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TIAGO ALMEIDA SARAIVA

ESSAYS ON INEQUALITY: DYNAMICS OF INCOME, WAGES UNDER CRISIS AND HUMAN DEVELOPMENT

FORTALEZA
2018

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Tese apresentada ao Programa de Pós-Graduação em Economia – CAEN, da Universidade Federal do Ceará, como requisito parcial à obtenção do título de Doutor em Ciências Econômicas: Área de concentração: Métodos Quantitativos.

Orientador: Prof. Dr. Fabrício Carneiro Linhares.

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Aprovada em: ___/___/______.

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A Deus.

À minha esposa e filha.

Aos meus pais e à minha irmã.

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“Nenhum país está condenado a ser pobre para sempre”
Daron Acemoglu

RESUMO

Esta tese é composta de ensaios sobre a dinâmica da renda e desenvolvimento humano. No primeiro capítulo, investigamos a dinâmica da desigualdade de renda entre os estados brasileiros aplicando o Modelo Bayesiano de Fatores Dinâmicos descrito em Otrok e Whiteman (1998) e Kose et al. (2003) para seis medidas de desigualdade no período 1976-2014. Nossos resultados indicam que o fator nacional responde por 12,8% dos co-movimentos das medidas de desigualdade; os estados mais ricos - e menos desiguais - estão mais expostos ao fator nacional. Empregamos um VECM para investigar a relação entre a flutuação macroeconômica e o fator nacional, e nossos resultados mostram que a macroeconomia Granger causa o fator nacional. O segundo capítulo avalia o impacto distributivo das recentes crises brasileiras de 2014-2015 e 2008-2009 sobre os salários, utilizando o procedimento de decomposição proposto por Rothe (2015). É um exercício interessante, pois essas crises tinham vários aspectos bem distintos. Apesar das diferenças, o efeito de estrutura sempre foi negativo para o quantil mais rico durante a crise. Essa constatação indica que os trabalhadores mais qualificados (e melhor remunerados) são um pouco mais sensíveis a choques salariais, provavelmente resultado de uma menor rigidez salarial no topo da distribuição salarial. Por outro lado, o *efeito de composição* atua na direção oposta, compensando parte do *efeito estrutura* negativo. Finalmente, no último capítulo, propomos um indicador semelhante ao índice de desenvolvimento humano (IDH) do PNUD. O novo índice tem as mesmas três dimensões que o PNUD-IDH, mas incluímos novas variáveis para tornar o IDH-BR mais responsivo e mais capaz de capturar os desafios brasileiros no desenvolvimento humano. A análise fatorial foi utilizada para atribuir pesos a cada variável em cada sub-índice, melhorando a qualidade técnica do IDH-BR. As *scores* captaram grandes diferenças regionais em termos de desenvolvimento humano entre as regiões e estados brasileiros.

Palavras-chave: Desigualdade de renda. Dinâmica salarial. Desenvolvimento humano.

ABSTRACT

This Thesis is composed of essays on economic the dynamics of income and human development. In first chapter, we investigate the dynamics of income inequality among Brazilian states by applying the Bayesian Dynamic Factor Model described in Otrok and Whiteman (1998) and Kose et al. (2003) to six inequality measures over the 1976-2014 period. Our results indicate that the national factor accounts for 12.8 percent of the inequality measures co-movements; the richest states — and less unequal — are more exposed to the national factor. We employ a VECM to investigate the relation between macroeconomics fluctuation and the national factor, and our results show that macroeconomics Granger-cause the national factor. The second chapter assess the distributional impact of the recent 2014-2015 and the 2008-2009 Brazilian crises on wages using the decomposition procedure proposed by (ROTHE, 2015). It is an interesting exercise as theses crises had several very distinct aspects. Despite the differences, the structure effect was always negative for the richest quantile during the crisis. This finding indicates that the more qualified (and better-paid) workers are somewhat more sensitive to shocks on wages, probably a result of less wage rigidity at the top of wage distribution. On the other hand, the composition effect acts in the opposite direction, compensating part of the negative structure effect. Finally, in last chapter we propose a composite indicator near the UNDP human development index (HDI). The new index has the same three dimensions as the UNDP-HDI, but we include new variables to make the BR-HDI more responsive and better able to capture the Brazilian challenges in human development. The factor analysis was used to assign weights to each variable in each sub-index, improving the technical quality of the BR-HDI. The scores captured large regional differences in terms of human development among Brazilian Regions and States.

Keywords: Income inequality. Wage dynamics. Human development.

CONTENTS

1. GENERAL INTRODUCTION

This Thesis is a collection of essays on quantitative methods applied to economic development using Brazilian state-level data. The first essay investigates the dynamics of income inequality among Brazilian states. The second essay evaluates the impact of 2008/2009 and 2014/2015 crisis on wages. Finally, the third essay proposes a composition indicator to measure human development that maximizes the data available, and it is designed to better capture Brazilian challenges.

This Thesis is about socioeconomic contrasts. Brazil is one of the most unequal countries in the world, more specifically, in a list of 115 economies with available data from the 2010-2014 period. Brazil is the 8th; however, the situation was worst in the past. During the 1980s, Brazil was the 2nd in the rankings[1]. Over the last 30 years, the Brazilian economy has experienced many economic shocks: several tries to reduce the inflation from hyperinflation during the 1980s and early 1990s[2]; the economic stabilization in mid-1990s; the Great Recession[3], and the last crisis that started in 2014[4]. However, during this period, Brazil has implemented one of the most successful income transfer programs in the world, playing an important role in income distribution[5][6].

The first essay analyzes the dynamics of income inequality among the Brazilian States by applying the Bayesian Dynamic Factor Model (DFM) to measures of inequality over 1976-2014. Our results indicate that national elements are an important driver of the dynamics of income inequality. Moreover, our results show that macroeconomics Granger-cause the national factor.

In the second essay, we decompose the change in log hourly wages of the Brazilian workers in order to investigate the impact of the crisis on the wage setting.

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[1] Deepak Nayyar, 'The Financial Crisis, the Great Recession and the Developing World', *Global Policy*, 2.1 (2011), 20–32 <https://doi.org/10.1111/j.1758-5899.2010.00069.x>.
[2] Francisco H. G. Ferreira, Phillippe G. Leite, and Julie A. Litchfield, 'The Rise and Fall of Brazilian Inequality: 1981–2004', *Macroeconomic Dynamics*, 12.S2 (2006), 1–40 <https://doi.org/10.1017/S1365100507070137>.
[3] Luiz Fernando Cerqueira, 'Déficit Público, Indexação, Mudanças de Regimes E Expectativas Inflacionárias: A Dinâmica Da Taxa de Inflação No Brasil Entre 1960 E 2005', *Perspectiva Econômica*, 3.2 (2007), 82–126.
[4] Fernando de Holanda Barbosa Filho, 'A Crise Econômica de 2014/2017', *Estudos Avançados*, 31.89 (2017), 51–60 <https://doi.org/10.1590/s0103-40142017.31890006>.
[5] Rodolfo Hoffmann, 'Transferencias de Renda E a Reducao Da Desigualdade No Brasil E Cinco Regioes Entre 1997 E 2004', *Economica*, v.8 (2006), 55–81.
[6] Carlos Góes and Izabela Karpowicz, 'Inequality in Brazil: A Regional Perspective Inequality in Brazil: A Regional Perspective', 2017, 34 <http://www.imf.org/en/Publications/WP/Issues/2017/10/31/Inequality-in-Brazil-A-Regional-Perspective-45331>.

Our results indicate that different degrees of wage rigidity over the quantiles imposes different dynamics of adjustment on wages, the top income earners, i.e., the more qualified works, are more sensitive to shocks, indicated by a negative *structure effect*, which is also responsible for a large amount of reduction in wage inequality. However, the *composition effect* tends to increase the wage gap between the income quantiles.

Finally, in the last essay, we propose an index near the UNDP Human Development Index (HDI). We incorporate new variables to the same dimensions of the HDI, but we innovate by using factor analysis to assign weights to variables in each dimension index. We captured large regional differences in human development across states in the general index and in the three sub-indexes proposed. These regional differences showed a clear pattern: States at North and Northeast are years lagged in comparison to the Southern, Southeastern, and Midwestern ones.

2. THE DYNAMICS OF STATE-LEVEL INCOME DISTRIBUTION AND THEIR RELATION TO MACROECONOMICS: BRAZIL 1976-2014

In this paper, we investigate the dynamics of income inequality among Brazilian states by applying the Bayesian Dynamic Factor Model described in Otrok and Whiteman (1998) and Kose et al. (2003) to six inequality measures over the 1976-2014 period. Our results indicate that the national factor accounts for 12.8 percent of the inequality measures co-movements; the richest states — and less unequal — are more exposed to the national factor. We employ a VECM to investigate the relation between macroeconomics fluctuation and the national factor, and our results show that macroeconomics Granger-cause the national factor.

Keywords: business cycles; Bayesian analysis; income inequality

2.1 Introduction

Brazil is a country of sharp socioeconomic contrasts, not only among individuals, but also between states and regions. According to Ferreira et al. (2006), during the 1980s, Brazil's inequality was the second highest in the world, narrowly behind Sierra Leone. Besides the high poverty and inequality reduction experienced in the more recent years, Brazil is still on the rank of the most unequal countries[1].

Furthermore, the macroeconomic performance was very poor between the 1980s and early 1990s. The average growth rate of GDP dropped from a Chinese performance of 8% per year in the 1970s to an average of 3% per year in the 1980s and 1990s. At the same time, the Brazilian annual inflation rate became the most pressing economic problem, and the unsuccessful tries of stabilization seem to accelerate the inflationary process[2]. Only in 1994, with the implementation of the Real Plan, the Brazilian inflation rates reduced from hyperinflation levels, but still high compared to developed world levels.

Income distribution and macroeconomic instability are, therefore, the central concerns in Brazil. The empirical literature that links these variables is vast, and the

[1]We catalog data from Word Bank Development Indicators (http://databank.worldbank.org), in a list of 115 countries with available data from 2010-2014 period, Brazil is the eight most unequal.
[2] See Barros and Corseuil (2000) and Cerqueira (2007).

results suggest that growth is pro-poor, but results on inflation are mixed for U.S. data (see Metcalf (1969), Thurow (1970), Blinder and Esaki (1978), Beach (1977), Coibion et al. (2017) and others), but cross-country evidence usually supports the hypothesis that macroeconomic instability (low growth, high unemployment, and inflation) isn't a good deal for the poor, as in Galli and Hoeven (2001), Easterly and Fischer (2001) and López (2003).

The empirical evidence focuses on the impact of macroeconomic variables on poverty or some measure of inequality. Yet, direct inequality measures capture not only the macroeconomic dynamics, but also captures regional and state-level policies, notably when the distribution of poverty (and prosperity) are space-dependent. For example, according to Hoffmann (2006), the Bolsa-Familia conditional cash transfer program accounts for 31% in inequality reduction in Brazil over 2002-2004; but in the Northeast region (the poorest one), 87% of the inequality reduction is due to the Bolsa-Família program. A question arises: how to measure the impact of macroeconomic variables on Brazilian inequality when regional forces are acting?

We deal with this problem by applying a Bayesian approach to estimate a dynamic latent factor model (DFM), a standard tool in measuring co-movements between variables, see Kose et al. (2003), Crucini et al. (2008), Neely and Rapach (2011), Kose et al. (2012), Hirata et al. (2013) and others. To give more robustness to our work, we proceed a multilevel DFM using six measures of inequality to extract the factors: Gini index, Theil index and the inequality ratios 1/99, 10/90, 10/40, and 20/20. For example, the variable 10/40 takes the ratio of the mean of the top 10% to the mean of the lowest 40% of incomes. The DFM decomposes the factors that explain the fluctuations in inequality measures in (i) national factor, which captures common fluctuations to all measures of inequality among the Brazilian States; (ii) state factor, refers to common fluctuations of inequality measures in each State; and (iii) idiosyncratic factor. By construction, the factors are orthogonal, so, any shock that affects all measures of inequality in all states will be captured by the national factor.

The idea behind the strategy is: while macroeconomic shocks potentially link co-movements in inequality measures across states, and so, it is better captured by the national factor; national policies against poverty, for example, tend to produce regional co-movements because it concentrates efforts in the poorest States.

So, our proceedings consist in two steps. First, we identify the national factor, which is more likely to be driven by the macroeconomic variables. Second, we proceed by analyzing the link between the national factor and the macroeconomics.

We contribute to the empirical literature analyzing the nature of the dynamics of the Brazilian income distribution, one of the most unequal countries in the world. We use data from 1976 to 2014, covering the high inflation period and the posterior macroeconomic stabilization, capturing two distinct regimes.

Our main finding is that the national factor explains in mean 12.7 percent of the inequality measures co-movements in Brazil, while the state factor explains 72.4 percent and the idiosyncratic factor accounts for 14.8 percent of the full sample. State's characteristics matter in the explanation of the dynamics of inequality: human capital, physical capital, and income are positively related to more dependence on the national factor. This explains why in North and Northeast (the poorer regions), the national factor explains 15 and 5 percent of the variation, respectively; while in South and Southeast (the richest regions), the national factor explains about 21 percent; the state factor explanation varies from 61 to 78 percent. We also test the influence of macroeconomics in the dynamics of the national factor using a VECM; our results show that national factor responds to macroeconomic shocks.

This paper is organized as follows. In section 2.2, we present the Bayesian Dynamic Factor Model. In section 2.3, we present the data and discuss the first empirical results. In section 2.4, we show the link between the national factor and macroeconomic variables. In section 2.5, we present the relation between the national factor and state's characteristics. Section 2.6 concludes.

2.2 Methodological aspects

The dynamic latent factor model (DFM) is specified as in Neely and Rapach (2011):

$$y_{i,t} = \beta_i^n f_t^n + \beta_j^s f_{j,t}^s + \varepsilon_{i,t} \qquad (1)$$

Where $y_{i,t}$ is the standardized and demeaned measures of inequality index for state i $(i = 1, \dots, N)$ from year $t-1$ to $(t = 1, \dots, T)$. The national factor, f_t^n, captures common fluctuations between the inequality measures of all states we consider[3]. The State factors, $f_{j,t}^s$, refers to co-movements of inequality measures in each of the $j = 22$ states. The factor loadings, β_i^n and β_j^s, captures the sensitivity of inequality measures to changes in the latent factors; and $\varepsilon_{i,t}$ is an idiosyncratic component capturing inequality measures, specific dynamics, and measurement errors.

The factors and the idiosyncratic component follow an autoregressive[4] process described in (2)-(4)

$$\varepsilon_{i,t} = \rho_{i,1}\varepsilon_{i,t-1} + \rho_{i,2}\varepsilon_{i,t-2} + \dots + \rho_{i,p}\varepsilon_{i,t-p} + u_{i,t} \qquad (2)$$

$$f_t^n = \rho_1^n f_{t-1}^n + \rho_2^n f_{t-2}^n + \dots + \rho_q^n f_{t-q}^n + u_t^n \qquad (3)$$

$$f_{j,t}^s = \rho_{j,1}^s f_{j,t-1}^s + \rho_{j,2}^s f_{j,t-2}^s + \dots + \rho_{j,q}^s f_{j,t-q}^s + u_{j,t}^s \qquad (4)$$

Where $u_{i,t} \sim N(0, \partial_i^2)$, $u_t^n \sim N(0, \partial_n^2)$, $u_{j,t}^s \sim N\left(0, \partial_{j,r}^2\right)$, and $E(u_{i,t}, u_{i,t-r}) = E(u_t^n, u_{t-r}^n) = E\left(u_{j,t}^s, u_{j,t-r}^s\right) = 0$ for $r \neq 0$. As pointed by Neely and Rapach (2011), the shocks in (2)-(4) are assumed to be uncorrelated contemporaneously to all leads and lags, implying that the national, state, and idiosyncratic factors are orthogonal.

The factor is unobservable, so we cannot use conventional regression techniques. According to (JACKSON et al., 2015), in one-factor case, the principal components analysis, a popular technique for estimating latent factor models, works well. However, as the complexity of the model increases, Bayesian approaches yielded more accurate results. So, in our three-factor case, we employ the Otrok-Whiteman Bayesian approach described in Otrok and Whiteman (1998) and Kose et al. (2003) to estimate the model.

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[3] We consider 22 States in our sample, 4 States and the Federal District were excluded due lack of data.

[4] We used AR(2) specification. Adding more lags did not change our results qualitatively.

To measure the importance of each factor in explaining the volatility of state-level inequality measures, we perform variance decompositions. By construction, all the factors are orthogonal to each other; the calculus of variance decompositions based on equation (1) is straightforward:

$$var(y_{i,t}) = (\beta_i^n)^2 var(f_t^n) + (\beta_i^s)^2 var(f_{j,t}^s) + var(\varepsilon_{i,t}). \qquad (5)$$

Then, the share of variance due to the national factor is:

$$\theta_i^n = (b_i^n)^2 var(f_t^n) / var(y_{i,t}) \ (i = 1, \dots N) \qquad (6)$$

The variance decompositions due to the other factor are calculated similarly.

2.3 Data and the factors

Our empirical analysis uses six annual income inequality measures from 22 Brazilian States. We use the Gini index; Theil index and the inequality ratios 1/99, 10/90, 10/40, and 20/20 to measure the inequality of per capita income among individuals. The data are taken from the Institute for Applied Economic Research (Ipea) database and cover the 1976-2014 period.

Table 2.1

Gini index summary statistics

State	Min	Max	Mean	Std.dev.	State	Min	Max	Mean	Std.dev.
North					Northeast				
Rondônia	0,424	0,642	0,520	0,0445	Maranhão	0,484	0,619	0,556	0,0357
Acre	0,476	0,633	0,565	0,0398	Piauí	0,492	0,666	0,582	0,0489
Amazonas	0,485	0,589	0,535	0,0285	Ceará	0,506	0,660	0,585	0,0396
Roraima	0,393	0,588	0,503	0,0538	Rio Grande do N.	0,496	0,625	0,580	0,0277
Pará	0,486	0,646	0,549	0,0358	Paraíba	0,492	0,656	0,587	0,0421
Amapá	0,429	0,658	0,514	0,0535	Pernambuco	0,502	0,630	0,579	0,0332
Southeast					Alagoas	0,498	0,644	0,572	0,0422
Minas Gerais	0,485	0,614	0,562	0,0375	Sergipe	0,485	0,624	0,564	0,0360
Espírito Santo	0,492	0,657	0,570	0,0439	Bahia	0,527	0,647	0,584	0,0309
Rio de Janeiro	0,525	0,658	0,568	0,0273	Midwest				
São Paulo	0,485	0,559	0,527	0,0206	Mato Grosso*	0,460	0,624	0,551	0,0394
South					Goiás*	0,450	0,638	0,553	0,0408
Paraná	0,453	0,600	0,551	0,0390	Distrito Federal*	0,564	0,634	0,602	0,0180
Santa Catarina	0,421	0,569	0,503	0,0415					
Rio Grande do S.	0,476	0,593	0,542	0,0322					

Author

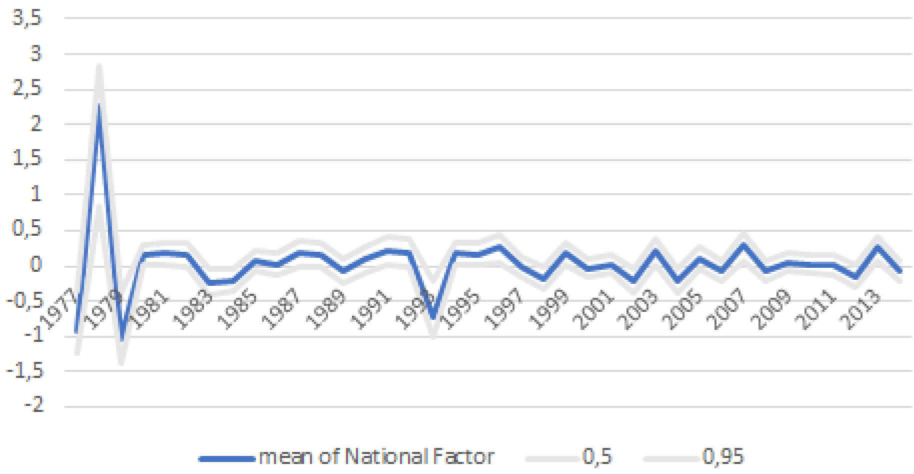
* We excluded the states from the Midwest due subdivisions

The summary statistics in Table 2.1 show that the Brazilian States have experienced high-income inequality during the 1976-2014 period. We decided to show only the Gini index summary statistics because it is the most commonly used measure of inequality, the summary statistics of other measures of inequality show a similar pattern: States at North and Northeast (the poorest ones) present the largest income inequality and States at South, the lowest, followed by Southeast and Midwest regions. The Distrito Federal[5] is the most unequal and the richest unit, and finally, Santa Catarina at South is the state where income is more equally distributed.

[5] The Federal District is the seat of the Brazilian capital and concentrates the public servants with more bargaining power, resulting in the highest inequality observed in our sample. Furthermore, the wage level

It was estimated a model of three dynamic factors: National Factor, State Factor (one for each state), and the idiosyncratic. Graph 1 displays the posterior mean of the National Factor and the bands (gray lines) that form a 90% probability coverage interval for the estimated factor. The behavior of the national factor reflects the macroeconomic environment: the standard deviation of the national factor fell from 0.68 in the 1977-1994 period to 0.16 after the macroeconomic stabilization 1994.

