Social Policy and Resilience:

A Geospatial Analysis of Climate Change's Impact on Migration Among Vulnerable Agricultural Producers

March 2025

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Article No. 09 (AR-IMDS-09-2025)

March 2025

Rio de Janeiro, RJ

www.imdsbrasil.org

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Abstract

This research analyzes how social policies influence the coping strategies of vulnerable agricultural households affected by climate change. We investigate the interplay between income shocks caused by extreme droughts and the benefits of the Brazilian *Bolsa Família* Program, focusing on how these factors influence the migration decisions of highly exposed individuals. Moving beyond traditional models that observe extreme weather events and migration patterns among administrative divisions, we develop a novel methodology to analyze migration both within and between Brazilian municipalities. We use high-resolution historical precipitation data at small grid units (0.05^o by 0.05^o) and geographical coordinates of households' addresses. Our findings reveal that short-distance migrations, within municipalities of origin, are five times more prevalent than long-distance ones, between municipalities. We estimate a panel with millions of vulnerable agricultural producers from 2015 to 2020. We find that social benefits can both favor or reduce the likelihood of individual migration depending on their level of exposure to droughts. Individuals exposed to the 1% most severe historical drought use the social benefits, on average, to increase migration; whereas those exposed to the 10% instance of drought use the social benefit as a resilience strategy, dampening migration. This effect is particularly pronounced among the benefit holders and heterogeneous to individual characteristics. On the other hand, the buffer mechanism of social programs tend to keep vulnerable individuals in places of poorer socioeconomic infrastructure compared to their migrating counterparts.

1 Introduction

Climate change has been associated to a rise in the frequency and severity of extreme natural events, resulting in significant economic and human losses globally (Dilley et al., 2005; Pindyck and Wang, 2013; Acharya et al., 2023). This situation is particularly dire for socioeconomically disadvantaged households, as climate change is projected to exacerbate existing vulnerabilities and inequalities (Hallegatte et al., 2017; Otto et al., 2017). One of the critical consequences for individuals in social and climate vulnerability is a heightened risk of displacement due to extreme weather events (Morrow-Jones and Morrow-Jones, 1991; Hallegatte et al., 2016). In this context, social policies and safety net programs may help vulnerable populations build resilience to climate shocks and navigate migration decisions.

This research investigates how social policy influences the coping strategies of vulnerable agricultural households affected by climate change in Brazil. We explore the relationship between exogenous income shocks, stemming from extreme drought impacts on crop yields, and the benefits of the Conditional Cash Transfer (CCT) Bolsa Família Program (BFP) to assess how social policy affects the migration decisions of the household members. In order to precisely identify individual migration patterns and exposure to extreme weather events, we developed a novel methodology that connects migration patterns within and between Brazilian municipalities with high-resolution historical precipitation data at small grid units.

Following a panel of individuals in vulnerable agricultural households from 2015 to 2020, we observed that 20% of them migrated at least once in a three-years period. Also, that migration to closer areas, within their municipality of residence, are five times greater than long-distance ones, to other municipalities. More striking, we found that social benefits can either boost or buffer individual migration decisions, depending on characteristics of both the extreme natural event and the individual. While the association between social benefits and exposure to the most severe 1% of drought events increased the probability of individual migration in subsequent periods: by 7% in the first year, 9% in the following two years, and 6% in the next three years; for those exposed to the most severe 10% of drought events, social benefits decreased migration probability in the following periods by -4% in the first year, -5% in the next two years, and -11% in the next three years. The effects were particularly pronounced among benefit holders. Notably, those who receive social benefits tend to remain in areas with poorer socioeconomic infrastructure compared to their migrating counterparts.

Migration is, indeed, one of the most common response mechanisms used by vulnerable individuals to withstand the consequences of extreme weather events (Berlemann and Steinhardt, 2017; Hunter, 2005; Ober, 2019). While safety net and social policy have significant importance for vulnerable households that have reduced access to traditional financial and non-financial responses to income-shocks (Dercon, 2002). The economic implications of resilient social policies are profound. By investing in adaptive capacity, governments can reduce the long-term costs associated with climate impacts. Therefore, social policy plays a pivotal role in enhancing household resilience to the multifaceted challenges posed by climate change. Safety nets that incorporate climate risk considerations not only protect against immediate shocks but also promote long-term development goals.

