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The heterogeneous effects of conditional cash transfers across geographical clusters: do energy factors matter?

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Abstract

Are the effects of antipoverty policies heterogeneous across geographical clusters? If so, do contextual factors affect these differences? This paper addresses these questions by examining the effects of a conditional cash transfer (CCT) program in Brazil. While extensive research has been conducted on the evaluation of the mean impacts of CCTs on human development, research examining the heterogeneity of the effects across areas and its determinants is lacking. This is a crucial issue as CCT programs are now implemented in many countries that are large and geographically heterogeneous. The empirical analysis in this study uses an augmented multilevel model for the case of *Bolsa Família* in Brazil. The findings show that the effects of the antipoverty policy adopted vary across geographic clusters, especially when considering the ultimate goals of these programs (e.g. health status), compared to the intermediate outcomes (e.g. school attendance). The findings also underline the major role of the energy infrastructure in explaining such heterogeneity, providing empirical evidence on the importance of energy for poverty reduction. The paper also indicates that additional policy interventions can complement direct cash transfers to make poverty reduction more effective.

Keywords

Conditional cash transfers, heterogeneity, effects, contextual factors, energy, Brazil

JEL Codes

I3 Welfare, Well-Being, and Poverty

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1. Introduction

It is estimated that antipoverty transfer programs in developing countries reach nearly one billion individuals (Barrientos, 2013). These programs are increasingly implemented by low and middle-income countries as a tool to directly address poverty. The programs include conditional (CCT) and unconditional (UCT) cash transfers. The former, popular especially in Latin America, focus more on the intergenerational transmission of poverty by making the transfer conditional on the fulfilment on conditions linked to human development. The latter are widely used in Sub-Saharan Africa.

Extensive research has been conducted to evaluate the mean impact of these programs on several outcomes. Conditional and unconditional cash transfers increase consumption levels of the beneficiaries, and decrease poverty. Such policies, and especially CCTs, also enhance human development with regards to the majority of intermediate and final outcomes related to health and education. While much attention has been placed on the mean impacts of these policies, much less has been done to explore the heterogeneity of the effects of these policies. In fact only a handful of studies focuses on quintiles of the outcomes of interest, gender differences, or general differences between rural and urban areas (Barrientos, Debowicz, & Woolard, 2016; Dammert, 2009; Djebbari & Smith, 2008; Galiani & McEwan, 2013).

Limited attention has also been given to how the effects of such policies may vary across geographic clusters and the relative importance of contextual factors. This comes as a surprise given the conclusions of many studies in economic geography and economic development that such differences matter in terms of policy implementation. Geographic clusters represent the context within which national policies are implemented. And local contexts may vary according to several factors, including socio-economic development, infrastructure or political institutions. There is therefore the need to have a better understanding of which factors influence the success of antipoverty programs.

The paper aims at filling this gap by empirically estimating the heterogeneity of program effects and its drivers. More specifically, the analysis presented investigates and quantifies the heterogeneity of the effects of a CCT between geographical clusters at different policy levels. By doing so, this paper also analyses two critical issues. First, the analysis also tests the importance of one key contextual factor - energy infrastructure - in explaining the heterogeneity of the effects. Energy infrastructure has been analysed because of its importance for both environmental goals as well as poverty reduction. A vast literature has shown how, for example, connection to electricity allows individuals to take advantage of more opportunities, to be more productive and to live better lives (Dinkelman, 2011). Second, the paper differentiates between intermediate and final outcomes.

The empirical setting of this study is the *Bolsa Família* program in Brazil. This case is relevant for two reasons. It was a policy that was implemented at the national level; it is thereby possible to analyse differences across different geographical clusters. Second, Brazil is a very heterogeneous country, with large variations between geographical clusters in relation to many dimensions. More specific to the issues addressed in this research, Brazil's energy infrastructure is underdeveloped and varies greatly between regions (Amann, Baer, Trebat, & Villa, 2016).

The empirical analysis draws on previous research that examined the effects of the *Bolsa Família* program on health and education outcomes, namely school attendance and child mortality (Barrientos et al., 2016; Rasella, Aquino, Santos, Paes-Sousa, & Barreto, 2013). The data used in this research comes from different sources. Estimations for school attendance use several rounds of the annual National Household Sample Survey (PNAD), containing information on labour and education variables. Child mortality estimations use official municipal level data on *Bolsa Família* coverage, health and other socio-economic indicators from 2004 to 2010. In addition the research uses data from the Brazilian Electricity Regulatory Energy (ANEEL) on the quality of the energy infrastructure. To estimate the heterogeneity of the effects of the program at the municipal level, an augmented version of a multilevel model is employed to explore differences in the effects across municipalities and states. The use of a multilevel model in a quasi-experimental setting is a novelty in the evaluation of conditional cash transfer programs; these models take advantage of the hierarchical nature of the data to estimate the variance of program effects and the significance of contextual factors.[1] This is not possible in the usual fixed-effects estimations.

The results of this paper show that the effects of the *Bolsa Família* program vary significantly across geographical clusters at both state and municipality levels. This is especially true for final outcomes such as child mortality. Moreover, energy infrastructure proves to be a significant factor in mediating the impacts of the *Bolsa Família* program on child mortality. These results suggest that to better understand the effects of social policies it is necessary to consider geographical clustering, as these clusters differ in relation to relevant characteristics. Different complementary policies can also be thought to make antipoverty programs more effective. This is in line with the recent launch of the *Brasil Sem Miséria* program (Paes-Sousa & Vaitsman, 2014). Within this program, *Bolsa Família* is just one component and it is complemented by other policies, one of which being the supply of electricity especially to rural areas.

[1] Luseno, Singh, Handa, and Suchindran (2014) use a multilevel model for the case of Malawi, focusing on the heterogeneity across families and not across regions. von Jacobi (2014) employs a multilevel model to study the conversion of *Bolsa Família* into human development across municipalities, but not in an experimental setting.

The paper contributes to the literature in several ways. First, it measures and demonstrates the importance of the heterogeneous effects of antipoverty and social policies. Second, it provides empirical evidence of the importance of contextual factors. This addresses a significant gap in the literature (Bastagli et al., 2016). One of these mediating and contextual factors has been found to be the access and quality of energy services. Third, the paper emphasizes the importance of energy for poverty reduction and provides initial empirical evidence in the context of antipoverty policies. Fourth, from an analytical and econometric point of view, the study demonstrates the usefulness of multilevel models in enabling the use of relevant information that is lost in fixed effects estimations (Bell & Jones, 2015).

The paper is organized as follows. In Section 2, the background and a summary of the literature is presented, focusing on three main aspects. The first regards the impacts of social protection programs and their heterogeneity. The second aspect focuses on the effects of energy factors on development and poverty eradication, while the third one relates to the case of Brazil. In Section 3, the data and methods are described and the model used in the econometric analysis to estimate the heterogeneity of program effects is outlined. Section 4 presents the results of the estimations. Finally, Section 5 discusses the policy implications and conclusions.

2. Background

The effects of CCTs

Direct antipoverty policies are increasingly being implemented by many developing countries (Barrientos, 2013). Among these policies, conditional cash transfers represent a significant component. The number of CCTs has been increasing in the past two decades, especially in Latin America (Grosh, Quintana, Alas, P, & Andrews, 2011), accounting now for 22 (out of 63) of these programs (Honorati, Gentilini, & Yemtsov, 2015). Moreover CCTs are not limited to developing countries; for example New York City rolled out a three-year pilot program, called Opportunity NYC (Baird et al., 2013). Therefore, a focus on CCTs is justified on the basis of their relevance and use for poverty reduction.

The other reason to focus on CCTs is that these programs have been accompanied in many cases by the implementation of experimental, and quasi-experimental, evaluations. This was, among other actors, a response to a strong political demand for evaluation (Barrientos & Villa, 2015). These evaluation studies have shown that CCTs have a positive impact on consumption and poverty reduction in general; this is especially true when considering measures such as poverty gap, as opposed to poverty headcount (Fiszbein & Schady, 2009). Consumption increases are aimed to be achieved through both a direct effect (the cash transfer from the program), and an indirect one. The latter mechanism is the key components of the longer-term strategy to break the intergenerational transmission of poverty. It is represented by a substitution effect, namely decreasing the relative price of schooling or health to enhance investments in human development.[2] Therefore the effects of CCTs have been studied also in relation to health and education outcomes, both intermediate and final ones (Baird et al., 2013; Bastagli et al., 2016; Fiszbein & Schady, 2009).[3] This distinction between intermediate (such as school attendance and health clinic visits) and final outcomes is crucial as intermediate outcomes are related to behavioural changes such as school attendance or health visits, and are more strictly linked to program conditions. Final outcomes (school test scores and health status or mortality rates) instead relate to the ultimate goals, such as better health or education attainment.[4]

Regarding education, CCTs have been found to significantly affect school enrolment and attendance, but the evidence on the effect of these programs on final educational outcomes is not clear (Ponce & Bedi, 2010). One of the explanations is that the increased demand for education and schooling is not matched with increased supply, such as the number of teachers and their quality. On the other hand, CCTs seem to have a significant effect on both intermediate and final health outcomes (Fiszbein & Schady, 2009). For intermediate outcomes, extant research provides evidence of positive program effects on growth and development monitoring visits to health centres by children (Bastagli et al., 2016). The effects are mixed for immunisation rates. Turning to final health outcomes, research (Barham, 2011; Rasella et al., 2013) has shown the positive effects of CCTs on infant mortality, as well as on many other final outcomes, such as child height and general health status (Fiszbein & Schady, 2009). In summary CCTs fostered investments in the human development of the beneficiaries. More specifically these programs increased the utilisation of education and health facilities. Still, the effects of these policies on final outcomes are stronger on health status than on educational attainment.