Graph 1: The National Factor



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The posterior mean of the loadings on the national factor is positively related to 20/20 inequality ratio in almost all states, while the loadings on the national factor for 10/40 and 10/90 ratios are negative in nearly all states. Usually, the loadings related to Amapá, Amazonas, Maranhão, and Minas Gerais are highly negative, except for 20/20 ratio. The loadings on the national factor for other inequality measures oscillates between positive and negative without a pattern. Thus, we cannot relate an increase in the national factor to an increase in the inequality in Brazil because of the existence of an inverse relationship between the national factor and some measures of inequality in some states.

adjustments may be more linked to political cycle than to the economic activity. See (LIMA, 2013) for more details.

Graph 2: loadings on the national factor

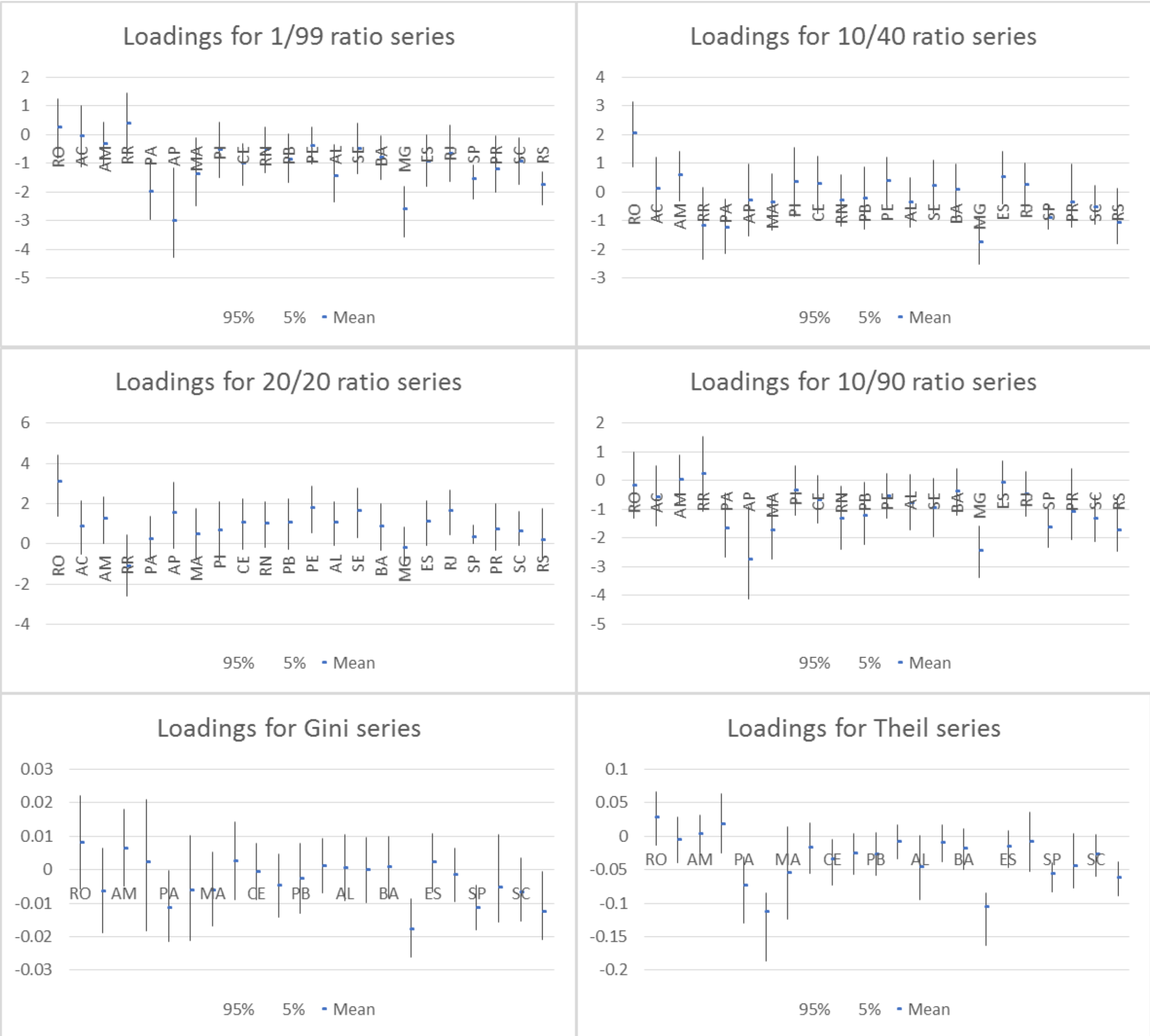

Table 2.2 and Table 2.3 shows the variance decompositions for the full sample. Analyzing the average by region in Table 2.3, we see that the State Factor is clearly the most important in the explanation of the dynamics of the inequality measures, explaining 70% percent of the variation. The poorest and unequal States, at the North and Northeast, are more exposed to the State Factor than the richer and less unequal states, at South and Southeast regions.

Table 2.2

Summary of the variance decompositions: the mean of the variance (of inequality measures) explained by each factor

Region	State	Common	State	Idiosyncratic
North	Rondônia	0,08	0,81	0,12
	Acre	0,01	0,78	0,21
	Amazonas	0,11	0,73	0,16
	Roraima	0,19	0,61	0,21
	Pará	0,33	0,61	0,05
	Amapá	0,20	0,70	0,10
Northeast	Maranhão	0,12	0,70	0,17
	Piauí	0,03	0,72	0,26
	Ceará	0,06	0,80	0,14
	Rio Grande do Norte	0,03	0,80	0,17
	Paraíba	0,09	0,75	0,16
	Pernambuco	0,05	0,84	0,11
	Alagoas	0,03	0,78	0,19
	Sergipe	0,04	0,79	0,16
	Bahia	0,04	0,82	0,14
Southeast	Minas Gerais	0,44	0,48	0,08
	Espírito Santo	0,05	0,79	0,17
	Rio de Janeiro	0,05	0,89	0,06
	São Paulo	0,30	0,60	0,10
South	Paraná	0,19	0,64	0,17
	Santa Catarina	0,09	0,67	0,24
	Rio Grande do Sul	0,34	0,55	0,12

Authors

The national factor responds to 16% of the total of inequality measures variation and is more powerful in explaining the dynamics of inequality of the richer States, at South and Southeast (20%), while at Northeast and North, 5% and 15% of the variation are due the National factor.

Table 2.3

Summary of the variance decompositions by region: the mean of the variance (of inequality measures) from States from the same geographic region explained by each factor

Region	*per capita* GDP(R$ 2014)	Common	State	Idiosyncratic
North	17.879,20	0,15	0,71	0,14
Northeast	14.329,13	0,05	0,78	0,17
Southeast	37.298,57	0,21	0,69	0,10
South	32.687,15	0,21	0,62	0,17
Mean		0,16	0,70	0,15

Authors

To verify the importance of the macroeconomic stabilization in 1994, we perform our sub-sample analysis, allowing for a breakpoint in 1994 when the Real Plan was implemented and reduced Brazilian inflation from hyperinflation levels. The results are shown in Table 2.4.

Table 2.4
Variance decompositions: sub-sample analysis

Region	National Factor			State Factor			Idiosyncratic		
	1976-1994	1995-2014	Δ	1976-1994	1995-2014	Δ	1976-1994	1995-2014	Δ
North	0,17	0,10	-0,07	0,71	0,72	0,02	0,12	0,17	0,05
Northeast	0,09	0,11	0,02	0,75	0,75	-0,01	0,16	0,14	-0,01
Southeast	0,18	0,08	-0,11	0,73	0,73	0,00	0,09	0,19	0,10
South	0,23	0,16	-0,08	0,60	0,66	0,06	0,17	0,18	0,01
Mean	0,17	0,11	-0,06	0,70	0,72	0,02	0,13	0,17	0,04

Authors

We found strong evidence that in the mean, national elements have become less important in driving the dynamics of inequality in Brazil after stabilization. By contrast, the importance of the state and the idiosyncratic factors has increased a little. The exception is the northeast region, whereas the importance of the national elements become more important after the stabilization.

In the next sessions, we relate the national factor to macroeconomic variables and states characteristics. However, we can anticipate that there is evidence linking the dynamics of the national factor to physical — and human capital — and the macroeconomic variables tested by us. Thus, the decrease in the importance of the national factor in explaining the variance of Brazilian inequality after the stabilization is straightforward: less macroeconomic volatility is being transmitted to inequality.

2.4 The national factor and the macroeconomy

What drives the national factor? We know that the answer is something that affects simultaneously the distribution of wealth in all Brazilian States, and as we see in the previous section, it is more powerful in explaining the dynamics of inequality in the more developed states (both richer and less unequal), notably in the pre-stabilization period, which leads us to examine the relationship between macroeconomic fluctuations and the national factor.

Thus, if the national factor reflects the macroeconomic environment, it is expected to find linkages between macroeconomic variables and the national factor, but there is no previous study on this topic. However, works on the link between macroeconomic variables and inequality in Brazil suggest that low inflation, low unemployment, and economic growth tend to reduce inequality Cardoso and Urani (1995) and Barros and Corseuil (2000).

Studies on U.S. data are vast and usually related increases in employment and growth to decreases in inequality or poverty while the effects of inflation are mixed. Metcalf (1969) results show that increases in real wage, employment rates, and in the price level are related to improvements in the relative position of low-income families, and to lower the relative position of high-income families. Thurow (1970) suggests that macroeconomic policies impacts on the income distribution of black and whites: for example, an increase in inflation concentrates income distribution for whites and leads to a more unequal income among blacks. On the other hand, growth does not have much impact on the distribution of income, but is the major factor leading to increases in average income for either blacks or whites. Beach (1977) claim that the bottom end of the income distribution is more sensitive to macroeconomic fluctuations. However, Blinder and Esaki (1978) findings indicate that the poor and the middle suffer less the effects on inflation than the rich, but these effects are much less important than those related to unemployment; similar results are found in Blank and Blinder (1985). In a more recent work, Coibion et al. (2017) concludes that a contractionary monetary policy systematically increases inequality; however, Romer and Romer (1999) conclude that monetary policy cannot permanently reduce inequality. It has impacts on employment and growth (and thus, on the income distribution), but the effect cannot last. Once the boom passes, inequality and poverty return to their normal levels.

In a review of cross-country evidence on the inflation-inequality relation, Galli and Hoeven (2001) concludes that the effect of inflation on income distribution is U-shaped, thus the effect is related to the initial rate of inflation; moving inflation from high to low rates tend to decrease inequality, but the inequality increases when the inflation moves from low to lower rates. Easterly and Fischer (2001) examine the impact of inflation on direct measures of poverty, and find that inflation lowers the share of the bottom quintile, furthermore, they analyzed the answers from 31,869 responders in 38 countries and found that the more vulnerable (the poor, the uneducated, and the unskilled) are more likely to mention inflation as the top national concern. López (2003) examines the impact of pro-growth policies on inequality, their results indicated that these policies can lead to higher poverty in the short run, while in the long run, the results are likely to be pro-poor. However, lower inflation levels would lead to growth and reduce inequality levels. Thus, macroeconomic stability policies belong to the category, which López called the win-win category (pro-growth policies that reduce inequality). Breen and García-Peñalosa (2005) explore the impact of macroeconomic instability (volatility) on inequality. Their results indicate that greater volatility redistributes income from middle quintiles groups to the top quintile. Albanesi (2007) claim that the observed cross-country inflation-inequality correlation is due to the distributional conflict between households of two types (low/high productivity) underlying the determination of the fiscal and monetary policy. Battisti et al. (2014) show that the impact of a reduction of the world interest rates depends on the wealth of the country, in rich countries the inequality increases, while, on the other hand, in poor countries, a reduction of word interest rates reduces inequality. Thus, there is a strong cross-country evidence that shows that it is important to account for the distributional impact of macroeconomic policies.

Our approach is similar to Romer and Romer (1999), Galli and Hoeven (2001) and Easterly and Fischer (2001). We use the annual consumer price index (IPC-Fipe) as our measure of inflation[6], the *per capita* GDP as our cyclical indicator, the overnight rate (SELIC) and real minimum wage. Our dependent variable, however, is the national factor instead of using a measure of inequality.

In this exercise, we employ a Vector Error Correction Model (VECM), and the purpose is to examine the dynamic response of the national factor to shocks on

[6] The IPC-FIPE reflects the cost of living in São Paulo city.

macroeconomic variables. The VECM is a restricted Vector Autoregression (VAR) designed to incorporate long-run relationship between cointegrated variables. Furthermore, it is designed for use with non-stationary time series, which is the case of Brazilian macroeconomic series, as shown in table 2.5.

Table 2.5
Unit Root tests

Tests on individual series in level			Tests on individual series in first differences		
	ADF t-Statistic	PP Adj. t-Stat		ADF t-Statistic	PP Adj. t-Stat
National factor	-5.82*	-14.50*			
Inflation (IPC)	-1.45	-2.74	Inflation (IPC)	-7,8*	-9.12*
Overnight rate (selic)	-1.65	-2.77	Overnight rate (selic)	-7.60*	-7.3*
Minimun wage (mwg)	-0.52	-0.73	Minimun wage (mwg)	-5.33*	-5.33*
per capita GDP (gdp)	-0.27	-0.19	*per capita* GDP (gdp)	-4.98*	-4.95*

* Indicate rejection of the unit root null hypothesis at 1% level. No trend.
Authors

The Akaike Information Criterion (AIC) indicated 3 lags in this model, and once the order of integration of our data is identified, we employ Johansen's method[7] to test for cointegration between the series. Table 2.6 presents conflicting results: trace test indicates the existence of two cointegrating vectors while the maximum eigenvalue test indicates one. Based on simulations of Lütkepohl et al. (2001), we apply the trace tests results.

Table 2.6
Unrestricted Cointegration Rank Tests

No. of cointegrating equations	Eigenvalue	Trace test Trace Stat.	Trace test Critical Value (5%)	Maximum Eigenvalue test Max-Eigen Stat.	Maximum Eigenvalue test Critical Value (5%)
r=0	0.9464	152.67**	69.818	102.459**	33.876
The R ≤ 1	0.5329	50.213**	47.856	26.645	27.584
r ≤ 2	0.3612	23.567	29.797	15.687	21.131

** denotes rejection of the hypothesis at the 5% level
Authors

The estimated output of the Vector Error Correction Model (VECM), considering intercept and trend in the cointegrating equation for the National factor, *per capita* GDP,

[7] See Johansen (1991) and Johansen (1995)

the Brazilian central bank's overnight rate (SELIC), minimum wage (MINW) and inflation (IPC) is in Table 2.7.

Table 2.7

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1	CointEq2			
National factor(-1)	1	0			
IPC(-1)	0	1			
SELIC(-1)	**0.000362***	**-1.015093***			
GDP(-1)	**-0.000292***	**0.147372***			
MINW(-1)	**0.002337***	**-1.125804***			
@TREND(77)	**0.107543***	**-53.11803***			
C	3.156932	-1669.624			
Error Correction:	D(C. Factor)	D(IPC)	D(SELIC)	D(GDP)	D(MINW)
CointEq1	**-0.994221***	-402.1461	419.2595	399.9537	141.0675
CointEq2	**-0.002081***	-0.608042	1.105831	-3.280580	0.106701
D(National factor(-1))	-0.364358	326.8214	-312.2041	-130.6050	-147.2515
D(National factor(-2))	**-0.372866***	253.3570	-31.16280	-671.8575	-130.4780
D(National factor(-3))	**-0.232548***	113.2979	34.29386	-601.0894	-46.60553
D(IPC(-1))	**0.002214***	1.001624	0.867346	2.860206	-0.157890
D(IPC(-2))	**0.001429***	**2.609898***	2.938309	0.759093	-0.067564
D(IPC(-3))	0.000274	**2.726508***	**3.033390***	-0.313963	0.083817
D(SELIC(-1))	**-0.001788***	-0.404429	-0.456678	-3.008407	0.038545
D(SELIC(-2))	**-0.001330***	**-2.134873***	-2.387351	-1.185018	0.049999
D(SELIC(-3))	-9.67E-05	**-2.302517***	**-2.654515***	-0.236608	-0.130687
D(GDP(-1))	5.92E-05	0.014148	0.020130	**0.404282***	**0.025925***
D(GDP(-2))	3.10E-05	0.022030	0.023697	0.181303	0.017531
D(GDP(-3))	**0.000129***	0.040436	0.025592	0.177958	0.013036
D(MINW(-1))	-0.000698	-0.409720	0.897649	-4.588511	-0.094266
D(MINW(-2))	0.000179	-0.425941	-1.637534	-5.796677	**-0.505063***
D(MINW(-3))	**-0.001325***	0.334804	-0.551319	-5.400760	0.189441
C	**-0.077326***	-20.50069	-6.938043	29.95309	-15.83307

Elaborated by Authors.
*Indicate significance 5%

The results in table 2.7 confirm, at a significance level of 5%, the significance of the coefficients related to overnight tax, per capita GDP, and minimum wage related to the cointegrating equation 1. Thus, according to VECM, in the long-run, SELIC, and MINW have a negative impact on the national factor and GDP has a positive impact on the national factor. The cointegrating equation 2 shows that SELIC, GDP, and MINW have a significant long-run effect on inflation. Note that in a VECM the signs of the coefficients are reversed in the long-run. In the short run, IPC and GDP have a positive and significant effect on the national factor, however, SELIC and MINW have a negative impact. We should be careful in interpreting the signs of the coefficients: a positive relationship between GDP and the national factor does not necessarily mean that GDP and inequality are positively related.

As noticed by Sarno et al. (2016), the sign of the relation between an economic variable and the factors does not determine the effect of the economic variable and the variables from where the factors were extracted, in our case, inequality. This happens because the factor loadings can be positive or negative; thus, an economic variable can have a positive relation to some measure of inequality, but is negatively related to the national factor. They focused their analysis on the statistical significance of their slopes and less on their signs.

Table 2.8

VEC Granger Causality/Block Exogeneity Wald Tests

Independent variables	Dependent variable				
	D(NATIONAL_FACTOR)	D(IPC)	D(SELIC)	D(GDP)	D(MINS)
D(NATIONAL_FACTOR)		2.073392	0.511779	3.130662	9.210597**
D(IPC)	33.84894*		19.79500*	3.366472	5.930406
D(SELIC)	50.55209*	100.5073*		5.225210	8.300639**
D(GDP)	16.29664*	0.834285	0.117772		5.955395
D(MINS)	7.937290**	0.570407	1.313844	7.738204	

* and ** Indicates significance at 1% and 5% level, respectively

Authors

In table 2.7, we establish that overnight tax, per capita GDP, and minimum wage and inflation are statically significant, and so, contribute to the variance of the national factor and, hence, to the variance of the inequality in Brazil. In addition, we provide the causal direction estimated by the VECM Granger causality test in Table 2.8, which shows that all macroeconomic variables Granger causes the national factor.

2.5 The national factor and State's characteristics

There are two main questions about factors in the literature: (1) what characteristics explain the state's (or country) sensitivity to factors? (2) what drives the factors? The pattern in Table 2.3 and previous evidence on the dynamics of inequality in Brazil may shed light on the first question.

Results of Hoffmann (2005) and Hoffmann (2006) showed two distinct dynamics: the richer and less unequal states (from South and Southeast regions) are better able to take advantages of the national process of increase in average income; on the other hand, poorer states (from Northeast) have a fundamental dependence on government transfer programs to decrease income inequality.

Thus, it indicates that the state's characteristics may be linked to the dynamics of income inequality measures. To check this argument, we proceed with a simple investigation. In Table 2.2, we present the mean of the variance of inequality measures explained by each factor, we denote θ_{μ}^{c} when it refers to the national factor. Similar to Neely and Rapach (2011) and Kose et al. (2003), we regress θ_{μ}^{c} on a group of potential explanatory variables[8].

Table 2.9
Bivariate Regressions
Dependent variable: mean of the variance decompositions

State characteristic (2014)	Slope	t-statistic	R^2
Illiteracy	-0.027**	-2.28	0.16
Years of study	0.048**	2.63	0.16
High school enrollment	0.005***	1.96	0.17
Work income	0.0001**	2.21	0.15
Proportion of formal work	0.003	1.54	0.11
Unemployment	-0.008	-1.17	0.03
Rate of urbanization	0.004	1.51	0.14
Proxy for physical capital[1]	0.133**	2.52	0.28
Life expectancy	0.015	1.46	0.10

Notes: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. [1] *per capita* electrical energy consumption at industry at 2000.
White heteroskedasticity-consistent standard errors
Authors

The results of the OLS regressions are in Table 2.4. All signs related to significant variables (physical capital, illiteracy, years of study, high school enrollment,

[8] See Neely and Rapach (2011) and Kose et al. (2003) for comments on the limitations of this kind of analysis.

and work income) are as we expected and showed that good educational outcomes (human capital), physical capital and income have a positive relation to θ_{μ}^{c}. It is not a surprise that these variables are significant and with the correct signs. Looking at Gini statistics in Table 2.1 and the results of the variance decomposition in Table 2.2, we already concluded that more income - and less inequality - are related to more dependence on the national factor in determining the dynamics of inequality. At the microeconomic level, work income, physical capital, and human capital are related to the notion of productivity. In a standard competitive market, firms hire labor up to the point that the marginal product of labor equals the real wage. If the firms invest more on equipment — and/or workers become more skilled — it is a consensus they will become more productive, and then firms will respond by adjusting wages. Thus, the results of the bivariate regression in Table 2.4 are as we expected and reflects the fact that the rich are both more capital-intensive and better educated. But how do we explain why the rich states are more likely to have their inequality dynamics governed by the national factor?

