

DISTRESS BEYOND POVERTY: SPATIAL PATTERNS AND GEOGRAPHIC ASPECTS OF VULNERABILITY IN BRAZILGRIES, Thomas^{*}PALNAU, Irene^{**}

Abstract: Random shocks may push households that are not identified as being indigent into poverty. While regional poverty profiles have been elaborated for Brazil, vulnerability to poverty, i.e. the risk of falling into poverty in the future, has gained little attention. Using the Brazilian National Household Sample Survey (PNAD), we apply a multilevel framework to calculate vulnerability measures and map the prevalence of vulnerability. We identify states and regions in which fluctuations in income produce disproportionately high rates of vulnerability. Hence, this is the first contribution that can draw a comprehensive regional picture of vulnerability, including rural areas. When discussing the determinants of vulnerability, recent literature typically focuses on current and often endogenous conditions, such as institutions or recent policies. However, we take up the idea of long term path dependence and link up our findings to clearly exogenous regional characteristics like geographic, climatic and historic aspects that potentially drive vulnerability.

Key words – vulnerability to poverty, spatial patterns, economic geography, Brazil

JEL classification – I32, N26, R11

1 Introduction

Households in Brazil are regularly hit by shocks like natural disasters, crop failure, illness, and job loss. The exposure and susceptibility to different types of shocks varies by regional location. On the one hand, the Brazilian territory is very diverse with regard to climate and the occurrence of extreme weather events that directly affect households' well-being. On the other hand, divergent socioeconomic and institutional patterns, shaped by distinct colonial waves, have evolved over time and affect the susceptibility to shocks and the ability to cope with shocks. Depending on the degree of resilience of households and the vicinities that they are situated in, shocks may cause strong income fluctuations, which may threaten the livelihoods of those who are close to the poverty line, and of those who are not close to the poverty line but prone to shocks. Security in income and consumption present aspects of wellbeing that remain concealed when looking at year-to-year poverty rates (Dercon and Krishnan 2000).

The design of policy measures that aim at alleviating poverty as well as reducing risk and increasing resilience, requires the assessment of households' propensity to poverty, i.e., their vulnerability (Holzmann 2001). The vulnerability concept expands the poverty concept to account for shocks. It incorporates the effectiveness of households' risk management and coping mechanisms (see, e.g., Ellis 2000; Kochar 1995; Udry 1995). Since both, poor and non-poor households, can be vulnerable to shocks, the

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groups that are to be targeted by programs to improve social security and safety nets are not necessarily the same as the groups to be targeted by poverty alleviation measures (Échevin 2013). A regional perspective of poverty and vulnerability prevalence, especially in the case of Brazil, where spatial disparities are extremely pronounced, helps to identify patterns of poverty and vulnerability that require distinct measures of welfare improvement.¹ In particular, we find that in the structurally weak Northeast vulnerability is most concentrated among the poor, whereas in the South, the region with the lowest poverty rates, the number of vulnerable households is disproportionately high. There, about 3.5 times more households are vulnerable than are observed to be poor.

The body of literature on the concept and measurement of vulnerability has grown rapidly over the past few years (see, e.g., Ligon and Schechter 2003; Calvo and Dercon 2005; Dutta, Foster and Mishra 2011). As it is still at an early stage, the literature has not converged towards a single common definition or measure (see, e.g., Dutta et al 2011: 744–745; Dutta et al 2011: 744–745; Günther and Harttgen 2009: 1223–1224; Hoddinott and Quisumbing 2008). The present paper is in line with the literature that defines vulnerability as expected poverty and operationalizes it as the probability of falling below the poverty line in the future.

Generally, the main restriction on analyzing vulnerability is the lack of panel data. This is also true for Brazil where many studies have addressed poverty (e.g., Ferreira, Lanjouw and Neri 2003; Guedes et al 2012; Rocha 2005), but only very few studies have so far addressed its dynamics. Studies related to the present work are those of Ribas and Machado (2007), Ribas, Machado, and Gogher (2011) and Machado and Ribas (2010), all of which are limited to urban areas only.

Although the present contribution cannot resolve the lack of data, it addresses this problem by inferring inter-temporal variation from cross-sectional variation under some stringent assumptions. We use the extensive Brazilian household sample survey PNAD 2012, which covers metropolitan, urban and rural households all over the country, of which 108,364 provide all necessary data for the present analysis. The approach hence allows us to reflect poverty dynamics in rural areas that so far could not be studied and map vulnerability countrywide. We find that the proportion of poor and vulnerable households differs strongly across states and explore some potential sources of these patterns. We draw on recent work by Naritomi, Soares, and Assunção (2012) on spatial patterns of colonial heritage in Brazil, distinguish between covariate and idiosyncratic shocks as proposed by Günther and Harttgen (2009), and account for spatial differences in the prevalence of natural disasters.

The paper is structured as follows. The next section introduces the general concept of vulnerability to poverty and is followed by a section on the analytical framework of this study. In the fourth section, results of the poverty and vulnerability assessment are

¹ Ravallion and Wodon (1999) discuss the value of programs targeting poor areas if there are no evident barriers to the mobility of capital or labor. They argue that such programs are still potentially valuable in the face of persistent regional disparities and diverging returns to endowments for two main reasons. First, mobility may involve high costs or considerable risk. Second, non-observable characteristics may cause systematic migration movements and thus be spatially autocorrelated.

mapped and discussed. The last section concludes with the main insights and lines for future research.

2 Concept and Measurement of Vulnerability

The present paper is in line with the literature that defines vulnerability as expected poverty and operationalizes it as the probability of falling below the poverty line in the future. Households are classified as vulnerable if the vulnerability measure exceeds a certain threshold, and as non-vulnerable otherwise. Those currently below the threshold are vulnerable, but those who are vulnerable must not necessarily be below the threshold at present. Vulnerable households are either already poor or face the risk of falling below the poverty line when being hit by an adverse shock. On the other hand, households that can be heavily affected by adverse shocks but are not likely to fall below the poverty line are not vulnerable, according to this definition. The concept of vulnerability reflects external threats to livelihood as well as internal coping capabilities, determined by factors such as assets and social networks.