It is important to note, however, that most of the extant literature on conditional cash transfers focuses on the mean impacts of such policies (Bastagli et al., 2016). This is motivated in part by methodological and data collection concerns, such as the use of

[2] On the other hand, UCTs act solely through an income effect (Baird et al., 2013)

[3] Moreover, looking at health and nutrition outcomes, (Glassman et al., 2013) divide the substitution effect into three different effects: the effects of conditionalities on preferences and attitudes of beneficiary families (knowledge effects resulting from health or nutrition training/talks); improvements in the supply of basic health services, either as part of the program or as a complementary strategy to expand health services in areas where the program is implemented; and finally, through preferential or facilitated access to services, especially in Latin American programs.

[4] Many mediating factors are relevant for the translation of intermediate outcomes to final ones (for example whether increased school attendance translates into better test scores and improved learning).

fixed-effects and randomised control trials (RCTs), as well as by the interest of policy makers in the overall success or failure of the policy. But average effects may hide significant heterogeneity. In fact, the issue of heterogeneity has begun to be addressed in more recent research. Some studies focus on the heterogeneous impacts of conditional cash transfers on the distribution of the outcome under consideration (Barrientos et al., 2016; Dammert, 2009; Djebbari & Smith, 2008; Galiani & McEwan, 2013; Hoddinott, Alderman, Behrman, Haddad, & Horton, 2013). Other studies look at differences of CCT effects across alternative dimensions, such as gender and rural versus urban areas (Bastagli et al., 2016). Despite a growing interest on the heterogeneity of the effects of CCTs, the number of these studies is still limited and more research is needed.

One area of further interest is the heterogeneity of effects across geographical clusters and the role of mediating (contextual) factors. The latter is an important issue as some contextual factors, such as infrastructure, might underpin the effectiveness of CCTs, (Glassman et al., 2013). Only a handful of papers consider the significance of mediating factors in relation to CCTs (Chiwele, 2010; Gertler, Patrinos, & Rubio-codina, 2007; Heinrich, 2007; Luseno et al., 2014; von Jacobi, 2014). Specifically these studies show that contextual factors, such as overall infrastructure levels, are important for the success of social policies and CCTs. Still, these studies do not measure the heterogeneity of the program effects between geographical clusters, nor do they consider energy as a contextual factor.

Energy as an enabling factor

It is common knowledge that many people in extreme poverty lack access to electricity and other modern energy services. There is a strong association between poverty (monetary and multidimensional) and the lack of (modern) energy (Karekezi, 2002). The link between energy and development is relevant, but the relationship is more complex. Access to (and use of) energy is an enabling factor for many human activities and development. But its importance for social and economic development has only recently begun to gain recognition and attention. In fact, while the Millennium Development Goals made little mention of energy (Cabraal, Barnes, & Agarwal, 2005), the Sustainable Development Goals have developed specific targets for access to energy (Schwerhoff & Sy, 2017).

The effects of access to modern energy on (monetary) poverty at the household level can be seen as acting through two channels The first one is a direct effect related to lower costs of modern energy and time saving (Khandker, Barnes, & Samad, 2012).[5] In this sense, access to modern energy could increase savings or divert expenditures and

[5] Increased earnings from agricultural and commerce then lead in turn to greater household demand for electricity (Wasserman and Davenport, 1983).

time towards more productive activities.[6] The second, indirect, effect is the enhanced capacity to start, or join, productive activities that will generate future income (Bensch, Peters, & Schmidt, 2012; Rao, 2013). This includes the running of micro-business and agricultural activities and productivity of local agro-industrial and commercial activities; but also opportunities for additional employment, especially for women, through new activities or the improvement of existing enterprises due to the reduction of energy costs (Barron & Torero, 2014; Dinkelman, 2011; S. R. Khandker, D. F. Barnes, & H. A. Samad, 2013; Lipscomb, Mobarak, & Barham, 2013; van de Walle, Ravallion, Mendiratta, & Koolwal, 2013). Among modern forms of energy, access to electricity is the most important factor identified in these studies (Barnes, Peskin, & Fitzgerald, 2002; Filmer & Pritchett, 1998; S. Khandker, D. F. Barnes, & H. Samad, 2013).

Access to modern energy[7] can have important positive effects on human development as well. The effects on health (Ezzati & Kammen, 2002) have been found to be significant, mainly on final outcomes (the health status of the population) compared to intermediate ones (visits at health clinics and checkups) at both the household and community levels (Cabraal et al., 2005; Riahi et al., 2012; Toman & Jemelkova, 2003). For example, access to electricity facilitates the refrigeration of medicines. In relation to education, research especially focuses on the role of electricity and electrification projects (Dasso & Fernandez, 2015; S. Khandker et al., 2013; Khandker et al., 2012; Lipscomb et al., 2013). For intermediate outcomes, access to modern energy increases school attendance and enrolment. This effect happens through two closely related mechanisms. The first, at the household level, is its role in increasing school attendance in rural areas as the time for daily chores related to energy provision is reduced; this is especially true for girls. The second effect, more indirect and at the community level, is related to the opportunity cost of going to school. If electrification brings new business, as seen previously, education can be preferred to work if it is perceived as paying off it the long run. On the other hand, mixed evidence has been found on the role of modern energy on final educational outcomes (Barnes et al., 2002; Glewwe, Hanushek, Humpage, & Ravina, 2011; Khandker et al., 2012; Kremer & Holla, 2009).

The case of Brazil

Brazil's importance in the global context had been rising in recent decades. One of its most noteworthy successes has been the combination of economic growth with decreasing poverty and inequality. Most of the success in improving social outcomes has to be given to progressive social policies, such as the conditional cash transfer *Bolsa Família*. The program started in 2003 and unified existing programs, run by different agencies and with separate information and financing systems (Foguel &

[6] One effect to keep into consideration is the rebound effect. In this case the households actually consume more energy given the favorable price and quality of modern energy.

[7] Defined as access to electricity and clean cooking.

Barros, 2010).[8] The CCT divided families in poverty into two groups: families in extreme poverty, and families in poverty. The latter received variable benefits depending on the number of children and breastfeeding mothers. The former received fixed benefits in addition to the variable ones. Variable benefits were dependent on three main conditionalities. From the point of view of education, children in school-age are required to have attendance rates of at least 85% school attendance. Considering health, the conditionalities include both immunization of children and medical evaluations for pregnant and breast-feeding women (Lindert et al., 2007).The amount of the benefits was the same across the entire country.

Municipalities are in charge of the program implementation, such as registering potential beneficiary families; and they receive federal funds based on poverty maps. Therefore the percentage of those eligible covered by the program can significantly differ between similar municipalities due to this decentralisation (Lindert et al., 2007).[9] But municipalities and other actors at different policy levels are also relevant in relation of other services that may affect the program (Paiva et al., 2016). One relevant example is the supply of energy and the energy infrastructure. During the "lost decade" of the 1980s, when Brazil underwent a serious debt crisis, investments in infrastructure were neglected (Amann & Baer, 2002). This was especially the case for energy infrastructure, which is now the main component of infrastructure investments (Amann et al., 2016). The electricity sector is the most important component and presents two main features. First, electrification issues were mainly related to rural areas where the majority of the poor live.[10] Second, the electricity sector in Brazil is mainly organised at a state level; this is true both in terms of investments from state actors (or at the state level), and in terms of concessionaires and distribution networks, which are assigned

[8] These programmes were the *Programa de Erradicação do Trabalho Infantil* (PETI), *Bolsa Escola, Bolsa Alimentação, Auxílio-Gás, Cartão Alimentação* (Lindert, Linder, Briere, & Hobbs, 2007).

[9] Differences between municipalities exist also in relation to conditionalities. On one hand *Bolsa Família* had always (since its launch in 2003) included educational conditionalities as part of the program. These conditionalities have been effectively monitored just from 2006, as school attendance information started to be collected by, and became responsibility of, the Ministry of Education and the Secretariats of Education at state and municipal levels (Paiva, Soares, Cireno, Viana, & Duran, 2016).The monitoring process is now based on a federative arrangement.

[10] This link between electricity and poverty (as well as between CCTs and complementary interventions) has been underlined by the Brazilian government under the new *Brasil Sin Miséria* program.

areas usually equal to single states. [11] Therefore the heterogeneity between states can be useful for the analysis.[12]

3. Data and methodology

Data and selected outcomes

The aim of the paper is to look at the heterogeneity of effects of *Bolsa Família* on human development. School attendance and child mortality have been specifically selected as they have been the most widely studied outcomes and for which data is available. In order to accomplish this, the data source draws upon extant research on the evaluation of *Bolsa Família*. Therefore, different sets of data are used in the analysis. The estimations regarding school attendance are based on several papers (Barrientos et al., 2016; de Brauw, Gilligan, Hoddinott, & Roy, 2015; Paiva et al., 2016), and include data from the *Pesquisa Nacional por Amostra de Domicílios (*PNAD), the Brazilian National Household Sample Survey. The survey is conducted annually by the Brazilian Institute of Geography and Statistics (IBGE) since 1981, and investigates several characteristics of the population such as household composition, education, labour, income and fertility. The waves between 2001 and 2006 of the PNAD data are used. The inclusion of early years as 2001 and 2002 is related to the fact that, as *Bolsa Família* started in 2003, a jump in the coverage around 2003 and 2004 is expected (in 2001 and 2002 the previous programs were operating). The use of data until 2006 is also driven by the fact that the conditionalities related to the program were not properly implemented until that year (Paiva et al., 2016). This could mean that increased coverage at the municipal level might not necessary imply higher school attendance rates. As just the 2004 and 2006 waves of PNAD have a direct question on the participation to *Bolsa Família*, the methodology developed by (Foguel & Barros, 2010) has been followed to estimate *Bolsa Família* coverage for the remaining years.