The literature about the importance of physical capital and human capital in explaining differences between the level of economic growth is vast. Physical capital is related to be the central concern on economic development since the seminal work of Solow (1957), in which workers and physical capital are elements that compose the aggregate production function. Mankiw et al. (1992) created a version of the Solow's model by including accumulation of human capital as well as physical capital as inputs of the aggregate production function; they are complementary and key factors to explain the dynamics of per capita income.

According to Lucas (1990), this complementary between physical and human capital is one of the reasons that restrict the capital flow to less developed countries. This argument may explain why there is large, physical capital inequality between Brazilian states: According to Barros and Mendonca (1995) Brazil is one of the countries with the highest degree of inequality in education, but it is also one of the countries with the highest sensitivity of wages to the educational level of the worker.

The literature also links the complementary between physical and human capital in explaining differences in income inequality. Griliches (1969) suggests that skill (or education) is more complementary with physical capital than unskilled or unschooled labor. Later, Krusell et al. (2000) claim that the "capital-skill complementarity hypothesis" may explain the rise of the skill premium over the postwar period. They argue that while unskilled workers are competing with cheaper and better capital equipment, the growth in the stock of equipment increases the marginal product of skilled labor, affecting the skill premium. Furthermore, Lindquist (2004) findings suggest that capital-skill complementarity is an important determinant of wage inequality over the business cycle.

If we believe in the capital-skill complementarity mechanism, the distribution of income will depend on the dynamics of investment by firms. As the investment depends on the risk perception by economic agents, consequently, it is expected that capital-intensive firms being more sensitive to economic fluctuations, under these circumstances, richer states are more sensible – in the sense that the level of investment depends more on the perception of risk[9] – to macroeconomics. For example, capital-intensive firms tend to suffer more on capital restrictions in moments of uncertainty. Thus, physical capital and human capital are key factors to account the level of economic growth differences, but also are determinants in the dynamics of inequality in Brazil; insofar these variables are significant on our regressions. These results suggest that more developed states are more likely to have the dynamics of their income inequality governed by the national factor.

[9] See Breen and García-Peñalosa (2005) and Rodrik (1999)

2.6 Concluding remarks

In this paper, we study the dynamics of the inequality for *per capita* income among the Brazilian States. Our results show that state-specific forces are the main drivers of the dynamics of inequality in Brazil while the national factor explains on average 12.7 percent of the variation in inequality. However, the richest (and less unequal, more capital-intensive and more educated) states are more exposed to the national factor dynamics, which is Granger caused by macroeconomic variables.

Hoffmann (2005) and Hoffmann (2006) results indicate that the richer states are better able to take advantages of the national process of increase in average income. Our results suggest that this phenomenon may be linked to the fact that richer states are - on average - more synchronized to the national factor that is driven by the national business cycles.

The remark from this paper to policymakers is to account for the probable change in income distribution due to macroeconomic policies. Furthermore, the results also suggest that reducing educational and physical capital inequality among Brazilian states may be a policy to put all Brazilian states in the same “social cycle.”

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3. DISTRIBUTIONAL CHANGES IN WAGES DURING CRISES: AN ASSESMENT OF COMPOSITION AND STRUCTURAL EFFECTS IN BRAZIL.

This paper assess the distributional impact of the recent 2014-2015 and the 2008-2009 Brazilian crises on wages using the decomposition procedure proposed by Rothe (2015). It is an interesting exercise as theses crises had several very distinct aspects. Despite the differences, the structure effect was always negative for the richest quantile during the crisis. This finding indicates that the more qualified (and better-paid) workers are somewhat more sensitive to shocks on wages, probably a result of less wage rigidity at the top of wage distribution. On the other hand, the composition effect acts in the opposite direction, compensating part of the negative structure effect.

Keywords: wage decomposition; wage inequality; crisis

3.1 Introduction

The vast literature on the impact of economic downturn on the labour market has shown that the intensity and pace of market ajustments to negative shocks depend crucially on the structure of economic sectors and labour market institutions. Fallon and Lucas (2002), for instance, show that currency depreciation during crisis tends to slightly increase labour in the tradeables sector but to decrease it in nontradeables one. The net result depends on the extend to which the decline in the aggregate demand is offset by a switch in demand toward tradeables. Bertola et al., (2012) argues that the effect of crises depends on country’s employment share by economic activity. It is expected that a financial crisis has stronger impact on labour market in USA than in Brazil. On the other hand, the latter will suffer relatively more if there is a sharp fall in agribusiness prices. Several papers also highlight the key role that labour regulations and employment protection programs play in explaining labour market response to crisis (EICHHORST et al., 2010; LESCHKE; WATT, 2010; KLUVE, 2010; CAZES; VERICK; HEUER, 2009). Although the overall negative impact on labour markets is somewhat a general consensus, the distributional effect of economic crisis is still an open (and empirical) question as it depends on several particular features of the economy and labour regulations.

According to Cazes, Verick and Heuer (2009), the labour demand adjusts to an economic shock by two ways: 1. Quantitative adjustment, by rising unemployment or reducing the number of working hours. 2. Price adjustment, through changes in real wages, which can be easy when the crisis is accompanied by high inflation rates. Once nominal wages are rigid downwards even in periods of recession (BRANTEN; LAMO; RÕÕM, 2018), the adjust can be made by not offering compensatory pay increments as inflation rises.

Notwithstanding the nominal wage rigidity, price adjustments as a reaction to crisis are not uncommon in developing countries and have distributional consequences. Analising the effect of 1990s financial crises Fallon and Lucas (2002) found that the dominant effect of the was cut in real wages, rather than employment or working hours. Moreover, the evidence suggests that structural adjustments in response to crisis have distributional consequences; deep wage cuts are related to sustain equality through the crisis (Indonesia, Turkey and Mexico), on the other hand, high unemployment rates and small wage cuts (Argentina, Korea and Thailand) might have exacerbated inequality. The Philippine labour market reacted to 2008-2009 crises by reducing real wages, but the decreases were most pronounced at the upper ends of wage distributions (VAN DER MEULEN RODGERS; MENON, 2012). Schmidt and Vaughan-Whitehead (2011) confirmed the decline in the real wages in some South-East Europe countries during the financial crisis. Distributional aspects are relevant: Hungary have experienced an increase in wage Gini coefficient and Romania limited increases in minimum salary, enlarging the disparities between bottom and top deciles.

It seems the more vulnerable groups during crisis are the low-skill workers, particularly the young people who are competing for the same jobs with the more experienced workers (VAN DER MEULEN RODGERS; MENON, 2012; AARONSON; BRAVE; SCHECHTER, 2009; CAZES; VERICK; HEUER, 2009); the woman, due discriminatory preferences in the labour market, as reported in Forbes(2011); the non-standard workers (temporary contracts), who have less access to social benefits and less stability of their jobs (EICHHORST et al., 2010; HIJMAN, 2009), and the workers in the informal sector, because of the absence of any labour-law protection and the non-guaranteed minimum wage.

This paper focused on the price adjustment mechanism of the labour demand in the private sector and its distributional consequences during the recent crises. We apply the decomposition procedure proposed by Rothe (2015) in the log hourly wages of the Brazilian workers, in order to investigate the wage setting under crisis, distributional aspects and its relation to workers characteristics. Brazil is an interesting case because it is one of the most unequal countries in the world and during the period analyzed Brazilian workers have experienced two crises according to the Business Cycles Dating Committee (CODADE): the great recession, marked by the bankruptcy of Lehman Brothers in 2008, and a deeper (and longer) – both political and economic - crisis, which started in 2014[1], resulting in a significant fall of the per capita gross domestic product, currency depreciation, increases in inflation and rising interest rate.

There are few reports on wage decomposition for periods of crisis, and they generally focused on the wage premia of certain group of workers. Dauth, Schmerer and Winkler (2015) found that the wage premium paid by the exporting firms in Germany during the 2007-2008 crisis started to be adjusted downward one year earlier than non-exporters. Capuano, Lai and Schmerer (2014) examines the wage premium of the US finance sector before and after the financial crises and found that the premium decreased slightly during the period. Nikolic, Rubil and Tomić (2017) results indicate that the 2008 crisis exacerbated the differences between public and the private sector wage distribution further and women employed in the private sector seems to be the most vulnerable group in Serbia and Croatia. In Italy, the average public sector wage premium decreased from 15% to 11%, because working in the public sector is associated with better wages and because women are more likely to be employed in the public sector, the gender gap increased from 4% to 8% between 2008-2012 (PIAZZALUNGA et al., 2016).

We use microdata collected by the Brazilian Institute of Geography and Statistics (IBGE). Our results indicate that the wage setting in response to crisis differs on quantiles. A strong negative structure effect – due to changes in the remuneration of the characteristics of the labour force - was found in the 90% quantile, i.e. the more qualified workers, at the top end of wages distribution are more likely to have their real wages adjusted downward. The composite effect, due to distributional changes in observed labour force characteristics (education, experience, union coverage, etc.) is positive, but does not offset the structure effect. This is also responsible for a large amount of reduction in wage inequality between quantiles. These results are robust for the 2014/2015 and 2008/2009 crises.

[1] A discussion about the determinants of the crisis that started in 2014 can be found in (BARBOSA FILHO, 2017).

The remainder of this paper is organized as follows. In next session, we discuss the methodological aspects of this paper. In section 3, we present the data and the summary statistics of the log hourly wages and the covariates used in the decomposition. Section 4 shows the results. Section 5 concludes.

3.2 Decomposition method

In this paper, we apply the method reported in Rothe (2015) to decompose between-group differences in distributional features of log hourly wages between two years in two components: *structural* and *composition effects*.

The first one refers to differences in the relationships that link the characteristics of the labour-force (covariates) to the log hourly wage (outcome); in other words, it reflects the return on these characteristics (RICHEY; ROSBURG, 2017) and is also called *price effect* as in Machado and Mata (2005) . For example, a decreasing demand in labour market may pressurize the remuneration of workforce characteristics downward (structural effect acting). The second refers to differences in the observable covariates across groups, for example: ceteris paribus, a gain in the mean of log hourly wages between certain time intervals may be explained by the increase in the rate of unionization of workers (composition effect acting).

These effects can also be obtained by the well-known Oaxaca-Blinder (BLINDER, 1973; OAXACA, 1973) procedures when the researcher restricts the relationships between the mean of the outcome and the covariates to a linear model. However, the results of this kind of decomposition depend on the order of the covariates in the model (the path dependent problem); general distribution features, such as quantiles, cannot be used and it is restricted to a linear specification. We can manage these issues by using other recent methods[2]; however, Rothe (2015) innovates by further decomposing the composition effect in three components (consider two covariates): (i) "direct effect" of each covariate (education and experience) - due to between-group differences in their respective marginal distributions. (ii) "two way" or "higher order effects" due to the interplay between two or more marginal distributions – measures the additional contribution to the fact that the population in $t = 1$ is both more educated and have more experience than in $t = 0$. The last effect captures the fact that distribution of education between different groups of experience differs between $t = 0$ and $t = 1$, and it is called "*dependence effect"*. Figure 1 shows the decomposition framework.

[2] Se (FIRPO; FORTIN; LEMIEUX, 2009) literature review

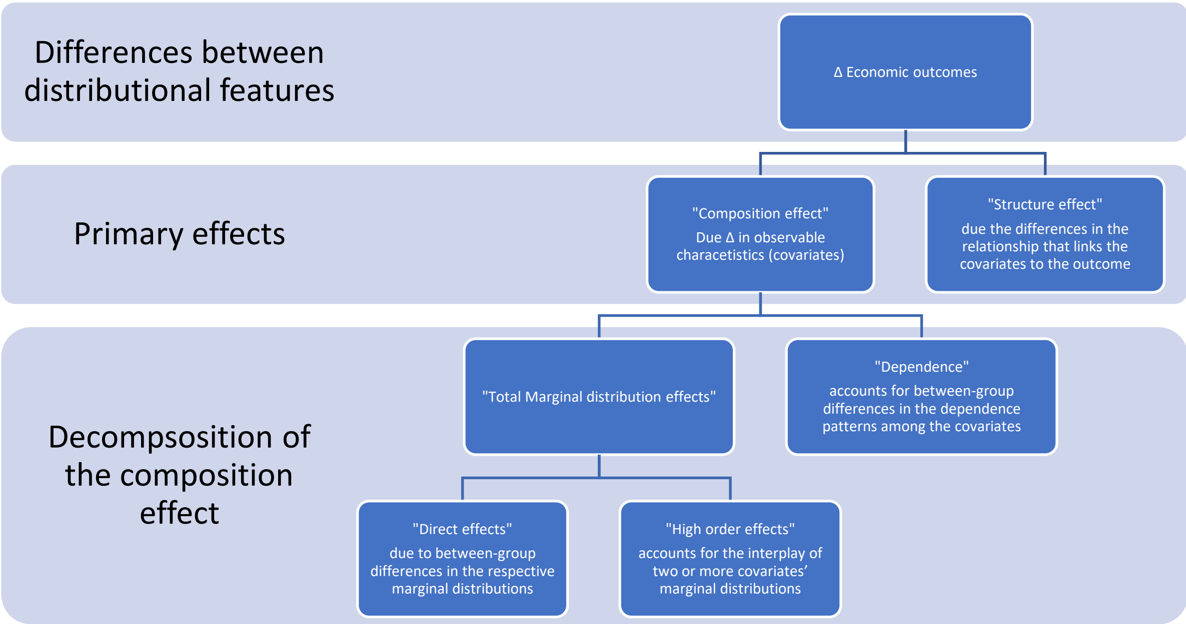


Figure 1: Rothe's (2015) decomposition scheme

Formally: Let $W_i^{t=0}$ be the log hourly wage for any individual i in the base year $t = 0$ and $W_h^{t=1}$ is the log hourly wage for any individual h in that year $t = 1$ and the corresponding distributions $F_W^{t=0}$ and $F_W^{t=1}$, or F_W^t, t ∈ {0,1}. For example, when we perform the analysis of the 2014/2015 crisis, the base year $t = 0$ is 2014 and $t = 1$ is 2015. Similarly, F_X^t is the distribution that corresponds to a d-dimensional vector of observable covariates (years of education, years of labour market experience and dummies for gender, race, informal sector workers, union coverage and a dummy that differentiates workers from the North/Northeast regions to workers from other regions); and finally, $v(F)$ is a distributional feature – mean, median, Gini, etc.

The objective is to understand how the observed difference between distributional features $v(F_W^t)$, equation (1), is related to differences between the distribution of the covariates, F_X^t.

$$\Delta_O^v = v(F_W^{t=1}) - v(F_W^{t=0}). \quad (1)$$

To this end, Rothe (2015) defines a counterfactual outcome distribution $F_W^{t|j}$ that combines the conditional distribution in time t with the covariate distribution in $j \neq t$:

$$F_W^{t|j}(\omega) = \int F_{W|X}^t(\omega, x) dF_X^j(x) \quad (2)$$

where $F_W^{t|j}(\omega)$ is the distribution of the outcomes after the counterfactual experiment, in which, $F_{W|X}^{t}(\omega, x)$ is the conditional distribution of log hourly wage given the values of the covariates in t, but the distribution of covariates in time is changed from F_X^t to F_X^j.

One can decompose the observed between-year, 2014-2015, difference, Δ_o^v in two effects:

$$\Delta_O^v = \Delta_S^v + \Delta_X^v \qquad (3)$$

where

$$\Delta_s^v = v(F_W^{2015}) - v\left(F_W^{2014|2015}\right) \text{ and } \Delta_x^v = v\left(F_W^{2014|2015}\right) - v(F_W^{2014}).$$

The first term Δ_S^v is a *structure effect,* solely due to differences in the conditional CDFs given values of covariates between the two years and Δ_X^v is a *composition effect*, solely due to differences in the distribution of the covariates between 2014-2015, as discussed in the introduction of this section.

Rothe (2015) highlights that in general, it is not usually possible to express the composition effect as the sum of terms that each depend on the marginal distribution of a single covariate only[3]. Because of the "interaction terms" resulting from the interplay of two or more marginal distributions and also the "dependence terms" resulting from between-group differences in the dependence pattern among the covariates. However, Rothe's decomposition disentangles the covariate's marginal distribution from their dependence structure, using results from copula theory.

We can write the CDF of X^t as

$$F_X^t(x) = C^t(F_{X_1}^t(x_1), \dots, F_{X_d}^t(x_d)) \text{ for } t \in \{0,1\}, \qquad (5)$$

where C^t is a copula function and $F_{X_k}^t$ is the marginal distribution of the kth component of X^t and $t \in \{0,1\}$ are the two non-overlapping subgroups, {2014, 2015} in our analysis. The copula function can be interpreted as the object that captures the dependence structure. The distributional transform C^t is not unique when the covariates are discrete, which is required to proceed with the decomposition. Thus, in

[3] See the "simple example" in Rothe's paper for an illustration.

the presence of discrete covariates Rothe (2015) imposes certain parametric restrictions on the functional form of the copula.

Further, we use the same notation as reported in Rothe (2015) to denote any element of the d-dimensional product set of $\{0,1\}^d$ by a boldface letter, we define the distribution of outcome in a counterfactual setting where the structure is as in group t, the covariate distribution has the copula function of group j, and the marginal distribution of the lth covariate is equal to the that in group $\boldsymbol{k}_l$ by

$$F_W^{t|j,\boldsymbol{k}}(\omega) = \int F_{W|X}^{t}(\omega, x) dF_X^{j,\boldsymbol{k}}(x) \qquad (6)$$

with

$$F_X^{j,\boldsymbol{k}}(x) \equiv C^t\left(F_{X_1}^{\boldsymbol{k}_1}(x_1), \dots, F_{X_d}^{\boldsymbol{k}_d}(x_d)\right). \qquad (7)$$

Once we capture the dependence structure using copulas, the composition effect can be decomposed into two parts: the *marginal effect* Δ_M^v, due to differences in the marginal distributions between-groups and a *dependence effect* Δ_D^v, due to differences between groups in their copula functions.

$$\Delta_X^v = \Delta_M^v + \Delta_D^v \qquad (8)$$

To further decompose the total marginal effect Δ_M^v into portions due to specific covariates, the “direct effect” of each covariate - due to between-group differences in their respective marginal distributions, and “two way” or “higher order effects” due to the interplay between two or more marginal distributions, we, as Rothe (2015) write $1 = (1, 1, \dots, 1)$ and $0 = (0, 0, \dots, 0)$ and denote by e^l the lth unit vector and put $|\boldsymbol{k}| = \sum_{l=1}^{d} \boldsymbol{k}_l$. For any distributional feature v we define the parameter

$$\beta^v(k) = v\left(F_X^{0|0,\boldsymbol{k}}\right) - v(F_X^0), \qquad (9)$$

which is interpreted as the effect of a counterfactual experiment conducted in group 0 that changes the respective marginal distribution of those $|\boldsymbol{k}|$ covariates in which $\boldsymbol{k}_l = 1$ to their corresponding counterpart in group 1, while holding everything else constant.

For $d = 2$ the composite effect is given by

$$\Delta_X^v = \Delta_M^v(e^1) + \Delta_M^v(e^2) + \Delta_M^v(1) + \Delta_D^v \qquad (10)$$

where

$$\Delta_D^v = v\left(F_X^{0|1,\mathbf{1}}\right) - v(F_X^{0|0,\mathbf{1}}) \text{ and } \Delta_M^v(1) = \beta^v(\mathbf{1}) - \beta^v(e^1) - \beta^v(e^1).$$

The first two terms $\Delta_M^v(e^1)$ *and* $\Delta_M^v(e^2)$ are the *direct effects* of the 1st and 2nd covariates to the composite effect. $\Delta_M^v(1)$ captures the "pure" interaction effect: $\beta^v(\mathbf{1})$ is the joint contribution of between-group differences in the marginal covariate distribution of between the two groups adjusted by the direct contribution of the 1st and 2nd covariate. Finally, Δ_D^v is the *dependence effect*.

3.2.1 Estimation Process

Rothe (2015) focused on standard statistical techniques to estimate the model described below. The composition effect is estimated by simulating the counterfactual experiment for any feature v in equation (6) and (7)

$$F_W^{t|j,\mathbf{k}}(\omega) = \int F_{W|X}^t(\omega, x) dF_X^{j,\mathbf{k}}(x) \qquad (6)$$

with

$$F_X^{j,\mathbf{k}}(x) \equiv C^t(F_{X_1}^{\mathbf{k}_1}(x_1), \dots, F_{X_d}^{\mathbf{k}_d}(x_d)) \qquad (7)$$

Each element is estimated as follows:

- The right side of equation (6) can be integrated by standard methods;
- The estimator for the univariates' distribution functions $F_{X_1}^t$ is the usual empirical CDF, given by $\hat{F}_{X_1}^t = \frac{1}{n_t} \sum_{i=1}^{n_t} \mathbb{I}\{X_{li}^t \leq x_l\}$;
- The conditional CDFs estimators $\hat{F}_{W|X}^t$ are obtained using the Foresi and Peracchi (1995) approach where the resulting estimate of the conditional CDF is given by $\hat{F}_{W|X}^t = \Phi(x'\hat{\delta}^t(y))$. The parameter $\hat{\delta}^t(y)$ is the maximum likelihood estimated in a Probit model;
- Copula functions are modeled using the Gaussian copula model given by $C_\Sigma(u) = \Phi_\Sigma^d(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)$ with Φ_Σ^d is the CDF of a d-variate standard normal distribution with correlation matrix Σ and Φ the standard normal CDF.

3.3 Data

The data used in this paper are taken from Brazilian National Survey of Households (PNAD), implemented by the Brazilian Institute of Geography and Statistics (IBGE) and covers the 2007-2015 period. We restrict our analysis to the log hourly wage of the private sector workers, residents in urban areas and aged between 18 and 65. After applying these filters, our sample contains information on more than 100,000 workers in each year.