Accordingly, the association between CCTs and migration decisions have been of great interest in the literature (Adhikari and Gentilini, 2018; Hagen-Zanker and Himmelstine, 2012; Stecklov et al., 2005; Cirillo, 2018). While programs that focus on local strategies of implementation tend to reduce migration, broader and universal programs may induce mobility. In Brazil, this association has been studied at the municipality level by Oliveira and Chagas (2018) and Silveira Neto (2008), with results suggesting that CCTs reduce individual probability of migration. However, research in this area often overlooks individual migration patterns within administrative regions, which limits our understanding of this phenomenon. We not only develop a new methodology to address this gap, but we also connect our findings to the challenges posed by climate change.

2 Climate Change, Social Policy and Migration

In recent years, the interplay between social policy and household resilience has garnered increasing attention, particularly in the context of socioeconomic vulnerabilities exacerbated by climate change. Cash transfer programs have emerged as a component of social policy able to bolster resilience among low-income households in developing countries.

These programs provide direct financial assistance to households, enabling them to manage immediate economic pressures while investing in adaptive strategies, particularly in rural areas where access to formal financial services is limited. This diversification is particularly important in regions facing increased climate risk, as it enables producers to buffer against crop failures or market fluctuations.

2.1 The Brazilian scenario

The Brazilian scenario is highly representative of such (WB, 2021). Between 2015 and 2020, approximately 14 million individuals lived in vulnerable agricultural households, beneficiaries from both social and agricultural programs.[1] Given the current technological standards, climate change is projected to reduce agricultural output per hectare in Brazil by 18% (Assunção and Chein, 2016). This decline is likely to lead to increased displacement of vulnerable populations.

In fact, data from the Brazilian specialized authorities, from the S2iD system, shows that 90% of recognized natural disasters in the Brazilian territory were hydrological instances, caused by either insufficient rainfall or excessive precipitation. Table 1 highlights the two primary natural disasters linked to rainfall scarcity: dry spells and droughts. Notice that drought instances, recognized by the Brazilian authority, affected up to 7% of municipalities in certain years.

There are, indeed, specific climatic characteristics of the Brazilian regions that make

[1]Members of families registered both on the CadÚnico and DAP/Pronaf programs.

Table 1: Drought and Dry Spell occurrences in Brazilian municipalities as acknowledge by the governmental authorities between 2015-2019

N of Municipalities	Dry Spell	Drought
2015	843 (15%)	394 (7%)
2016	802 (14%)	370 (7%)
2017	109 (2%)	44 (1%)
2018	100 (2%)	132 (2%)
2019	37 (1%)	43 (1%)

Source: Authors, with data from the Integrated System of Information on Disasters (S2iD) and historical data on Federal Recognition of Emergency Situations and Public Calamity provided by the Ministry of Regional Integration and SEDECs.

them more susceptible to such events. For instance, the Northeastern region, of semi-arid and arid climate, accounts for almost 80% of the cases of drought and dry spell phenomenons. As a result, there are existing government programs designed to help communities in these areas cope with exposure to extreme natural events, such as the *Garantia Safra* and the First and Second Water Cisterns programs (CP1A and CP2A) (Bobonis et al., 2022; Da Mata et al., 2023). Additionally, special funds have been allocated to assist affected populations, covering approximately 20% of the cases between 2015 and 2020.

The following sections present how we developed our methodology for analyzing individual migration patterns across the Brazilian territory in association with high-resolution historical precipitation data. We will then present a basic model for individual migration along with our estimations. First, however, we will introduce the datasets utilized in these analyses.

3 Data

In this section, we present the data sources used to construct our methodology for observing individual migration in association with the historical precipitation index. We combined administratively restricted data with publicly available information from multiple sources concerning low-income individuals and households in Brazil.