Estimations on child mortality are based on datasets used by Rasella et al. (2013), also given the lack of appropriate health data in the PNAD questionnaire. Municipal level data from the Ministry of Health (MS) has been used (these data include mortality information system, primary care information system on live births outpatient information system) to gather information on the necessary variables, such as under-5

[11] In Brazil, funding resources were to be divided among the various actors, with the federal government taking the largest share (71.5% of investments covered by the federal government's power sector funds, 13% by the states and 15.5% by the concessionaires). More than half of distribution companies have been allocated one particular state to cover. And eight of the concessionaires are operated by state governments.

[12] Brazil represents a case where the link between energy (electricity) and development (and poverty) is very strong and explicit. For example, the coverage of the *Luz Para Todos* program was based on the HDI index.

deaths, live births, and admissions to hospital.[13] As a complement, data from the Ministry of Social Development (MDS) to calculate *Bolsa Família* coverage, and from IBGE for socio-economic variables (obtained mostly from the 2000 and 2010 Census), has been used.[14]

Finally, data related to energy factors is obtained from ANEEL, and are related to the quality of energy infrastructure. The variables used in the analysis are the (standardided) duration (DEC), and (standardised) frequency (FEC) of electricity blackouts, and the percentage of losses in the electricity distribution.[15] The use of energy variables related to the infrastructure, in comparison to monetary investments, is preferred as the efficiency of the latter is uncertain (Pritchett, 1999).

Descriptive statistics

[13] Under-5 mortality rates are constructed as the number of under-5 deaths per 1,000 live births.

[14] Data from Census (IBGE) is from 2000 and 2010; values for the remaining years are obtained through linear interpolation. Some trimming of the data has been necessary to account for the presence of outliers and data issues. A mortality rate threshold of 150 (Shei, Costa, Reis, & Ko, 2014) has been used. The results are similar.

[15] "DEC/DIC (Equivalent Interruption Duration): the number of hours, on average, that a consumer goes without electricity during a period, usually monthly. FEC/FIC (Equivalent Interruption Frequency per Consumer Unit): how many times, on average, there was interruption in the consumer unit" (ANEEL, 2008, pag. 27).

Table 1 outlines the summary statistics of the data for the outcomes of interest and the coverage of *Bolsa Família*; the estimates presented are unweighted average of estimates from available municipalities. The first column refers to the estimations on school attendance. The mean municipal coverage of *Bolsa Família* is around 12%, with a high variance. The coefficient of variation, measured as the ratio between the standard error and the mean is larger than one (the number of observations for each variable is 4,902 which is equal to the number of municipalities in the sample, 817, multiplied by the number of years, six). The coverage of Bolsa Família increased as well. This is also confirmed by the fact that the initial target of 11 million households (corresponding to around 44 million people) was reached in 2006. School attendance rates are high and with lower dispersion. Its values have also been increasing from 94.2% in 2001 to 96.2% in 2006.

Table 1: Descriptive statistics, outcomes and *Bolsa Família* (PNAD)

	(1) Mean/sd	(2) Mean/sd
BF	.1289003	.3070888
	.1311709	.1825759
School attendance	.9521192	
	.0403692	
Child mortality		22.90927
		13.23173
Observations	4,902	31,935

Source: Author's elaboration

The second column presents the data on the descriptive statistics for the child-mortality estimations.[16] As in the previous case, the values refer to unweighted averages for all years and all municipalities. In this case the total number of observations is 31,935 (from 5,293 different municipalities), this time related to an unbalanced panel.[17] As PNAD data under-represents small geographical clusters, which are rural and poorer municipalities, the coverage of *Bolsa Família* in this second set is higher.[18] As for the other set of data, the *Bolsa Família* coverage increased between 2004 and 2010 from around 20% on average to 37%. The unweighted municipality average for under 5 mortality was 22.9 deaths every 1,000 live births.

[16]These outliers are possibly the consequence of two main issues. The first is the presence of incorrect estimates in the original data sources. The second results from the use of different data sources which might have relied on different underlying data (for example different population values in calculating per capita estimates). In this case outliers have been considered observations with mortality rates higher than 100 and *Bolsa Família* coverage rates higher than 100%.

[17] Compared to the previous case using PNAD data, in this case the panel is unbalanced as some observations were missing for some years for some municipalities.

[18] For the child mortality estimations, a sample with all the Brazilian municipalities that have relevant information for the analysis is used. On the other hand, PNAD data is based on a three stages probabilistic sample (Silva, Pessoa, & Lila, 2002). The PNAD sample includes a balanced panel of 817 municipalities which was representative of the Brazilian population. But the sample focuses on metropolitan areas and auto representative municipalities which are included with a probability of inclusion equal to one.

The final set of data relates to energy factors. As previously mentioned, external data as a proxy for energy infrastructure are used.[19] The same energy variables (but related to the years under consideration) are used for both the sets of estimations (child mortality on one side, school attendance on the other). From Table 1 (in the Appendix) it is possible to observe that the highest average standardized number of annual electricity blackouts in the sample is 66 and the longest average duration is 73 hours. On the other hand, the corresponding minimum values are seven and five hours. From additional analysis not presented here, the quality of the electricity system seems to be lower in the states where the majority of the poor live (in the north of the country).

In sum, from these descriptive statistics, two things emerge. First, *Bolsa Família* coverage has been increasing, while the main outcomes of interest are improving. Second, there is a large difference in energy (electricity) infrastructure across states. These differences, dependent of investments and policies at the state-level, may impact differently the implementation of *Bolsa Família* at the municipal level. And from the previous sections, it is clear that the outcomes under study differ between (municipalities and) states. The econometric analysis examines possible heterogeneities also in the effects of the program between states and municipalities.

Econometric model and multilevel models

The paper follows the majority of the literature on *Bolsa Família* (Barrientos et al., 2016; Foguel & Barros, 2010; Guanais, 2015; Paiva et al., 2016; Rasella et al., 2013; Shei et al., 2014) in employing an ecological approach.[20] The impacts of the program are estimated at an aggregate level, taking the municipality as the unit of analysis.[21] To analyse and quantify the heterogeneity of the effects across geographical clusters, the paper employs an augmented version of a multilevel model. This model allows us to take into account the hierarchical nature of the data and estimate the heterogeneity of the effects, as well as which factors explain the variance, while maintaining the quasi-experimental setting. Figure 1 represents in a simplified way how multilevel models work in this case. Measurement occasions (years) represent level one, municipalities represent level two (as repeated observations are nested in municipalities, meaning

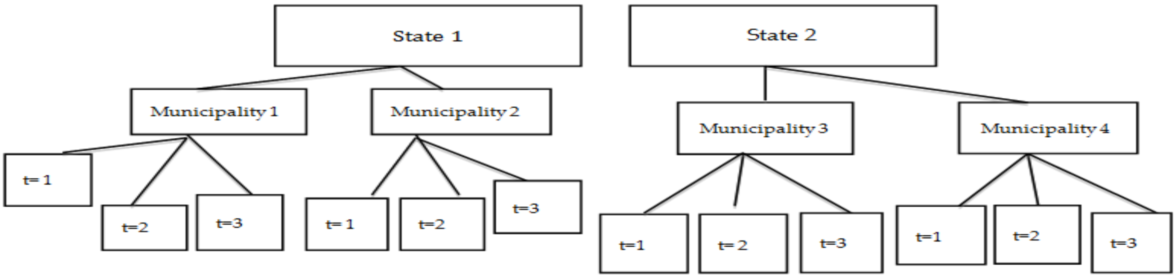
[19] Additional variables tested are prices, consumer satisfaction, electricity rates, and night-lights.

[20] The evaluation data available to assess the impact of Bolsa Família has been collected during two waves: 2005 and 2009. But a proper comparison between a treatment and a control group cannot be estimated as the program started in all municipalities at the same time. Therefore, more artificial control groups have been used, limiting the precision of the data for the estimations.

[21] In some cases schools are considered as the level of analysis (Simões & Sabates, 2014).

that for each municipality there are different observations), and states represent level three (each state includes different municipalities).[22]

Figure 1: Hierarchy in the data



Source: Author's elaboration

Analytically a null (without covariates) multilevel model is of the form

$$\gamma_{00j} = \beta_{0ij} + \varepsilon_{tij}$$
(1)

where

$$\beta_{0ij} = \gamma_{00j} + u_{ij} \quad \text{and} \quad \gamma_{00j} = \beta_0 + v_j$$
(2)

where t is referred to the time occasion, i represents the municipality, j the state. β_{0ij} is the constant term, which is composed of a fixed component γ_{00j} equal for all municipalities in state j, and a random term u_{ij} different for each municipality i; γ_{00j} is in turn composed of a fixed part β_0 and a random term v_j different for each state j. Therefore v_j, u_{ij} and ε_{tij} represent the estimation of the variance at each level and estimates the importance of data hierarchy and clustering. To decompose the total variance into variance *between* and *within* clusters the Intraclass Correlation Coefficient (ICC) can be calculated.[23] The ICC is defined as the proportion of between group variance out of the total variance.[24]

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[22] Alternative classification would have been to consider municipalities nested in time occasions, nested in states, or the use of cross-classification.

[23] When using OLS estimations it is assumed that ICC is 0.