The wages are expressed in 2015 prices using the IPCA[4] index. The covariates are years of education, years of labour market experience[5] and dummies for gender, race, informal sector workers, union coverage and a dummy that differentiates workers from North/Northeast regions to workers from other regions (South, Southeast, and Midwest).

The summary statistics are in Table 3.1. Between 2006-2015 the log hourly wage rose from 3,14 to 3,47; the average mean years of education and the experience rose one year; the union coverage in the period is volatile, starting at 17% in 2006, fell to 9,4% in 2009 and returns to the 2006 level in 2015. The increase in participation of the formal work and non-whites in the economy is noticeable (about 5 percentage points), but the change in the participation of Northern and Northeastern workers in the total sample is less significative.

Table 3.1

Descriptive Statistics

	2006	2007	2008	2009	2011	2012	2013	2014	2015
Log hourly wage	3,14	3,19	3,24	3,27	3,37	3,44	3,48	3,5	3,47
Education (years)	9,44	9,54	9,71	9,85	9,99	10,19	10,29	10,38	10,54
Experience (years)	21,2	21,16	21,42	21,41	21,33	21,51	21,78	22,11	22,55
Union coverage %	17,18	15,93	16,43	15,93	15,06	9,40	13,76	14,56	17,09
Informal sector %	45,48	44,64	42,70	42,33	40,36	39,97	39,03	39,78	40,69
Male %	59,39	59,37	59,33	59,08	58,96	58,71	58,42	58,43	58,61
White %	53,34	52,76	51,41	51,53	50,37	48,85	48,87	47,46	47,30
NNE %	27,18	27,12	27,39	27,25	26,85	27,50	27,37	27,96	27,88

Source: Authors calculation from PNAD microdata. Wages are expressed in 2015 prices.

[4] IPCA is a national consumer price index elaborated by IBGE and focused on urban families, with monthly income, from any source, ranging from 1 (one) to 40 (forty) minimum wages. From www.ibge.gov.br

[5] Defined as age minus the age of the first job.

To better understand the trends in the composition of the labour force in a context of a highly unequal country, we present the graph of summary statistics by quantiles in the Annex 1, for recent years. The graphs describe the high inequality in wages and covariates. The richest 10% earn almost 20 times more than the poorest 10% and the difference in education is about six years. By in large, the high-income earners are male, white, live in South, Southeast or Midwest regions, and work in the formal sector.

The differences in workforce composition are large not only between the extreme quantiles but also between neighboring quantiles. For example, the mean wage of the 9^{th} is less than 50% of the mean wage in the 10^{th} quantile and the participation of informal workers in the first quantile is more than three times higher than in the second quantile. However, quantiles in the middle tend to be less uniform.

Besides the well-observed increase in education and experience, the participation of non-whites is increasing in all deciles, the male participation presents a slight decrease over 2009-2015 and NNE workers are losing participation in the richest deciles and increasing participation in the poorest ones (the participation of NNE on the Brazilian total population is 35,6%). The data show not only race and gender discrimination in the labour market but also large regional and sectoral disparities.

3.4 Results

Table 2 presents the results of the estimated decomposition of differences in the distribution of log hourly wages of workers in 2014 and 2015, the first years of the most recent recession in Brazil, for four distributional features: mean, and the quantiles at 10%, 50%, and 90%. The elements of the proposed decomposition defined in the previous section are shown in Table 3.2.

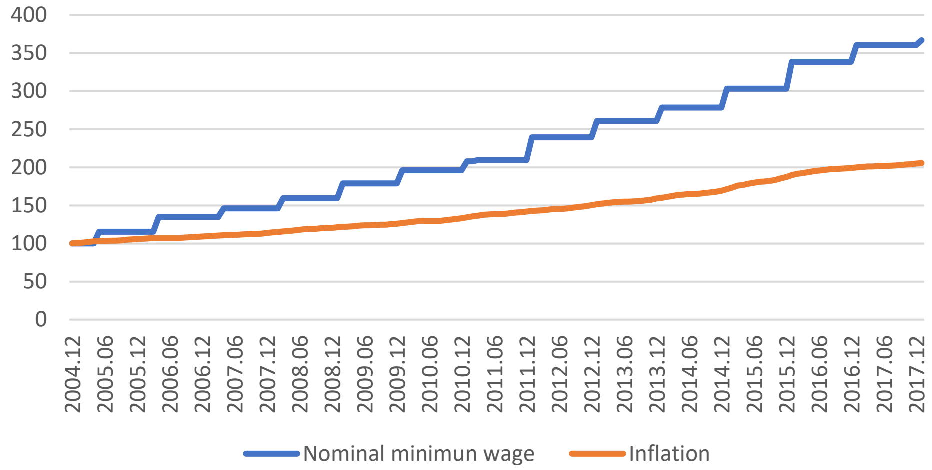
Table 3.2
Estimated Decomposition of Differences in Distribution of Log Hourly Wages of Workers in 2014 and 2015

	mean	se	Q90	se	Q50	se	Q10	se
Observed Difference	-3,422	0,519	-4,037	1,772	-2,735	0,512	-1,091	0,615
Structure Effect	-5,399	0,322	-9,155	1,597	-2,823	0,450	-0,979	0,442
Composition Effect	1,978	0,422	5,118	1,786	0,088	0,221	-0,112	0,416
Dependence Effect	-0,153	0,393	2,099	2,156	0,007	0,211	-0,180	0,416
Marginal Distr. Effect	2,131	0,190	3,019	1,117	0,080	0,223	0,068	0,071
"Direct" effects								
Education	1,381	0,147	1,909	0,253	0,046	0,123	0,068	0,036
Experience	0,566	0,062	0,727	0,100	0,023	0,114	0,022	0,006
Union coverage	0,210	0,033	0,375	0,067	0,010	0,082	0,001	0,004
Informal sector	-0,100	0,028	0,017	0,009	-0,001	0,021	-0,032	0,014
Male	0,035	0,063	0,032	0,053	0,001	0,047	0,002	0,006
White	-0,012	0,026	-0,017	0,035	0,000	0,012	0,000	0,002
NNE	0,038	0,055	0,014	0,018	0,002	0,037	0,005	0,01
"Two-Way" effects	0,013		-0,038		-0,001		0,002	

Estimated by authors

The observed difference is negative for all distributional features, indicating a decrease in log hourly wages between 2014-2015. However, the structure and the composition effects are acting in opposite directions. The composition effect, due to differences in the distribution of the covariates (characteristics) between 2014-2015 is positive and significant (at 1% level) in mean and in 90% quantile. This reflects the direct effects of the increase in education and experience years and the expansion of union coverage among the mean and 90% quantile; however, the increase in the participation of informal workers acts reducing the log hourly wages. Years of experience and a dummy for informal sector are significant at 1% and 5% respectively for the 10% quantile. The “direct” effects due to other covariates, the “two-way” interactions and the dependence effect are insignificant at 5% level. The structure effect, due to the differences in the relationship that links the characteristics of the worker to the outcome, reflects the return on these characteristics, and is negative in all measures. The negative structure effect is stronger at 90% quantile, and decreases over the 50% and 10% quantiles, indicating that the return on observed characteristics – the price effect - decreased more among the richest group than the poorest.

Figure 3.2: Minimum wage vs Inflation



Source: IPEADATA. Inflation is measured by the IPCA index. Base: 2004.12 = 100

Between 2014.09 – 2015.09, the period in which our microdata was collected, the accumulated Brazilian official inflation rate, measured by the IPCA, was 8,57%. The strong negative structure effect may be reflecting the adjustments in salary below the inflation rate, and thus, a decrease in real wages during the period. In turn, lowering the lower wages through inflation may not be an option, once the minimum wage is ruled by an equation that precludes the employers from conceding adjustment below the inflation rate (see Graph 2). Therefore, the firms face nominal wage rigidity in Brazil, but at the lower quantiles of the distribution of salary (near the minimum wage), there is some degree of downward real wage rigidities (MALONEY; MENDEZ, 2004) even in high inflation periods, due the indexation of the minimum salary to prices. This may explain why the price adjust at the upper tail of the log hourly wages distribution is more pronounced than at the bottom. Moreover, Messina and Sanz-de-Galdeano (2014) results indicate that indexation in Brazil affects on average 43 percent of the workforce, which is much more than the percentage of workers receiving the minimum wage (about 9%).

Now we again discuss the union coverage. It is important to highlight that the bargaining power of the Brazilian unions is reported to have prevented real salaries from decline after the economic stabilization. Messina and Sanz-de-Galdeano (2014) and a rise in unionism is associated with higher average wages (MENEZES-FILHO et al., 2008) . Table 3.1 shows the ratio of workers covered by unions, the rise from 14,56% in 2014 to 17% in 2015, is particularly concentrated in the richest groups (see the annex), while at the median, the share of unionized workers decreased and at the bottom, the share remains stable. These distributional aspects are reflected in our decompositions; the positive and significant at 1% estimate associated to the richest quantile and mean indicated that being unionized is a good deal. The distributional changes in the share of unionized workers at median and at the bottom of the distribution does not make a difference, even if the literature relates declines in union coverage to a negative impact on mean wages (ROTHE, 2015). Perhaps these wages in the neighborhood of the minimum wage are already protected by the indexation mechanism.

Thus, firms responded to the 2014/2015 crisis by reducing the return of covariates, indicated by a strong negative structural effect, however, the wage setting in response to macro shocks differs on quantiles – top income earners tend to be more exposed - but the change in workers' characteristics (more education, more experience, and more union coverage) have reduced the negative impact of the price adjustment on the richest quantile.

Table 3.3

Distributional impacts in Log Hourly Wages of Workers in 2014 and 2015

	Variance	se	q90q10	se	q90q50	se	q50q10	se
Observed Difference	0,775	1,061	-2,946	1,998	-1,301	1,831	-1,645	0,708
Structure Effect	-1,836	0,370	-8,175	1,587	-6,331	1,654	-1,844	0,529
Composition Effect	2,611	0,983	5,230	1,962	5,030	1,784	0,200	0,453
Dependence Effect	1,505	0,981	2,279	2,323	2,092	2,174	0,187	0,438
Marginal Distr. Effect	1,106	0,108	2,951	1,125	2,938	1,133	0,013	0,221
"Direct" effects								
Education	0,573	0,086	1,840	0,252	1,862	0,285	-0,022	0,131
Experience	0,249	0,035	0,706	0,097	0,705	0,148	0,001	0,114
Union coverage	0,169	0,029	0,374	0,067	0,366	0,111	0,008	0,082
Informal sector	0,135	0,037	0,049	0,020	0,019	0,023	0,030	0,025
Male	0,003	0,006	0,030	0,047	0,031	0,057	-0,001	0,045
White	-0,005	0,012	-0,016	0,033	-0,017	0,033	0,000	0,011
NNE	-0,015	0,023	0,009	0,008	0,012	0,034	-0,003	0,035
"Two-Way" effects	-0,003		-0,041		-0,040		0,000	

Estimated by authors

The distributional impact of the 2014/2015 crisis on wages is found in Table 3.3. The observed total change is negative, but it is significant only for Q50-10 difference. This is due to the effect of opposing forces: while the price effect is strong and negative in all measures considered, it is counterbalanced by the composition effect in Q90-10 and Q90-50, but, as the composition effect in Q50-10 is small, it does not offset the structure effect. In sum, the price effect acts reducing the log hourly wage inequality between the quantiles and the variance of the distribution, but the differences in the composition of the workforce acts in the opposite way, raising the differences between quantiles and the variance.

We proceed with our analysis by applying the same procedures to the previous - and less deep - recession, between 2008-2009. The 90% quantile did not suffer wage reduction because the negative structure effect and the positive composition effects are almost equivalent. However, the price effect is positive for other distributional features, and surprisingly, the composition effect is highly negative for the poorest quantile. Results in Table 3.4.

Table 3.4

Estimated Decomposition of Differences in Distribution of Log Hourly Wages of Workers in 2008-2009

	mean	se	Q90	se	Q50	se	Q10	se
Observed Difference	1,911	0,810	-0,996	2,229	2,774	0,712	-3,485	2,089
Structure Effect	2,222	0,321	-5,088	1,335	2,737	0,622	2,279	0,866
Composition Effect	-0,311	0,796	4,092	1,991	0,038	0,183	-5,764	2,117

Distributional impacts in Log Hourly Wages of Workers in 2008-2009

	Variance	se	Q90-10	se	Q90-50	se	Q50-10	se
Observed Difference	2,286	1,377	2,489	3,507	-3,770	2,251	6,259	2,126
Structure Effect	-1,836	0,355	-7,367	1,528	-7,825	1,151	0,457	1,062
Composition Effect	4,122	1,260	9,856	3,271	4,055	1,963	5,802	2,098

Estimated by authors

The results are qualitatively equivalents: higher wages are more sensitive to price adjustments, which reduces the wage inequality between quantiles and the variance of the distribution and the composition effects act in the opposite direction.

To understand how the wage setting responds to a different macroeconomic background, we proceed with a decomposition for the 2009-2013 interval, a period of expansion according to CODACE. Tables 3.5 and 3.6.

Table 3.5

Estimated Decomposition of Differences in Distribution of Log Hourly Wages of Workers in 2009 and 2013

	mean	se	Q90	se	Q50	se	Q10	se
Observed Difference	19,934	0,592	13,949	2,398	19,563	0,55	26,807	1,467
Structure Effect	16,429	0,295	11,034	2,199	16,405	0,205	24,12	1,324
Composition Effect	3,505	0,552	2,914	1,282	3,158	0,51	2,687	2,11
Dependence Effect	-0,522	0,515	0,374	0,643	-0,103	0,089	-2,619	2,473
Marginal Distr. Effect	4,026	0,208	2,54	0,912	3,261	0,453	5,306	0,798
"Direct" effects								
Education	3,931	0,175	2,782	0,91	3,292	0,457	2,697	0,593
Experience	0,352	0,077	0,331	0,517	0,317	0,117	0,06	0,044
Union coverage	-0,302	0,033	-0,612	0,487	-0,296	0,068	-0,058	0,037
Informal sector	0,716	0,044	0,083	0,19	0,385	0,082	2,396	0,53
Male	-0,285	0,061	-0,338	0,299	-0,312	0,101	-0,132	0,066
White	-0,362	0,032	-0,636	0,548	-0,355	0,095	-0,115	0,055
NNE	0,02	0,052	0,006	0,023	0,023	0,066	0,02	0,087
"Two-Way" effects	-0,044		0,924		0,207		0,438	

Estimated by authors

Table 3.6

Distributional impacts in Log Hourly Wages of Workers in 2009 and 2013

	Variance	se	q90q10	se	q90q50	se	q50q10	se
Observed Difference	-3,335	1,193	-12,858	3,108	-5,614	2,436	-7,243	1,383
Structure Effect	-5,129	0,347	-13,085	2,503	-5,371	2,166	-7,715	1,349
Composition Effect	1,794	1,239	0,228	2,856	-0,244	1,32	0,471	2,015
Dependence Effect	1,21	1,208	2,993	2,916	0,477	0,641	2,516	2,456
Marginal Distr. Effect	0,584	0,11	-2,766	1,109	-0,721	0,94	-2,045	0,947
"Direct" effects								
Education	1,3	0,092	0,085	1,002	-0,51	0,94	0,595	0,831
Experience	0,231	0,04	0,271	0,51	0,015	0,523	0,256	0,091
Union coverage	-0,197	0,028	-0,554	0,485	-0,316	0,487	-0,238	0,066
Informal sector	-0,629	0,038	-2,313	0,545	-0,303	0,203	-2,011	0,525
Male	-0,017	0,009	-0,206	0,295	-0,026	0,302	-0,18	0,085
White	-0,134	0,017	-0,522	0,545	-0,281	0,551	-0,241	0,094
NNE	-0,011	0,03	-0,014	0,077	-0,017	0,058	0,003	0,035
"Two-Way" effects	0,041		0,487		0,717		-0,229	

Estimated by authors

The most important results in Table 3.5 and 3.6 are: (i) the return on the workforce characteristics in the expansion period increases as wages (and skills) decrease, thus, the structure effect is responsible to the retraction of wage inequality over 2009-2013, probably due to a rising demand for low-skill workers in the expansion period; (ii) the composition effect is positive (and significant) in mean, Q90 and Q50, i.e. distributional changes in workforce composition are wage-increasing, but has no impact on measures of inequality; (iii) decomposing the composition effect we identify that more education, more experience and the decline in the share of the informal sector between 2009-2013 are related to increased wages and decreased inequality; (iv) on the other hand, the decline in the union coverage has a negative direct impact on wages but reduces inequality; (v) finally, the dummies for gender and race are significant for certain groups. Looking at Table 1 we identify an increase in non-white and women participation, but due racial and gender discrimination in the labour market, being non-white or a woman is related to lower wages in Brazil; thus, this explains why the direct impact of these covariates is negative on the distributional features, but produces good distributional outcomes for variance and q50-q10 difference.

3.5 Conclusion

This paper shows that Brazilian firms responded to the economic downturn by adjusting wages, but the impact is not uniformly distributed among the log hourly wage distribution. However, changes in workforce composition mitigate the negative impact on some groups. These dynamics further contribute to a decline in wage inequality during the periods analyzed. In the inter-crises period, the structure effect increases wages and also acts to reduce inequality between quantiles, while the composition effect is not significant.

High-income earners – more qualified workers – are more likely to have their wages adjusted downward (the price adjustment) indicated by a negative structure effect. However, the changes in composition of the labour force – they become more educated, experienced and more covered by unions – has a positive impact on wages (positive composition effect), and thus, acts to reduce the negative impact of the adjustment of the labour demand. Changes in labour force composition has no impact on median of wages during both the 2008/2009 and 2014/2015 crises; but the effects on the lowest quintile are dubious: while it is insignificant on the more recent crisis, it is highly negative between 2008/2009.

The results of 90%-10% and the 90%-50% quantiles differences in log hourly wage for 2008/2009 and 2014/2015 periods indicates that structure effect is responsible for a large amount of reduction in wage inequality, but, as the composition effect is acting in the opposite way, the overall change in the observed differences in quantiles, is in part, compensated by distributional changes in covariates, i.e. while differences in characteristics between individuals (composition effect) tend to increase the wage gap between the quantiles, the return to these characteristics (structure effect) acts in the opposite direction.

In our view, the rationale of these results is explained by two forces: inflation and minimum salary policy. Because the minimum salary is not determined by the labour market, but by a formula that considers inflation and past growth, in practice, adjustment of minimum salary below inflation is not allowed even when the GDP growth rate is negative. Thus, the different degrees of wage rigidity over the quantiles imposes different dynamics of adjustments: while inflation can drop the real salary of the high earners, the minimum salary policy tends to preclude firms from lowering the real wage by inflation at the bottom quantiles.

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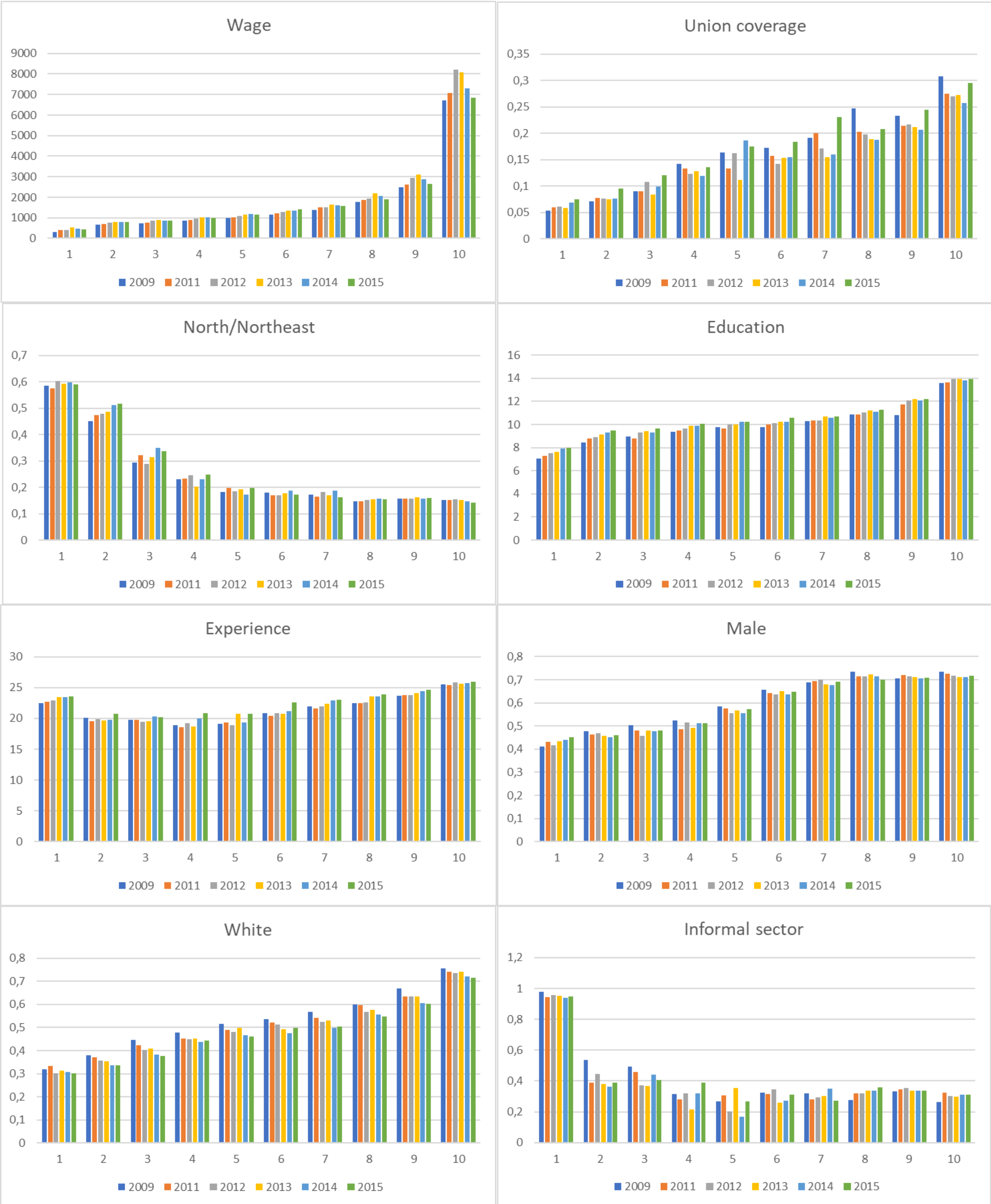
Annex

Descriptive statistics: graphs per decile 2009-2015.