3.1 *Cadastro Único* (CadÚnico)

The *Cadastro Único para Programas Sociais*(CadÚnico)[2] of the Federal Government is a database that identifies and characterizes the universe of low-income households in Brazil.[3] It was created by the Decree No. 3,877/2001 (Brasil, 2001), structured within the Ministry of Social Development[4] in 2001. Over the decades, CadÚnico has emerged as an important tool in supporting public policies design aimed at improving the lives of the low-income households. It provides managers with information on the risks and vulnerabilities to which the poor and extremely poor population of Brazil is exposed to.

In 2012, the system underwent a major improvement after Ordinance No. 177/2011 (Brasil, 2011). The information on Bolsa Família Program beneficiaries was, then, restructured within version 7 of CadÚnico, a newer and better connected infrastructure. Thus, it began to include a wider range of socioeconomic and demographic variables of registered households and individuals. Particularly important for our analysis, the introduction of the address information for each household. However, this information was not fully registered since the beginning. For instance, there is no address information for 42% of the households in 2012. It only significantly improved by 2015, when 96% of the households presented reliable address information; from 2016 onward, missing addresses were less than 1% of the households. Thus, we decided to use active records for households and individuals from 2015 until 2020, period of highly reliable data.

3.2 *Declaração de Aptidão ao Pronaf* (DAP/Pronaf)

The *Declaração de Aptidão* (DAP) *ao Programa Nacional de Fortalecimento da Agricultura Familiar* (*Pronaf*)[5], is a federal government administrative record that identifies and qualifies

[2]Unified Registry for Social Programs, in free translation

[3]Low-income households are defined as those with a monthly *per capita* income of up to half the current minimum wage or a total household income of up to three times the minimum wage.

[4]Between the years 2019 and 2022, it was called the Ministry of Citizenship.

[5]Declaration of Aptitude (DAP) for the National Program for Strengthening Family Farming (Pronaf), in free translation

Family Agricultural Production Units and their organized associative forms of Brazil. The DAP system identifies family farmers and beneficiaries of agrarian reform who can apply for rural credit and access to other government programs. We use DAP information to identify vulnerable individuals and households whose primary income is derived from crop production, making them particularly susceptible to the significant impacts of extreme drought on household income. Their climate and socioeconomic vulnerability is underscored by the fact that all of them are also registered in the *CadÚnico* for social programs.

3.3 CHIRPS: *Climate Hazards Group InfraRed Precipitation with Station data*

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 43 plus years quasi-global daily, pentadal, and monthly precipitation dataset. Spanning 50^o S - 50^o N (and all longitudes) and ranging from 1981 to near-present, CHIRPS incorporates the climatology, CHPclim, 0.05^o resolution satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. CHIRPS was developed to support the United States Agency for International Development Famine Early Warning Systems Network (FEWS NET). Building on approaches used in successful thermal infrared (TIR) precipitation products and current state-of-the-science interpolated gauge products, CHIRPS uses a "smart interpolation" approach, working with anomalies from a high resolution climatology.

We use monthly precipitation information at the grid-level of 0.05^o[6] for the Brazilian territory between January 1981 to December 2019 to develop a standardized historical precipitation index for each household address in our sample.

[6] 0.05^o = 5.55 km or 3.44 miles, approximately.

3.4 Sistema Integrado de Informações sobre Desastres (S2iD)

The *Sistema Integrado de Informações sobre Desastres* (S2iD)[7] is a national dataset compiled by the Ministry of Regional Integration of the federal government.[8] It works as a platform of the National Civil Protection and Defense System, integrating various systems from the National Civil Protection and Defense Secretariat (Sedec). Its aim is to enhance and provide transparency in risk and disaster management in Brazil through the digitization of processes and the availability of systematized information and resources. We used S2iD data to control for the occurrence of any publicly acknowledged weather disaster in the Brazilians municipalities between 2015 and 2020.

3.5 Garantia Safra

The *Garantia Safra*[9] is an initiative within the Pronaf aimed at ensuring minimum living conditions for family farmers in municipalities that are systematically subject to severe crop losses due to drought or excessive rainfall. It works as a subsidized insurance, which rural producers, local- and higher-levels governments contribute to a fund available to cover confirmed crop losses due to extreme weather events. We use *Garantia Safra* information as a control for other governmental programs that may be linked to individual exposure to extreme drought and the benefits provided by social programs.