Generally, the lack of lengthy panel data is a main reason for the scarcity of studies that analyze poverty dynamics in developing countries. In recent years, attempts to overcome data restrictions by inferring inter-temporal variation from cross-sectional data have flourished. Among these are Azam and Imai (2012), Deressa (2013), Jha and Dang (2012), Novignon, Nonvignon, Mussa, and Chiwaula (2012) and Gasparini, Cruces, Bergolo, and Ham (2010). As an approach that has gained acceptance over the last few years, the work of Chaudhuri, Jalan, and Suryahadi (2002) is based on an interpretation of income disparities between otherwise equal households. Inter-temporal aspects of poverty are inferred from the unexplained variance in income or consumption between otherwise equal households. The variance between households is interpreted as inter-temporal variance. This, in turn, is modeled as being dependent on household characteristics, thus yielding an insight into how strongly households with particular attributes are affected by shocks.

It is possible that some of the variance that is interpreted as inter-temporal variance may actually be not shock related but due to unobserved heterogeneity or measurement error. According to Drewianka (2010), there is a difference between more and less developed countries. For the former, studies tend to find that most cross-sectional variation in earnings reflects unequal lifetime incomes, while for the latter a larger share of overall variation is attributable to transitory shocks.²

² For Venezuela, Freije and Souza (2002) find that the permanent component of earnings inequality makes up about 22% of total variation while the stochastic component amounts to 77% and 1% is due to serial correlation. This contrasts the findings for industrialized countries, where the permanent component has been found to be at least as large as the transitory component, see, e.g. Kennedy (1989) for Canada and Haider (2001) for the US. Burkhauser, Holtz-Eakin, and Rhody (1997) analyze labor earnings mobility and inequality in the US and Germany and find that in both countries a large fraction of the differences in earnings are due to yearly random shocks, while for German men random shocks have a stronger impact on the future earnings path than for American men.

Santos and Souza (2007) use a variance component model to decompose earnings variance of prime-age male workers in the formal labor market in the state of São Paulo into transitory variance and permanent variance. They thus determine the degree to which earnings inequality results from permanent individual characteristics or from idiosyncratic shocks. They find that 84% of earnings variance is permanent while 16% is transitory. Furthermore, 39% of the permanent component are explained by education and age. However, Santos and Souza note that their findings present the lower bound of the transitory component in Brazil because the analyzed group has possibly the most stable earnings in the whole private economy. The formal sector inherently encompasses higher income security. Moreover, entry into the formal labor market in São Paulo is subject to selection of individuals with relatively high educational attainments. As highly educated workers are typically furthest away from the poverty line, unobserved heterogeneity between them is unlikely to cause a strong bias in vulnerability estimates. Nevertheless, the issues of permanent income inequality due to structural differences between geographic entities and unobserved heterogeneity between households and measurement error have to be taken seriously.

We take the following measures to address these issues. First, we empirically distinguish between idiosyncratic and covariate variance in a multilevel framework. Unobserved heterogeneity may arise at the household level and at higher levels, stemming from the pronounced structural differences between communities and regions. If unobserved, heterogeneity between municipalities may lead to an aggregation bias in poverty and vulnerability assessments (see, e.g., Ayala, Jurado and Pérez-Mayo 2011). The distinction between idiosyncratic and covariate variance prevents aggregation bias and furthermore allows us to discuss the potential effect of unobserved heterogeneity at household vs. municipal level. Second, we account for a wide range of socioeconomic characteristics that may drive persistent income inequality. Third, we conduct robustness checks to see, whether our results stand up to different assumptions about the share of measurement error, which is reflected in the idiosyncratic variance component.

3 Analytical Framework

The first step when assessing vulnerability is to estimate the distribution of future income for every household. Mean expected income is determined by relevant characteristics such as education and age of the household head, whereas variance is determined by the severity and frequency of shocks and the presence and effectiveness of insurance mechanisms. In the second step, the estimated income distribution is used to generate a statistic that measures the degree of vulnerability. Different approaches to estimating the distribution of future income in the first step and producing the vulnerability measure in the second step can be mixed and matched (Ligon and Schechter 2004).

3.1 Multilevel Model

For the first step, we build on the work of Günther and Harttgen (2009), who propose a multilevel framework (see, e.g., Goldstein 2011) to evaluate empirically the relative impact of idiosyncratic vs. covariate shocks on households' vulnerability, even with cross-sectional data at hand. Related works that apply the multilevel method include Échevin (2013; 2014) and Jadotte (2011). We distinguish between shocks at household

level and shocks at the municipal level in a random intercept model. Households within the same municipality share some observable and unobservable characteristics that can be relevant to the mean expected income. Furthermore, they share the experience of covariate shocks and some collective risk management and coping mechanisms that influence the variance in income.

When vulnerability is assessed using cross-sectional data, future mean and inter-temporal variance of income have to be inferred from data without a time dimension. To do so, one has to make a number of assumptions about the stochastic process that generates income. In particular, we assume that diverging per-capita income levels of otherwise equivalent households capture the impact of shocks, as proposed by Chaudhuri et al. (2002). The impact of shocks in turn depends on household and municipality characteristics, i.e. the variance in income is heteroscedastic. We furthermore implicitly assume that idiosyncratic as well as covariate shocks are identically and independently distributed over time, thus ruling out unobservable sources of persistence over time, like serially correlated shocks or unobservable household-specific effects. The structure of the economy is assumed to be stable over time, i.e., there are no aggregate shocks.