Source: PNAD microdata. Elaborated by authors.

4. A BRAZILIAN REGIONAL HUMAN DEVELOPMENT INDEX (BR-HDI) PROPOSAL

In this paper, we propose a composite indicator near the UNDP human development index (HDI). The new index has the same three dimensions as the UNDP-HDI, but we include new variables to make the BR-HDI more responsive and better able to capture the Brazilian challenges in human development. The factor analysis was used to assign weights to each variable in each sub-index, improving the technical quality of the BR-HDI. The scores captured large regional differences in terms of human development among Brazilian Regions and States.

Keywords: human development; composite indicator; regional development

4.1 Introduction

Composite indicators – an aggregated index comprising individual performance indicators (JACOBS; SMITH; GODDARD, 2004) - summarize information and make it more easily understood, facilitating communication between the non-governmental organization, governments, and population. It is also a tremendous public policy tool, indicating the relative performance of some socioeconomic subjects of a Country, State, or City, and the distance from goals to be achieved by the policymakers.

The Human Development Index (HDI) is a composite indicator that summarizes achievements in three dimensions (sub-indexes): health, education, and standard of living. HDI made possible cross-country comparative analysis of nations regarding the well-being of the population. It is a people-centered approach that “focused on the richness of human lives rather than on simply the richness of economies” (UNDP, 2016).

Its simplicity is the key to its success. The 2016 HDI version is composed by four indicators easily found in almost all countries: life expectancy, expected years of schooling, mean years of schooling, and gross national income per capita[1]. However, its simplicity is the source of the most criticism, which are focused, according to Hou, Paul and Zhang (2015) in three broad groups: The first one refers to the choice of

[1] In power purchasing parity

dimensions included in HDI. The second centers on the way the weights are assigned to each variable and the way the dimensions are aggregated. The last group concerns about the of combining stock and flow variables in an index.

These criticisms refer to the question: how human development should be measured? Some indices incorporate new dimensions to HDI, such as employment and freedom (SALAS-BOURGOIN, 2014), environmental aspects (BRAVO, 2014) and ethnic tolerance (BRASIL; MACEDO, 2016); Different aggregation and/or normalization methods were suggested, as (NOORBAKHSH, 1998), (CHAKRAVARTY, 2003) and (LUQUE; PÉREZ-MORENO; RODRÍGUEZ, 2016); and an index based only in “flow” variables was constructed (HOU; PAUL; ZHANG, 2015). Even a satellite data delivered “night light index” (ELVIDGE et al., 2012) was proposed.

The HDI is constrained by a body of theory and almost 30 years of practice; thus, we constructed an index in “the neighborhood” of HDI. However, we apply some modifications to make the BR-HDI more discriminating to the Brazilian context. The same three dimensions were used, however, because we add some variables to each dimension. A question arises: how aggregate are these variables in each dimension? We deal with these problems by assigning data-drive weights, using factor analysis. Once no theoretical framework justifies assigned weights, the use of an agnostic approach seems more prudent than an arbitrary one.

Our objective in creating a composite indicator near the HDI is not to replace it, but to contribute to public policy analysis by constructing an annual composite index with long span data, applicable to Brazilian context, made to compare States and regions over the time.

The Brazilian Regional Human Development Index (BR-HDI) has some guidelines that make it superior to HDI in the measurement of human development in Brazil. The BR-HDI is made to cover the longest span of data as possible, using annual State-level data. The new index has the three dimensions also present in HDI; however, we made some adjustments to make the BR-HDI more responsive to Brazilian challenges.

Therefore, a proposal for a BR-HDI incorporates some modifications:

(i) Heath dimension: Besides life expectancy, this dimension also includes infant mortality. However, life expectancy is unlikely to be very responsive to the epidemic violence problem[2], and due to several tropical diseases related to water conditions, we decide to improve this dimension by including two more variables: homicide rate and access to water and sewage.

(ii) Education dimension: Besides mean years of schooling, we also include adult illiteracy, school lag, and school enrollment. Default variables in the measurement of educational performance, and also present in other works, as in Burd-Sharps, Lewis and Martins (2008) and in elderly HDI versions.

(iii) Income dimension includes per capita income, the incidence of poverty, and the Gini index. Given the fact that Brazil is one of the most unequal countries in the world, distributional aspects of income matter. This justifies the inclusion of the Gini index in our index and, including a poverty line based on calories, allows this dimension to better capture, for example, the impact of macroeconomic instability on the standard of living of the population at the bottom of the income distribution.

(iv) We use factor analysis to assign weights to variables in each dimension index.

Some efforts to measure human development at a regional level were made: as Burd-Sharps, Lewis and Martins (2008) for United States; Hardeman and Dijkstra (2014) for European Union; Silva and Lopes (2012) for Portugal; and several initiatives in the National Human Development Reports, introducing innovations in human development measurement, whose initiatives have been reviewed by (Lengfelder and Cazabat (2016) and Gaye and Jha (2010). We highlight the index of Human Development adjusted by violence in Colombia (PROGRAMA DE LAS NACIONES UNIDAS PARA EL DESARROLLO, 2011).

In this work, we use Factor Analysis to construct a composite indicator using microdata taken from the Brazilian National Survey of Households (PNAD), implemented by the Brazilian Institute of Geography and Statistics (IBGE) and information from Public Healthcare System (SUS), covering the 1981-2014 period (details in Table 1). Large regional asymmetries are found. States in North and Northeast are lagged in comparison to the South, Southwest, and Midwest States, but

[2] Violence is highly concentrated at youth, and, as the life expectancy at the older population is increasing, the net result is an increasing life expectancy over time, even in a high incidence of violence context.

the differences have become smaller over the time. Policymakers can use the BR-HDI not only to evaluate human development, but also to evaluate a wide range of public policies, given the fact that our indicator can be decomposed in three sub-indexes, covering educational, health, and income aspects.

Such an index captured the large regional differences in human development in Brazil. The distribution of BR-HDI scores among Brazilian States shows a clear pattern: States of North and Northeast regions are about 20 years lagged in terms of human development in comparison to States at South, Southeast, and Midwest regions. However, since 1981, the distance between minimum and maximum scores of BR-HDI have become smaller, signalizing a decrease in regional human development disparities in Brazil over the time.

The paper proceeds as follows. In section 2, we present the variables in BR-HDI and discuss its importance in measuring human development in the Brazilian context. In section 3, we present and justifies the normalization procedures, the first step to compose the indicators, since variables are expressed in different measures. Section 4 presents the method used to assign weighs and the structure of the BR-HDI. Section 5 shows the results and extends the analysis to dimensional indices. In Section 6, we proceed with the robustness tests, applying to different sets of variables and different weighting methods. Section 7 concludes.

4.2 The variables

In the ’90s, most countries with high HDI have achieved high levels of basic compatibilities, such as: high adult literacy rate and high per capita GDP, so the only variable that induces some variation in HDI for highly developed countries is the life expectancy (even so, the numbers are similar). So, in 1994, HDI report (Anand and Sen (1994) argue that HDI has not much cutting power to distinguish between the performance of highly developed countries and suggests adding some variables to make HDI more refined and discriminative, able to capture some variation besides the very elementary achievements.

In “health” dimension, they add the maternal mortality rate and under-5 mortality; in “education” dimension, they add tertiary enrollment and secondary enrollment; and in the “income” category, they add Gini and incidence of poverty.

Table 4.1
Variables in the BR-HDI

Dimension	Variable Name	Variable Definition	Data Source	Start Date
Health and violence	Acces to water and sewage (WASH)	Percentage of people living in private homes with access to sewage facilities (exclusive bathroom, drainage connected to the sewage or rainwater collection network or to a eptic tank)	IPEADATA	1981
	Homicide rate	Intentional homicides (per 100,000 people)	DATASUS	1980
	[1]Infant Mortality	Mortality rate, infant (per 1,000 live births)	DATASUS	1990
	[2]Life expectancy	Life expectancy at birth, total (years)	Pnad/IBGE	1991
Standard of living	[1]Poor Households	This poverty line criteria is based on per capita expenditure level at which an average per capita calorie intake based on recommendations from FAO and WHO.	IPEADATA	1981
	[2]Income	Per capita income in 2014 $ PPP	IPEADATA	1981
	[1]Inequality	Gini Index for per capita income	IPEADATA	1981
Education	[1]Illiteracy	Percentage of people (aged 15 or over) who cannot read or write a single ticket	IPEADATA	1981
	School Lag	Percentage of people with a school delay of one year or longer	IPEADATA	1981
	[1]School attendance	Ratio between the number of people from 7 to 14 years old who attend school and the total number of people in this age group.	IPEADATA	1981

²Mean Years Schooling	Ratio of the sum of the number of schooling years completed by persons aged 25 years or over and the number of people in this age group.	IPEADATA	1981

Notes: IPEADATA is an online database on Brazilian economy compiled by the Institute of Applied Economic Research (IPEA). Most of the data used in this paper are from Brazilian National Survey of Households (PNAD), implemented by the Brazilian Institute of Geography and Statistics (IBGE). DATASUS is the Information Technology Department of the Public Health Care System (SUS).
[1]variables also present in 1994 HDI supplementary criteria to measure Human Development in the advanced countries (adapted to Brazilian data)
[2]variable present in current (2016) HDI (adapted to Brazilian data)

In the within-country analysis, levels of variables tend to be similar, producing poor discriminative results. Then, we decide to add some indicators to the latest version of the HDI, capturing actual problems in Brazil and basic capability achievements, which is very important, since our data stars in the early ’80s. Some of the indicators we add are also present in 1994 HDI for countries with a “high” level of human development.

4.2.1 The Health Dimension

Life expectancy is proxy in HDI for “long and healthy life” in HDI and it is a “summary measure of the health of a population, which can reflect climate, culture, and public investment in preventive care, all of which tend to change slowly and have lasting effects” (HOU; PAUL; ZHANG, 2015). However, Klugman, Rodríguez and Choi (2011) argue that life expectancy tells us nothing about the health of people during the time they are living; it is only a measure of longevity. Thus, to better capture the idiosyncrasies of the Health dimension in Brazil, we decide to add some variables:

4.2.1.1 Violence, measured by homicide rates.

Violence has grown into a major public health problem in Brazil (MURRAY; CERQUEIRA; KAHN, 2013). In 2016, more than 61,500 lives were lost due to violence in Brazil, which is equivalent to deaths caused by the atomic bomb that annihilates Nagasaki in 1945 (“Segurança Pública em Números 2017”, 2017). Violence-related deaths are highly concentrated in poor youth, a recent report of United Nations Children's Fund (2017), shows that the homicide rate among adolescents aged 10 to

19 in Brazil is the seventh worst. Moreover, (Auger et al., (2016) found that in 2010, homicide by firearm was the most critical cause that lowered life expectancy of men in Brazil compared to Canada.

Brazil is inserted in a high violent context - Latin America is probably the most violent region in the world. According to United Nations Children's Fund (2017), Latin America concentrates less than 10% of the world's adolescents, but almost half of all homicides among adolescents occurred there in 2016. The homicide rate is four times higher in Latin America and Caribbean (LAC) than the global average, and also, 47 of the 50 cities in the world with the highest murder rates are in LAC (VILALTA; TORRES; CASTILLO, 2016).

The violence-related socioeconomic costs are large, and the estimative vary from 3.14% to 5.4% of Brazilian GDP, according to Jaitman (2017) and Cerqueira (2016). Losses of human capital due to deaths caused by violence are also accounted. The impact of violence on an individual’s quality of life is vast and includes physical injuries that may result in death and temporary or permanent disability. The fear of crime is related to poor mental health (STAFFORD; CHANDOLA; MARMOT, 2007), (CHANDOLA, 2001) and induces changes in social behavior (MORRALL et al., 2010). Crime-related Post Traumatic Stress Disorder (PTSD), such as depression and other psychological disturbances, may not disappear over time with no treatment (ROBINSON; KEITHLEY, 2000).

4.2.1.2 Infant Mortality Rate (IMR)

Infants are also a sensitive age-specific group and infant mortality express the degree of health inequality of a society. High Infant Mortality Rates (IMR) are associated with socioeconomic deprivations, such as marginality, poverty, education, and health services (MEDINA-GOMEZ; LOPEZ-ARELLANO, 2011).

According to Clark (2011), economic development improves life expectancy more than it reduces infant mortality among developing countries. The mechanism is well known: the distribution of health benefits of growth is distorted by high-income inequality. Thus, improvements in “life expectancy” does not mean improvements in all age-specific groups, and stagnation in infant mortality rates may coexist with increasing life expectancy in some cases. Then, a public policy designed to act on social determinants of IMR is needed.

4.2.1.3 Access to water and sewage (WASH)

Millions suffer from water-, sanitation-, and hygiene-related diseases. Only diarrheal diseases are responsible for 1 billion episodes of morbidity and 2.2 million of deaths (MONTGOMERY; ELIMELECH, 2007). Annually, about 2.4 million deaths could be prevented with appropriate hygiene, sanitation, and water (HSW) (SORENSON; MORSSINK; CAMPOS, 2011). The control of many neglected tropical diseases (NTDs) is directly related to improvements in HSW (FREEMAN et al., 2013; HOTEZ et al., 2008), including Dengue and Zika, both related to water storage management. Lack of access to HSW is highly concentrated in developing countries, including India, China, and Brazil, whereas 7.2 million practice open defecation (GULLAND, 2012).

Access to safe water and sanitation is one of the United Nations Millennium Development Goals (MDGs) and the return on a US$1 investment in improvements required to meet MDG range from U$5 to US$28 (HUTTON; HALLER, 2004) or U$5 to US$46 (HUTTON; HALLER; BARTRAM, 2007), depending on the intervention. Most of the economic benefits are associated with time-saving access to water and sanitation. Women and children are the most common water carriers, and its activity is associated to back injuries, micronutrients deficiencies due high caloric expenditure during the scarcity of food periods (SORENSON; MORSSINK; CAMPOS, 2011). Thus, improving access to HSW is cost-effective and is one of the most effective mean to improve public health and save lives (MONTGOMERY; ELIMELECH, 2007), and it is a solution that contributes to meet practically all MDGs (BARTRAM; CAIRNCROSS, 2010).

4.2.2 The Standard of Living Dimension, a pro-poor approach[3]

A decent standard of living depends on the distributional aspects of income, which is a central concern in developing countries. Furthermore, economic growth

[3] According to (GRIFFITH; ROSE, 2016), “pro-poor growth” happens when some measure of poverty falls with that growth.

combined with income distribution would accelerate the poverty reduction (KAKWANI; NERI; SON, 2010). However, the newer versions of HDI do not incorporate income inequality on its measure by default, but it motivates several modified versions of the HDI, such as Herrero, Martínez and Villar (2010); Harttgen and Klasen (2012) and Hicks (1997) and the Inequality-adjusted Human Development Index (IHDI), introduced in the 2010 human development report.

Distributional aspects of income are also important to distinguish between growth and poverty-reducing growth, since developing countries have experienced episodes of high macroeconomic volatility over the past years and the literature associates high inflation rates to greater income inequality (ALBANESI, 2007) and both inflation and income inequality tend to increase poverty (AGÉNOR, 2004; FERREIRA; LEITE; LITCHFIELD, 2008).

This paper uses a poverty line based on calories, a measure of inequality (Gini index), and the per capita income expressed in $ 2014 PPP[4] indicators to capture the idiosyncrasies of the Brazilian "standard of living" dimension. We are in line with the view that the elimination of poverty, to ensure that everybody satisfies his/her basic needs, is the main goal for development and requires policies based on distribution and income growth (BOURGUIGNON, 2004). Thus, distributional aspects of income cannot be omitted in a human development analysis.

4.2.3 The Education Dimension (human capital)

The literature about the Human Capital outcomes is vast and relates investment in education to better monetary outcomes (MINCER, 1958, 1975; BECKER, 1975) and non-monetary outcomes, such as: crime, health, and good citizenship (LOCHNER; MORETTI, 2004; LOCHNER, 2011; HECKMAN, 2017). Thus, human capital is not only related to job-market competences, but also to multidimensional benefits that enlarge individual opportunities and freedoms.

This dimension measures the stock of human capital in a society (mean years of schooling) and how a society is improving their future generation human capital

[4] We keep the income expressed in $ 2014 PPP to use the same minimum and maximum values present in (LOCKWOOD, 2004)

(school lag and school attendance). This dimension also accounts for freedom from illiteracy among adults.

Furthermore, these educational indicators are widely used for the measurement of a range of indices of global competitiveness, business, and the investment environment (NARAYANA, 2009).

4.3 Normalization of data

Normalization is required prior to any data aggregation since variables are expressed in different measures, range, and scales, so researchers must normalize them to avoid “adding up apples and oranges (OECD/JRC/EUROSTAT, 2008).

Several normalization methods exist, as reported in (OECD/JRC/EUROSTAT, 2008) handbook. Nevertheless, the Min-Max normalization seems to be more often used in composite indicators, as in the KOF Globalization Index (DREHER, 2006), Human Development Index (ANAND; SEN, 1994) and (GRIFFITH; ROSE, 2016), Index of Innovation Performance (FREUDENBERG, 2003), Economic Freedom of the World (JAMES GWARTNEY, ROBERT LAWSON, 2015) and several other indexes. Min-Max normalizes variables to have an identical range [0,1], whereas higher values denote more development. When higher values for the original variable indicates more development, the following normalization rule is applied (Vi-Vmin)/(Vmax- Vmin). However, when higher values for the original variables indicates less development, we apply the following formula (Vmax-Vi)/(Vmax-Vmin). These normalizations guarantee that all variables lie in [0,1] interval and higher values for the transformed variables always indicates higher development.

The choose of extreme values (goalposts) is the central concern when Min-Max normalization is applied. The Lockwood (2004) approach for the calculus of Vmin and Vmax values, called *annual normalization*, are calculated by taking the extreme values for each year in the sample. It is the best and worst performers at that point in time. An alternative method is to take extremal values for the entire sample (*panel normalization*). However, the variation of the extreme values may change the ranking in another year[5]. The Human Development Index (GRIFFITH; ROSE, 2016) deal with this question by assuming Vmin and Vmax exogenously; for example, the maximum expected years of schooling, 18, is equivalent to achieving a master’s degree in several countries.

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[5] An example is provided in (GYGLI; HAELG; STURM, 2018)

Table 4.2
Minimum and Maximum values

Dimension	Variable Name	Minimun	Maximum
Health and violence	Acces to water and sewage (WASH)	0	100
	Homicide rate	0	139
	Infant Mortality	0	224
	Life expectancy	20	85
Standard of living	Poor Households	0	100
	Income (2014 PPP $)	0	$ 75000
	Inequality	0	1
Education	Illiteracy	0	100
	School Lag	0	100
	School attendance	0	100
	Mean Years Schooling	0	18

Author

The extreme values of some variables are predefined by its nature. For example, the limits of the variables expressed in percentage are [0 100], and the Gini index lies in [0 1] interval. However, the limits for some variables are not clear, and the extreme values are taken from literature. Minimum and Maximum values of Life expectancy [20 85], years of schooling [0 18], and gross national income per capita (PPP $) [100 75000][6] are based on HDI index. The maximum for Intentional homicide per 100k people [0 139] and Infant Mortality [0 224] are based on Sierra Leona values, the highest found in the World Bank database[7]. Once extreme values of the variables do not vary over time, as in Lockwood (2004), we can not only measure the relative performance of the States at a point in time, but also over time and space.

[6] U$75,000 dollars in PPP (2014) is equivalent to R$129,750 per year or R$10,812.50 per month.
[7] https://data.worldbank.org

4.4 The weights

How do we decide which variable is more important to describe some dimensions of socioeconomic development? In the Human Development Index, all dimensions are weighted equally, reflecting the idea that they are equally important (LOCKWOOD, 2004). However, if we expect that our index condenses all information about the data in a one-dimensional variable, the weights must be chosen in a way to capture the maximum variation through the data. We mixed these two concepts.

First, as in HDI, we construct sub-indexes describing three dimensions of socioeconomic development: Education; Standard of living; Health and violence. The overall index is aggregated using the geometric mean of the three sub-indexes. In other words, we agree to the restriction imposed on the construction of HDI, and each dimension has the same importance in the socioeconomic development process.

$$Overall\ Index = \sqrt[3]{D_{Education} . D_{Standard\ of\ living} . D_{Health\ and\ violence}} \quad (1)$$

Second, without a priori reasoning for the weights of the variables in each sub-index, the weights were statically calculated using Factor Analysis. The objective is to construct sub-indexes that resume much of the information in the original data in a linear combination of indicators. Figure 1 shows our weighting strategy.

