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THE EFFECTIVENESS OF EDUCATION AND HEALTH SPENDING AMONG BRAZILIAN MUNICIPALITIES

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ABSTRACT/RÉSUMÉ

The effectiveness of education and health spending among Brazilian municipalities

This paper uses a large dataset combining census, household survey and budgetary data for nearly 4 000 Brazilian municipalities to estimate the impact of government spending on education and health outcomes. We deal with the multi-dimensional nature of the population's social status by estimating structural equation models with latent variables using a limited-information two-stage least square (2SLS) estimator. Robustness of the baseline regressions to heterogeneity in the data is assessed on the basis of quantile regressions. The main empirical findings are that government spending is a powerful determinant of education outcomes, but this is not the case for health, and that spending on non-education programmes are also at least as important. In addition, there appears to be scope for gains in economies of scale in the provision of education and health care services, at least for selected segments of the conditional distribution of social outcomes. Finally, there are cross-sectoral effects in service delivery: health (education) outcomes affect the population's education (health) status. This Working Paper relates to the 2009 *OECD Economic Survey of Brazil* (www.oecd.org/eco/surveys/brazil).

JEL classification number: I12; I18; I21; I31

Keywords: Brazil; structural equation modelling; quantile regression; latent variable; education; health care

L'efficacité des dépenses d'éducation et de santé des administrations municipales brésiliennes

Ce document utilise une grande base de données combinant des informations issues des enquêtes réalisées auprès des ménages et des recensements, aussi que des budgets de près de 4 000 municipalités brésiliennes pour estimer l'effet des dépenses des administrations publiques en matière d'éducation et de santé. Le caractère multidimensionnel des indicateurs sociaux est pris en compte par un modèle d'équation structurelle avec des variables latentes estimé par le double moindre carré à information limité. Des régressions quantile ont été estimées pour évaluer la robustesse des résultats de base en tenant compte de l'hétérogénéité des données. Les principaux résultats sont que les dépenses des administrations publiques sont particulièrement déterminantes pour la performance de l'éducation mais pas de la santé et que les dépenses des programmes hors éducation sont aussi importantes. En outre, les résultats en matière de santé ont un impact sur les indicateurs d'éducation, et vice versa. Finalement, il apparaît que des économies d'échelle pourraient être exploitées pour la fourniture des services d'éducation et santé au moins pour les collectivités situées sur certains segments de la distribution conditionnelle des résultats en matière d'éducation et santé. Ce Document de travail se rapporte à l'*Étude économique de l'OCDE du Brésil, 2009* (www.oecd.org/eco/etudes/brésil).

Classification JEL: I12 ; I18 ; I21 ; I31

Mots clés : Brésil ; modèle d'équation structurelle ; régression quantile ; variable latente ; éducation ; santé

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The effectiveness of education and health spending among Brazilian municipalities

Luiz de Mello and Mauro Pisu¹

1. Introduction

It has become conventional to gauge the efficiency of government spending on social programmes by estimating “social production functions” following the seminal contributions of Coleman *et al.* (1966) and Grossman (1972a and 1972b).² Emphasis is often placed on education and health care, which together account for the bulk of social spending and a large share of government outlays in most countries. A variety of social indicators, such as literacy rates, educational attainment rates, student scores in standardised tests and longevity/mortality rates are conventional measure of social outcomes. Spending on education and health care, which can be publicly or privately funded, are important input indicators. Technical parameters, such the density of medical and teaching personnel in the population, are additional standard inputs in social production functions. Estimation can be carried out using parametric and non-parametric techniques.³ Cross-country studies dominate the literature, although evidence is also available from sub-national levels of government within the same country.

The empirical literature is confronted with two basic problems that this paper aims to address. *First*, it is very difficult to control for differences in institutional settings in cross-country analysis, especially when non-parametric techniques are used. Control for fixed effects using estimators for pooled data goes some way in dealing with heterogeneity, but it is not entirely satisfactory, because most of the variation in the data is of a cross-sectional nature. *Second*, most of the literature treats the population’s social status as a one-dimensional concept that can be proxied by a limited number of outcome/output indicators. Use of non-parametric estimators does not solve this problem, because it does not address the issue of how to measure the dependent variable. Estimation of social production functions using structural equation models with latent variables, developed by Jöreskog and Sörbom (1986), explicitly addresses this problem, but the estimation methodologies are often computationally demanding, especially for large data sets. Another consideration is that the use of full-information maximum likelihood (FIML) techniques to estimate the

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1. This paper contains background material used in the OECD *Economic Survey of Brazil*, published in July 2009 under the authority of the Secretary General of the OECD and discussed at the Economic and Development Review Committee (EDRC) on 4 June 2009. The views expressed in this paper do not necessarily reflect those of the OECD and its Member countries. Special thanks are due to Anne Legendre for research assistance and Mee-Lan Frank for excellent technical assistance.
 2. Coleman *et al.* (1966) was the first to estimate an education production function using data on student achievement as output and school characteristics, coupled with students’ socio-economic background, as inputs. Grossman (1972a and 1972b) focused on the empirical analysis of the determinants of health status.
 3. For empirical studies based on non-parametric estimations of social production functions see, for instance, Tulkens and Van den Eeckaut (1995).

structural equation models requires the residuals to be homoskedastic and normality distributed, hypotheses which are likely to be violated in many applications.

This paper aims to shed further light on the estimation of social production functions by focusing on the experience of Brazilian municipalities in the provision of education and health care services. We use a large data set combining census, household survey and budget execution data. Motivation for the focus on Brazil, in addition to the wealth of data available, comes from the fact that the municipalities account for the bulk of government spending on primary and lower-secondary education, as well as on health care (Afonso and de Mello, 2002), while enjoying considerable autonomy to set policy and to allocate funds received from higher levels of government according to their priorities. The focus on a single country's local governments has the advantage of reducing the scope for heterogeneity among the units of observation that arises from differences in institutional settings, culture and social norms. We deal with remaining heterogeneity in the data by testing the robustness of the empirical findings using an instrumental-variable quantile regression technique developed by Chernozhukov and Hansen (2005, 2006 and 2008).