3.6 Portal da Transparência

The *Portal da Transparência*[10] is a Brazilian government portal dedicated to making public all expenditures of the federal government. It lists all expenses and cash transfers the federal government, including the individuals receiving social benefits, such as the *Bolsa Família* and the *Garantia Safra*, and how much they have received.

[7] Integrated Disaster Information System, in free translation.

[8] This dataset was made available by the ministry through a Freedom of Information Act (LAI) process, number 59016.001820/2022-14.

[9] Crop-Guarantee, in free translation.

[10] Transparency Portal, in free translation: https://portaldatransparencia.gov.br/download-de-dados

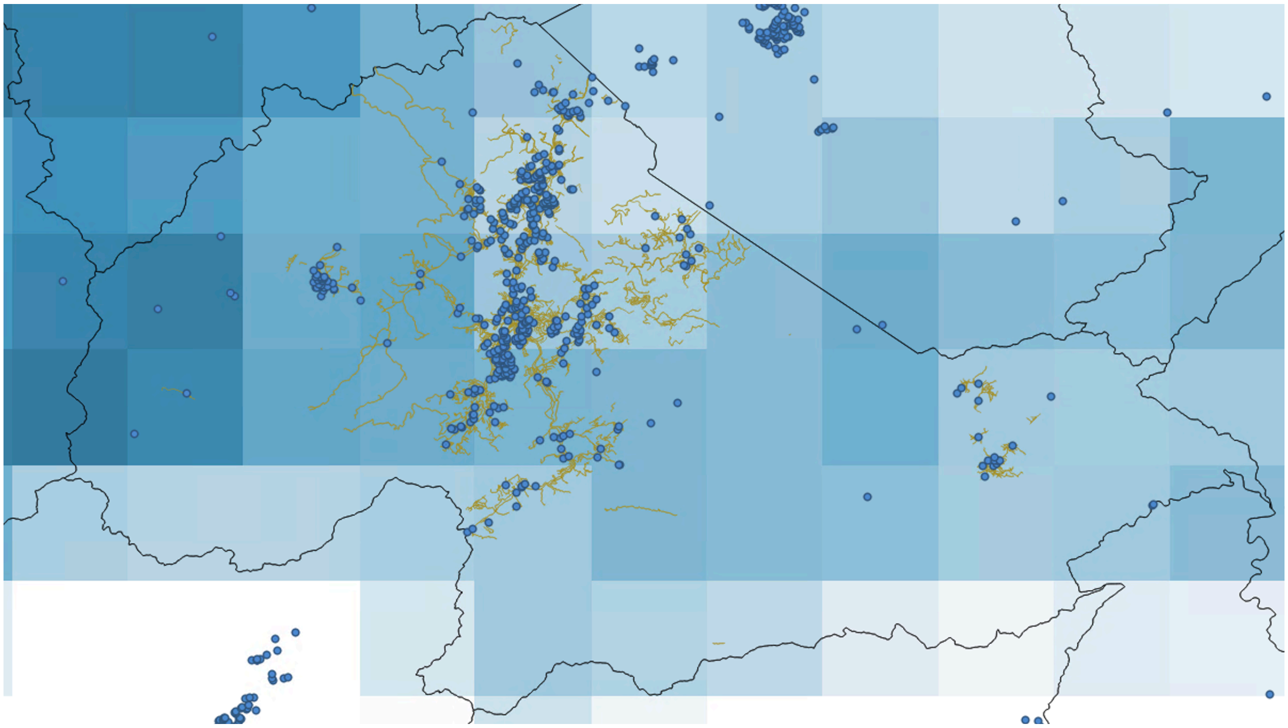
4 Methodology

One of the biggest concerns over the geospatial analysis of climate change and extreme natural events is the ability to observe affected units with high precision. Previous work relied on observation at the municipality-, county-, or district-levels, which misses a lot of variation for individual and household analysis (Cattaneo et al., 2019). In this paper we develop a new methodology which is able to overlap each place of residence (at the street level) of vulnerable households members and historical precipitation associated to small grids of 0.05° by 0.05°.[11] The high-resolution grids of precipitation data, combined with the proximity of agricultural producer families to their crop fields, enable us to accurately estimate the impact of extreme weather events on their income.