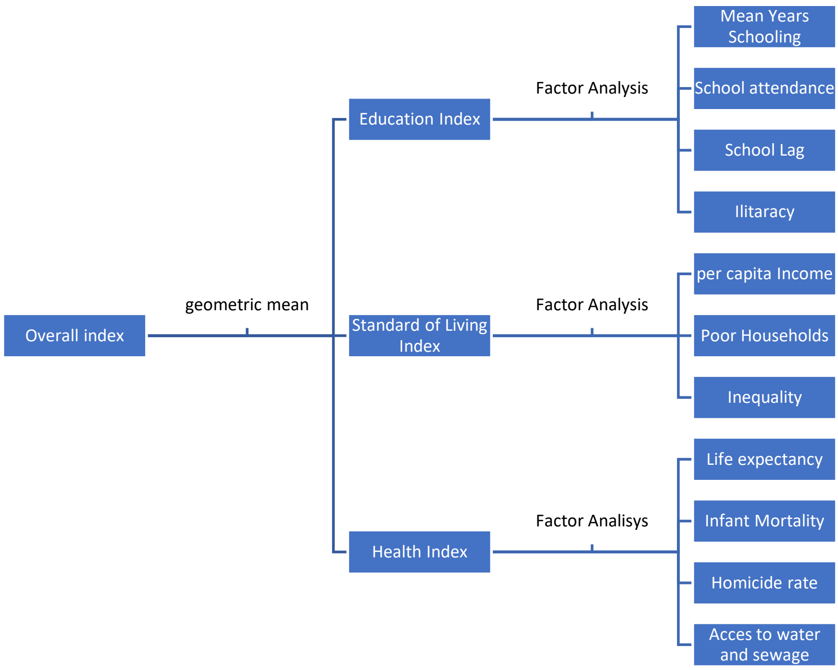


Figure 4.1 - Index structure

What Factor Analysis do?

The factor-based indicators summarize the information of a set of variables by reducing the original information in a vector designed to preserve the maximum as possible of the total variation.

According to Tryfos (1998), factor analysis investigates whether a number of variables of interest $Y_1, Y_2, \ldots, Y_l$, are linearly related to a smaller number of unobservable factors $F_1, F_2, \ldots, F_k$. The objective is to describe the correlation structure among variables in terms of a few vectors.

Let's use an example adapted from Tryfos (1998) and Johnson and Wichern (2007) to show how it works. Say H_1, H_2, H_3 and H_4 represents respectively the four variables[8] in Education Index and suppose that the variables are functions of two unobservable factors F_1 and F_2. The factor model is given by:

$$H_1 = \beta_{11}F_1 + \beta_{12}F_2 + \epsilon_1 \tag{2}$$
$$H_2 = \beta_{21}F_1 + \beta_{22}F_2 + \epsilon_2 \tag{3}$$
$$H_3 = \beta_{31}F_1 + \beta_{32}F_2 + \epsilon_3 \tag{4}$$
$$H_4 = \beta_{41}F_1 + \beta_{42}F_2 + \epsilon_4 \tag{5}$$

Each variable is linearly related to factors F_1 and F_2; the error terms $e_1, \ldots, e_4$, also called *specific factors*, indicates that each H_i are not totally explicated by the common factors; β_{ij} are constants called *factor loadings*.

The general model is given by:

$$H_{(p\times 1)} = \beta_{(p\times m)}F_{(m\times 1)} + \epsilon_{(p\times 1)} \tag{6}$$

To estimate the factor, we have to impose some assumptions about the relationship among variables.

$$E(F) = 0_{(m\times 1)}, \qquad Cov(F) = E[FF'] = I_{(m\times m)} \tag{7}$$

[8] As common in factor analysis, all variables are standardized with zero mean and unit variance.

$$E(\epsilon) = 0, \qquad Cov(e) = E[\epsilon\epsilon'] = \sigma^2{}_{(p\times p)} = \begin{bmatrix} \sigma^2{}_1 & 0 & \dots & 0 \\ 0 & \sigma^2{}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \sigma^2{}_p \end{bmatrix} \tag{8}$$

$$Cov(\epsilon F) = E(\epsilon F') = 0_{(p\times m)} \tag{9}$$

Where m are the numbers of common factors and p represents the number of standardized variables to have zero mean and unit variance.

Applying the variance operator in the model described in equation 2, and using the restrictions described above, we have:

$$Var(H_1) = \beta_{11}{}^2 Var(F_1) + \beta_{12}{}^2 Var(F_2) + Var(\epsilon_1) \tag{10}$$

$$= \beta_{11}{}^2(1) + \beta_{12}{}^2(1) + \sigma_1^2 \tag{11}$$

Implies that

$$Var(H_i) \ = \beta_{i1}{}^2 + \beta_{i2}{}^2 + \sigma_i^2. \tag{12}$$

Where $\beta_{i1}{}^2 + \beta_{i2}{}^2$ is called c*ommunality,* and it is the proportion of the variance of the i-esime variable explained by the common factors. The portion σ_i^2 is the specific variance, due to a specific factor, in practice, is the part of the $Var(H_i)$ that's not due to common factors.

It is easy to see that for each pair of H_i and H_j, the covariance is

$$Cov\left(H_i, H_j\right) = \beta_{i1}\beta_{j1} + \beta_{i2}\beta_{j2}. \tag{13}$$

Consider S_i^2 be the observed variance of the i-esime variable, the Principal Factor method to estimate the loadings consists in approximate the total communality as close as possible to the sum of observed variances. More formally explanations are found in Johnson and Wichern (2007), chapter 9.

Table 4.3
Elements of Principal Factor Method

Variables	Observed Variances	Communality
H_1: Illiteracy	$S_1^2 = 1$	${\beta_{11}}^2 + {\beta_{12}}^2$
H_2: School Lag	$S_2^2 = 1$	${\beta_{21}}^2 + {\beta_{22}}^2$
H_3: School attendance	$S_3^2 = 1$	${\beta_{31}}^2 + {\beta_{32}}^2$
H_4: Mean years of schooling	$S_4^2 = 1$	${\beta_{41}}^2 + {\beta_{42}}^2$
Total	$T_0 = 4$	T_t

Adapted from Tryfus (1998)

The principal factor method to estimate the factor loadings chooses values of β_1 and β_2 that approximates the values of total communalities and the total of observed variances. The estimate of Uniqueness is the simple difference between the unit variance and the estimate of communalities, as described in equation 10.

$$\underbrace{1}_{Observd\ variance} = \underbrace{{\beta_{i1}}^2 + {\beta_{i2}}^2}_{Communality} + \underbrace{\sigma_i^2}_{Uniqueness} \tag{14}$$

One crucial point in factor analysis is called *stopping rules*. It is about the decision of a number of factors that must be in the model. An arbitrary solution is to set the number of factors, according to economic literature. However, a data-driven approach can be used.

Σ is the sample covariance matrix (for standardized data, the sample covariance matrix is the sample correlation matrix, R) and have eigenvalue-eigenvectors pairs $(\hat{\gamma}_1\hat{e}_1), (\hat{\gamma}_2\hat{e}_2), \dots, (\hat{\gamma}_p\hat{e}_p)$, where $\hat{\gamma}_1 \geq \hat{\gamma}_2 \geq \cdots \hat{\gamma}_p$ and $m < p$ are the number of common factors.

The matrix of estimated factor loadings, using principal component analysis is:

$$\tilde{L} = [\sqrt{\hat{\gamma}_1}\hat{e}_1 \ \vdots \ \sqrt{\hat{\gamma}_2}\hat{e}_2 \ \vdots \ \dots \ \vdots \ \sqrt{\hat{\gamma}_m}\hat{e}_m]$$

As pointed by Jackson (1993), the most common stopping rule convention is to set m equal the numbers of eigenvalues of R greater than one (i.e. Kaiser-Guttman criterion).

After applying the principal component method to estimate the factors we have:

Table 4. 4
Estimation output

Variables	β_1	β_2	Communality	Uniqueness
H_1: Illiteracy	0.91	0.05	0.82	0.18
H_2: School Lag	-0.18	0.34	0.15	0.85
H_3: School attendance	0.65	-0.25	0.49	0.51
H_4: Mean years of schooling	0.82	0.22	0.74	0.26
Total variance explained	0.90	0.10		

Author

The results indicate that illiteracy, school attendance, and mean years of schooling are longer loaded on factor 1 and school lag is loaded on factor 2. However, the communality of school lag indicates that only 15% of the total variance is explained by the two-factor model.

The next step to obtain weights from factor analysis is to perform the rotation of the factors. The objective, according to (Johnson and Wichern, 2007) is to obtain a “simpler structure” of the factors. The method maximizes the variance of the squared loadings for each factor.

Finally, we use the square of the rotated factor loadings to construct the weights. As the proportion of total unit variance explained by the factors, the communalities don’t change after the rotation; therefore, the square of the factor loadings represents the proportion of the sample variance explained by each factor. We follow the Nicoletti, Scarpetta and Boyland (1999) approach to transform the squared rotated loadings on weights for each indicator in a composite index.

1) Scale the squared factors to unit sum. Ex: (43=.78/1.84)
2) Group the higher factor loadings into an intermediate composite indicator. They are highlighted in table 5.

Table 4.5
Square of the rotated loadings

Variables	${\beta_1}^2$	${\beta_2}^2$	${\beta_1}^2$	${\beta_2}^2$
			Scaled to unit sum	
H_1: Illiteracy	0.78	0.04	**0.43**	0.11
H_2: School Lag	0.01	0.14	0.00	**0.39**
H_3: School attendance	0.31	0.18	0.17	**0.49**
H_4: Mean years of schooling	0.74	0.00	**0.40**	0.00
Total	1.84	0.36	1	1

Author

3) The two intermediate composites are aggregated assigning a weight to each one of them equal to the proportion of the explained variance in the dataset. For example, (0.38=0.43*0.90), where 0.43 is the first element of the first intermediate composite and 0.90 is the total variance explained by the factor 1.

4) The weights obtained are rescaled to unit sum.

Table 4.6
Final weights

Variables	Intermediate composite			Final weights
	$\beta_1{}^2$	$\beta_2{}^2$		
H_1: Illiteracy	0.43		0.38	**0.46**
H_2: School Lag		0.39	0.04	**0.05**
H_3: School attendance		0.49	0.05	**0.06**
H_4: Mean years of schooling	0.40		0.36	**0.43**
Total			0.83	1

Author

In factor-based indicators, each variable is weighed according to its contribution to the overall variance in the data, without considering the economic relevance of each variable, and, consequently, the beliefs of the analysts. Therefore, in the education sub-index for 2014, it is assigned more weights to illiteracy and mean years of schooling due to the large cross-states variance of these indicators. Similarly, fewer weights are assigned to school enrollment and school lag (table 4.6).

Table 4.7
Example of Ceará (2014)

Variable	Normalized values (a)	Weights (b)	(a)x(b)
Iliteracy	0.984	0.46	0.452
School Lag	0.277	0.05	0.014
School Attendance	0.982	0.06	0.059
Mean years of schooling	0.354	0.43	0.152
		2014 Education Index for Ceará	**0.677**

Note: values are rounded.

Note that for different years, different weights are assigned. Table 8 shows the results for 1994 education index for Ceará State. Different weights reflect the fact that the cross-state variance of the variable has changed along the 1994-2014 period. In addition, when some variable reaches the maximum value for all States, for example, when all people from 7 to 14 years old are attended in school in all Brazilian States, at that point in time, the weight will tend to zero. However, the school lag is still too high for all States, and the normalized values indicate a small improvement in this indicator since 1994, but the cross-variance between States is low, and so, less weight is assigned.

Table 4.8
Example of Ceará (1994)

Variable	Normalized values (a)	Weights (b)	(a)x(b)
Iliteracy	0.811	0.30	0.452
School Lag	0.235	0.16	0.014
School Attendance	0.698	0.30	0.059
Mean years of schooling	0.196	0.24	0.152
		1994 Education Index for Ceará	**0.537**

Note: values are rounded.

Factor-based indicators yield different weights over the time, given the fact that the correlation between variables is not statical.

4.5 Results

First, we show the result for the general index in table 9. Due to space limitation, we selected only 12 years to show (see the Online Appendix for the complete sample). We apply a graduated color scale on the table to facilitate the analysis, the highest values are in blue and the lowest are in red. Blank cells represent values within the mean. The States are organized according to IBGE geographical classification. Codes starting at 1 represents States in the North, 2 in the Northeast, 3 for the Southeast, 4 for the South, and 5 for the Midwest.

Table 4.9

BR-HDI for all Brazilian States. Selected years

COD	State	1981	1984	1987	1990	1993	1996	1999	2002	2005	2008	2011	2014
11	Rondônia	0,496	0,540	0,507	0,560	0,568	0,623	0,630	0,587	0,584	0,633	0,657	0,633
12	Acre	0,500	0,497	0,488	0,497	0,561	0,596	0,591	0,580	0,551	0,603	0,616	0,614
13	Amazonas	0,561	0,522	0,559	0,570	0,540	0,596	0,566	0,578	0,594	0,615	0,621	0,635
14	Roraima	0,616	0,587	0,651	0,628	0,624	0,666	0,649	0,568	0,582	0,639	0,670	0,659
15	Pará	0,512	0,488	0,523	0,505	0,535	0,561	0,563	0,565	0,566	0,610	0,612	0,612
16	Amapá	0,467	0,514	0,550	0,573	0,549	0,603	0,571	0,582	0,604	0,628	0,634	0,644
17	Tocantins	na	na	na	na	0,497	0,510	0,513	0,525	0,561	0,614	0,629	0,627
21	Maranhão	0,343	0,351	0,371	0,375	0,415	0,469	0,463	0,496	0,504	0,567	0,578	0,583
22	Piauí	0,323	0,316	0,362	0,364	0,439	0,476	0,480	0,494	0,511	0,573	0,605	0,621
23	Ceará	0,372	0,367	0,415	0,389	0,448	0,489	0,495	0,526	0,536	0,593	0,614	0,605
24	Rio G. do Norte	0,408	0,367	0,411	0,408	0,475	0,532	0,531	0,541	0,557	0,604	0,632	0,628
25	Paraíba	0,366	0,366	0,396	0,391	0,448	0,499	0,524	0,514	0,537	0,582	0,620	0,623
26	Pernambuco	0,394	0,358	0,392	0,406	0,453	0,511	0,498	0,501	0,522	0,574	0,615	0,623
27	Alagoas	0,362	0,334	0,374	0,349	0,423	0,469	0,480	0,466	0,485	0,542	0,572	0,586
28	Sergipe	0,409	0,389	0,427	0,439	0,491	0,532	0,524	0,549	0,567	0,607	0,629	0,611
29	Bahia	0,429	0,399	0,433	0,413	0,459	0,508	0,518	0,527	0,543	0,590	0,614	0,619
31	Minas Gerais	0,529	0,508	0,539	0,545	0,585	0,630	0,631	0,631	0,650	0,679	0,694	0,680
32	Espírito Santo	0,522	0,500	0,511	0,528	0,585	0,627	0,631	0,623	0,654	0,679	0,700	0,682
33	Rio de Janeiro	0,601	0,576	0,586	0,588	0,599	0,654	0,660	0,649	0,667	0,688	0,701	0,690
35	São Paulo	0,619	0,587	0,617	0,632	0,633	0,681	0,677	0,664	0,683	0,705	0,721	0,706
41	Paraná	0,499	0,487	0,518	0,523	0,589	0,628	0,622	0,635	0,652	0,684	0,699	0,690
42	Santa Catarina	0,554	0,543	0,580	0,580	0,630	0,668	0,668	0,676	0,689	0,705	0,723	0,709
43	Rio G. do Sul	0,568	0,554	0,561	0,581	0,625	0,657	0,655	0,649	0,664	0,686	0,703	0,690
50	Mato G. do Sul	0,480	0,462	0,492	0,487	0,582	0,604	0,601	0,603	0,613	0,655	0,677	0,659
51	Mato Grosso	0,474	0,468	0,474	0,505	0,583	0,603	0,608	0,613	0,624	0,661	0,670	0,658
52	Goiás	0,462	0,465	0,488	0,518	0,577	0,613	0,606	0,611	0,623	0,656	0,682	0,666
53	Distrito Federal	0,630	0,615	0,637	0,651	0,633	0,680	0,684	0,677	0,693	0,717	0,733	0,716

Author

The geographical distribution of the BR-HDI shows a clear pattern: States in the North and Northeast regions are less developed than States at South, Southeast and Midwest regions. In addition, States at Northeast are less developed than States at North. Furthermore, differences in BR-DHI within regions are clearly stronger in the Northeast region. These geographical patterns of Human Development are clear at figure 2 for 1981 and show that even neighboring States differ markedly on their scores if they are classified by different regions.