We deal with the multi-dimensional nature of the social status indicators by estimating the social production functions using structural equation models with latent variables. These models use observable social indicators as determinants of an unobservable (latent) variable, as in traditional factor analysis, instead of regressing them directly on the conventional inputs, as in the conventional approach to the estimation of social production functions. In particular, we use a limited-information two-stage least squares (2SLS) methodology pioneered by Jöreskog and Sörbom (1986) and extended by Bollen (1996) and Bollen *et al.* (2007), which yields parameter estimates that have lower bias and allow for more accurate hypothesis testing than FIML. Robust standard errors are also available without the need for bootstrapping, which facilitates hypothesis testing.

The paper's main findings are as follows:

- In line with the literature, income appears to be the main determinant of social outcomes. Government spending affects education status positively, whereas the same is not true for health. In addition, we find that government spending on programmes other than education also matters: its impact on education status is actually stronger and more robust than that of spending on education alone. A focus on sector-specific spending, which is common in empirical analysis, would therefore result in an underestimation of the role of government in promoting social development by excluding other spending items that may play a complementary role. The effects of income and government spending are stronger among the municipalities that have low conditional education status.
- The composition of government spending and economies of scale in service delivery appear to have a bearing on health and education outcomes. Local governments that spend a higher share of their budgetary appropriations on capital than on current outlays tend to have better conditional outcomes, at least for jurisdictions with the lowest conditional education status and for selected segments of the conditional distribution of health outcomes. In addition, the worst performing municipalities do not appear to be able to reap the benefits of economies of scale in the delivery of education services. This finding implies that the better-performing jurisdictions may well already operate at their optimal scale.
- There appears to be strong cross-sectoral effects between education and health outcomes. The population's education status is a powerful determinant of health outcomes and vice versa, an effect that is stronger among the municipalities with low conditional (education and health)

outcomes. This is consistent with the large literature that has reported a bi-directional causal association between education and health status.

This paper is organised as follows. Section 2 briefly surveys the empirical literature, with emphasis on Brazilian sub-national jurisdictions. Section 3 describes the methodology for estimating the latent variable model. Section 4 presents the data and the baseline estimation results. Section 5 reports the results of the quantile regression analysis. Section 6 concludes and presents some policy implications of the empirical analysis.

2. A survey of the literature

The cross-country empirical literature based on parametric estimations of social production functions often reports fairly weak correlations between government expenditure and social indicators. This is regardless of the estimation technique used and of whether or not the sample includes developing countries. The government spending-outcomes nexus tends to be especially weak, or even negatively signed, for health care (Filmer, Hammer, and Pritchett, 2000; Or, 2000; Jack, 1999; Thornton, 2002; Baldacci, Guin-Siu and de Mello, 2003; Self and Grabowski, 2003; Fayissa and Gutema, 2005). With regards to education, the correlation between government spending and social outcomes is often stronger, although income remains the most powerful predictor (Gupta, Verhoeven and Tiongson, 2002). Other determinants, such as the quality of governance, measured for instance on the basis of corruption perception and quality-of-bureaucracy indicators, have also been shown to affect the relationship between government spending and social outcomes (Rajkumar and Swaroop, 2008). Moreover, credit constraints and income volatility are likely to affect education outcomes (Flug, Spilimbergo and Watchenheim, 1998).

A growing body of literature has emphasised the role of cross-sectoral effects, whereby education (health) outcomes are important determinants of the population's health (education) status. For example, Levine and Schanzenbach (2009) use US data and show that educational attainment tends to improve among children with better health status at birth, which in turn depends on public health insurance coverage. The studies investigating the effect of education "gradients" on health outcomes show that this finding cannot be explained by income alone (Cutler and Lleras-Muney, 2006; Grossman, 2003 and 2006).

There is a large empirical literature on the efficiency of government spending using Brazilian sub-national data. Most studies use expenditure data available from sub-national budgets and conventional social indicators, such as literacy and mortality rates, longevity and educational attainment (available from household survey and census data). For example, following a literature pioneered by Sampaio and Sousa Ramos (1999a and 1999b), Brunet, Berte and Borges (2008) constructed non-parametric efficiency frontiers for the provision of primary and secondary education through the public school network using state- and municipality-level data for 2005 and 2007. The authors show that the correlation between spending and performance is fairly weak when using state-level data, since the best-performing jurisdictions of the South do not spend as much as the South-Eastern states, whose social indicators are worse. Boueri (2007) uses municipal data on outcome indicators in health, education and urbanisation and finds considerable inefficiency in spending. Sampaio and Stosic (2005) and Sampaio, Cribari Neto and Stosic (2008) estimate a non-parametric frontier using municipal data on education and health indicators and show that size, measured by the resident population, is a powerful determinant of expenditure efficiency. The cost of public services tends to be higher in smaller jurisdictions, possibly due to their failure to exploit economies of scale.

In a parametric setting, Sa (2005) estimates a two-equation system by 3SLS for the demand and supply of health care using municipal data. The author finds a negative relationship between government spending and health outcomes, measured by infant mortality, while controlling for urbanisation, schooling and regional effects. Government spending depends negatively on service delivery costs, measured by the

average wage of medical personnel, and positively on income. Soares (2007) estimates the determinants of life expectancy and infant mortality across Brazilian municipalities using dynamic panel techniques. He finds that income per capita is the most important determinant of life expectancy and infant mortality.⁴ Alves and Belluzzo (2005) report similar findings for infant mortality: the effect of income is negative and statistically significant, whereas education and health infrastructure appear to have a more limited impact.

3. The methodology

To deal with the multi-dimensional, unobservable nature of the population's social status, we estimate the social production functions using a structural equation model (SEM) with latent variables. SEM uses the observable social indicators as determinants of an unobservable (latent) variable, as well as the information available in the covariance matrix of the explanatory variables and social indicators to uncover the empirical association between the inputs and the unobservable outputs of a social production function. SEM includes two different models: *i*) a measurement or confirmatory factor analysis model, and *ii*) a standard structural model, where the relevant variables are not affected by measurement errors, as in the standard regression analysis.

The estimation of SEM has traditionally relied on full information maximum likelihood (FIML), as developed by Jöreskog and Sörbom (1986) and made popular by the software LISREL.⁵ The main feature of the FIML methodology is that all parameters are estimated simultaneously. When the model is correctly specified and the data do not violate the assumptions on which SEM is based, the FIML estimator is consistent, asymptotically efficient and asymptotically normally distributed. However, some of these assumptions, particularly those relating to homoskedastic and normality of the error terms, are likely to be violated in many applications.⁶ Moreover, because all equations are estimated simultaneously, specification errors in one part of the system are likely to bias all parameter estimates. Another disadvantage of FIML is that it cannot easily accommodate the inclusion of categorical variables. This can be an important limitation in many applications when dummy variables can be used to control for unobserved heterogeneity.