We model every household i ($i = 1, \dots, I$) to be nested in a municipality j ($j = 1, \dots, J$). The household income per capita r_{ij} depends on a set of household characteristics X_{ij} and municipality characteristics Z_j :

$$\ln r_{ij} = \gamma_{00} + \gamma_{01} Z_j + \gamma_{10} X_{ij} + u_{0j} + e_{ij}. \quad (1)$$

The model contains a fixed effects part and a random effects part. The fixed effects part contains the intercept of the income equation γ_{00} and the effects of the municipality and household characteristics. The random effects part contains the error term at municipal level u_{0j} (random intercept) capturing the effect of covariate shocks, and the error term at household level e_{ij} capturing idiosyncratic shocks. The incomes of households within the same municipality are conditionally independent given the random variables (Rabe-Hesketh and Skrondal 2008: 56). The error terms are in turn modeled to depend on household and municipality characteristics.³

$$(e_{ij}^2 + u_{0j}^2) = \theta_0 + \theta_1 X_{ij} + \theta_2 Z_j + \theta_3 X_{ij} Z_j. \quad (2)$$

$$e_{ij}^2 = \theta_0 + \theta_1 X_{ij} + \theta_2 Z_j + \theta_3 X_{ij} Z_j, \quad (3)$$

$$u_{0j}^2 = \tau_0 + \tau_1 Z_j, \quad (4)$$

Separate estimations are conducted for the income variance that is due to both

³ Since we assume heteroscedasticity for u_{0j} and e_{ij} the model has to be estimated with robust standard errors. The model is estimated via maximum likelihood using the Huber/White sandwich estimator, yielding consistent and asymptotically efficient coefficients, see Maas and Hox (2004). The likelihood is a marginal likelihood where the random intercept has been integrated out, see Rabe-Hesketh and Skrondal (2008: 258–261).

idiosyncratic and covariate shocks (2), idiosyncratic shocks only (3), and covariate shocks only (4).

3.2 Vulnerability Measure

In the second step, we calculate a vulnerability measure that is based on Pritchett, Suryahadi, and Sumarto . Given the expected mean and variance in income and assuming that income is log-normally distributed, the vulnerability of a household i (with characteristics X_{ij}) in municipality j (with characteristics Z_j) is given by:

$$\hat{v}_{ij} = \hat{P}(\ln r_{ij} < \ln z_j | X_{ij}, Z_j) = \phi \left(\frac{\ln z_j - \ln \hat{r}_{ij}}{\sqrt{\hat{\sigma}_{ij}^2}} \right), \quad (5)$$

where z_j denotes the regional poverty line, $\phi(\cdot)$ is the cumulative standard normal distribution function, $\ln \hat{r}_{ij}$ is the expected mean of log per capita household income and $\hat{\sigma}_{ij}^2$ is the estimated variance of the log per-capita income. Idiosyncratic, covariate, or total variance can be inserted for $\hat{\sigma}_{ij}^2$, depending on whether vulnerability to idiosyncratic, covariate, or both shock types is of interest. In order to classify a household as vulnerable or non-vulnerable, a threshold has to be defined which is a function of the relevant time horizon $t+k$ and the critical probability of falling below the poverty line. It can be expressed as

$$v_{ij,t+k} = 1 - (P(\ln r_{ij} > \ln z_j))^k \quad (6)$$

(see Günther and Harttgen 2009: 1229,1232). In the literature, households are often classified as being vulnerable if they have a probability of 50% or higher of being poor in the near future, with the near future commonly a time horizon of $t+2$ (see, e.g., Chaudhuri et al 2002; Pritchett et al; Günther and Harttgen 2009). Inserting the probability and time horizon into equation (6) this corresponds to a vulnerability threshold of 0.29.

3.3 Data

While panel data would be the first choice for the analysis of income dynamics, the availability of panel data for Brazil is limited, especially for rural areas. For metropolitan areas only, the Brazilian Geographical and Statistical Institute IBGE (Instituto Brasileiro de Geografia e Estatística) issues the Monthly Employment Survey (PME), a panel on labor and income from work. For the whole country, there is data from the Demographic Censuses that were conducted in 2000 and 2010 plus data from two countrywide cross-sectional surveys: the Consumer Expenditure Survey POF (Pesquisa de Orçamentos Familiares), which has so far only been carried out in 2002-2003 and 2008-2009, and the more frequently conducted National Household Sample Survey PNAD (Pesquisa Nacional por Amostra de Domicílios). Panel data that covers the whole country is under way with the PNAD *Contínua* but available data is restricted to income from work and, in contrast to the repeated cross-sectional data of the established PNAD survey, does not allow for identification of households belonging to the same municipality, which is an entity of interest for the analysis of

vulnerability.⁴ The coverage of the PNAD has gradually expanded since 1967. Since 2004 it has covered the whole country, urban as well as rural areas. It is conducted every year except for the years of the Demographic Censuses.

To analyze income vulnerability in Brazil, we use the 2012 wave of the established PNAD. It contains data on a wide range of socioeconomic characteristics such as education, employment, income, housing, fertility, and migration for a sample of 108,364 households.⁵ Due to the complex sampling design, inverse probability weights have to be taken into account.⁶ Despite its richness, the data is still rarely exploited by international researchers. One possible explanation for the lack of interest is that the data and most of the documentation are available only in Portuguese. With a large number of groups (1,101 municipalities) and sufficiently large cluster sizes (about 130 households per cluster on average)⁷, the PNAD lends itself to multilevel analysis in which within- and between-municipality variance components can be separated. While our data contains a lot of information at the household level and we know in which state or region the household is located, little is known at the intermediate. What is known at the intermediate level is which households belong to the same municipality. Having this information, we can construct municipality averages of the socioeconomic characteristics of interest. This allows us to leverage the multilevel framework to capture the unexplained variance at the municipal level by a latent variable and assess its size relative to the unexplained variance at the lower level.

The variables that are included in the analysis, as described in Table 1 in the appendix, are divided into municipal and household level characteristics. Fontes, Simões, and Oliveira (2010) have formerly shown that wage disparities between workers with similar individual characteristics that live in different Brazilian areas are largely explained by local economic and labor market factors. We thus include available municipality-level averages that reflect major labor market factors. These are the mean years of education and the shares of employers, self-employed and formal employees. Along these factors, we include the share of migrants, the regional poverty line (to control for the different costs of living), a set of dummies for the region that the municipalities are located in, and further variables that matter with regard to the

⁴ Different stratification strategies are followed in the PNAD and the PNAD Contínua. In the PNAD Contínua municipalities are grouped into layers with similar administrative classification. This shall ensure that households from all administrative classifications are included. This, however, comes with a loss of information on geographic association in the PNAD Contínua microdata.