Figure 2: 1981 Brazilian Regional Human Development Index scores

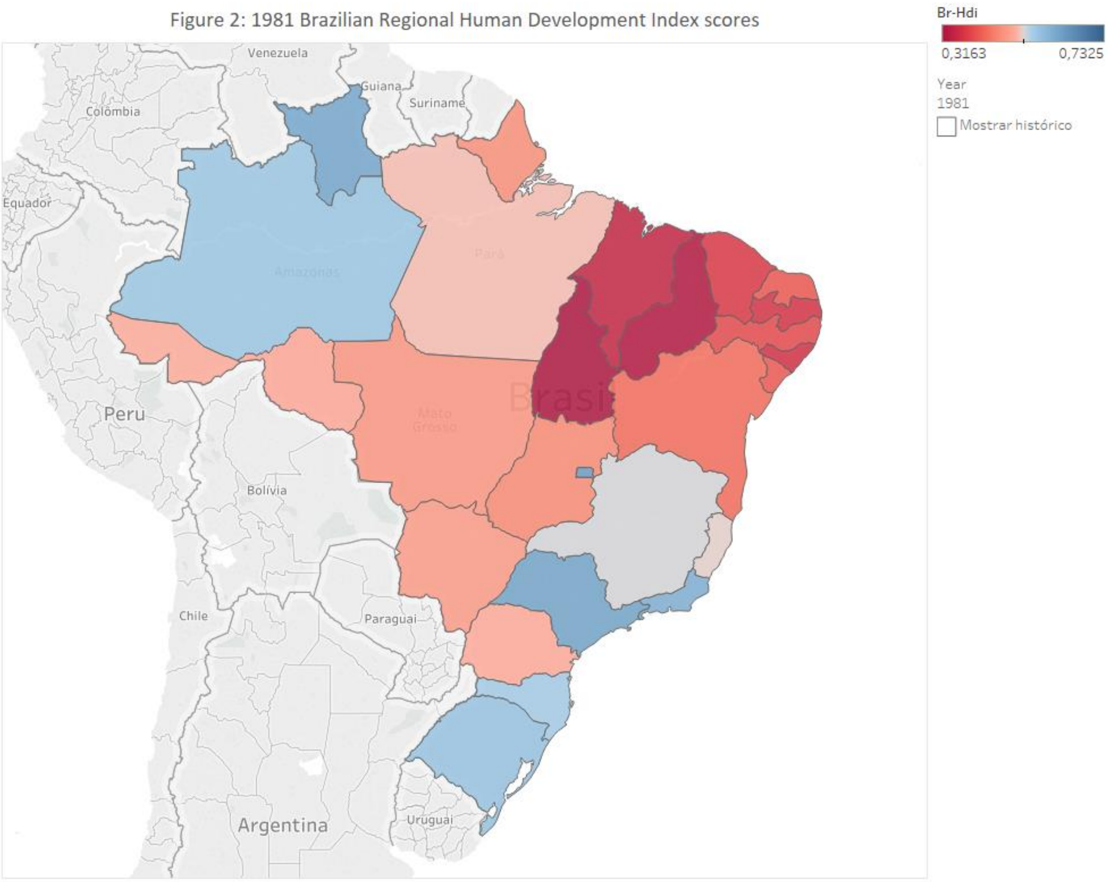


Figure 3: 1999 Brazilian Regional Human Development Index scores

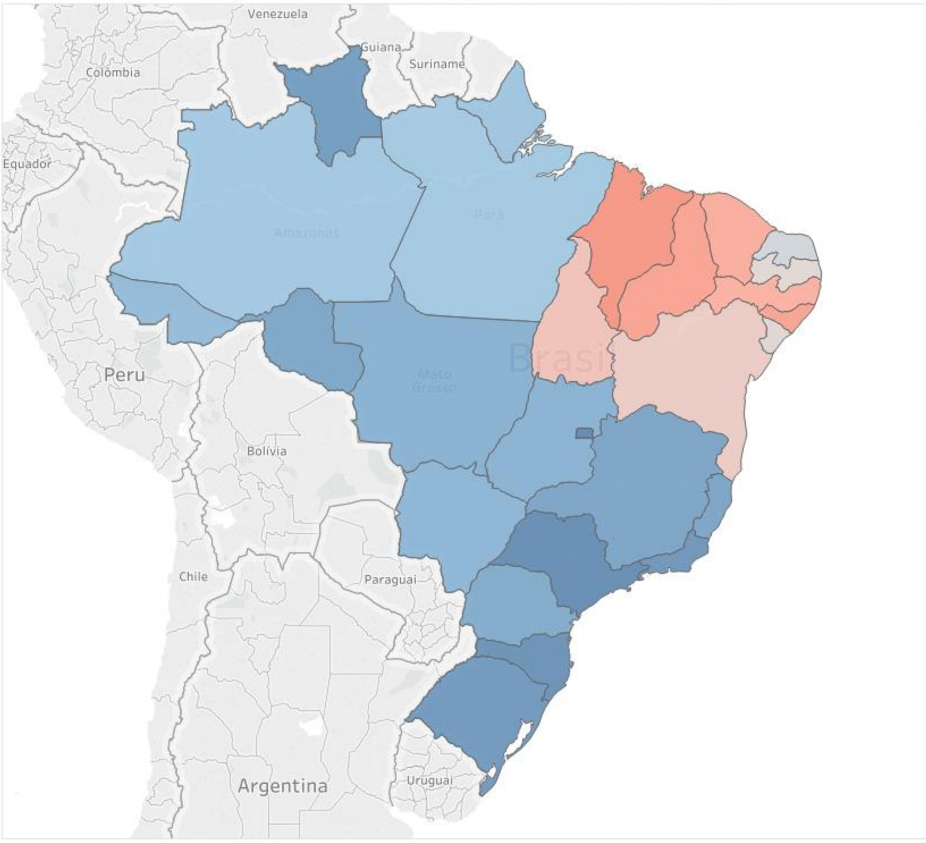
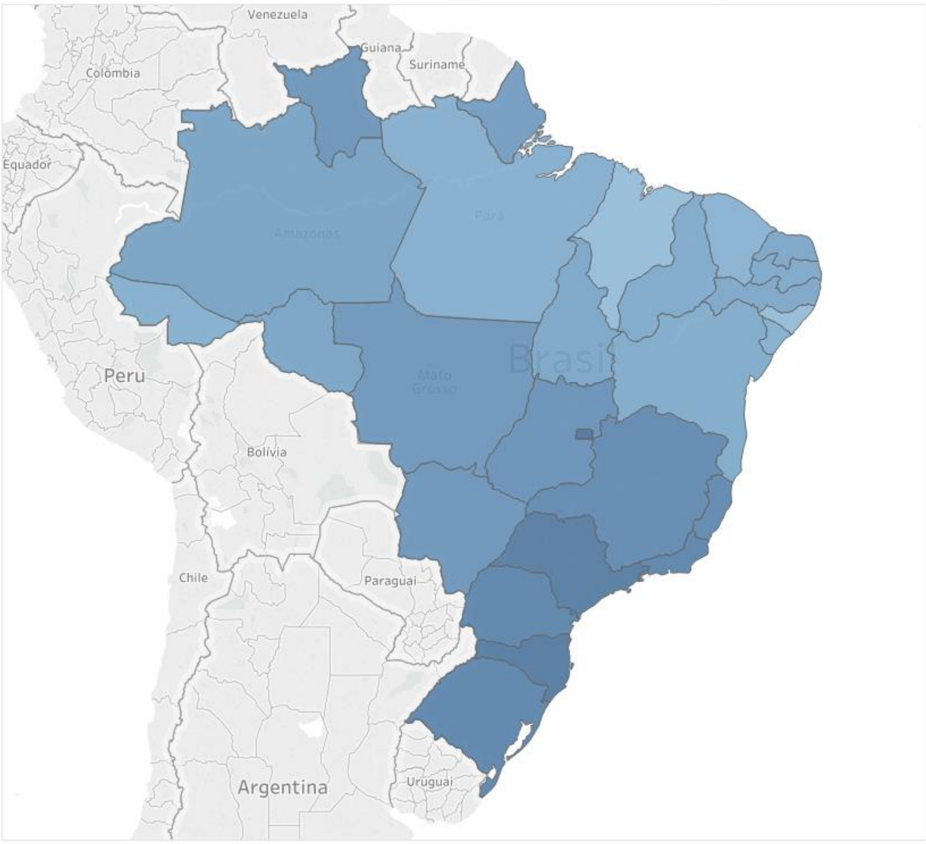


Figure 4: 2014 Brazilian Regional Human Development Index scores



1981 BR-HDI data shows that low values are concentrated at the Northeast and the Midwest States and larger within regional differences. Figure 3 and 4 shows that 1999 BR-HDI low scores are highly concentrated in the Northeast region; however, with great improvements in Human Development compared to 1981.

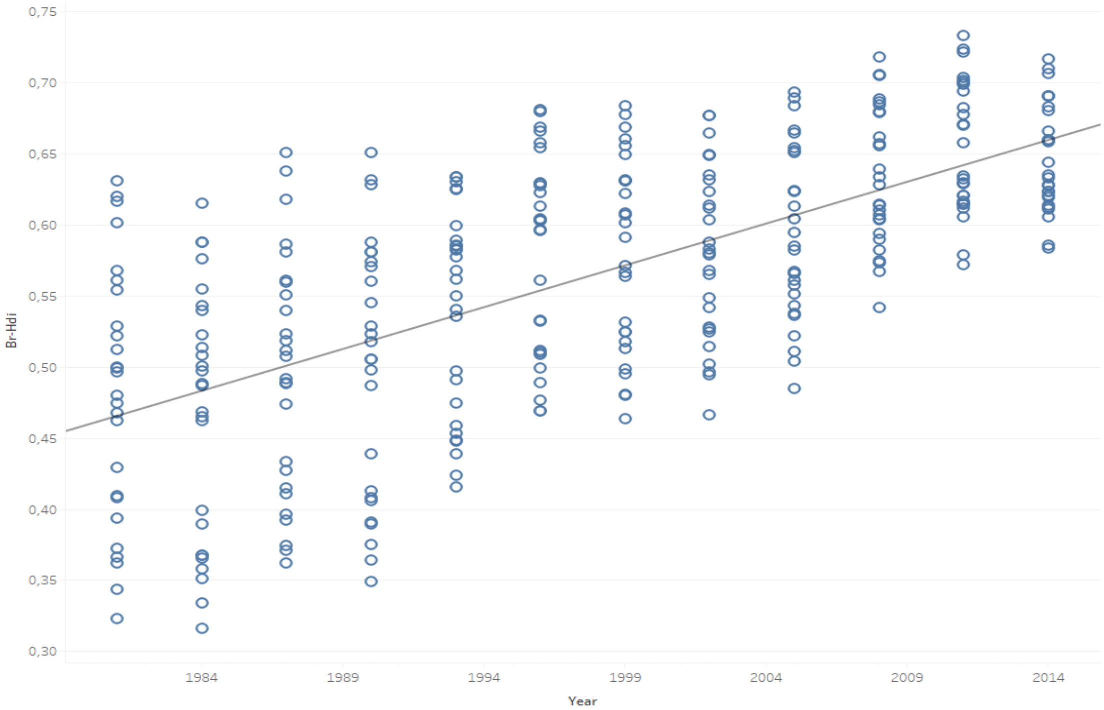
Table 4.10
Descriptive statistics

	1981	1984	1987	1990	1993	1996	1999	2002	2005	2008	2011	2014
Min	0,32	0,32	0,36	0,35	0,42	0,47	0,46	0,47	0,48	0,54	0,57	0,58
Max	0,63	0,61	0,65	0,65	0,63	0,68	0,68	0,68	0,69	0,72	0,73	0,72
% Difference	95%	94%	80%	86%	52%	45%	47%	45%	43%	32%	28%	23%
Desv. Pad	0,09	0,09	0,09	0,09	0,07	0,07	0,07	0,06	0,06	0,05	0,05	0,04
Average	0,48	0,47	0,49	0,50	0,54	0,58	0,58	0,58	0,59	0,63	0,65	0,65

Author

Figure 5 and Table 10 show the dispersion graph and the descriptive statics for selected years. Levels of human development have all been improved over the Brazilian States, the average values have increased by 35% between 1981-2014. Least developed States increased more. Minimum values of BR-HDI have changed from 0.32 to 0.58, over 1981-2014 period. While, at the same period, maximum values

Figure 5: BR-HDI dispersion over 1981-2014



have moved from 0.63 to 0.72. The result is a significant and persistent decrease in distance between the extreme values of BR-HDI, signalizing a decline in regional

Human Development disparities, which is also captured by the dynamics of the standard deviation of BR-HDI over the time.

It is clear that over the 1981-2014 period, the distance on Human Development between the Brazilian States has become smaller; however, larger regional disparities in Human Development still persist, and none of all scores above the tendency line in Figure 5 belongs to the Northeast States. The mean values of a 2014 BR - HDI for the Northeast Region is 0.611 - mean value reached in 1993 by the South States; in 1994 by Southeast; in 1995 Midwest, and 2008 at North. Thus, the performance of Human Development in the Northeast region in about 20 years lagged in comparison to the more developed regions.

On the top of the BR-HDI in almost the entire sample is the Federal District, followed, in order, by the States of Santa Catarina and São Paulo since the 2000s. The top three ranking States are formed by the States from the Midwest, South, and Southeast regions, but at the bottom of the list are only Northeastern States; Maranhão, Alagoas, Ceará, and Piauí alternates the worst scores in Human Development measures over 1981-2014.

4.6 BR-HDI sub-index results

In order to understand the wide range of Human Development levels among Brazilian States, we proceed with a sub-index analysis. Table 11 shows the 2014 BR-HDI ranking and each sub-index ranking, and the larger States' variations are marked.

Table 4.11

2014 BR-HDI sub-index ranking

Rank	Health	Education	Income	BR-HDI
1º	São Paulo	Distrito Federal	Santa Catarina	**Distrito Federal**
2º	Distrito Federal	São Paulo	Paraná	**Santa Catarina**
3º	Santa Catarina	Rio de Janeiro	Distrito Federal	**São Paulo**
4º	Rio Grande do Sul	Amapá	Mato Grosso	**Rio Grande do Sul**
5º	Rio de Janeiro	Roraima	Mato Grosso do Sul	**Rio de Janeiro**
6º	Espírito Santo	Santa Catarina	Goiás	**Paraná**
7º	Minas Gerais	Amazonas	Rio Grande do Sul	**Espírito Santo**
8º	Paraná	Paraná	São Paulo	**Minas Gerais**
9º	Roraima	Rio Grande do Sul	Minas Gerais	**Goiás**
10º	Piauí	Mato Grosso	Espírito Santo	**Roraima**
11º	Pernambuco	Espírito Santo	Rio de Janeiro	**Mato Grosso do Sul**
12º	Rio Grande do Norte	Mato Grosso do Sul	Rondônia	**Mato Grosso**
13º	Paraíba	Goiás	Amapá	**Amapá**
14º	Amazonas	Minas Gerais	Roraima	**Amazonas**
15º	Bahia	Rondônia	Tocantins	**Rondônia**
16º	Goiás	Tocantins	Rio Grande do Norte	**Rio Grande do Norte**
17º	Acre	Acre	Sergipe	**Tocantins**
18º	Tocantins	Pará	Amazonas	**Pernambuco**
19º	Mato Grosso do Sul	Pernambuco	Paraíba	**Paraíba**
20º	Sergipe	Rio Grande do Norte	Pará	**Piauí**
21º	Mato Grosso	Paraíba	Piauí	**Bahia**
22º	Pará	Bahia	Bahia	**Acre**
23º	Ceará	Ceará	Pernambuco	**Pará**
24º	Alagoas	Maranhão	Ceará	**Sergipe**
25º	Amapá	Sergipe	Acre	**Ceará**
26º	Maranhão	Piauí	Alagoas	**Alagoas**
27º	Rondônia	Alagoas	Maranhão	**Maranhão**

Author

Highlighted States are a good example of the importance of the multidimensional criteria to measure human development versus the use of only one indicator as a measure of welfare. These 11 indicators grouped in three dimensions are proxies to the underlying concept of human development, and all dimensions have the same relevance, aggregated using geometric mean, also applied to HDI since the 2010 Human Development Report. The geometric mean aggregation of the dimensions reduces the perfect substitutivity of the three dimensions and penalizes unbalanced development (FELICE; VASTA, 2014). Some results call attention; people living at Amapá are more likely to have better education; however, they receive one of the worst scores at health dimension; in the opposite situation is Piaui. The State of Mato Grosso is one of the top-ranked at income dimension, but the health outcomes are very poor. The State of Rondônia is at the bottom of the health ranking, but near the median at other dimensions. The 2014 BR-HDI at the last column shows that, despite the large variability at each dimension ranking, the highlighted States are close in the aggregated index.

4.6.1 Standard of Living Index (BR-SLI)

Table 12 presents the scores of the income dimension in BR-HDI, called Standard of Living Index (BR-SLI); we also present its components. This sub-index is composed by the Gini index, the percentage of households above a poverty line and the per capita income, as described in Table 1. However, here we present the variables without normalization.

Table 4.12

The Standard of Living Index (BR-SLI) and its components. 2014 results.

Rank	BR-SLI	State	Gini	Poverty Line	Monthly Income (2014 R$)	Var
1º	0,539	Santa Catarina	0,421	3,12	1.503,32	1
2º	0,520	Paraná	0,453	4,24	1.329,71	4
3º	0,519	Distrito Federal	0,582	4,18	2.279,70	-2
4º	0,516	Mato Grosso	0,460	3,67	1.204,76	4
5º	0,515	Mato Grosso do Sul	0,487	2,86	1.325,22	2
6º	0,515	Goiás	0,450	3,79	1.132,91	5
7º	0,515	Rio Grande do Sul	0,476	5,26	1.444,65	-3
8º	0,512	São Paulo	0,493	5,22	1.497,76	-5
9º	0,502	Minas Gerais	0,485	4,93	1.133,58	1
10º	0,502	Espírito Santo	0,492	4,83	1.170,18	-1
11º	0,498	Rio de Janeiro	0,525	6,16	1.435,48	-6
12º	0,479	Rondônia	0,470	10,97	950,16	0
13º	0,477	Amapá	0,470	11,00	911,83	1
14º	0,462	Roraima	0,502	13,50	946,82	-1
15º	0,450	Tocantins	0,515	15,33	894,20	0
16º	0,443	Rio Grande do Norte	0,496	17,46	762,77	4
17º	0,442	Sergipe	0,485	18,22	719,02	5
18º	0,435	Amazonas	0,530	17,89	833,68	-2
19º	0,435	Paraíba	0,513	18,67	780,25	0

20º	0,434	Pará	0,486	20,02	676,49	5
21º	0,433	Piauí	0,501	19,56	705,31	2
22º	0,432	Bahia	0,527	18,68	804,65	-5
23º	0,431	Pernambuco	0,507	20,27	759,70	-2
24º	0,428	Ceará	0,506	20,55	691,11	0
25º	0,422	Acre	0,542	20,45	791,68	-7
26º	0,410	Alagoas	0,501	25,21	592,98	1
27º	0,396	Maranhão	0,529	27,18	614,20	-1

Author

Brasília is the federal capital of Brazil, and besides the massive presence in the public sector, it also concentrates the top income public servants. The result of this combination is the highest *per capita* income among Brazilian States (almost four times higher than the *per capita* income of Alagoas), the highest income inequality, and a low percentage of households below the poverty line. Because this dimension accounts distributional aspects of income, the Federal District is not on the top of BR-SLI, as shown in the last column of table 12, the Federal District has lost 2 positions in relation to the index formed only by the *per capita* income.

Santa Catarina is on top of BR-SLI, followed by Paraná; both are Southern States. Like other States in the South region, the percentage of households below the poverty line is considerably lower for Brazilian parameters and presents the lowest income inequality measured by the Gini index and the second higher *per capita* income. Due to the good distributional aspects of income in Paraná, this State has 4 advanced positions in relation to the benchmark ranking.

Table 4.13

Geographical distribution of the 2014 BR-SLI results

Region	BR-SLI	Gini	Poverty Line	Annual Income ($ 2014 PPP)
North	0,451	0,502	15,59	5.889
Northeast	0,428	0,507	20,64	4.905
Southeast	0,503	0,499	5,28	8.988
South	0,524	0,450	4,21	9.789
Midwest	0,516	0,495	3,63	10.199

Author

The data show a division between South/Southeast/Midwest (SSM) States above the yellow line in table 13, and North/Northeast (NNE) States at the bottom. The mean percentage of households below the poverty line in the North and Northeast are astonishing and more than four and five times higher than the same variable for the

Midwest. The per capita income in NNE is almost 50% of the value found in SSM, and the income inequality in NNE is considerably higher, as shown in table 13.

4.6.2 Health Index (BR-HI)

The Health indicator, the BR-HI, among the three composite indicators proposed to substitute the UN-HDI dimensions, is the one that present larger variation in rank compared to the benchmark rank (ordered according to life expectancy). The variable that most contribute to this variation is the percentage of people with access to sewage facilities: WASH.

Table 4.14

The Health Index (BR-HI) and its components. 2014 results.

Rank	State	BR-HI	WASH	Homicide rate	Infant mortality	Life expectancy	Var
1º	São Paulo	0,924	0,95	14,05	10,5	77,5	+3
2º	Distrito Federal	0,916	0,97	29,55	11,0	77,6	0
3º	Santa Catarina	0,910	0,85	13,54	9,8	78,4	-2
4º	Rio Grande do Sul	0,891	0,83	24,31	10,2	77,2	+1
5º	Rio de Janeiro	0,889	0,92	34,74	12,3	75,6	+3
6º	Espírito Santo	0,886	0,86	41,42	9,6	77,5	-3
7º	Minas Gerais	0,884	0,81	22,78	12,0	76,7	-1
8º	Paraná	0,872	0,76	26,89	10,1	76,5	-1
9º	Roraima	0,850	0,88	33,06	17,6	70,9	+15
10º	Piauí	0,839	0,81	22,45	20,4	70,7	+16
11º	Pernambuco	0,820	0,65	36,19	14,0	73,1	+5
12º	Rio Grande do Norte	0,819	0,66	47,00	16,1	75,2	-3
13º	Paraíba	0,818	0,70	39,33	18,0	72,6	+6
14º	Amazonas	0,811	0,68	32,01	19,4	71,4	+8
15º	Bahia	0,807	0,65	40,01	18,9	73,0	+2
16º	Goiás	0,805	0,60	44,26	15,8	73,8	-5
17º	Acre	0,797	0,54	29,40	18,4	73,3	-2
18º	Tocantins	0,781	0,45	25,45	16,9	72,8	0
19º	Mato Grosso do Sul	0,780	0,37	26,72	14,9	75,0	-9
20º	Sergipe	0,773	0,52	49,42	17,9	72,1	0
21º	Mato Grosso	0,771	0,45	42,12	17,7	73,7	-9
22º	Pará	0,768	0,48	42,68	17,7	71,7	-1
23º	Ceará	0,764	0,44	52,31	15,8	73,4	-9
24º	Alagoas	0,754	0,55	62,80	22,4	70,8	+1
25º	Amapá	0,753	0,38	34,10	23,7	73,4	-12
26º	Maranhão	0,750	0,46	35,94	23,5	70,0	+1
27º	Rondônia	0,749	0,40	33,06	20,8	70,9	-4

Author

Low-life expectancy States (in which the life expectancy is about 70 years), like Roraima and Piauí, presents good scores on the WASH indicator. Table 14 also reveals that in these States, levels of homicide and infant mortality are smaller than other low-life expectancy States, and the result is a high variation in rank order. On the contrary situation is Ceará and Amapá; in both States, the expected life is 73.4 years. However, access to sewage facilities is very restricted in both States, and Ceará has the second highest homicide rate in Brazil.

Table 4.15

Geographical distribution of the 2014 BR-HI results

Region	BR-HI	WASH	Homicide rate	Infant mortality	Life expectancy
North	0,787	0,55	32,82	19,21	72,06
Northeast	0,794	0,61	42,83	18,56	72,32
Southeast	0,896	0,89	28,25	11,10	76,83
South	0,891	0,81	21,58	10,03	77,37
Midwest	0,818	0,60	35,66	14,85	75,03

Author

2014 data reveal that if Alagoas, the most violent State, were a country, it would be on top of the worst homicide rates ranking according to the UN Office on Drugs and Crime's International Homicide Statistics database[9]. Southern States are less violent in Brazil (table 15), but compared to international data, the mean homicide rate in the South is seven times bigger than in OECD countries (Table 21).

Health indicators' differences among Brazilian regions are considerable: Five years in life expectancy separate Northeastern and Southern States; twice more infants per 1000 births dies in North than in the South; twice more homicides per 100,000 people happens to Northeast than in the South and, in the North and Northeast regions, where people are more vulnerable to water-related diseases (due to different reasons), access to sewage facilities are poor.

4.6.3 Education Index (BR-EI)

There are no notable changes in BR-EI rank in comparison to relation to mean years of schooling rank. This happens due to the low variation of school lag and school enrollment variables among Brazilian States in 2014. The major source of variability is the illiteracy rates, but it is not sufficient to produce large rank variation.

[9] The first is El Salvador, followed by Honduras and Venezuela.

There is a noticeable change in the higher part of table 16 compared to the other three sub-indexes proposed. Amapá and Roraima, States from North, are on top five States, according to BR-EI methodology (and according to the benchmark rank). At the bottom, there is no surprise, and Northeastern States present poor educational scores.

Table 4.16

The Education Index (BR-EI) and its components. 2014 results.