To overcome these difficulties, we use a limited-information two-stage least squares (2SLS) methodology for estimating SEM, as put forward by Bollen (1996). To compare the performance of these two methodologies in the case of a misspecified model, Bollen *et al.* (2007) conducted Monte Carlo simulations to show that 2SLS yields parameter estimates that have lower bias and allow for more accurate hypothesis testing than FIML. It is possible to rely on standard specification tests when estimating SEM by 2SLS, because parameter estimates are asymptotically normal, even if the error terms are not normally distributed. In addition, robust standard errors are available without the need for bootstrapping. Another advantage of 2SLS is that it allows for the inclusion of dummy variables to control for unobserved heterogeneity.

In particular, using the same notation as Jöreskog and Sörbom (1993), in which Greek and Latin letters identify, respectively, latent and observable variables, a standard structural model can be written as:

$$\boldsymbol{\eta} = \boldsymbol{\alpha} + \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \quad (1)$$

-
4. Soares (2007) does not control explicitly for health spending. Health infrastructure is measured by the percentage of population living in homes connected to the public sewerage system.
 5. See Baldacci, Guin-Siu and de Mello (2003) for the estimation of social production functions for a cross-section of countries using these techniques.
 6. Robust standard errors could be generated *via* bootstrap.

where $\boldsymbol{\eta}$ is a $m \times 1$ vector of latent endogenous variables, \mathbf{B} is a $m \times m$ matrix of coefficients, with zero diagonal elements, capturing the effects of the latent variables on each other; $\boldsymbol{\xi}$ is a $n \times 1$ vector of latent exogenous variables; $\boldsymbol{\Gamma}$ is a $m \times n$ matrix of the coefficients of the impact of $\boldsymbol{\xi}$ on $\boldsymbol{\eta}$; $\boldsymbol{\alpha}$ is a vector of constants; $\boldsymbol{\zeta}$ is a $m \times 1$ vector of error terms with $E(\boldsymbol{\zeta}) = \mathbf{0}$ and $E(\boldsymbol{\zeta}\boldsymbol{\zeta}') = \mathbf{0}$.

The measurement part of SEM can be written as:

$$\mathbf{x} = \boldsymbol{\tau}_x + \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta} \quad (2)$$

$$\mathbf{y} = \boldsymbol{\tau}_y + \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon} \quad (3)$$

where \mathbf{x} is vector of q indicator variables generated by the corresponding factors $\boldsymbol{\xi}$; $\boldsymbol{\Lambda}_x$ is a $q \times n$ matrix of factor loadings in which each λ_{xij} measures the correlation between the latent variable ξ_j and the observed variable x_i , for $i=(1, \dots, q)$ and $j=(1, \dots, n)$; $\boldsymbol{\tau}_x$ is $q \times 1$ vector of constants; $\boldsymbol{\delta}$ is a vector of measurement errors with $E(\boldsymbol{\delta}) = \mathbf{0}$, $E(\boldsymbol{\xi}\boldsymbol{\delta}') = \mathbf{0}$, whose elements are uncorrelated. Analogously, in the measurement equation for $\boldsymbol{\eta}$, \mathbf{y} is a $p \times 1$ vector of indicators; $\boldsymbol{\Lambda}_y$ is a $p \times m$ matrix of factor loadings in which each λ_{yij} measures the effect of the latent variable η_j and the observed variable y_i , for $i=(1, \dots, p)$ and $j=(1, \dots, m)$; $\boldsymbol{\tau}_y$ is p dimensional vector of constants; $\boldsymbol{\varepsilon}$ is a vector of measurement errors with $E(\boldsymbol{\varepsilon}) = \mathbf{0}$, $E(\boldsymbol{\eta}\boldsymbol{\varepsilon}') = \mathbf{0}$, whose elements of are uncorrelated.

Identification requires the latent variable model to be scaled. A conventional option is to set the factor loading of one indicator per latent variable equal to one and its intercept to zero.⁷ In doing so, in a model with m latent endogenous variables and n latent exogenous variables, there are m and n scaling variables.

FIML estimation of Equations (1)-(3) involves the selection of those parameter estimates that minimise the distance between the actual covariance matrix of the observable variables and that implied by the data. To implement 2SLS, Bollen (1996) noted that, once the scaling variables have been selected, it is possible to partition vectors \mathbf{y} and \mathbf{x} , such that:

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix} = \boldsymbol{\tau}_y + \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon} \quad \text{and} \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} = \boldsymbol{\tau}_x + \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta}, \quad (4)$$

where \mathbf{y}_1 is the $m \times 1$ scaling vector of $\boldsymbol{\eta}$ and \mathbf{x}_1 the $n \times 1$ scaling vector of $\boldsymbol{\xi}$. Because of this partitioning, the first m (n) elements of vector $\boldsymbol{\tau}_y$ ($\boldsymbol{\tau}_x$) are equal to zero, and all elements of the first m (n) rows of $\boldsymbol{\Lambda}_y$ ($\boldsymbol{\Lambda}_x$) are equal zero, except for the one of them that is set to one. Given this scaling strategy, it is possible to write:

$$\boldsymbol{\eta} = \mathbf{y}_1 + \boldsymbol{\varepsilon}_1, \text{ and (4)}$$

$$\boldsymbol{\xi} = \mathbf{x}_1 + \boldsymbol{\varepsilon}_1. \quad (5)$$

Substituting Equations (4) and (5) into Equation (1) yields:

7. We also assume that the scaling variable is affected by a single factor.

$$\mathbf{y}_1 = \boldsymbol{\alpha} + \mathbf{B}\mathbf{y}_1 + \boldsymbol{\Gamma}\mathbf{x}_1 + \mathbf{u}, \quad (6)$$

$$\text{where } \mathbf{u} = \boldsymbol{\varepsilon}_1 - \mathbf{B}\boldsymbol{\varepsilon}_1 - \boldsymbol{\Gamma}\boldsymbol{\delta}_1 + \boldsymbol{\zeta}.$$

Equation (6) contains only observable variables, except for the error term, which is correlated with both \mathbf{y}_1 and \mathbf{x}_1 by construction, because it is a function of $\boldsymbol{\varepsilon}_1$ and $\boldsymbol{\delta}_1$. The latter are the measurement errors of \mathbf{y}_1 and \mathbf{x}_1 and are therefore correlated with them. To deal with this problem, Equation (6) can be estimated using an instrumental variable technique (applied on each equation separately). The i^{th} equation can be written as:

$$y_{1i} = \alpha_i + \mathbf{B}_i\mathbf{y}_1 + \boldsymbol{\Gamma}_i\mathbf{x}_1 + u_i, \quad (7)$$

where y_{1i} is the i^{th} indicator variable in \mathbf{y}_1 ; \mathbf{B}_i and $\boldsymbol{\Gamma}_i$ are the i^{th} rows of the \mathbf{B} and $\boldsymbol{\Gamma}$ matrices; α_i and u_i are the i^{th} elements of the $\boldsymbol{\alpha}$ and \mathbf{u} vectors.