The following subsections detail our process for retrieving the geographic coordinates (latitudes and longitudes) of all vulnerable households in the *CadÚnico* between 2012 and 2020. We then explain how we overlapped this data with the historical precipitation index from the CHIRPS project using geographic information system software, QGIS. An example of the monthly snapshots with geographical points associated with the precipitation data can be observed in Figure 1.

[11]The same methodology is applied in our paper with preliminary title "Resilience in Adversity: How Social Policies Amend Labor and Capital Mobility in the Face of Extreme Weather Events" in collaboration with the UNU-WIDER and IMDS.

Figure 1: Household units and CHIRPS precipitation index for the city of Nova Friburgo, RJ/Brazil



Source: The authors, with data from the CHIRPS project and *CadÚnico* in the QGIS software. Blue dots are the geographic coordinates of household's addresses, in yellow the streets covered by IBGE in the Census, in black the municipality's territory limits, and in shades of blue squares the precipitation index for each grid and month/year.

4.1 Retrieving the geographical coordinates of households' addresses

We retrieved the geographical coordinates for the entire period of *CadÚnico* data available from 2012 to 2020, although we decided to include only data from 2015 until 2020 in our sample, as explained in Subsection 3.1. We began by concatenating all available address location information for each year for each year in the *CadÚnico* household datasets.[12] Next, we combined the datasets from 2012 to 2020, ensuring that each identical entry was represented only once, along with the relevant variables. This resulted in a dataset with 14,701,031 uniquely identified addresses, which we then processed through the HERE platform's Geocode algorithm to obtain the most accurate latitude and longitude coordinates.

[12]Variables: $cod\_munic\_ibge\_fam$, $nom\_localidade\_fam$, $nom\_tip\_logradouro\_fam$, $nom\_tit\_logradouro\_fam$, $nom\_logradouro\_fam$ + the name of the municipality and state.

Table 2 presents summary statistics of the quantity and quality of this methodology by groups of municipalities. We were able to retrieve geographic coordinates for 99.3% of the addresses. Among these, only 15% were accurately matched to the municipality's geocentric coordinates by the algorithm, while the remaining 85% matched within-municipality locations.

After a thorough analysis, we concluded that the quality of information provided by end-users correlates directly with the municipality size; smaller towns with larger rural areas tend to present greater challenges for the algorithm find street-level address geographic coordinates approximations. This is a result of the quality of the data registered in the *CadÚnico* system and the territorial coverage of the HERE algorithm. In many cases, we were unable to retrieve a more accurate address placement due to improper registration of street address information by end-users or the algorithm's inability to find a perfect match within the available datasets.

Table 2: Geocoding of households' unique addresses in the 2012-2020 *CadÚnico*

Groups	Capitals		Inhab. > 100,000		40k < Inhab. < 100k		15k < Inhab. < 40k		Inhab. < 15k		**Total**	
Addresses	N	%	N	%	N	%	N	%	N	%	N	%
Processed	2,227,957	100%	3,918,161	100%	2,676,148	100%	3,406,160	100%	2,472,605	100%	**14,701,031**	**100%**
Geocoded	2,221,164	99.7%	3,899,134	99.5%	2,652,450	99.1%	3,375,225	99.1%	2,452,639	99.2%	**14,600,612**	**99.3%**
Not found	6,723	0.3%	19,027	0.5%	23,698	0.9%	30,935	0.9%	19,966	0.8%	**100,349**	**0.7%**
					Quality of the Geocoding							
Street or similar	1,958,402	88%	3,359,339	87%	2,121,535	80%	2,332,668	69%	1,421,619	57%	**9,751,466**	**77%**
Locality:	262,832:	12%:	539,795:	14%:	530,915:	20%:	1,042,557:	31%:	1,031,020:	42%:	**3,407,119:**	**23%:**
Postal Code	41,984	2%	87,745	2%	33,691	1%	35,353	1%	29,549	1%	**228,322**	**2%**
District	181,939	8%	303,972	8%	137,365	5%	159,142	5%	134,944	6%	**917,362**	**6%**
Municipality	38,909	2%	148,078	4%	359,859	14%	848,062	25%	866,527	35%	**2,261,435**	**15%**

Source: Authors, with household data from the *CadÚnico* for Social Programs from 2012-2020. HERE Platform Geocoding API. The quality analysis conveys the information from the output variable retrieved from the HERE Geocoding algorithm.