Rank	State	BR-EI	Illiteracy	School Lag	School enrollment	Years of Schooling	Var
1º	Distrito Federal	0,77	0,39	72,45	99,31	10,08	0
2º	São Paulo	0,74	0,53	73,76	99,38	8,92	1
3º	Rio de Janeiro	0,74	0,48	78,11	98,99	8,95	-1
4º	Amapá	0,74	0,67	66,68	99,17	8,70	0
5º	Roraima	0,73	0,78	66,44	98,65	8,29	0
6º	Santa Catarina	0,73	0,33	74,50	99,14	8,25	0
7º	Amazonas	0,72	1,14	67,61	97,76	8,17	0
8º	Paraná	0,72	0,57	73,28	98,81	8,13	0
9º	Rio Grande do Sul	0,72	0,79	77,12	98,69	7,94	0
10º	Mato Grosso	0,72	0,58	70,80	99,11	7,76	2
11º	Espírito Santo	0,71	0,68	74,60	97,28	7,80	-1
12º	Mato Grosso do Sul	0,71	1,24	72,91	98,49	7,77	-1
13º	Goiás	0,71	0,65	72,85	99,23	7,61	0
14º	Minas Gerais	0,71	0,73	74,36	98,76	7,49	0
15º	Rondônia	0,71	0,66	70,77	99,21	7,28	0
16º	Tocantins	0,70	0,92	68,63	99,10	7,16	0
17º	Acre	0,69	2,64	64,20	96,53	6,88	1
18º	Pará	0,69	1,52	71,38	98,24	6,76	1
19º	Pernambuco	0,69	2,43	73,87	98,31	6,91	-2
20º	Rio Grande do Norte	0,68	1,61	75,34	99,36	6,55	1
21º	Paraíba	0,68	1,46	73,91	97,52	6,46	1
22º	Bahia	0,68	2,32	75,04	98,50	6,61	-2
23º	Ceará	0,68	1,59	72,22	98,24	6,39	0
24º	Maranhão	0,67	2,47	68,07	98,25	6,08	1
25º	Sergipe	0,67	2,74	74,37	97,70	6,24	-1
26º	Piauí	0,66	2,82	73,12	98,79	5,81	0
27º	Alagoas	0,65	3,60	71,42	97,06	5,65	0

Author

Table 17 shows that Northeast region is one step behind the North region in BR-EI, while on BR-SLI and BR-HI, these two regions present similar results. The percentage of people that cannot read or write a ticket in the Northeast is twice more than reported in the North, and there are about 1.3 more schooling years in North than in the Northeast. Despite the great scores compared to the Northeast, the North scores are lagging compared to South, Southeast, and Midwest educational indicators.

Table 4.17

Geographical distribution of the 2014 BR-EI results

Region	BR-EI	Illiteracy	School Lag	School enrollment	Mean Years Schooling
North	0,71	1,19	67,96	98,38	7,61
Northeast	0,67	2,34	73,04	98,19	6,30
Southeast	0,73	0,60	75,21	98,60	8,29
South	0,72	0,56	74,96	98,88	8,11
Midwest	0,73	0,71	72,25	99,04	8,30

Author

Compared to international data (Table 21), Brazil is in a noticeable position. Illiteracy rates among persons aged at 15-24 years are lower in Brazil than in UMI and LAC countries, and substantially lower than the world average. However, the mean years of schooling in Brazil are lower than in UMI, LAC, and the world average. In terms of policy-making, this indicates a priority on the educational agenda.

4.7 Robustness tests

Similar to Hardeman and Dijkstra (2014), we compare differences in scores and ranks in a range of situations to test the robustness of the proposed index. More specifically, we test alternative variables and alternative weights.

Due to the lack of data, it is not possible to substitute every indicator in BR-HDI, so the alternative variables tests are limited to four variables. The alternative indexes constructed from alternative sets of variables follow the same methodological aspects of BR-HDI.

- VA: Instead of "homicide rate," we use the "probability of dearth between 15-19 years old" as our measure of violence. The measure of income inequality is given by the Theil index, instead of the Gini index. The illiteracy rates are measured between a younger group, 10-14 years old and the school enrollment refers to 5-6 years old interval;
- VX: All variables in BR-HDI and in VA are included.

Table 18 shows the BR-HDI ranking and the VA and VX ranking. Changes proposed in VA do not produce noticeable changes in rank compared to BR-HDI and there are some advantages in using the sets of variables in table 1 instead of the alternatives in VA: First, the Gini index is a more common measure of income inequality, and it was also applied in 1994 HDI to produce more discriminative results for high human developed countries; Secondly, illiteracy among adults is a problem more difficult to solve than at younger ages, it represents the educational debt to past generations, and enrollment between 7-14 years old refers to larger age-group; Lastly, the probability of death between 15-19 is only available for recent years.

The rank based in VX reflects the inclusion of all variables; thus, income inequality is measured by two variables, as well as violence, illiteracy, and school enrollment, and because of this, there are double counting problems in VX, which produce biased weights. This results in a very different ranking compared to BR-HDI; however, a NNE/SSM division still exists.

Table 4.18
BR-HDI and alternative sets of variables ranking

Rank	BR-HDI	VA	VX
1	Distrito Federal	Distrito Federal	Santa Catarina
2	Santa Catarina	Santa Catarina	Paraná
3	São Paulo	São Paulo	São Paulo
4	Rio Grande do Sul	Paraná	Rio Grande do Sul
5	Rio de Janeiro	Rio Grande do Sul	Espírito Santo
6	Paraná	Rio de Janeiro	Minas Gerais
7	Espírito Santo	Espírito Santo	Goiás
8	Minas Gerais	Minas Gerais	Mato Grosso
9	Goiás	Mato Grosso do Sul	Rio de Janeiro
10	Roraima	Goiás	Distrito Federal
11	Mato Grosso do Sul	Mato Grosso	Amapá
12	Mato Grosso	Roraima	Mato Grosso do Sul
13	Amapá	Amapá	Roraima
14	Amazonas	Rondônia	Rondônia
15	Rondônia	Rio Grande do Norte	Rio Grande do Norte
16	Rio Grande do Norte	Tocantins	Pernambuco
17	Tocantins	Amazonas	Sergipe
18	Pernambuco	Pernambuco	Piauí
19	Paraíba	Paraíba	Pará
20	Piauí	Sergipe	Tocantins
21	Bahia	Bahia	Paraíba
22	Acre	Acre	Amazonas
23	Pará	Piauí	Ceará
24	Sergipe	Ceará	Bahia
25	Ceará	Pará	Acre
26	Alagoas	Alagoas	Alagoas
27	Maranhão	Maranhão	Maranhão

Author

Since an alternative set of variables does not produce large rank variations, we proceed with the robustness tests. BR-HDI uses Factor Analysis to assign weights of each indicator to all dimensions, then the dimensions are aggregated using the geometric mean. Now is considered seven alternatives for the setting weights:

- $W1$: BR-SLI, BR-HI, and BR-EI are constructed using factor analysis, and then the three dimensions are arithmetically aggregated;
- $W2$: All dimensions are constructed using the arithmetic mean of the indicators, then the dimensions are aggregated using geometric mean, as in UNDP (2016), Harttgen and Klasen (2012) and Hardeman and Dijkstra (2014);

- $W3$: This alternative index does not consider the three dimensions of BR-HDI, all indicators are aggregated into an index using factor analysis; thus, W3 is an agnostic index, as in Dreher (2006)[10].
- $W4$: All indicators are arithmetically aggregated, as in Hou, Paul and Zhang (2015) and Transparency International (2017);
- $W5$: All indicators are geometric aggregated, as in (Salas-Bourgoin (2014)[11];
- $W6$: Dimensions are constructed using arithmetic mean of the indicators, then the dimensions are aggregated using the arithmetic mean, as in older versions of HDI;
- $W7$: BR-SLI, BR-HI, and BR-EI are constructed using factor analysis, then the three dimensions are aggregated using factor analysis[12], as in Nicoletti, Scarpetta and Boyland (1999).

The ranking based on the alternative weights is in table 19 and 20. There are no noticeable changes in the rank produced by $W1$ index compared to BR-HDI, and the maximum rank shift is only two positions (Pernambuco shift from 18 to 16). These results are due to the geometric mean aggregation of dimensional indices, which penalizes large dimensional disparities in scores.

Table 4.19

BR-HDI and alternative weights (part I)

Rank	BR-HDI	$W1$	$W2$	$W3$	$W4$
1	Distrito Federal	Distrito Federal	Santa Catarina	Distrito Federal	São Paulo
2	Santa Catarina	São Paulo	São Paulo	Santa Catarina	Distrito Federal
3	São Paulo	Santa Catarina	Distrito Federal	São Paulo	Santa Catarina
4	Rio Grande do Sul	Rio de Janeiro	Paraná	Paraná	Rio Grande do Sul
5	Rio de Janeiro	Rio Grande do Sul	Rio Grande do Sul	Rio Grande do Sul	Paraná
6	Paraná	Paraná	Rio de Janeiro	Rio de Janeiro	Rio de Janeiro
7	Espírito Santo	Espírito Santo	Minas Gerais	Minas Gerais	Minas Gerais
8	Minas Gerais	Minas Gerais	Espírito Santo	Espírito Santo	Espírito Santo
9	Goiás	Roraima	Roraima	Mato Grosso do Sul	Roraima
10	Roraima	Goiás	Goiás	Roraima	Goiás
11	Mato Grosso do Sul	Mato Grosso do Sul	Mato Grosso do Sul	Goiás	Amazonas

[10] Uses Principal Component analysis, a similar approach to factor analysis. The newer version of KOF Globalization Index (Relatório de desenvolvimento humano, 2009-2010: Brasil ponto a ponto; consulta pública, 2009) follows an approach similar to W1 index.

[11] Uses the same variables present in HDI and other three indicators, the index is the geometric mean of these six indicators,

[12] Weights assigned to each dimension: BR-HI (0,25), BR-EI (037) and BR-SLI (0,38).

12	Mato Grosso	Mato Grosso	Mato Grosso	Mato Grosso	Piauí
13	Amapá	Amapá	Amapá	Amapá	Mato Grosso do Sul
14	Amazonas	Amazonas	Amazonas	Amazonas	Mato Grosso
15	Rondônia	Rio Grande do Norte	Piauí	Rondônia	Amapá
16	Rio Grande do Norte	Pernambuco	Rondônia	Tocantins	Pernambuco
17	Tocantins	Rondônia	Tocantins	Pernambuco	Tocantins
18	Pernambuco	Tocantins	Rio Grande do Norte	Acre	Paraíba
19	Paraíba	Paraíba	Pernambuco	Piauí	Rio Grande do Norte
20	Piauí	Piauí	Paraíba	Paraíba	Acre
21	Bahia	Bahia	Acre	Rio Grande do Norte	Rondônia
22	Acre	Acre	Bahia	Bahia	Bahia
23	Pará	Pará	Pará	Pará	Pará
24	Sergipe	Sergipe	Sergipe	Sergipe	Sergipe
25	Ceará	Ceará	Ceará	Ceará	Ceará
26	Alagoas	Maranhão	Maranhão	Maranhão	Maranhão
27	Maranhão	Alagoas	Alagoas	Alagoas	Alagoas

Author

$W2$, $W3$, and $W4$, despite the different methods of aggregation used, the results are very close to BR-HDI. In other words, there is no significant change in index when weights are assigned to variables without considering dimensional indexes ($W3$ and $W4$), and when arithmetic mean, the simplest method, is used to assign dimensional weights.

Table 20 shows the ranks of $W5$, $W6$, and $W7$ indexes compared to BR-HDI. There is no alteration at the bottom of the table and a few shifts at the top; Federal District shifts -2 positions in $W6$ compared to BR-HDI. Large shifts in rank are found in the middle area, whereas, for example, Rio Grande do Norte shifts from 16 in BR-HDI to 21 in $W5$, Tocantins shifts from 17 to 20 in $W7$, and Rondônia shifts from 15 in BR-HDI to 20 in $W6$ and 19 in $W7$.

Table 4.20
BR-HDI and alternative weights (Part II)

Rank	BR-HDI	$W5$	$W6$	$W7$
1	Distrito Federal	Distrito Federal	São Paulo	Distrito Federal
2	Santa Catarina	São Paulo	Santa Catarina	Santa Catarina
3	São Paulo	Santa Catarina	Distrito Federal	São Paulo
4	Rio Grande do Sul	Paraná	Rio Grande do Sul	Rio Grande do Sul
5	Rio de Janeiro	Rio Grande do Sul	Paraná	Rio de Janeiro
6	Paraná	Rio de Janeiro	Rio de Janeiro	Paraná
7	Espírito Santo	Minas Gerais	Minas Gerais	Espírito Santo
8	Minas Gerais	Espírito Santo	Espírito Santo	Minas Gerais
9	Goiás	Roraima	Roraima	Roraima
10	Roraima	Goiás	Goiás	Goiás
11	Mato Grosso do Sul	Mato Grosso	Mato Grosso do Sul	Mato Grosso do Sul
12	Mato Grosso	Mato Grosso do Sul	Mato Grosso	Mato Grosso
13	Amapá	Amazonas	Amazonas	Amazonas
14	Amazonas	Amapá	Piauí	Amapá
15	Rondônia	Tocantins	Amapá	Rio Grande do Norte
16	Rio Grande do Norte	Acre	Tocantins	Piauí
17	Tocantins	Piauí	Pernambuco	Pernambuco
18	Pernambuco	Rondônia	Paraíba	Paraíba
19	Paraíba	Pernambuco	Rio Grande do Norte	Rondônia
20	Piauí	Paraíba	Rondônia	Tocantins
21	Bahia	Rio Grande do Norte	Acre	Bahia
22	Acre	Bahia	Bahia	Acre
23	Pará	Pará	Pará	Pará
24	Sergipe	Sergipe	Sergipe	Sergipe
25	Ceará	Ceará	Ceará	Ceará
26	Alagoas	Maranhão	Maranhão	Alagoas
27	Maranhão	Alagoas	Alagoas	Maranhão

Author

Factor analysis is justified in constructing summary-indicators when there are no beliefs about the importance of each indicator, which is a problem when a dimension is composed of more than one indicator. One alternative method to assign weights is asking people to rate topics according to their importance on well-being, as the OECD Better Life Index[13], based on Stiglitz-Sen-Fitoussi Commission report (STIGLITZ; SEN; FITOUSSI, 2009), but this kind of information is not available. Although there was a public consultant (Pnud, 2009) asking people what needs to change in Brazil to improve their lives, however, it is difficult to transform the answers on weights once the variables available in BR-HDI and in themes in consultant aren't the same.

[13] http://www.oecdbetterlifeindex.org/

The successful experience of HDI in measuring human development preclude us to use other kinds of dimensional index aggregation, such as Factor Analysis or Principal Component Analysis. In almost 30 years of the HDI, two conceptions did not change: Human development is measured by three dimensions (income, health, and education) and all are equally important[14]. For these reasons, the BR-HDI indicators are divided into the same UN-HDI's dimensions and geometric mean aggregated.

[14] Changes to the Human Development Index methodological aspects can be found in (KLUGMAN; RODRÍGUEZ; CHOI, 2011)

4.8 Conclusion

This paper proposes an alternative index that maximizes the use of available data and is better able to measure human development between the Brazilian States. The suggested approach improves the technical quality of the BR-HDI since we used factor analysis to assign weights due to the lack of theoretical foundations that justify an exogenous (and arbitrary) decision on the weights of the indicators in the dimensional indices, but, to maintain the central concept of the HDI, the dimensions were equally weighted.

Previous works on human development measures concentrate efforts on creating a more discriminating index for developed countries and regions (BURD-SHARPS; LEWIS; MARTINS, 2008; HARDEMAN; DIJKSTRA, 2014; HERRERO; MARTÍNEZ; VILLAR, 2010). On the other hand, BR-HDI focused on developing countries - and within countries - challenges. Variables included in BR-HDI are more sensitive to capturing the human developmental phenomena in Brazil, one of the most unequal and most violent countries in the world, but also applicable to other developing economies.

Such an index captured the large regional differences in human development in Brazil. The distribution of BR-HDI scores among Brazilian States shows a clear pattern: States of North and Northeast regions are about 20 years lagged in terms of human development in comparison to States at South, Southeast, and Midwest regions. However, since 1981, the distance between minimum and maximum scores of BR-HDI have become smaller, signalizing a decrease in regional human development disparities in Brazil over the time.

This study calls attention to within-country human development contrasts and provides an analytical tool that can be used by policymakers and researchers, to better understand the dynamics of regional human development over the time once we have built an index that covers more than 30 years of spam.

Table 4.21

International Indicators

	GINI index (World Bank estimate)[1]*	Poverty headcount ratio at $3.20 a day (2011 PPP) (% of pop.)[12]*	GNI per capita, PPP (current international $)[3]	Improved sanitation facilities (% of population with access) (2014)[4]	Intentional homicides (per 100k people) (2014)[5]	Mortality rate, infant (per 1,000 live births)[6]	Life expectancy at birth, total (years)[7]	Illiteracy rate, youth total (% of people ages 15-24)[8]*	Average number of years of education. 25 and older (2013)[9]
Brazil	0,515	7,9	15870	83	28	15	75	1,15	7,2
World	0,37	20,97	15235	68	5	32	72	8,81	8,41
OECD Members	0,329	1,15	40340	98	3	6	80	near zero	11,37
Upper middle income	0,389	6,29	15375	80	7	13	75	1,83	8,99
Latin America & Caribbean	0,465	13,19	15008	83	23	16	75	1,94	8,45

Author. Data from https://data.worldbank.org/ and http://hdr.undp.org

* denotes the latest value between 2012-2015 interval

Notes from the source of data:

[1] World Bank, Development Research Group. Data are based on primary household survey data obtained from government statistical agencies and World Bank country departments.

[2] Data for high-income economies are from the Luxembourg Income Study database

[3] World Bank, International Comparison Program database

[4] WHO/UNICEF Joint Monitoring Programme (JMP) for Water Supply and Sanitation

[5] UN Office on Drugs and Crime's International Homicide Statistics database.

[6] Estimates Developed by the UN Inter-agency Group for Child Mortality Estimation (UNICEF, WHO, World Bank, UN DESA Population Division) at childmortality.org. Projected data are from the United Nations Population Division's World Population Prospects.

[7] Derived from : (1) United Nations Population Division. World Population Prospects, (2) Census reports and other statistical publications from national statistical offices, (3) Eurostat: Demographic Statistics, (4) United Nations Statistical Division. Population and Vital Statistics Report (various years), (5) U.S. Census Bureau: International Database, and (6) Secretariat of the Pacific Community: Statistics and Demography Programme.

[8] United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics.

[9] Barro and Lee (2013) and UNESCO Institute for Statistics

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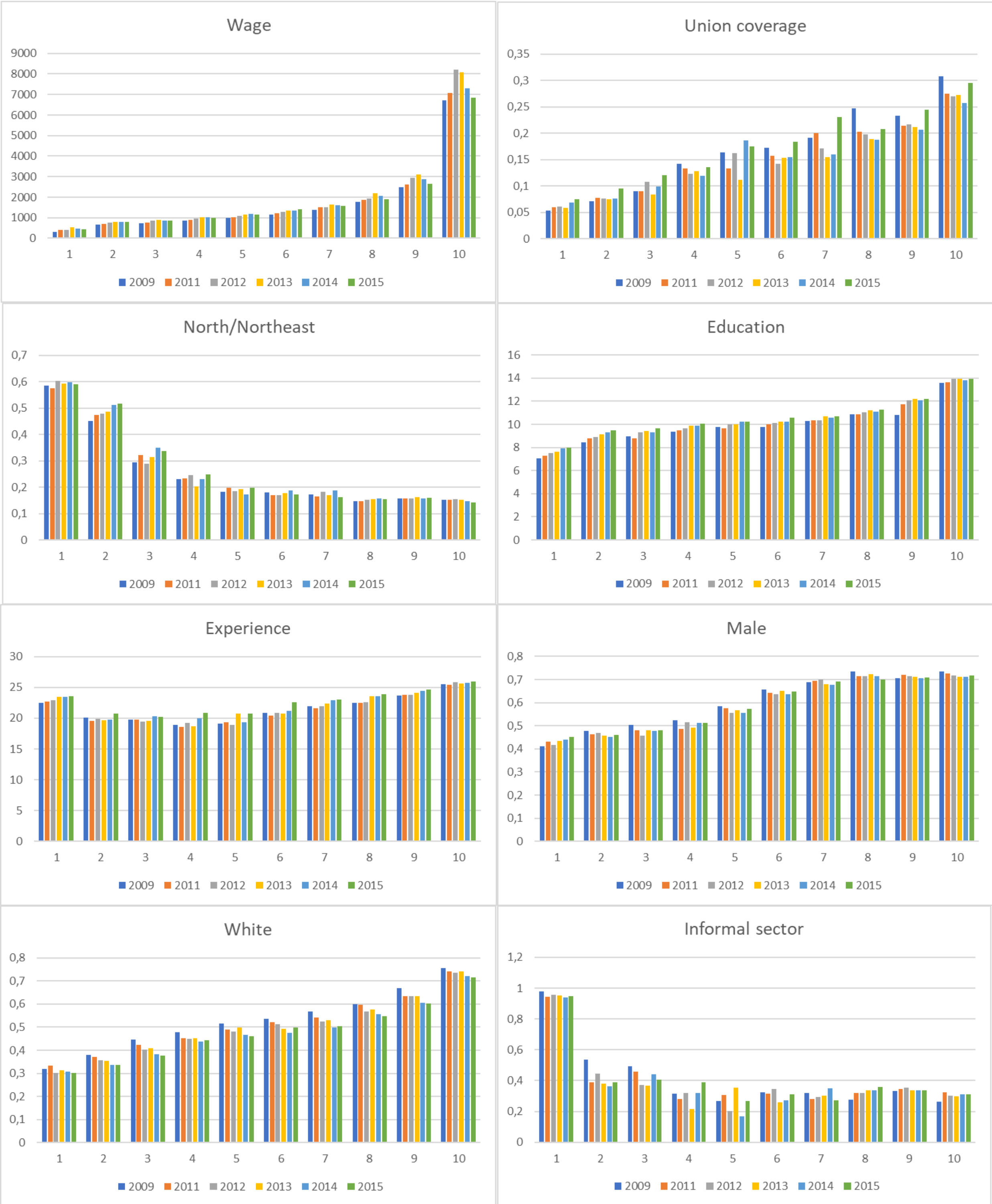
Annex

Descriptive statistics: graphs per decile 2009-2015.



Source: PNAD microdata. Elaborated by authors.