Consistent estimation of Equation (7) requires good instruments for the indicator variables. As shown by Bollen (1996), good candidates for instruments are those variables that are affected by the same factor determining the indicator to be instrumented. In other words, if η_j is the factor of indicator y_{1j} appearing on the right-hand side of Equation (7), then the other indicators of η_j are valid instruments of y_{1j} .

In what follows, we assume that vector $\boldsymbol{\xi}$ of exogenous variables in Equation (1) is measured without errors. This is because the data set we use has a large number of exogenous explanatory variables that closely match the determinants that are hypothesised to affect education and health statuses. As a result, \mathbf{x}_1 is not correlated with the error term in Equation (7) and, therefore, we need to correct only for the endogeneity bias created by construction for \mathbf{y}_1 .

4. Data and main findings

Data

We use municipality-level data available from IPEA. The data set covers Brazil's 5 591 municipalities, although the actual sample size used in the regressions was reduced to at most 4 000 observations due to data omissions. Descriptive statistics are reported in Table 1.

As for the social indicators used as outputs in the regressions, we include the Human Development Indicator sub-indices for longevity and educational attainment calculated by IPEA following the UNDP methodology for Brazil's municipalities in 2000 (when the most recent population census was conducted). We also use data on the average years of schooling of the resident population, life expectancy at birth and under-5 infant mortality (all for 2000). As a technical input indicator, we rely on information on resident doctors per 1 000 population.

Information on government spending is available from municipal budgets. Budgetary data on total expenditure, compiled and disseminated by the federal Treasury, are available for all municipalities in the sample. Information on outlays according to a functional classification, thereby disaggregating expenditure on health care and sanitation, and education and culture, from other expenditure items, is available for a smaller set of jurisdictions. Budgetary data are also reported according to an economic classification for a sub-set of municipalities, based on which we extracted information on current and capital outlays. We also use data on transfers received from higher levels of government, which can be disaggregated into current or capital.

Because the social indicators are available for 2000 (discussed below), we use budgetary data for 1995, so as to allow for lagged effects in the relationship between spending and social indicators. Additional variables are used to control for differentials among the municipalities in living standards (income per capita in 1991, so as to ensure exogeneity) and to proxy for scale effects (resident population in 2000) and market potential (transport cost from the reference municipality to the city of São Paulo, the largest municipality in the country, in 2000).

Table 1. **Descriptive statistics**¹

Variable	Mean	Median	Min	Max	Standard deviation	Kurtosis
Education indicators						
Years of schooling (2000)	4.04	4.07	0.81	9.65	1.29	2.76
HDI index (educational attainment) (2000)	0.78	0.80	0.42	0.98	0.09	2.55
Health indicators						
HDI index (longevity) (2000)	0.71	0.72	0.49	0.89	0.08	2.47
Resident doctors per population (2000)	0.27	0.00	0.00	7.27	0.52	21.67
Under-5 mortality rate (2000)	44.72	33.07	6.16	134.84	29.72	2.60
Explanatory variables						
Income per capita (1991)	4.64	4.67	3.22	6.37	0.58	2.17
Transport cost to São Paulo (1995)	7.11	7.08	2.30	9.26	0.82	4.21
Ratio of current to capital spending (2000)	1.97	1.93	-2.30	6.46	0.70	6.66
Resident population (2000)	9.36	9.25	6.68	16.16	1.11	4.54
Education spending (1995)	13.46	13.27	5.00	20.43	0.99	7.63
Non-education spending (1995)	14.52	14.27	12.11	22.35	1.02	7.49
Health spending (1995)	12.75	12.59	6.19	20.60	1.18	6.33
Non-health spending (1995)	14.66	14.43	12.28	22.32	1.00	7.37

1. The explanatory variables are in logarithmic form.

Source: IPEA.

Regression results

We started by estimating Equations (1)-(3) for education and health statuses without cross-equation effects (*i.e.* matrix \mathbf{B}_i in Equation (7) is set to zero). These models were estimated by OLS, because there is no endogeneity in the absence of cross-equation effects. We then proceeded to estimate the same regressions with the education and health outcomes affecting each other using the instrumental-variable technique discussed above.

Education (no cross-equation effects)

The results of the education status equation are reported in Table 2. We used the HDI sub-index for educational attainment as the scaling (dependent) variable. Similar results (not reported) are obtained using the average years of schooling of the resident population as the scaling variable. In line with the empirical literature, the estimated coefficients show that income per capita is the most powerful determinant of the population's education status. A 10% increase in per capita income leads to an improvement in the HDI index by 0.7 standard deviations. Transport costs, included in the equation as a gauge for market potential, are inversely related to education status.

Scale effects, as captured by the resident population, are also important and tend to affect education status in a non-linear manner: an increase in the size of municipalities appears to be associated with a fall in educational attainment for smaller municipalities and positive for larger municipalities. Nevertheless, the magnitude of the coefficients on the log of population and its square implies that the turning point in

the relationship between size and education status is unrealistically high.⁸ This finding, which is consistent with previous literature (Sampaio and Stosic, 2005), suggests that the municipalities may be unable to reap the benefits of economies of scale in service delivery.