[24] In analytical terms, for example, the ICC for state variance is $v_j/(v_j + u_{ij} + \varepsilon_{tij})$. An ICC larger than 10% is considered large enough to the use of a multilevel model as opposed to a

To estimate the effect of *Bolsa Família* covariates are added, including the one related to the *Bolsa Família* coverage, the control variables and the contextual factors. One of the assumptions of multilevel (and random effects) models is that the random effects need to be uncorrelated with the covariates.[25] But this might not be the case. If the *within* and *between* effects are different, then the coefficient is an "uninterpretable weighted average of the three processes" (Bell & Jones, 2015). A solution, which allows for this heterogeneity bias to be corrected and explicitly modeled, is given by (Mundlak, 1978), and further developed into a *within-between* formulation by (Bell & Jones, 2015; Snijders & Bosker, 2011). Compared to the original formulation from (Mundlak, 1978) their solution includes one additional term in the model for each time varying covariate that accounts for the *between* effect, the higher-level mean. The additional variables are treated in the same way as any higher-level variable. This type of model, with the inclusion of higher-level means for each lower level variable, can also be referred to as correlated random effects (CRE) model (Wooldridge, 2013). The within-between model with random effects becomes of the form:

$$Y_{tij} = \beta_0 + \beta_1 X_{tm} + \beta_2 X_{im} + \beta_3 \overline{X_J} + \beta_4 Z_j + \left[\left(v_{0j} + u_{0ij}\right) + \left(v_{1j} + u_{1ij}\right) * X_{tm} + \varepsilon_{tij}\right] \quad (3)$$

where , X_{im} , equal to $(\overline{X_{\iota J}} - \overline{X_J})$, represents a vector of centred variables at the municipal level, and its coefficient captures the within state variation; X_{tm}, equal to $(X_{tij} - \bar{X}_{ij})$, represents the within municipality variation and is the coefficient of interest. The newly added terms are v_{1j} and u_{1ij}, which are the municipality and state random effects (coefficients).

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classical statistical modelling approach. But the justification of the use of a multilevel model is usually established by a likelihood ratio test.

[25] The assumptions for the three-level random intercept model are: linearity at each level, level-1 residuals ε_{ij} normally distributed, level-2 random effects, u_{ij} and level-3 random effects, v_j, have a normal distribution, level-1 residual variance is constant (homoscedasticity), level-1, level-2 and level-3 residuals are uncorrelated and observations at highest level are independent of each other.

Table 2**Error! Reference source not found.** below summarizes the interpretation of the coefficients of the final model.[26] This paper generalizes their formulation from a two-level model to a three-level model.

[26] The inclusion of random coefficients means a further layer in the assumptions, as now the level 1 residuals have to have a multivariate normal distribution. Further assumptions of independency have to be respected. The level-3, level-2 and level-1 random effects are assumed normally distributed and independent across levels. The level-1 residual error variance is assumed homogenous across of level-1 units.[26]

Table 2: Interpretation of the coefficients of the final model

Coefficient	Interpretation
β_0	Overall mean: across all states, all municipalities and all years
β_1	Within-municipalities: effect of *within* municipality change
β_2	Between municipalities, within states: effect of the difference *between* municipalities *within* states
β_3	Between states: effect of state mean on the outcome.
β_4	Contextual variable(s) effect: effect of state variable (contextual) on the outcome
β_5	Cross-level Interaction effect
v_{0j}	State random intercept: difference between state j mean and the overall mean
u_{0ij}	Municipality random intercept: difference between the municipality i mean and the state j mean
v_{1j}	State random intercept: difference in the effect of X_{tm} between state j mean and the overall mean
u_{1ij}	Municipality random intercept: difference in the effect of variable X_{tm} between municipality i mean and state j means
ε_{tij}	Residual error term: difference between time t score and municipality i mean

Source: Author's elaboration.

The *within-between* formulation has three main advantages over the original formulation (Mundlak, 1978). First, when using temporal data, the coefficients of the demeaned variables are easy to interpret. The *within* and *between* effects are in fact separated (Snijders & Bosker, 2011). Second, if there is correlation between $X_{tij}$and $\bar{X}_{ij}$ and $\bar{X}_j$, by group mean centreing this collinearity is lost. This also means more stable, precise estimates (Raudenbush, 1989). Finally, if multicollinearity exists between multiple $\bar{X}_j$ and other time-invariant variables, $\bar{X}_j$s can be removed without the risk of heterogeneity bias returning to the occasion-level variables. The main point is that this formulation addresses the key sources of correlation (Bartels, 2008). And if correlation exists between mean-centred variables and their respective error terms, this is no more likely than in fixed effects models.

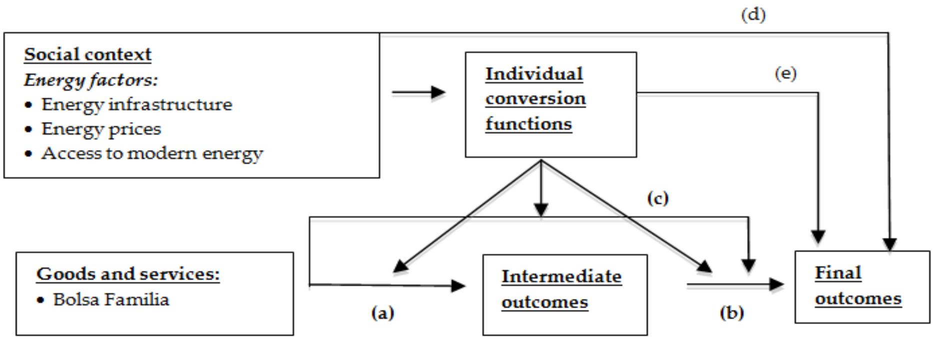
Finally, cross-level interactions between the *within* effect of *Bolsa Família* and state contextual variables are added.[27] The final model will therefore be:

$$Y_{tij} = \underbrace{\beta_0 + \beta_1 X_{tm} + \beta_2 X_{im} + \beta_3 \overline{X_J} + \beta_4 Z_j + \beta_5 (X_{tm} * Z_j)}_{\text{Fixed part}} + \underbrace{\left[\left(v_{0j} + u_{0ij} \right) + (v_{1j} + u_{1ij}) * X_{tm} + \varepsilon_{tij} \right]}_{\text{Random part}} \quad (4)$$

An initial application of a multilevel model for the case of *Bolsa Família* has been performed by von Jacobi (2014). Her analysis, using data from the *Cadastro*, employs a standard multilevel model to analyse the correlation between the length of participation in, and the amount received from, *Bolsa Família* and different composite human development measures across municipalities. Conversely, the research in this paper looks at estimating the effects of the program in a quasi-experimental setting with panel data by using an augmented multilevel model. Through the use of such methodology, the research question previously outlined and presented in Figure 2 may be analysed. The effect of *Bolsa Família* on intermediate (a) and final outcomes (b and c) is different between municipalities; it depends on how the municipality implements the program (the individual conversion function), given the funds received from the federal government. In turn, this heterogeneity also depends on contextual factors at the state level. One of these factors is related to the case of the electricity sector in Brazil which is mostly managed at the state level. The empirical analysis aims to estimate these effects and channels.

[27] In the estimations the Stata command 'xtmixed' is used. The model is fitted by default using the expectation maximisation algorithm until convergence or until 20 iterations have been reached, where maximisation switches to a gradient based method if the option emonly is specified the maximisation stops. This option is used mainly because the default options are very slow to iterate. Finally, regressions are not weighted as interest lies in the variance between geographical clusters and not at the effects at the national level.

Figure 2: Conceptual framework with energy contextual factors



Source: Author's elaboration.

4. Results

4.1. Intermediate outcomes: school attendance

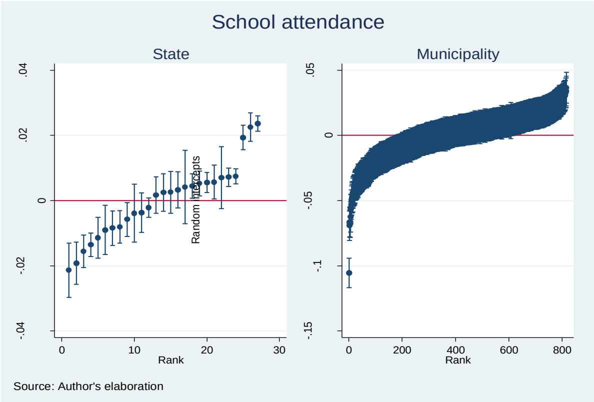
The appropriateness of a multilevel model can be inferred by the null model (one with no explanatory variables). This model (equation 1) considers the hierarchical nature of the data, showing if the variance of the dependent variable depends on the clustering and hierarchy. For the estimations of school attendance rates, the Intraclass Correlation Coefficient (ICC), the likelihood ratio test, and other tests (AIC and BIC) confirm the preference for a three-level multilevel model. [28] More specifically, when considering the ICC, the variance at the state level represents around 10% of the total. At the same time, the ICC for the municipal level is much more significant (37%).[29] Figure 3 graphically represents the intercepts for each state (left part) and municipality (right part), ordered from lowest to highest values. The random intercept can be defined as the "effect" of being part of a particular state (or municipality) on the outcome. If the bar for the state, or municipality, does not cross the red line it means that the average value of the outcome for the state (or municipality) is statistically different from the average at the 95% significance level. Figure 3 shows that 33% (nine out of 27) of states have significantly different intercepts for school attendance. Conversely, the significantly different intercepts for municipalities are 16% (130 out of 817). While states significantly differ more than municipalities in proportional terms, the majority of the the total variance comes from the muncipal level. Figure 9 in the

[28] The AIC and BIC are used to compare models. They take into account the number of parameters estimated and penalize the model for complexity. The lower the value, the better the fit. Comparatively, the BIC penalizes models for complexity more than the AIC. See http://www.stata.com/manuals13/restatic.pdf

[29] Usually 10% is considered the threshold for the ICC.

appendix shows the distribution of the predicted municipality random intercepts for each state using a box plot; this takes into consideration the constant, the state and municipality random intercept. For the municipal effects on school attendance the number of outliers is low. Moreover, the distributions within states seem to approximate a normal one.

Figure 3: State and municipal random intercepts (school attendance)



The heterogeneity of *Bolsa Família* effects is presented in

Table 1. Covariates, apart from the one related to the within effect, are not included in the table for space reasons. The first column presents the estimations from a model with no random coefficients (similar then to a fixed effects regression, as used in the literature). The program coverage has a positive effect on school attendance at the 1% significance level. A 1% increase in program coverage at the municipal level increases school attendance by 0.02%, similar to the findings of previous research. Furthermore, using the coefficient and the average values of the outcomes and *Bolsa Família* coverage, the estimated elasticity of schooling is significantly low, around 0.2%. This is due to the fact that the value of the attendance rate is bound between 0 and 100% and the initial school attendance rates are already high.