⁵ Missing information mainly concerns either income or years of education of the household head. Households with per capita incomes higher than 6000 R\$ are excluded in order not to inflate the variance by positive outliers.

⁶ See Pfeiffermann, Skinner, Holmes, Goldstein, and Rasbash (1998) for weighting in multilevel models.

⁷ The calculation of the average cluster size is based on Ukoumunne, Gulliford, Chinn, Sterne, and Burney (1999: 21). Using the arithmetic mean cluster size when estimating variance components may lead to an underestimation of the between-cluster variance component if cluster sizes vary.

complex sampling scheme of the survey.⁸

On the lower level, some general family and household characteristics are included. Dummies for single-mother households and other types of families that are different from married couples are included, along with size of the household, number of children under the age of 14 living in the household, and a dummy for rural households. Other characteristics refer to the household head only. General characteristics such as age, race, ethnic background, and years of education are included, alongside occupation-related characteristics. The latter are economic activity, employment status, employment sector and the type of job position of the household head. As the dataset contains a number of households without any income, and those households should not be excluded from the analysis since they are of central interest with respect to vulnerability, generating the log of household per capita income requires some prior transformation of the data. A constant is added to household income. The value 0.005 is chosen so as to approximately match the observed and predicted poverty rates in the population after an OLS regression.

Due to spatial differences in the cost of living, studies of poverty in Brazil commonly use either regional poverty lines or spatial price deflators (see, e.g., Ferreira et al 2003; Rocha 2005; Ribas and Machado 2007; Ferreira and de Barros 1999). We use the regional poverty lines developed by Rocha (2005: 43–75), which are based on the Brazilian Consumer Expenditure Survey (POF), in order to allow for a comparison of our results with the previous extensive work on Brazilian poverty profiles and structural differences between regions by Rocha (2005).⁹

We furthermore take data on natural disasters from publications of the Brazilian Statistical Office (IBGE 2013) and the National Confederation of Municipalities (CNM 2010) into consideration to compare official statistics with our estimations of covariate variance. Additionally, we consult climatological data to discuss our findings.¹⁰ We also refer to the study of Naritomi et al. (2012) to discuss our findings against the background of the recent literature on path dependence of socioeconomic and institutional conditions.

4 Results and Discussion

In the following, we first sketch the results of the multilevel income estimation and the residual regressions, which are used to generate the vulnerability measure. Second, we present the resulting vulnerability statistics for Brazil and map them by regions and federal units. We contrast poverty and vulnerability measures in order to highlight the additional insights from the consideration of income variability. Third, we show how the vulnerability rate reacts to changes in the threshold used to define vulnerable households, distinguishing households by the observed poverty status.

⁸ The municipality type should be included because it is relevant for the sampling. However, it is also interesting in its own right. Bahia et al (2006) find inferior health plan coverage in not self-representative municipalities, which may affect the occurrence of health shocks as well as the effectiveness of coping strategies.

⁹ The poverty lines are downloadable under <http://www.iets.org.br/dado/pobreza-e-indigencia>.

¹⁰ The climatological data come from the IBGE Directorate of Geosciences and is publicly accessible under ftp://geoftp.ibge.gov.br/mapas_tematicos/mapas_murais/shapes/clima/.

4.1 Distribution of Intertemporal Income

As described earlier, the expected mean (log) income is estimated in a first step to obtain the individual measures of location for each household's approximated income distribution. In a second step, the squared residuals from this estimation are regressed on the same dependent variables to yield the respective measure of dispersion. The results are then used to estimate the probability of falling below the poverty line. In this section, the regression results for the first two steps are briefly summarized.

The coefficients of the multilevel model estimation for the expected mean (log) income carry the expected signs.¹¹ The model explains 84.53% of the variance at the municipal level and 25.67% at the lower level. The relative size of variance at the municipal level is rather low in comparison to the variance at the lower level (0.018 and 2.242). Even if Brazil is characterized by strong spatial disparities, this is not surprising. The disparities largely go along with unevenly distributed household characteristics (see Rocha 2005: 179–184), which are reflected in the lower-level variance.

We find for the five Brazilian regions that income levels are lower in the Northeast than in the Southeast, South and Central-West, but do not differ significantly from the income levels in the North. Incomes are higher in those municipalities where household heads on average have higher education levels and where the proportion of heads who are employers is higher. The same holds for municipalities with higher proportions of formally employed heads and heads with a migration background.

The variance in income that is assumed to stem from shocks is based on the squared residuals from the multilevel income estimation. The regression of the squared residuals on the same set of municipal and household characteristics, as in the first step, indicates that the impact of shocks is indeed related to several municipal and household characteristics. These explain 15.7%, 15.6%, and 2.9% of the total, household-level and municipal-level variance.

Table 2 in the appendix summarizes the average expected mean and standard deviation in (log) income by states and regions. The predictions of the mean expected (log) income and variance in (log) income from the above estimations are used to approximate the households' individual income distributions. Relating them to the regional poverty lines then yields the households' vulnerability statistics, which we present in the following.

4.2 Regional Patterns of Poverty and Vulnerability

The five regions of Brazil, i.e. the North, the Northeast, the Central-West, the Southeast and the South (see Fig. 3 in the appendix), differ significantly with regard to climate (see Fig. 4 to 6 in the appendix), economic factors, and socioeconomic aspects. These are closely related to the prevalence of poverty and vulnerability (see, e.g. Rocha 2005). The territory extends from the tropical Amazon rain forest in the northwestern area, over a central plateau, to the coastal lowlands in the Northeast, to the most urbanized areas with moderate climate in the Southeast, and to the only area that experiences change in seasons in the southern part (Boraas 2001: 9–18). In the following, poverty and vulnerability measures are considered on a regional level.

