21	62 608.21	62 707.29	62 818.08	Gaussian	0.04
2003	59 862.64	59 862.11	59 854.56	59 862.11	59 861.94	59 862.19	60 001.84	60 081.74	Plackett	0.17
2004	62 795.18	62 772.10	62 781.08	62 789.63	62 762.61	62 798.06	62 911.15	63 044.55	Frank	0.35
2005	30 236.94	30 237.76	30 237.74	30 237.76	30 237.37	30 237.68	30 345.47	30 325.17	Gaussian	-0.05
2006	69 608.50	69 579.25	69 619.57	69 575.62	69 548.41	69 630.96	69 791.28	69 691.63	Frank	0.40
2007	67 346.47	67 343.70	67 346.40	67 338.88	67 344.33	67 343.86	67 446.72	67 602.64	AMH	-0.06
2008	71 689.75	71 685.56	71 690.11	71 688.38	71 683.67	71 690.03	71 786.05	71 870.61	Frank	0.08
2009	71 421.38	71 416.94	71 394.93	71 405.32	71 392.06	71 422.50	71 558.94	71 661.80	Frank	0.32
2011	57 894.80	57 855.66	57 895.93	57 894.48	57 852.15	57 893.46	57 962.15	58 066.96	Frank	-0.40
2012	59 163.44	59 161.87	59 163.91	59 161.87	59 153.91	59 163.03	59 313.24	59 361.31	Frank	-0.31

Source: Prepared by the authors.

[a] For details of the copula functions and calculation of θ, see Kendall in Nelsen (2006).

Table A1.2
Brazil: Gini coefficient of unfair inequality by state, 1995-2012

Federative Unit	1995	1996	1997	1998	1999	2001	2002	2003	2004	2005	2006	2007	2008	2009	2011	2012
Acre	0.422	0.423	0.403	0.415	0.425	0.448	0.425	0.432	0.456	0.473	0.475	0.467	0.442	0.447	0.483	0.452
Alagoas	0.508	0.472	0.499	0.473	0.456	0.511	0.479	0.508	0.458	0.530	0.549	0.488	0.507	0.525	0.454	0.501
Amapá	0.414	0.436	0.457	0.455	0.396	0.433	0.390	0.414	0.399	0.426	0.419	0.426	0.417	0.445	0.400	0.421
Amazonas	0.379	0.363	0.386	0.368	0.361	0.392	0.390	0.391	0.413	0.426	0.433	0.391	0.382	0.380	0.417	0.378
Bahia	0.569	0.578	0.529	0.548	0.546	0.528	0.539	0.547	0.520	0.537	0.541	0.518	0.529	0.524	0.518	0.498
Ceará	0.739	0.721	0.715	0.707	0.713	0.698	0.661	0.649	0.648	0.672	0.624	0.606	0.616	0.616	0.613	0.635
Espírito Santo	0.444	0.420	0.435	0.443	0.436	0.420	0.426	0.429	0.425	0.412	0.398	0.391	0.418	0.406	0.376	0.372
Federal District	0.267	0.269	0.272	0.274	0.277	0.274	0.275	0.272	0.271	0.271	0.275	0.272	0.269	0.273	0.267	0.265
Goiás	0.412	0.406	0.416	0.418	0.407	0.400	0.392	0.390	0.389	0.390	0.389	0.392	0.404	0.396	0.359	0.362
Maranhão	0.554	0.528	0.616	0.579	0.555	0.529	0.493	0.557	0.545	0.557	0.563	0.602	0.563	0.510	0.596	0.558
Mato Grosso	0.459	0.460	0.458	0.462	0.467	0.442	0.445	0.448	0.439	0.448	0.451	0.440	0.428	0.430	0.388	0.398
Mato Grosso do Sul	0.460	0.443	0.434	0.441	0.444	0.420	0.428	0.434	0.424	0.427	0.421	0.432	0.416	0.417	0.394	0.392
Minas Gerais	0.488	0.453	0.471	0.475	0.477	0.469	0.479	0.478	0.465	0.471	0.459	0.450	0.449	0.449	0.443	0.429
Pará	0.506	0.487	0.482	0.481	0.502	0.472	0.467	0.449	0.569	0.544	0.535	0.533	0.518	0.515	0.508	0.516
Paraíba	0.640	0.603	0.602	0.590	0.617	0.564	0.578	0.563	0.573	0.553	0.560	0.550	0.546	0.566	0.546	0.540
Paraná	0.486	0.455	0.439	0.454	0.443	0.441	0.436	0.436	0.428	0.437	0.428	0.419	0.425	0.415	0.397	0.387
Pernambuco	0.560	0.573	0.568	0.596	0.563	0.612	0.610	0.673	0.598	0.606	0.603	0.594	0.583	0.549	0.542	0.513
Piauí	0.625	0.652	0.622	0.595	0.623	0.578	0.640	0.596	0.613	0.604	0.552	0.565	0.588	0.562	0.549	0.537
Rio de Janeiro	0.347	0.351	0.333	0.356	0.332	0.348	0.347	0.350	0.351	0.354	0.359	0.359	0.351	0.340	0.339	0.336
Rio Grande do Norte	0.567	0.545	0.560	0.584	0.555	0.587	0.552	0.545	0.531	0.541	0.524	0.534	0.516	0.540	0.493	0.492
Rio Grande do Sul	0.406	0.411	0.415	0.401	0.406	0.409	0.399	0.398	0.402	0.388	0.388	0.384	0.390	0.386	0.356	0.363
Rondônia	0.454	0.467	0.486	0.454	0.444	0.443	0.460	0.455	0.568	0.569	0.539	0.533	0.530	0.530	0.484	0.496
Roraima	0.365	0.391	0.434	0.413	0.470	0.411	0.415	0.494	0.490	0.599	0.503	0.512	0.424	0.470	0.489	0.441
Santa Catarina	0.443	0.440	0.430	0.442	0.437	0.406	0.416	0.418	0.391	0.417	0.413	0.402	0.402	0.393	0.373	0.369
São Paulo	0.347	0.346	0.346	0.342	0.340	0.336	0.347	0.350	0.333	0.344	0.340	0.333	0.336	0.333	0.333	0.333
Sergipe	0.433	0.448	0.476	0.459	0.430	0.430	0.427	0.431	0.436	0.406	0.433	0.415	0.426	0.425	0.413	0.437
Tocantins	0.575	0.678	0.590	0.581	0.535	0.552	0.557	0.570	0.557	0.575	0.544	0.536	0.535	0.526	0.542	0.507

Source: Prepared by the authors.
Note: All values significant at 1%.

Table A1.3
Descriptive statistics of the sample

Variable	Mean	Standard deviation	Minimum	Maximum
Entropy	0.47	0.085	0.33	0.74
Real per capita GDP (R$ billion)[a]	8.70	5.746	1.41	32.44
Real per capita health expenditure (R$ million)	390.50	901.000	5.20	7758.00
Real per capita education expenditure (R$ million)	292.20	578.800	1.50	5479.00
Years of schooling – men	7.33	1.272	4.20	10.48
Use of schooling – women	8.46	1.224	4.91	11.31
Degree of informality	0.21	0.044	0.11	0.44

Source: Prepared by the authors.
Note: GDP: Gross domestic product.
[a] Values expressed as natural logarithms.