Table 2. **Education and health models: OLS regressions¹**

	Education		Health	
	Coefficient	t-ratio	Coefficient	t-ratio
Income per capita	0.0730	29.84	0.0685	24.55
Transport costs	-0.0060	-3.51	-0.0109	-4.92
Current-to-capital spending	-0.0028	-3.17	-0.0046	-4.49
Resident population	-0.0331	-4.50	-0.0145	-2.44
Population squared	0.0009	2.13	0.0000	0.08
Education spending	0.0098	4.27		
Non-education spending	0.0146	5.52		
Health spending			0.0002	0.20
Non-health spending			0.0066	2.88
Constant	0.3831	8.17	0.5192	11.24
R-squared		0.83		0.69
No. of obs.		3 966		3 945

1. Heteroskedasticity robust absolute *t*-statistics are reported. The HDI sub-indices for educational attainment and longevity are the scaling (dependent) variables in the education and health models, respectively. All models include 23 dummy variables (not reported) to identify the municipalities belonging to a metropolitan region and 26 dummy variables to identify the states in which the municipalities are located (São Paulo is the reference state).

Source: Data available from IPEA, and authors' estimations.

Turning to the public finance variables, outlays on education and government size, measured by total municipal expenditure in sectors other than education, are positively associated with education status. The point estimate of government size is comparable to that of education spending: a 1% increase in either category of spending is associated with an improvement in educational attainment by slightly less than 0.01 standard deviation.⁹ The finding that municipal non-education expenditure affects education status indicates that there may be an association between education status and health spending, which is the largest individual spending item in municipal budgets other than education. This hypothesis is tested below through the estimation of SEMs that control for the presence of cross-equation effects. Finally, the composition of government spending between capital and current outlays also matters. Municipalities that allocate a larger share of spending to investment tend to have better education outcomes than their counterparts that spend comparatively more on operations and maintenance and payroll, for example.

Finally, two sets of dummy variables were included in the regressions to identify the municipalities located in one of Brazil's 23 metropolitan regions and the states in which the municipalities are located (the reference state is São Paulo). Motivation for inclusion of the metropolitan dummies is to account for the scope of externalities in service delivery, which tends to rise among neighbouring jurisdictions. The estimated coefficients (not reported) show that, conditional on the observable characteristics of each municipality, education status tends to be higher in the local governments that belong to one of the country's metropolitan regions. There are exceptions, nevertheless, including a few of the largest and most developed metropolitan areas (Campinas, São Paulo, Curitiba, Londrina and Porto Alegre), a finding that

8. Comparable results (not reported but available upon request) are obtained using a spline function of resident population with five cut-offs, instead of a quadratic term. These results show a negative effect of resident population on educational attainment for all population brackets, which is stronger for smaller municipalities.
9. The null hypothesis that the coefficients of education spending and government size are equal cannot be rejected (*p*-value is 0.28).

may be attributed to negative externalities in service delivery. Turning to the state dummies, there also appears to be strong regional effects. As in the case of the metropolitan dummies, the municipalities located in less developed states do not necessarily fare worse than their counterparts in the state of São Paulo, controlling for additional determinants. This finding is consistent with those reported in Sampaio and Stosic (2005) and Sampaio *et al.* (2008).

Health (no cross-equation effects)

The HDI sub-index for longevity was used as the scaling variable for the health status model. The results (also reported in Table 2) suggest that, as in the case of education, more prosperous and smaller municipalities that are closer to large consumer markets fare better than their larger, less prosperous counterparts located in remote areas. Again, there appear to be non-linear scale effects among the determinants of the population's health status: conditional on other observable determinants, larger municipalities fare better than smaller ones. Nevertheless, the estimated turning point is, as in the case of education, unrealistically high. This finding points to an inability on the part of local governments to exploit economies of scale in the provision of health care services.

Turning to the public finance variables, unlike the case of education status, the effect of government spending on health status is small in magnitude and statistically insignificant, a finding that is consistent with previous literature (Sa, 2005). As in the case of education, we also find that health status is positively associated with government size, defined as total outlays on programmes other than health care, and negatively correlated with the ratio of current to capital spending. This suggests that there may be other expenditure items, rather than outlays on health care, such as education, which are strongly correlated with health status. We also find that local governments that allocate a larger share of their budgets to investment tend to have a more beneficial impact on the health status of the resident population.

The metropolitan region effects are much weaker than in the case of education status. Several dummies are statistically insignificant, suggesting that a municipality located in a metropolitan region does not fare necessarily better than those outside those areas. Yet, there are local governments in large metropolitan regions, such as those of São Paulo and Baixada Santista, which fare worse than their peers that do not belong to any metropolitan area. In this case, to the extent that the metropolitan dummies proxy for the presence of cross-border externalities in service delivery, the findings suggest that the municipal governments located in these large metropolitan areas might suffer from negative externalities, possibly associated with congestion in service delivery. Neither does there appear to be a strong correlation between economic development and conditional health status. According to our estimates, those jurisdictions with the highest conditional health statuses (São Luís, Recife and Manaus) are located in the less prosperous North and North-Eastern regions. In the case of the state dummies, the relative magnitude of our parameter estimates suggests that the states of Santa Catarina, Rio Grande do Sul and Ceará are the best performers in terms of their conditional health statuses.

Interconnections between education and health outcomes

The regressions reported above do not control for the presence of mutually reinforcing effects between education and health outcomes. It is nevertheless reasonable to expect that a better educated population would also be healthier, because better educated individuals tend to have a preference for healthier diets and life styles. On the other hand, better education outcomes are also supposed to improve health status. The vast literature on the effect of education on health status (see Cutler and

Lleras-Muney (2006) and Grossman (2003 and 2006) for reviews) shows that there tends to be causal associations between education and health status.¹⁰

To test this hypothesis, the education (health) status equation was re-estimated including a health (education) outcome indicator as an additional regressor. To correct for the bias associated with measurement errors in education and health status on the right hand-side of Equation (7), the HDI indexes for longevity and educational attainment were instrumented, as suggested by Bollen (1996), using the other observable variables (average years of schooling for education status, and infant mortality and doctors per population for health status).

The results of the 2SLS regressions allowing for cross-sectoral effects are reported in Table 3. The education model shows that health outcomes are powerful determinants of the population's education status. The effects of the other determinants are comparable to those estimated by OLS, although the estimated coefficients are somewhat smaller in magnitude. Even after controlling for health status, the municipalities located within the metropolitan regions enjoy better conditional education status than those outside these areas. As in the case of the OLS regressions, the municipalities located in well-off states do not necessarily have higher conditional health statuses than their counterparts located in less prosperous states. The result of the Sargan test for overidentifying restrictions does not reject the null hypothesis that the instruments are valid.