In total, 12.07% of Brazilian households are classified as poor. The incidence of

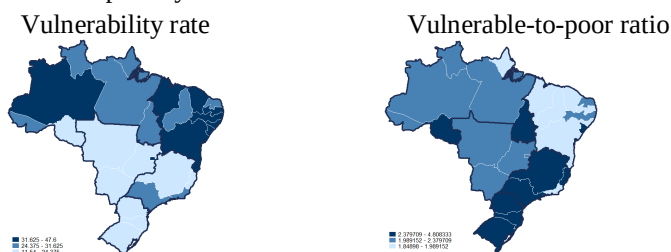
¹¹ Estimation results can be found as online supplement.

poverty is highest in the Northeast (19.72%), followed by the North (14.01%), Midwest (10.77%), and is lowest in the South (3.77%). Comparing our calculated poverty rates with those of Rocha (2005) that are based on the same operationalization of poverty, it becomes obvious that poverty has reduced significantly over the past few years but remains a serious issue. Silveira-Neto and Azzoni (2012) show that regional inequality in terms of income has decreased recently, but is still pronounced.¹² They identify the conditional cash transfer program Bolsa Família as an important driving factor behind this development, despite the clearly non-spatial design of the program.

Overall, poverty rates that we calculate by household characteristics reaffirm the corresponding findings of Rocha (2005) with regard to which kinds of households show particularly high poverty rates. Strong regional disparities in socioeconomic characteristics and structural conditions manifest in divergent poverty profiles. Rocha (2005: 182–184) contrasts poverty in the rural Northeast with poverty in the metropolitan area of São Paulo. The Northeast shows a kind of poverty that is typical for societies that are at the edge of rural-urban growth. The large number of poor households forms a relatively homogenous subpopulation with regard to their characteristics. In comparison to the metropolitan area of São Paulo, the size of poor families is larger with a higher number of children and fewer households headed by women. Agriculture is the source of income of most poor families. In contrast to this, Rocha characterizes poverty in the metropolitan region of São Paulo as a kind of poverty that is typical for dynamic national commercial centers. Interactions between poor and non-poor subpopulations are relatively frequent.

We estimate that there are 2.2 times as many households in Brazil threatened by poverty than are actually observed to be poor, i.e. 26.50% of the Brazilian population has a probability of more than 50% to face poverty within the next 2 years. The regional pattern of vulnerability is outlined in the left panel of Fig. 1. As for poverty, vulnerability rates are highest in the Northeast, followed by the North, Midwest and Southeast, and lowest in the South. However, the vulnerable-to-poor ratio, mapped in the right panel reveals that the shares of poor and vulnerable households are far from proportional.

Fig. 1: Vulnerability to income poverty in Brazil

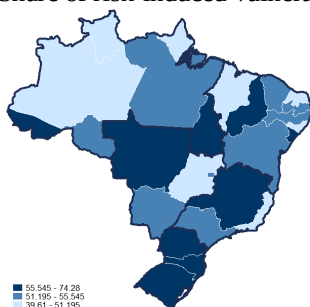


¹² Regarding inequality, Novotný (2007) shows in a cross-country study, that Brazil is among the countries with the largest regional components to inequality. However, Freguglia and Menezes-Filho (2012) consider individual wages before and after migration and find that inter-regional wage differentials are significantly altered once workers' fixed-effects are taken into consideration, i.e. wage differentials are not purely spatial in nature but related to unevenly spread individual characteristics. According to Menezes, Silveira-Neto, and Azzoni (2012), the dynamics in Brazilian regional income inequality differ across generations.

If the poverty and vulnerability rates measured the same concept, the ratio would be the same across states and groups of households, which we find not to be the case. The disproportionality of poverty and vulnerability becomes most obvious in the South. There, the poverty rate (3.77%) is by far the lowest compared to the other regions but 3.5 times more households are vulnerable than are observed to be poor. In contrast, the vulnerable-to-poor ratio is below 2.0 in most parts of the Northeast.

Fig. 2 shows the share of risk-induced vulnerable households, which is a supplementary statistic that yields an insight into the main driver of vulnerability (see Günther and Harttgen 2009: 1229–1230). If households are vulnerable but have an expected income above the poverty line, they are referred to as risk-induced vulnerable. If the expected income is already below the poverty line, households are classified as poverty-induced vulnerable. Again, in the South the share of risk-induced vulnerable households is relatively large. For the other regions, the share of risk-induced vulnerable households varies strongly between states.

Fig. 2: Share of risk-induced vulnerable households



4.3 Discussion of Regional Disparities

Which regional factors drive the distinct patterns of vulnerability across the country? Generally, there are at least three factors that affect the proneness to poverty through shocks. First, covariate shocks, in particular climatic shocks, are a direct source of covariate income variability in Brazil. According to the Brazilian Statistical office (IBGE 2013), 40.9% of Brazilian municipalities have been hit by at least one natural disaster over the period 2008–2013. The number of states of emergency in the period 2003–2009 reported by the Brazilian Confederation of Municipalities (CNM 2010) is particularly high in the states of Rio Grande do Sul (1690), Paraíba (1216), Ceará (1088), Minas Gerais (1086), and Santa Catarina (918).

Second, the spatial differences in households' socioeconomic characteristics and levels of urbanization go along with the exposure to different types of shocks on the one hand and different available insurance and coping mechanisms on the other hand. However, in foresight of shocks, households may in turn reduce their exposure to risk in the income generating process by diversifying their income generating activities or by choosing low-risk activities, often at the expense of returns (see, e.g., Morduch 1995; Kochar 1995; Dercon 2002). Household characteristics are thus endogenous to the (potential) exposure to shocks.

Third, the institutional setting, in particular the smoothness of coordination between central government institutions and local authorities, matter for successful regional development and effectiveness and efficiency in the handling of covariate risk. The

other way around, the threat of shocks may impose political pressures for changes in the institutional setting (see, e.g. Eakin and Lemos 2006). Reverse causality thus complicates the assessment of the determinants of vulnerability.