Table 1: Effect of *Bolsa Família,* on school attendance

	(1) **School attendance**	**(2)** **School attendance**
	Coefficient (std. error)	Coefficient (std. error)
Bolsa Família *(within effect)*	0.0259*** (0.0069)	0.0304*** (0.0091)
var(BF_state)		0.00034
var(_state)		0.00016
cov(state)		-0.0000906
var(BF_mun)		0.00477
var(_mun)		0.000302
cov(mun)		-0.000493
var(Residual)		0.000937
Other covariates	Yes	Yes
States	27	27
Municip.	817	817
Obs.	4,902	4,902

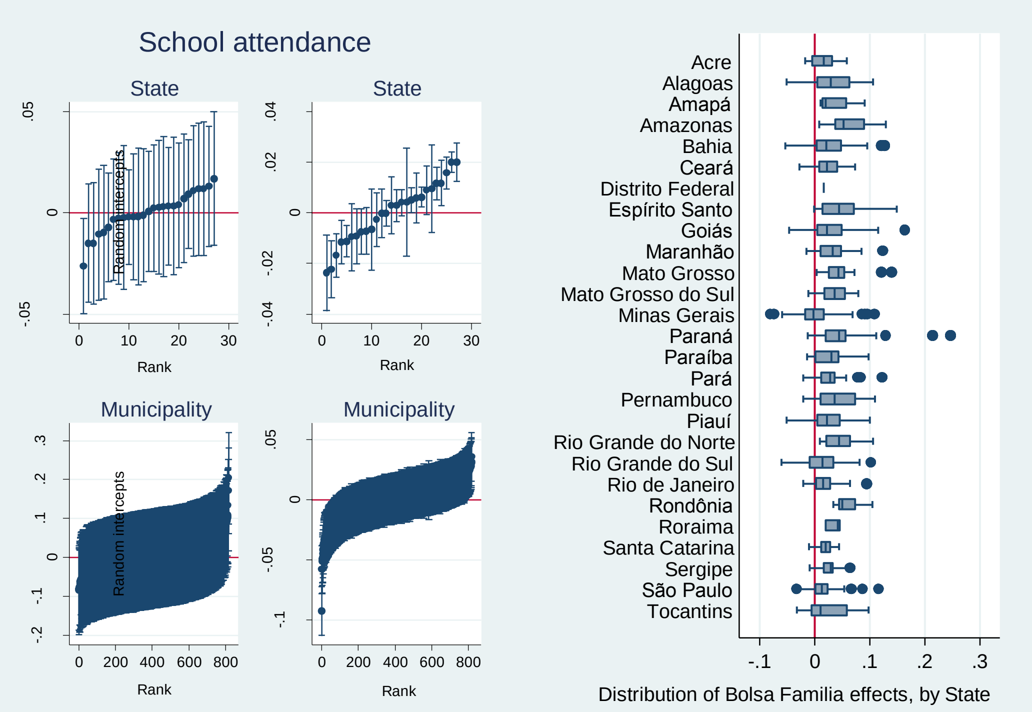
Significance levels:*** = 1%, ** = 5%, * = 10%.

Source: Author's elaboration.

The second column presents the estimations in the case of a multilevel model with random intercepts and random coefficients, at both the municipal and state levels. In this model, the effect of *Bolsa Família* is allowed to vary both between municipalities (within states) and between states. The *within effect* is similar to the first column. The variables *var(BF_state)* and *var(BF_state)* are the random coefficients at the state and municipality levels, *var(_state)* and *var(_state)* are the random intercepts. The model with random slopes at both levels (state and municipality) is preferred to the ones with no random slopes or with a random slope just at one level, demonstrating the importance of the random effects.[30]

[30] Comparing random slope versus random intercept models (through a likelihood ratio tests), the models with random slope are preferred.

Figure 4: State and municipal random effects (school attendance)



Source: Author's elaboration.

The findings on the heterogeneity of the effects of *Bolsa Família* on school attendance can also be analysed by looking at the number of states and municipalities where the coefficient is significantly different. The upper right quadrant in Figure 4 shows that just one state has a significantly different coefficient. On the other hand, for the municipalities the number is four (bottom right quadrant). Therefore, the analysis shows that the variability of the effects of *Bolsa Família* between states and municipalities, despite being empirically demonstrated, is not very high for school attendance.

Similarly, as done previously with the null model, we can see how the predicted effect of *Bolsa Família* is distributed (right part of Figure 4). The number of outliers when considering the municipal random effects of *Bolsa Família* on school attendance is significantly smaller.

4.2. Final outcomes: child mortality

Starting by considering a null model, the estimations for child mortality show a low ICC (3%) at the state level, while the ICC for the municipal level is much more significant (29%). But even if the ICC for across-state variance is under 10%, the likelihood ratio and the AIC and BIC tests all significantly prefer a three-level multilevel model. Figure 5 graphically represents the intercepts for each state (graph on left) and municipality (graph on right): 48% of states, and 13% of municipalities have statistically different values at the 95% significance level. Similarly, to school attendance it can be concluded that, according to the values of under-5 mortality rates, a three-level model is justified.

Figure 5: State and municipal random intercepts (child mortality)

Source: Author's elaboration

Figure 9 in the appendix shows the distribution of the predicted municipality random intercepts for each state using a box plot for child mortality. While the municipal-level effects within states seem to be distributed normally (as the line representing the median is approximately in the centre of the box and whiskers), there is a significant number of outliers on the right (positive) side. These outliers represent municipalities that have significantly higher under-5 mortality rates compared to the state average. This is also confirmed by Figure 12 plotting the distribution of the residuals in the appendix. While the distribution of the residuals at the state level resembles a normal distribution, the one at the municipal level presents heavier tails. Gelman and Hill (2007) state that this does not constitute an issue for the parameter estimates in multilevel models. Moreover, in this paper the focus is on state-level effects as energy factors are at that level. It is just as important, for the interpretation of the results, that estimations might be driven by the presence of outliers when municipalities are compared.

Table 2: Effect of *Bolsa Família* on child mortality

	(1) Child mortality	**(2) Child mortality**	**(3) Child mortality**	**(4) Child mortality**
	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)
Bolsa Família (within effect)	-0.0415***	-0.0556**	-0.0553**	-0.0709***
	(0.0115)	(0.0221)	(0.0222)	(0.0223)
Energy quality			-0.1235***	-0.1304***
			(0.0370)	(0.0371)
Energy quality Bolsa Família*				-0.0028*
				(0.0015)
var(BF_state)		0.0066	0.0067	0.0053
var(_state)	7.603	2.4420	1.4572	1.4496
cov(state)		0.0506	0.0252	0.2341
var(BF_mun)		0.0558	0.0559	0.0559
var(_mun)	40.126	41.054	41.050	41.058
cov(mun)		-0.1361	-0.135	-0.134
var(Residual)		118.885	118.881	118.875
Controls	Yes	Yes	Yes	Yes
States	27	27	27	27
Municip.	5,293	5,293	5,293	5,293
Obs.	31,935	31,935	31,935	31,935

*Significance levels:*** = 1%, ** = 5%, * = 10%.*

Source: Author's elaboration

The coefficients of the regressions estimating the effect of the program are presented in

Table 2.[31] The first column, presenting a multilevel model with no random coefficients, shows that *Bolsa Família* has a significant effect, on child mortality, at the 1% level. More specifically a one per cent increase in *Bolsa Família* decreases child mortality by around 0.04 deaths per 1,000 live births. Even if this latter seems small, it has to be considered that the number of infant deaths is not large. In fact, to better understand the size of the effects, an elasticity of 5% is estimated for child mortality (similarly to Shei et al. (2014)). This means that a 10% increase in the coverage of the program decreases child mortality by 0.5%. This elasticity is higher compared to the previous case of school attendance.

The second column shows the results from the model including random intercepts and the random coefficients for effect of *Bolsa Família*, at both at the municipal and state levels.[32] The coefficients resemble the findings from the null model previously analysed. Again, the likelihood ratio tests and the AIC and BIC suggest that the three-level multilevel model, with random intercepts and random coefficients, is the preferred one.[33] This underlines the importance of considering differences in the program effect across municipalities and states.