Table 3. **Education and health models with cross-equation effects: Instrumental-variable estimations**¹

	Education		Health	
	Coefficient	<i>t</i> -ratio	Coefficient	<i>t</i> -ratio
Health status	0.2213	13.06		
Education status			0.3453	13.17
Income per capita	0.0578	21.45	0.0434	13.09
Transport costs	-0.0035	-2.18	-0.0092	-4.35
Current-to-capital spending	-0.0018	-2.08	-0.0037	-3.73
Resident population	-0.0301	-4.24	-0.0032	-0.54
Population squared	0.0009	2.24	-0.0003	-0.84
Education spending	0.0090	4.14		
Non-education spending	0.0137	5.39		
Health spending			0.0001	0.09
Non-health spending			-0.0017	-0.75
Constant	0.2702	5.83	0.3939	8.58
Sargan test statistic	1.0549		.	
<i>p</i> -value	0.3044			
R-squared		0.84		0.71
No. of obs.		3 927		3 927

1. Heteroskedasticity robust absolute *t*-statistics are reported. The HDI sub-indices for educational attainment and longevity are the scaling (dependent) variables in the education and health models, respectively. All models include 23 dummy variables (not reported) to identify the municipalities belonging to a metropolitan region and 26 dummy variables to identify the states in which the municipalities are located (São Paulo is the reference state). In the education model, health status is proxied by the HDI longevity index and instrumented using the mortality rate and doctors per population. In the health model, education is proxied by the HDI educational attainment index and instrumented with average years of schooling.

Source: Data available from IPEA, and authors' estimations.

10. The correlation between the coefficients of the metropolitan dummies in the education and health equations also suggests the presence of cross-sectoral effects. The Pearson correlation and Spearman rank correlation coefficients among the coefficients in both regressions are, respectively, 0.73 and 0.60 (both significant at the 1% level). This is indicative that education and health statuses might actually have beneficial effects on each other, at least in the metropolitan areas. However, there does not appear to be a strong correlation between the state dummies in the education and health status equations.

The results of the health model, where education outcomes are allowed to affect health status, are also reported in Table 3. The parameter estimates confirm the hypothesis that education outcomes affect the population's health status. As in the OLS estimates, health status improves with income and is adversely affected by distance from dynamic markets, population (in a non-linear fashion) and a composition of local spending that favours current outlays to the detriment of investment. As before, health spending does not seem to have a significant impact on health status. But, unlike the OLS findings, government spending on programmes other than health care no longer appears to affect health status at classical levels of significance. The Sargan test for over-identifying restrictions could not be applied, because the system is just identified. However, the first-stage regression results (not reported) show that the relevant instrument (average years of schooling) is a valid predictor of education outcomes.

As in the OLS regression, local governments located in metropolitan regions fare worse than their counterparts that are not located in these areas, suggesting the presence of negative externalities in service delivery. As for the state dummies, again, the findings are consistent with the OLS results in that municipalities located in more prosperous states do not necessarily fare better than their peers in poorer states.

5. Quantile regression analysis

The technique

Our data set is likely to contain outliers. To deal with the effect of extreme observations on our parameter estimates, we re-estimated the status equations using the instrumental-variable quantile regression technique developed by Chernozhukov and Hansen (2005 and 2006). Median regressions, introduced by Koenker and Bassett (1978), produce estimates that are more robust to outliers than regression lines fitted through the conditional mean. In addition, by fitting regression lines across different conditional quantiles of the response variable, it is possible to investigate the impact of explanatory variables on the whole conditional distribution, and not just at its mid-point.

The Chernozhukov and Hansen (2005 and 2006) estimator is computed as follows. Define the quantile regression for a given quantile τ as $y_i = \alpha(\tau) d_i + \beta(\tau) x_i + e_i$ and $Q_\tau(y_i | x_i) = \alpha(\tau) d_i + \beta(\tau) x_i$, where $Q_\tau(y_i | x_i)$ denotes the conditional quantile of the response variable (y), and d and x are the endogenous and exogenous variables, respectively. Quantile regressions leave the distribution of the error term unspecified; therefore, the methodology is essentially semi-parametric.

For a given quantile τ , estimation of the instrumental-variable quantile regression involves two steps. *First*, the grid of possible values of the parameter α ($\alpha_j, j = 1, 2, \dots, J$) is defined, the τ -quantile regressions are run for $y_i - \alpha_j d_i$ on x_i and ψ_i (where ψ_i is either z_i or the least square projection of d_i on x_i and z_i , where z_i is the set of excluded instruments), and the parameter estimates $\hat{\beta}(\alpha_j, \tau)$ and $\hat{\gamma}(\alpha_j, \tau)$ are recovered. *Second*, among the different values for α_j ($j = 1, 2, \dots, J$), a given $\hat{\alpha}(\tau)$ is selected as a consistent estimate of α for which the value of $W_n = \hat{\gamma}(\alpha_j, \tau)' A \hat{\gamma}(\alpha_j, \tau)$ is closest to zero (A is the inverse of the asymptotic variance-covariance matrix of $\hat{\gamma}(\alpha_j, \tau)$).¹¹ A consistent estimate of β is $\hat{\beta}(\hat{\alpha}(\tau), \tau)$.

11. W_n is a Wald statistic to test the null hypothesis that $\hat{\gamma}(\alpha_j, \tau) = 0$. It has a χ^2 distribution with $\dim(\gamma)$ degrees of freedoms (*i.e.* the number of variables in z_i). This is particularly useful in those cases where there is more than one endogenous variable.

For both the education and health models, we re-ran the regressions in step one of the procedure for a range of parameter values for the endogenous variable set between 2 and -2, with a 0.01 interval.¹² The significance level of the parameter of the endogenous variable is based on the dual-inference procedure suggested by Chernozhukov and Hansen (2008). Following their methodology, the 95% confidence interval of the parameter of the endogenous variable can be obtained by inverting W_n , which involves finding the range of values of $\hat{\alpha}(\tau)$ for which W_n is below its 5% critical value. Chernozhukov and Hansen (2008) show that inference based on this inverse statistic is robust to weak and partial identification and remains valid, even if identification fails completely. Confidence intervals for the other parameters were retrieved through bootstrapping the regression at step one 1 000 times, setting $\alpha_j = \hat{\alpha}(\tau)$.¹³

Regression results

Table 4 reports the estimation results for the education model. The positive and significant effects of health status, income per capita, education outlays and non-education government spending, reported in Table 3, appear to be robust to the presence of outliers in the sample. They seem to hold across the conditional distribution of the response variable, although the effects of health status, income and government spending on education appear to be stronger in the municipalities with lower conditional education status. The relationship between education status and municipality size is still negative and significant, except at the bottom tail of the conditional distribution of the response variable, whereas the effect of the composition of spending between current and capital outlays is negative and significant only for municipalities with low conditional education status. The negative effect of transport costs reported in Table 3 is not robust across the whole conditional distribution of education status; the point estimates are comparable to those obtained for the mean equations, but confidence intervals are much larger.