Spatial differences in socioeconomic conditions and the institutional setting are at least partly inherited from initial conditions. The concept of path dependence, stimulated by David (1985, 1992, 1994) and Arthur (1989), has been recognized as an important factor that shapes economic geography (see Krugman 1991, 1998 on the “New Economic Geography” and Boschma and Martin 2010 on “Evolutionary Economic Geography”), the institutional framework (North 1991) and comparative development (Acemoglu, Johnson and Robinson 2001).¹³

Increasing returns and “lock-in” by historic occasion are key elements behind the concept of path dependence. Under dynamically increasing returns, economies may gradually get locked up in outcomes that are not necessarily superior to alternatives, reluctant to change and hardly predictable in advance (Arthur 1989). North (1991) further elaborates the role of institutions and economic and political organizations in path-dependent economic development. He characterizes the economic landscape by an institutional matrix where political and economic organizations seize the opportunities provided by the institutional setting. In following private interest, economic organizations are inclined to restrict market entry and factor mobility and political organizations may prefer to establish property rights that aim at redistributing rather than raising income. Increasing returns, network externalities, and complementarities between institutions and political and economic organizations produce distinct spatial patterns of development that ultimately stem from the initial (enforced) rules of the game, given by the institutional setting. Acemoglu et al. (2001) follow in this line and provide empirical support.

Apart from initial circumstances and historic accident, the location of economic activity in space may also be shaped by and geographic conditions. The location of economic activity in space may be affected by geographic conditions through the initial attraction of settlement, but also more directly through transportation costs, the spread of disease and agricultural productivity (see Gallup, Sachs and Mellinger 1999). While the literature is not concordant with regard to direct effects of geography on comparative development¹⁴, an apparent direct link exists between geographic factors, in particular natural disaster and disease, and households’ vulnerability to poverty.

Naritomi et al. (2012) show for Brazil, that in particular the sugar cane boom and the gold boom, which are the two major episodes of extractive policies by the Portuguese colonial government, have affected the distinct development of institutions and are correlated with the current provision of public goods. The sugar cane boom took place in the early phase of colonialization starting in the 16th century and affected mainly the

¹³ Evolutionary and institutional economic geography are sometimes distinguished along methodological lines, see Boschma and Frenken (2006); (2009). Others favor the use of evolutionary and institutional concepts within a geographical political economy, see Grabher (2009), MacKinnon, Cumbers, Pike, Birch, and McMaster (2009), and Essletzbichler (2009).

¹⁴ In using settlers’ mortality rates as an instrument for colonial institutions, Acemoglu, Johnson, and Robinson (2001) disregard a direct effect of geography on comparative development.

coastal areas in the current states Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Bahia Espírito Santo, and Rio de Janeiro. The episode was characterized by an oligarchic society where the gains from slavery-based production were concentrated among powerful local elites. The gold boom affected mainly the inland areas in the states of Bahia, Goiás, Mato Grosso, Minas Gerais, and Rondônia. The political apparatus served the core objective of supervision and extraction of mining activities, creating a “constant struggle against civil society” (Naritomi et al 2012: 403). Poorer and institutionally weak regions that have evolved over time do not necessarily catch up. Azzoni (2001) Resende (2011) and Cravo and Resende (2013) find indications of regional income convergence in Brazil and reaffirm the importance of space for the process of economic development.

We regress the mean poverty and vulnerability indicators at state level on the number of disasters reported by the CNM (2010), see Fig. 4 in the appendix, and dummies capturing the affectedness of the states by the sugar boom and the gold boom, clustering at state level. Table 1 shows that while the frequency of natural disasters has no significant effect on the prevalence of poverty or vulnerability separately, the vulnerable-to-poor ratio significantly increases with the number of natural disasters, i.e. a higher frequency of natural disasters renders more non-poor households vulnerable and increases the spread between the shares of poor and vulnerable. Furthermore, the covariate share of estimated standard deviation in household income (the covariate share of column 2 in Table 2 in the appendix) also increases with the number of natural disasters. Looking only at the vulnerable part of the population, we find that the share of risk-induced households increases with the number of natural disasters. For Brazil, the affectedness by natural disasters is a major concern especially in the Northeast, where extreme drought and extreme rainfall affect large shares of households and in the South, where in addition storms and hails present major threats.

Table 1: OLS Regression results for the effects of state level variables on poverty and vulnerability

	Poverty rate [%]	Vulnerability rate [%]	Vulnerable- to-poor ratio	Covariate share of estimated std. dev. [%]	Share of risk-induced vulnerable households [%]
	(1)	(2)	(3)	(4)	(5)
natural disasters [per mill]	-0.032 (0.019)	-0.050 (0.029)	0.648** (0.233)	0.006* (0.003)	0.062*** (0.012)
state affected by sugar cane boom	0.068** (0.024)	-0.019 (0.031)	-0.483** (0.144)	-0.003 (0.005)	-0.057** (0.016)
state affected by gold boom	-0.009 (0.017)	-0.019 (0.031)	-0.190 (0.187)	0.003 (0.005)	0.007 (0.019)
constant	0.124*** (0.015)	0.271*** (0.026)	2.278*** (0.111)	0.084*** (0.002)	0.533*** (0.01)
R^2	0.346	0.305	0.404	0.188	0.510

We find that the states that were directly affected by the sugar boom show higher poverty rates compared to the states that were not affected while the vulnerability rate does not differ significantly. However, for the vulnerable-to-poor ratio we find that for the states that were strongly influenced by the sugar cane boom the ratio is

significantly lower. This indicates on the one hand, that the non-poor households in these states face a lower risk of falling into poverty in the future, and on the other hand, that household poverty is rather a structural than a transitional phenomenon. The share of households that are risk-induced vulnerable is lower in the states that were subject to the sugar cane boom, i.e. a larger share of households is vulnerable because their income level is already below the poverty line.

We find no significant effects of the gold boom. This may be due to the lower degree of societal polarization that was produced during the gold boom compared to the sugar cane boom (Naritomi et al 2012: 402). Municipalities that were affected by the sugar cane boom were shaped by highly concentrated landownership and power that precluded social mobility for the population with little resources. The sugar cane boom and its strongly polarized economy appears to have built up a legacy reflected in a relatively low state of development in terms of income poverty. In contrast, the gold boom areas were still characterized by some degree of workers' bargaining power and social mobility. While Naritomi et al. (2012) find that municipalities affected by the gold boom are still characterized by a lower quality of local governance and worse provision of public goods, the lower state of development is not as apparent in terms of income poverty and vulnerability.