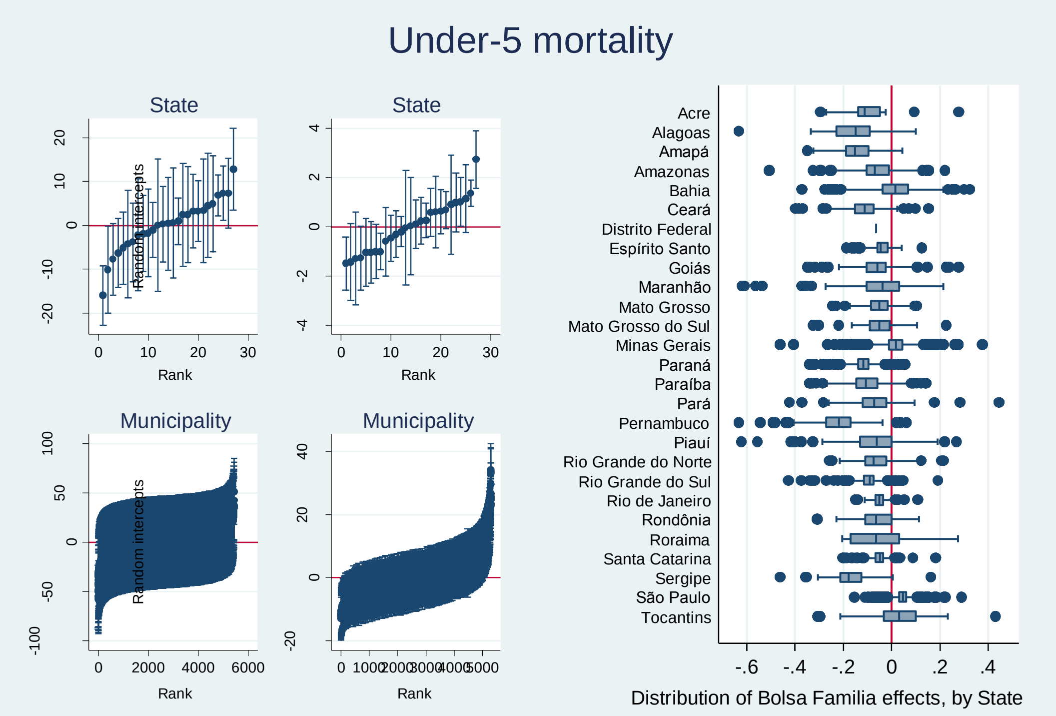
Figure 6 represents graphically the heterogeneity of *Bolsa Família* effects across states and municipalities. The upper left quadrant of Figure 6 shows that that for six states the effect of *Bolsa Família* on child mortality is significantly different from the average at the 95% significance level. The right part of Figure 6 shows how the predicted effect of *Bolsa Família* is distributed. As for the case of random intercepts, the distribution of *Bolsa Família* effects on child mortality presents few outliers. As previously explained, this does not represent a problem for the estimations.

[31] Full regression tables are not presented for space reasons

[32] As in the case for school attendance the model with random intercepts and slopes is the preferred one.

[33] The tests are not presented here.

Figure 6: State and municipal random effects (child mortality)



Source: Author's elaboration.

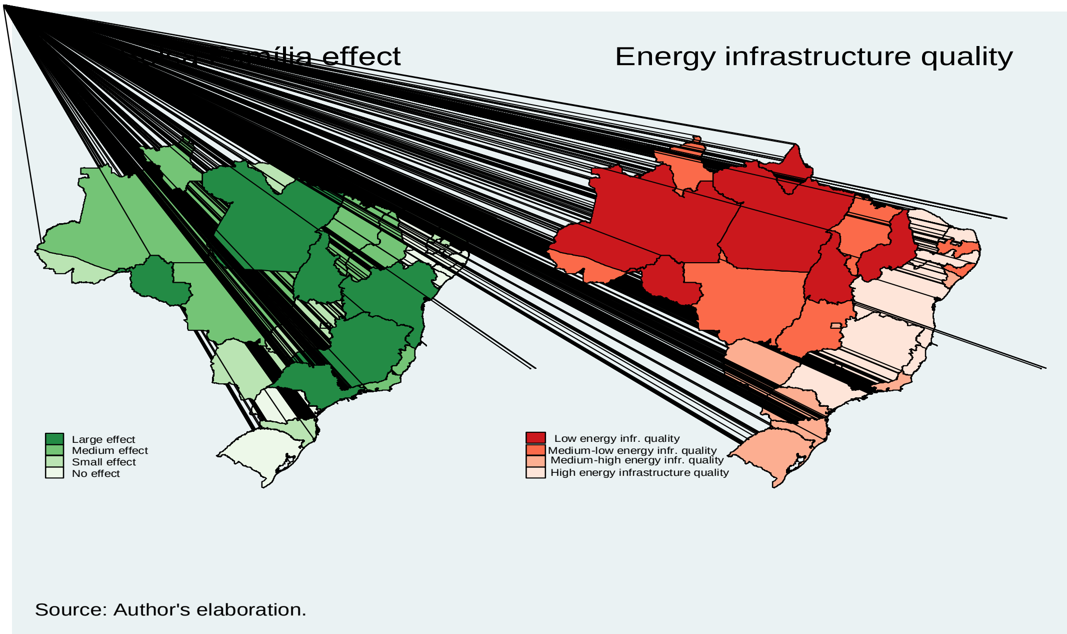
Finally, given the heterogeneity of the effects between states and municipalities especially for child mortality, it is interesting to investigate the relationship between the coefficients of the slope and of the intercept. A negative covariance means that municipalities (or states) with a high intercept (higher initial outcome) tend to have a flatter slope (effect of *Bolsa Família*). At the same time, clusters with a lower than average outcome, benefit more from *Bolsa Família* (higher slope). A negative correlation can therefore be seen as an equalising effect of the program on the outcome of interest. By contrast, a positive correlation can mean increasing differences between clusters due to the effects of the program. Figure 10 in the appendix shows the relationship between the random coefficients and the random intercepts for both states and municipalities, just for the case of child mortality.[34] The relationship between coefficients and intercepts is not very strong but is slightly negative for states and positive for municipalities. This means that municipalities with higher mortality witness a larger effect of *Bolsa Família*. The opposite relationship is true when states are considered.

[34] As the effects of the program on school attendance are not significantly heterogeneous across clusters.

4.3. Role of energy infrastructure

Compared to the fixed effects estimations used in the literature, the augmented multilevel model used in this paper permits to assess the effects of time invariant and higher level (contextual) explanatory variables on lower level outcomes, as well as the extent to which they can explain the variance. In this specific analysis, it is possible to analyse the mediating effects of the state-specific energy infrastructure on child mortality and the importance of this contextual factor in explaining the variability of the *Bolsa Família* effects across states and municipalities. The analysis is not replicated for the case of the case of school attendance as the model including the interaction between the energy variable and *Bolsa Família* is not preferred to the one excluding them. Moreover the previous two sections showed that the effect of *Bolsa Família* was found to be more heterogeneous in the case of child mortality.

Figure 7: *Bolsa Família* effect and energy infrastructure, by state



Source: Author's elaboration.

To start, Figure 7 maps, at the state level, the random coefficient of *Bolsa Família* on child mortality (on the left; a darker area means a larger effect of the program), and the level of energy infrastructure (on the right; a darker area means a lower quality of the energy infrastructure). From the figure, a relationship between larger effects of *Bolsa Família* and better energy infrastructure can be noticed.

This relationship is explored more formally in the last two columns of

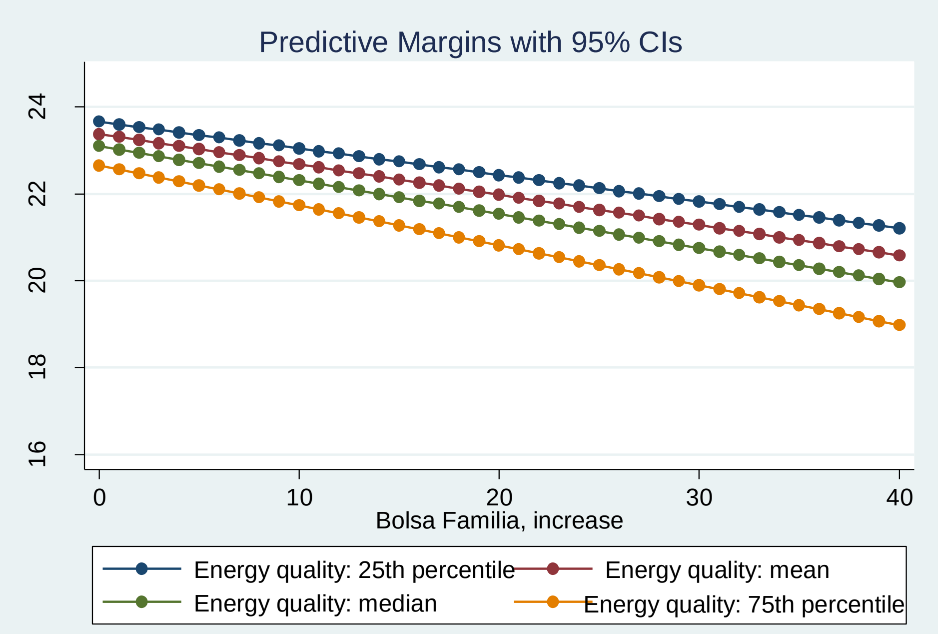
Table 2, where state level covariates related to energy factors are added. In column 3 the coefficient related to the quality of energy infrastructure is significant and negative.[35] This means that better energy infrastructure at the state level is associated with lower child mortality rates at the municipal level. The importance of the energy factors is also confirmed from the value of the random intercept, which decreases with the inclusion of the contextual energy variable in the model. The value of *var(_state),* in fact, has decreased from 2.4420 to 1.4572 from the second column (where the energy infrastructure variable was excluded); this is equal to approximately a decrease of 32%. This means that one third of the differences in child mortality between states can be explained by the quality of energy infrastructure.

Finally, cross-level interactions are added in column 4.[36] This specification tests for the interaction between changes in *Bolsa Família* coverage at the municipal level (level 1) and state energy factors (level 3); and it also analyses whether the inclusion of this interaction term explains the differences in effectiveness of the program between states (in analytical terms this is represented by the change of *var(BF_state*). The results show that the interaction between child mortality and the state energy quality state is significant and negative. The sign of the coefficient indicates that where the infrastructure quality is high, the reduction of child mortality from *Bolsa Família* is larger. Moreover, the value of the random coefficient related to the effect of *Bolsa Família* at the state level (*var(BF_state)*) decreased by 21% (from 0.0067 to 0.0053) further suggesting that the inclusion of the cross-level interaction explains a significant part (around a quarter) of the variability of the effects between states. Figure 8 gives a graphical representation of the above described results, by dividing states according to the quality of their energy infrastructure. It can be seen, in fact, that better energy infrastructure translates into lower mortality rates for the same increase of *Bolsa Família* coverage.

[35] In Table 1 the energy quality variable refers to the frequency of outages (FEC). Table 5 in the Appendix shows the results when using DEC.