Table 4. Instrumental-variable quantile regressions: Education outcomes¹

	10 th percentile	25 th percentile	50 th percentile	75 th percentile	90 th percentile
Health status	0.2300*	0.2700*	0.2000*	0.1900*	0.2000*
Income per capita	0.06113*	0.05567*	0.05302*	0.05078*	0.05091*
Transport cost	-0.00186	-0.00352	-0.00283	0.00095	0.003
Current-to-capital spending	-0.00304*	-0.00217	-0.00194	-0.00175	-0.00024
Resident population	-0.01451	-0.02129*	-0.02727*	-0.02564**	-0.01965*
Population squared	0.00006	0.00057	0.00076*	0.00073	0.0005
Education spending	0.01393*	0.00961*	0.00526*	0.00498	0.00611
Non-education spending	0.0106*	0.01039*	0.01732*	0.01659**	0.01317*

1. Statistical significance at the 5% level is denoted by (*) based on bootstrapped 95% confidence intervals (not reported). The HDI sub-index for educational attainment is the scale (dependent) variable. Health status is proxied by the HDI sub-index of longevity and instrumented using the mortality rate and doctors per population. All regressions include metropolitan region and state dummies. The number of observations is 3 927.

Source: Data available from IPEA, and authors' estimations.

The results of the estimation of the health status equations are reported in Table 5. Overall, as in the case of education, the parameter estimates confirm the previous findings: education status and income have a bearing on the population's health status, especially among the municipalities with low conditional health status. The effects of transport costs and the current-to-capital spending ratio are significant only for

12. For both the education and health models, the series of parameter estimates for the endogenous variable were well behaved in the sense that they had a clear global minimum within the range of values considered. We used as ψ_i in the step-one regressions the least square projection of d_i on x_i and z_i .
13. The regressions also include the full set of metropolitan and state dummies. Their parameter estimates are not reported due to space constraints but are available upon request.

selected segments of the conditional distribution of the dependent variable. In addition, population, health outlays and non-health government spending do not have any statistically significant association with health status.

Table 5. Instrumental-variable quantile regressions: Health outcomes¹

	10 th percentile	25 th percentile	50 th percentile	75 th percentile	90 th percentile
Education status	0.3500*	0.3100*	0.3600*	0.3300*	0.2800*
Income per capita	0.05325*	0.05481*	0.04535*	0.035*	0.03729*
Transport costs	-0.01427*	-0.00695*	-0.00726*	-0.00574	-0.00378
Current-to-capital spending	-0.00408*	-0.00253	-0.00448*	-0.00319*	-0.00341
Resident population	-0.00163	-0.00108	-0.00788	-0.01065	-0.01518
Population squared	-0.00026	-0.00034	0.00014	0.00014	0.00029
Health spending	0.00183	-0.00177	0.00011	-0.00056	0.00112
Non-health spending	-0.00464	-0.00068	-0.00646*	-0.00078	-0.00086

1. Statistical significance at the 5% level is denoted by (*) based on bootstrapped 95% confidence intervals (not reported). The HDI sub-index of longevity is the scale (dependent) variable. Education status is proxied by the HDI sub-index of educational attainment and instrumented using average years of schooling. All regressions include metropolitan region and state dummies. The number of observations is 3 927.

Source: Data available from IPEA, and authors' estimations.

4. Conclusions

This paper used Brazilian municipality-level data to shed further light on the relationship between government spending on health care and education and social outcomes. By focusing on sub-national jurisdictions within the same country, the paper avoids the problems arising from the presence of unobservable effects associated with differences in institutional settings, which are difficult to deal with in cross-country analysis. The empirical analysis follows the literature on the selection of social indicators and production inputs but deviates from it by estimating the production functions in a latent-variable setting. This is because the social status of the population is unobservable and, as such, cannot be fully captured by a limited number of imperfectly measured social indicators.

The empirical findings reported above have direct implications for policy. *First*, there is a role for government action to improve social outcomes, especially among the municipalities with low conditional education status, despite the fact that income is the most powerful determinant of social outcomes in health and education. In the case of health, however, an increase in local government spending is unlikely to yield significant improvements in outcomes. *Second*, a focus on education spending alone, which is common in empirical analysis, would result in an underestimation of the role of government in social development. This is because increases in local government spending on non-education programmes were found to matter at least as much for education outcomes as spending on education *per se*. *Third*, there is some scope for gains in economies of scale in the provision of education services among the lowest-performing jurisdictions, which are likely to operate below their optimal service delivery scale, and for different segments of the conditional distribution of health status. *Finally*, there is strong evidence of complementarities between education and health outcomes. This is important, because most empirical studies exclude such cross-sectoral effects. Therefore, policy initiatives in the area of education (health care) that seek complementarities in health care (education) are likely to enhance the effectiveness of government action in support of social development.