Distinguishing between idiosyncratic and covariate variance in income, we find that the disproportionality between poor and vulnerable households is mainly driven by idiosyncratic variance. As the share of the idiosyncratic shock component is potentially inflated by measurement error, we use the multilevel structure to test the robustness of our findings. In line with Carter (1997) and Günther and Harttgen (2009), we test the robustness of our results against different assumptions about the magnitude of measurement error. When there is no measurement error, the ratio between the idiosyncratic and covariate shares in the estimated standard deviations is 14.70. Assuming that 25%, 50% and 75% of the unexplained variance at the household level are due to measurement error, the ratio decreases to 12.73, 10.40, and 7.35 respectively, and still indicates a clear dominance of the impact of idiosyncratic shocks over covariate shocks. Moreover, the regional patterns of poverty and vulnerability displayed in Fig. 1 and Fig. 2 remain stable to the different assumptions about the size of measurement error.

5 Conclusion

Policies that aim at fostering livelihoods need to be informed not only about the overall prevalence of poverty, but also about whether poverty is a structural phenomenon or caused by uninsured income fluctuations. We use the concept of vulnerability to poverty to assess the degree to which households in different states and regions of Brazil are prone to income poverty and gauge the share of vulnerability that is driven by fluctuations in income. Specifically, we apply the multilevel method of Günther and Harttgen (2009) to assess vulnerability from cross-sectional data within a multilevel framework. We infer inter-temporal income variability from unexplained variability between otherwise similar households and municipalities. We apply the method to the Brazilian household survey PNAD 2012, one of the largest surveys available for developing or emerging economies, which covers more than 100,000 households from all over the country.

While the states with the highest household vulnerability rates are also the states with

the highest poverty rates and vice versa, the ratio between the two measures varies strongly between states. In particular, the ratio is relatively low in the Northeast, indicating that vulnerability is largely concentrated among the poor, and comparatively high in the South, showing that there is a considerable share of households that are not observed to be poor but face a high risk of falling into poverty in the future. The distinction between idiosyncratic and covariate variability indicates that idiosyncratic shocks are a more important driver of vulnerability than covariate shocks at the municipality level. The findings are robust to different assumptions about the level of measurement error. In exploring potential exogenous sources of vulnerability, we find that vulnerability is more concentrated among the observed poor in those states that were under the influence of the sugar cane boom, a major colonial extractive episode that shaped an oligarchic, strongly polarized economy.

The strong, partly inherited, regional disparities in Brazil produce divergent poverty and vulnerability profiles that require distinct measures for fostering livelihoods. While we have mapped indicators of income vulnerability, a comprehensive assessment of the needs for action requires further investigation in several directions. First, it has to be assessed which types of households drive vulnerability in different areas. Second, the degree to which income fluctuations can or cannot be smoothed in terms of consumption needs to be evaluated for different areas and types of households. Third, the degree to which the lack of effective risk insurance and coping mechanisms causes income skewing should be taken into consideration.

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Appendix**Table 2: Average expected means and standard deviations in income**

		Ø Estimated mean of p.c. log income	Ø Estimated std. dev. of p.c. log income
		(1)	(2)
Overall		6.22	1.20
North		5.89	1.28
	Rondônia	6.11	1.25
	Acre	5.93	1.23
	Amazonas	5.85	1.39
	Roraima	5.98	1.55
	Pará	5.80	1.23
	Amapá	6.00	1.31
	Tocantins	6.02	1.28
Northeast		5.77	1.31
	Maranhão	5.50	1.38
	Piauí	5.84	1.08
	Ceará	5.79	1.25
	Rio Grande d. N.	5.94	1.29
	Paraíba	5.86	1.28
	Pernambuco	5.81	1.38
	Alagoas	5.63	1.33
	Sergipe	5.90	1.29
	Bahia	5.77	1.33
Southeast		6.42	1.16
	Minas Gerais	6.30	1.10
	Espírito Santo	6.34	1.16
	Rio de Janeiro	6.34	1.22
	São Paulo	6.51	1.16
South		6.50	1.10
	Paraná	6.50	1.08
	Santa Catarina	6.56	1.06
	Rio Grande d. S.	6.48	1.14
Midwest		6.41	1.17
	Mato Grosso d. S.	6.45	1.09
	Mato Grosso	6.35	1.13
	Goiás	6.35	1.15
	Distrito Federal (DF)	6.61	1.34