[36] In general, models with interaction effects should also include the main effects of the variables that were used to compute the interaction terms, even if these main effects are not significant. Otherwise, main effects and interaction effects can get confounded.

Figure 8: (Fixed) Effect of *Bolsa Família*, by energy infrastructure



Source: Author's elaboration.

In summary, the results from the analysis show that the effectiveness of *Bolsa Família* is different between states and municipalities especially in the case of child mortality (final outcomes). Moreover, the results also show that the quality of the energy infrastructure at the state level partially explains this difference between states in the impact of *Bolsa Família*, confirming the importance of energy for human development. Therefore, this study underlined the significant heterogeneity in the effects of antipoverty policies, as well as the importance of mediating factors.

5. Summary and conclusions

This paper has investigated the heterogeneity of the effects of social protection policies, in the form of a conditional cash transfer program, on human development outcomes, namely school attendance and child mortality. After confirming the literature with regards to the overall positive effect of *Bolsa Família*, the study shows that the effectiveness of these programs varies significantly from one geographic area to another, considering both states and municipalities. Because these clusters are also characterised by large differences in socio-economic development and by independent institutions that determine local level policies, these findings are particularly significant. They suggest, in fact, that studies at the national level provide only a partial understanding of the effectiveness of social policies in eradicating poverty. A better understanding requires a closer examination of the interaction between national level policies and the local contexts in which these policies are implemented.

The analysis also shows that the variations in terms of the effectiveness of conditional cash transfer programs across clusters can be explained in part by energy factors. As the municipality is the unit of analysis, the state represents the cluster context within which the municipality actors operate. And in the case of Brazil, energy (proxied by electricity) policies and infrastructure are mainly defined and managed at the state level. The results indicate that in states where there is a better energy infrastructure, municipalities witnessed a greater effect in decreasing child mortality rates due to *Bolsa Família*. By contrast, differences across states in terms of school attendance do not seem to be impacted by the quality of energy infrastructure.

These findings have a few important policy implications. First, there is the need to expand research on the heterogeneous impacts of social protection programmes, and of conditional cash transfers in particular. This study has shown, in fact that examining only the mean impacts of policies leads us to ignore several factors that are relevant to policy effectiveness. Few scholars have taken contextual factors into consideration in their analyses, looking at their importance on policy effectiveness (Barrientos, 2013; Lindert et al., 2007; Rasella et al., 2013; Rawlings & Rubio, 2005; Stewart, 1987). Moreover, this paper suggests that there is the possibility of using a methodology to solve the evaluation problems that drive the exclusion of considering contextual factors.

Second, this research confirms the importance of energy for human development. The findings of this paper go further to suggest that investments in energy (infrastructure) may also work as an indirect support and complement to more direct programs aimed at the eradication of poverty (Barrientos, 2013). The conclusions that may be drawn from this study, in fact, are that, conditional cash transfer programs will be more effective in regions where the energy infrastructure provides the local population with sufficient electricity to be able to take full advantage of the benefits and requirements of such programs. In terms of the conditions imposed by these programs, it means having schools and medical centres equipped with electricity and therefore able to provide basic services. In terms of the benefits, it may mean having access to household items that alleviate the constraints to development and participation in public services and labour markets.

Moreover, the different impact of energy between intermediate and final outcomes sheds light on the importance of the specification of the type of the goals of human development programs. These programs have conditionalities related to intermediate outcomes, such as school enrolment or health visits, which depend on many factors. But the impact on final outcomes also depends on additional factors, including energy-related factors. Therefore, it is important to analyse the effectiveness of conditional cash transfers in achieving both intermediate and final outcomes, as well as the reasons underpinning the differences in the effectiveness of such programs.

Brazil is a very interesting case for the research questions under examination, as it underlines the joint responsibilities in economic development and poverty reduction across actors and policy levels; this is made clear in the recent flagship government program *Brazil Sem Miséria* (Brazil Without Extreme Poverty Plan), launched in 2011 (Paes-Sousa & Vaitsman, 2014; Paiva, Falcão, & Bartholo, 2013). This plan included poverty eradication as part of a three-pillar plan, alongside inclusion in the labour market and productive activities, as well as access to services (such as electricity and modern energy). The case of Brazil and the *Brazil Sem Miséria* program underlines that in order to eradicate poverty also in rural and underdeveloped areas where poverty traps are exacerbated, a joint effort between different agents and policy levels need to be implemented. And that the provision of additional services is therefore fundamental for the success of antipoverty policies.[37]

[37] Brazil is also a case where the link between energy (electricity) and development (and poverty) is very strong and explicit. For example, the coverage of the *Luz Para Todos* program was based on the Human Development Index.

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6. Appendix

Table 1: Descriptive statistics, energy variables at the state level

Variable	**Period available**	*min*	*mean*	*max*
Average duration of electricity blackouts (DEC), annual hours (standardised by number of consumers)	2001-2010	7.1	25.2	72.8
Average frequency of electricity blackouts (FEC), annual (standardised by number of consumers)	2001-2010	5.2	20	65.5
% loss in electricity distribution	2005 and 2010	7%	21%	41%

Source: Author's elaboration based on ANEEL.[38]

Table 2: Variables and data sources used for the child mortality estimation

variable	**description**	**Source**
Under-5 mortality rate, residents	Number of under-5 deaths for the following causes, for 1,000 live births (both deaths and births are considered of residents)	*MS (2015)*
Bolsa Familia coverage, %	% of the population living in a family with a recipient of BF	*IBGE (2015),MDS (2015)*
Households without access to adequate sanitation, %	% of population living in a household with inadequate sanitation	*IBGE (2015)*
Municipal health expenditure per capita	Per capita annual health expenditures at the municipal level (constant 2010 *Reales)*	*IPEA (2015), World Bank (2015)*
Fertility rate	Number of births per 100 women in the 15-49 age range	*UNDP et al. (2016)*[39]
Hospitalization rate, residents	Rate of admission to hospital per 100 residents	*UNDP et al. (2016)*
Education, %	% of the over with completed cycle of education	*UNDP et al. (2016)*
Income per capita	Income per capita (constant 2010 *Reales*)	*UNDP et al. (2016)*

Source: Author's elaboration.

[38] Data from IPEA and *Luz Para Todos* have values only for 26 states.

[39] See http://www.atlasbrasil.org.br/2013/en/home/

Table 3: Descriptive statistics, covariates (PNAD)

VARIABLES	(1) N	(2) mean	(3) s.d.	(4) min	(5) max
Age of working-age people (years)	4,902	36.53	1.69	31.25	51.97
Share of income from work	4,902	82.94	19.43	26.23	100
Share of income from other sources	4,902	17.06	19.43	0	73.77
Years of schooling	4,902	7.39	1.61	2.50	12.38
Female working-age indiv. (share)	4,902	50.91	3.13	16.67	67.60
White or Asian (share)	4,902	50.62	25.55	0	100
Black (share)	4,902	5.84	0.06	0	.5652
Illiterate adult (share)	4,902	16.12	12.37	0	66.92
Workers in agriculture (share)	4,902	28.37	24.53	0	90.91
Workers in industry (share)	4,902	21.68	12.11	0	79.85
Workers in commerce (share)	4,902	16.10	7.75	0	47.96
Documented employees (share)	4,902	19.00	9.49	0	53.86
0-14 age kids per household	4,902	0.96	0.28	0.33	2.32
Married household heads (share)	4,902	68.12	7.26	40.36	90.79
Per capita household income (*Reales* per month)[40]	4,902	346.53	191.28	58.60	1,605.28
Municipal Gini index	4,902	47.12	6.92	21.90	78.69
Residences with piped water (share)	4,902	82.65	19.51	0	100
Rural (share)	4,902	22.67	23.36	0	100
North region	4,902	7.83	26.87	0	100
Northeast region	4,902	29.01	45.38	0	100
Southeast region	4,902	33.90	47.34	0	100
South region	4,902	19.58	39.69	0	100
Central-west region	4,902	9.67	29.56	0	100
Population < 5,000	4,902	0	0	0	0
Population between 5,000 and 10,000	4,902	0	0	0	0
Population between 10,000 and 20,000	4,902	0.10	3.192	0	100
Population between 20,000 and 50,000	4,902	3.84	19.21	0	100
Population between 50,000 and 100,000	4,902	14.50	35.22	0	100
Population between 100,000 and 500,000	4,902	77.25	41.92	0	100
Population >= 500,000	4,902	4.30	20.30	0	100

Source: Author's elaboration based on PNAD 2001-2006 (IBGE).

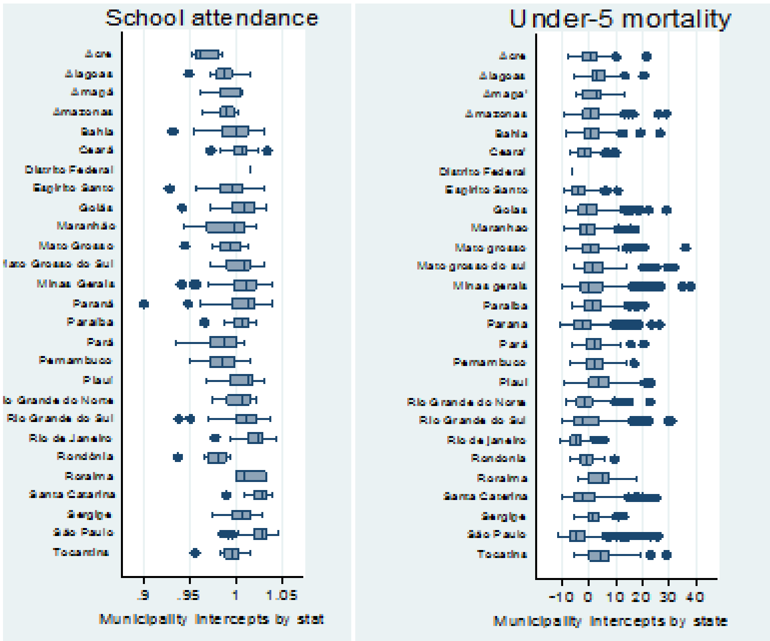
[40] Current prices.