Bibliography

- Afonso, J.R. and L. de Mello (2002), "Brazil: An Evolving Federation", in E. Ahmad and V. Tanzi (eds.), *Managing Fiscal Decentralization*, Routledge, London.
- Alves, D. and W. Belluzzo (2005), "Child Health and Infant Mortality in Brazil", *Research Network Working paper*, No. R-493, Inter-American Development Bank, Washington, D.C.
- Baldacci, E., M.T. Guin-Siu and L. de Mello (2003), "More on the Effectiveness of Public Spending on Health Care and Education: A Covariance Structure Model", *Journal of International Development*, Vol. 15, pp. 1-17.
- Bollen, K.A. (1996), "An Alternative Two Stage Least Squares (2SLS) Estimator for Latent Variable Equations", *Psychometrica*, Vol. 61, pp. 109-21.
- Bollen, K.A., J.B. Kirby, P.J. Curran, P.M. Paxton and F. Chen (2007), "Latent Variable Models Under Misspecification", *Sociological Methods and Research*, Vol. 36, pp. 48-86.
- Boueri, R. (2007), "Uma Avaliação da Eficiência dos Municípios Brasileiros na Provisão dos Serviços Públicos Usando Data Envelopment Analysis", in R. Boueri and M. Saboya (Eds.), *Aspectos do Desenvolvimento Fiscal*, IPEA, Brasília.
- Brunet, J.F.G., A.M.A. Bertê and C.B. Borges (2008), *Qualidade do Gasto Público em Educação nas Redes Públicas Estaduais e Municipais*, Secretaria do Tesouro Nacional (STN), Brasília.
- Chernozhukov, V. and C. Hansen (2005), "An IV Model of Quantile Treatment Effect", *Econometrica*, Vol. 73, pp. 735-51.
- Chernozhukov, V. and C. Hansen (2006), "Instrumental Quantile Regression Inference for Structural and Treatment Effect Model", *Journal of Econometrics*, Vol. 132, pp. 491-524.
- Chernozhukov, V. and C. Hansen (2008), "Instrumental Variable Quantile Regression: A Robust Inference Approach", *Journal of Econometrics*, Vol. 142, pp. 379-98.
- Coleman, J.S., E.Q. Campbell, C.J. Hobson, J. McPartland, A.M. Mood, F.D. Weinfeld and R.L. York (1966), *Equality of educational opportunity*, US Government Printing Office, Washington, D.C.
- Cutler, D.M. and A. Lleras-Muney (2006), "Education and Health: Evaluating Theories and Evidence", *NBER Working Paper Series*, No. 12352, National Bureau of Economic Research, Washington, D.C.
- Fayissa, B. and P. Gutema (2005), "Estimating a Health Production Function for Sub-Saharan Africa (SSA)", *Applied Economics*, Vol. 37, pp. 155-64.
- Filmer, D., J.S. Hammer and L.H. Pritchett (2000), "Weak Links in the Chain: A Diagnosis of Health Policy in Poor Countries", *World Bank Research Observer*, Vol. 15, pp. 199-224.

- Flug, K., A. Spilimbergo and E. Watchenheim (1998), “Investment in Education: Do Economic Volatility and Credit Constraints Matter?”, *Journal of Development Economics*, Vol. 55, pp. 465-81.
- Grossman, M. (1972a), “On the Concept of Health Capital and the Demand for Health”, *Journal of Political Economy*, Vol. 80, pp. 223–255.
- Grossman, M. (1972b), *The Demand for Health: A Theoretical and Empirical Investigation*, Columbia University Press, New York, N.Y.
- Grossman, M. (2003), “Household Production and Health”, *Review of Economics of the Household*, Vol. 1, pp. 331-42.
- Grossman, M. (2006), “Education and Non-Market Outcomes”, in E. Hanushek and F. Welch (eds.), *Handbook of Economics of Education*, Vol. 1, North-Holland, Amsterdam.
- Gupta, S., M. Verhoeven and E.R. Tiongson (2002), “The Effectiveness of Government Spending on Education and Health Care in Developing and Transition Economies”, *European Journal of Political Economy*, Vol. 18, pp. 717-37.
- Jack, W. (1999), *Principles of Health Economics for Developing Countries*, Institute of Development Studies, World Bank, Washington, D.C.
- Jöreskog, K.G. and D. Sörbom (1986), *LISREL VI: Analysis of Linear Structural Relationship by Maximum-likelihood, Instrumental Variables and Least Square Methods*. Mooresville, IN.
- Jöreskog, K.G. and D. Sörbom (1993), *LISREL 8*. Mooresville, IN.
- Koenker, R. and G. Bassett (1978). “Regression Quantiles”, *Econometrica*, Vol. 46, pp. 33-50.
- Levine, P. and D.W. Schanzenbach (2009), “The Impact of Children’s Health Insurance Expansions on Educational Performance”, *Forum for Health Economics and Policy*, forthcoming.
- Or, Z. (2000), “Determinants of Health Outcomes in Industrialised Countries: A Pooled, Cross-Country, Time-Series Analysis,” *Economic Studies*, No. 30, OECD, Paris.
- Rajkumar, A.S. and V. Swaroop (2008), “Public Spending and Outcomes: Does Governance Matter?”, *Journal of Development Economics*, Vol. 86, pp. 96-111.
- Sa, E.B. (2005), *Federalismo Fiscal e Descentralização na Atenção Pública à Saúde: O Impacto da Emenda Constitucional 29*, Secretaria do Tesouro Nacional (STN), Brasília.
- Sampaio, M.C.S., F. Cribari Neto and B. Stosic (2008), “Explaining DEA Technical Efficiency Scores in an Outlier Corrected Environment: The case of Public Services in Brazilian Municipalities”, *unpublished manuscript*, University of Brasília, Brasília.
- Sampaio, M.C.S. and B.D. Stosic (2005), “Technical Efficiency of the Brazilian Municipalities: Correcting Non-Parametric Frontier Measurements for Outliers”, *Journal of Productivity Analysis*, Vol. 24, pp. 157-81.
- Sampaio, M.C.S. and F. Sousa Ramos (1999a), “Measuring Public Spending Efficiency in Brazilian Municipalities: A Non-Parametric Approach”, in G. Weternann (ed.), *Data Envelopment Analysis in the Service Sector*, DUV, Gabler, Wiesbaden.

Sampaio, M.C.S. and F. Sousa Ramos (1999b), “Eficiência Técnica e Retornos de Escala na Produção de Serviços Públicos Municipais”, *Revista Brasileira de Economia*, Vol. 53, pp. 433-61.

Self, S. and R. Grabowski (2003), “How Effective is Public Health Expenditure in Improving Overall Health? A Cross-Country Analysis”, *Applied Economics*, Vol. 35, pp. 835-45.

Soares, R.R. (2007), “Health and the Evolution of Welfare across Brazilian Municipalities”, *Journal of Development Economics*, Vol. 84, pp. 590-608.

Thornton, J. (2002), “Estimating a Health Production Function for the US: Some New Evidence”, *Applied Economics*, Vol. 34, pp. 59-62.

Tulkens, H. and P. Van den Eeckaut (1995), “Non-Parametric Efficiency, Progress and Regress Measures for Panel Data: Methodological Aspects”, *European Journal of Operational Research*, Vol. 80, pp. 474–99.

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