Fig. 3: Territorial division



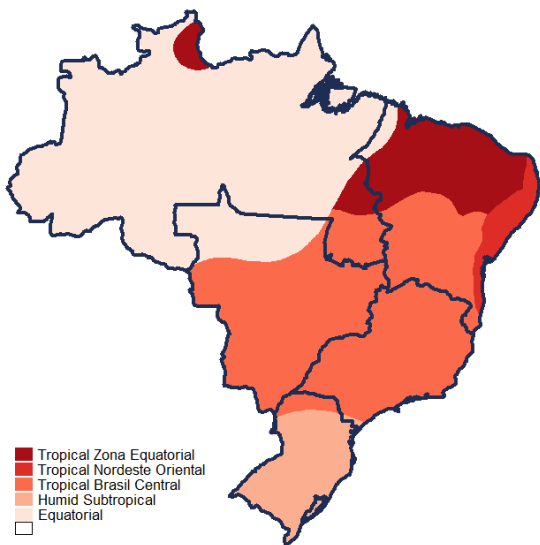
Table 1: Description of Variables

Variable name	Description
Level two (municipality) characteristics	
not self-representative	Dummy variable for the type of municipality; metropolitan or self-representative municipality is the reference category
probability of municipality selection	Variable reflecting the probability of selection into the sample; surrogate for design variables, see Pfeffermann and Sverchkov (2009: 463–464); the probability is equal to 1 for self-representative and metropolitan municipalities and proportional to the inhabitant population for not-self representative municipalities
ln poverty line	Natural logarithm of the regional poverty line (the value 0.00033 is added to the poverty line before the logarithmic transformation since income is transformed in the same way); reflects the living costs
North Southeast South Midwest	Dummy variables for the region; northeast is the reference category
mean years of education	Years of education of the household head; municipality average
mean employers	Household heads being employers
mean self-employed	Household heads being self-employed; municipality average
mean formal employees	Household heads being formally employed, i.e. having a <i>carteira assinada</i> ; municipality average
mean migrant	Household heads having been born abroad or in another Brazilian state; municipality average
Level one (household) characteristics	
log income p.c.	Log of household income per capita (dependent variable)
single mother other family type	Dummy variables for the family type; married couple is the reference category
rural	Dummy variable; urban sector is the reference category
household size	Number of people living in the household (pensioners, non-family domestic workers and their parents excluded)
squared household size	Squared number of people living in the household
children u14	Number of children under 14 living in the household
squared children u14	Squared number of children under 14
years of education	Years of education of the household head
squared years of education	Squared years of education of the household head
age	Centered age of the household head; the mean has been calculated ignoring the multilevel design and using the PNAD household weights

Table 1 (continued): Description of Variables

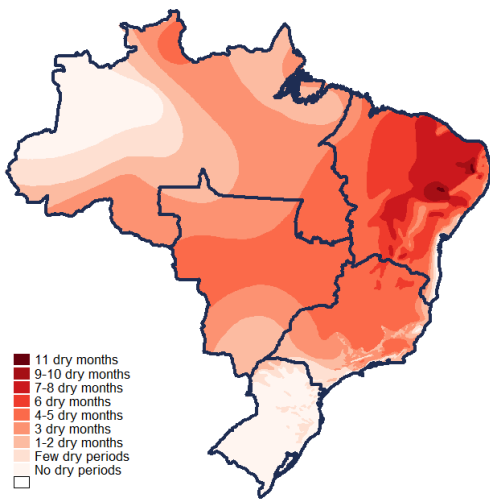
white or Asian	Dummy variable for the ethnicity of the household head; white and Asian household heads are coded 1, all other heads make up the reference category
migrant	Dummy variable for households heads with a migration background (international migration or internal migration from one state to another)
no economic activity	Dummy variable for economic inactivity and interaction term between economic inactivity and a dummy variable indicating high age; rural unemployed heads are the reference group
no economic activity over 55	
urban unemployed	Dummy variable; rural unemployed heads are the reference group
registered self-employed	Dummy variable for self-employed heads with(out) registration in the <i>Cadastro Nacional da Pessoa Jurídica</i> ; rural unemployed heads make up the reference category
unregistered self-employed	
registered employer	Dummy variable for heads that are employers with(out) registration in the <i>Cadastro Nacional da Pessoa Jurídica</i> ; rural unemployed heads make up the reference category
unregistered employer	
formal employee	Dummy variable for heads that are employees with(out) <i>carteira assinada</i> ; rural unemployed heads make up the reference category
informal employee	
not remunerated	Dummy variable for heads that do not receive pay; rural unemployed heads make up the reference category
agriculture industry construction trade tourism transport public administration education, health or social services	Dummy variables for household heads working in agriculture, industry, construction, tourism, transport, public administration, in the commercial sector and in educational, health or other social services; household with heads that are economically active but not working in either of these sectors are the reference group
high level employment	Dummy variable for household heads working in leading positions or being professionals in science or arts
probability of sector selection	Variable reflecting the probability of selection into the sample; surrogate for design variables, see Pfeiffermann and Sverchkov (2009: 463–464); sectors are selected within municipalities with a probability proportional to the inhabitant population; residential areas that have recently cropped up are included in the sample but sector probabilities are not given in the PNAD dataset; in the estimations where these new residential areas are included the probability is set to 1

Fig. 1 Climatological Zones in Brazil



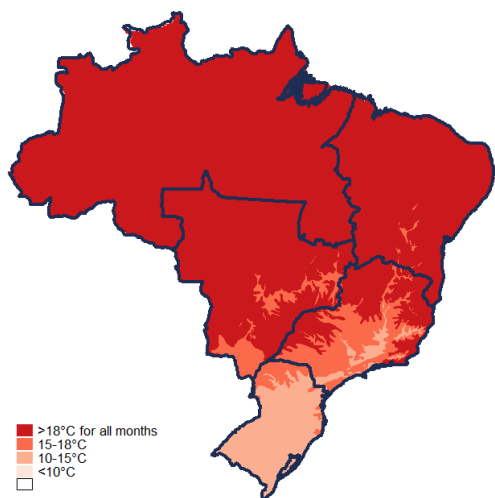
Source. Based on data from IBGE Directorate of Geosciences.

Fig. 2 Prevalence of Dry Periods



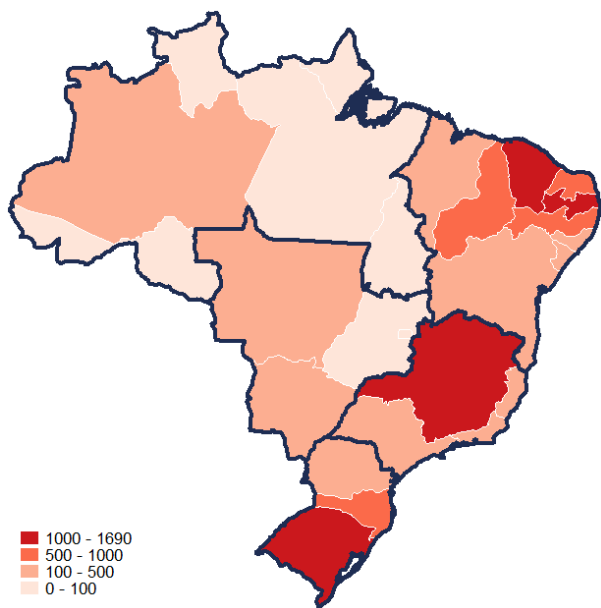
Source. Based on data from IBGE Directorate of Geosciences.

Fig. 3 Mean Temperatures



Source. Based on data from IBGE Directorate of Geosciences.

Fig. 4 Number of Registered Natural Disasters 2003-2009



Source. Based on data from CNM (2010).