Table 4: Descriptive statistics, covariates (second set)

Variable	count	mean	s.d.	min	max
Hospitalization rate, residents	31,935	6.61	0.06	2.47	0.07
Households without access to adequate sanitation, %	31,935	23.79	3.29	18.13	0.00
Municipal GDP per capita	31,935	941.72	12,514.54	1,118.68	136.75
Fertility rate	31,935	606.71	339.58	184.28	51.21
Education, %	31,935	34.98	1.29	11.35	7.64

Source: Author's elaboration based on different data sources.

Figure 9: Box plots of random intercepts[41]



[41] The upper line of the box represents the 75% percentile (upper hinge), while the lower line the 25% percentile. The middle line is the median. The extremes of the whiskers represent the upper and lower adjacent values, and the points outside the whiskers are the outside values or outliers (more than 3/2 times of upper quartile or less than 3/2 times of lower quartile).

Table 5: Effect of *Bolsa Família* on child mortality, using DEC

	(1) Child mortality	**(2) Child mortality**
	Coefficient (std error)	Coefficient (std error)
Bolsa Família (within effect)	-0.0546** (0.0222)	-0.0685*** (0.0223)
Energy quality	-0.1233*** (0.0296)	-0.1252*** (0.0295)
Energy quality Bolsa Família*		-0.0024* (0.0013)
var(BF_state)	0.0067	0.0054
var(_state)	1.1940	1.1918
cov(state)	0.0101	0.1460
var(BF_mun)	0.0559	0.0559
var(_mun)	41.052	41.059
cov(mun)	-0.135	-0.135
var(Residual)	118.874	118.871
Controls	Yes	Yes
States	27	27
Municip.	5,293	5,293
Obs.	31,935	31,935

*Significance levels:*** = 1%, ** = 5%, * = 10%.*
Source: Author's elaboration

Figure 10: Correlation between random intercepts and coefficients, states and municipalities

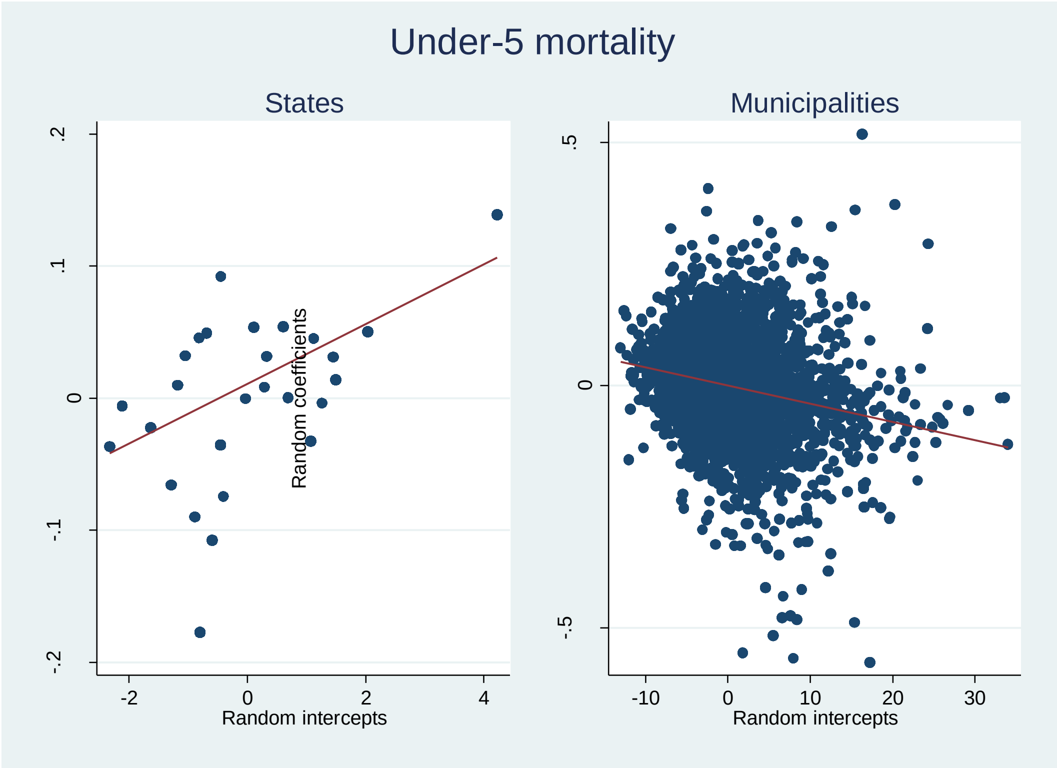
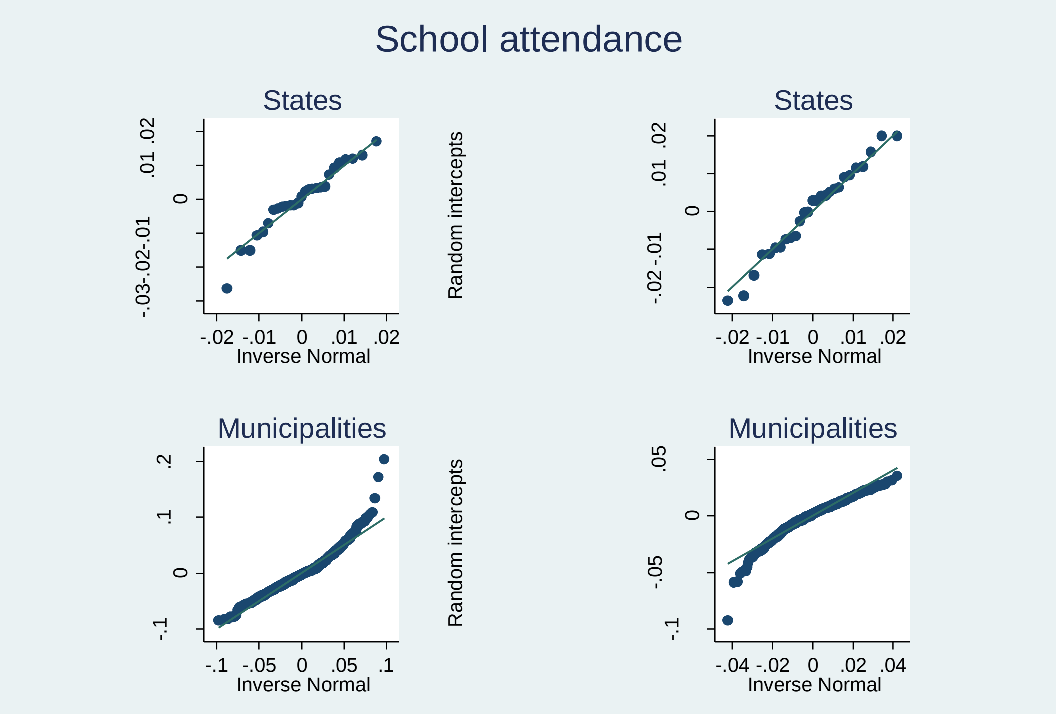
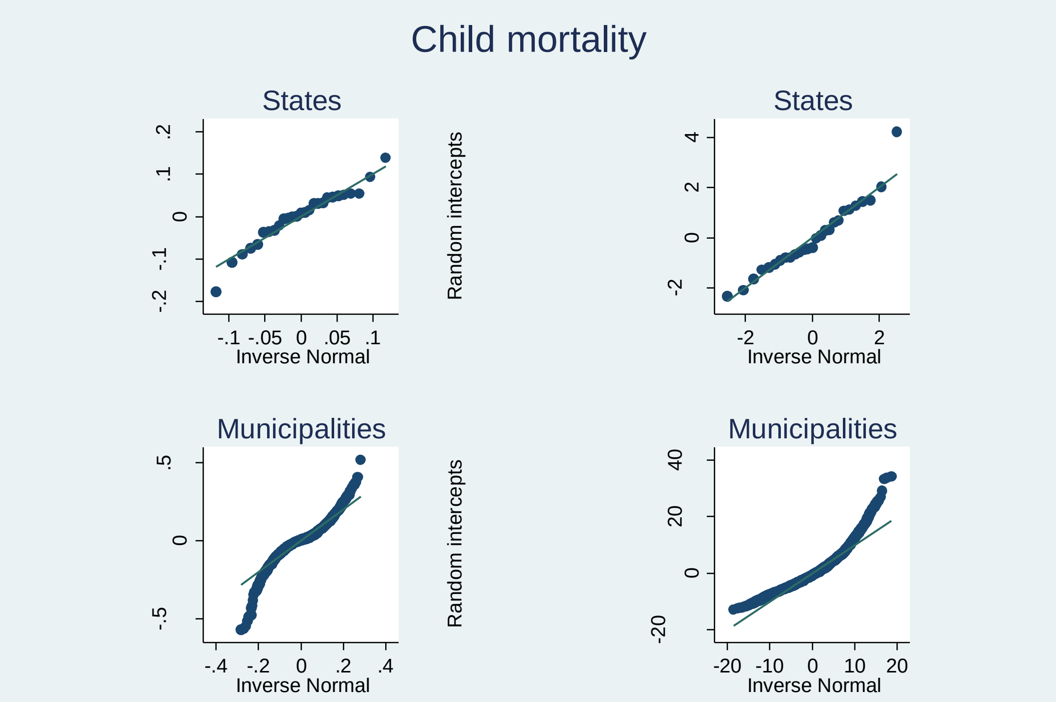


Figure 11: Normality of residuals, school attendance



Source: Author's elaboration.

Figure 12: Normality of residuals, child mortality



Source: Author's elaboration.