Tables 9 and 10 in Appendix A do also present the Geocoding outcomes for a panel with all the household and individual observations, respectively. Relevant to our coming analysis is the result for the addresses of vulnerable agricultural households between 2015 and 2020: 57% at the street-level or similar; 6% at the district-level; 37% at the municipality-level.

4.2 Associating the Precipitation Index with Household Addresses

In this section, we describe the process of linking the precipitation index to the geographic coordinates of vulnerable households. By integrating these datasets, we aim to analyze how variations in precipitation impact household income, particularly in the context of extreme weather events.

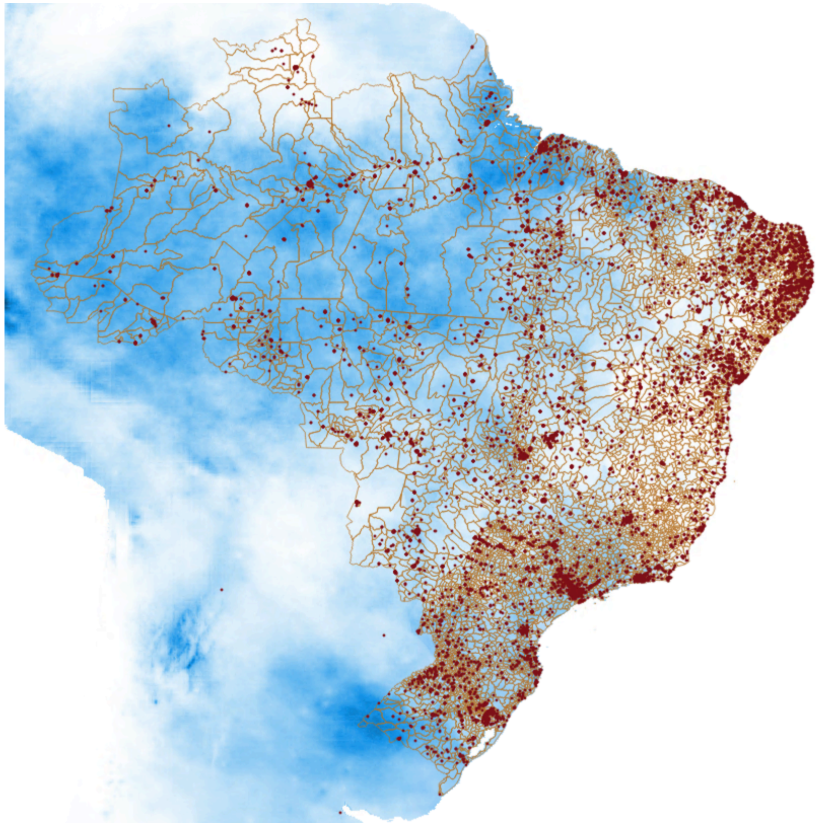
First, we imported the historical precipitation data from the CHIRPS project into the QGIS software. This dataset contains high-resolution (0.05° by 0.05°) precipitation measurements from January 1981 until December 2019. We then overlaid the precipitation data onto the geographic coordinates of the households.

Using spatial analysis tools in QGIS, we extracted precipitation values for each household based on their geographic location. This allowed us to create a comprehensive dataset that includes not only household coordinates but also corresponding historical precipitation data, facilitating our subsequent analysis of the effects of extreme weather on income and migration patterns.

By correlating these two datasets, we can better understand the relationship between precipitation extremes and the socioeconomic vulnerabilities of the affected populations.

As an example, Figure 2 presents the CHIRPS precipitation data (squares in shades of blue) for the Brazilian territory with the municipalities' administrative borders in brown and the geographical distribution of vulnerable agricultural households in red dots for January 2019.

Figure 2: CHIRPS precipitation index for January 2019 - Brazil



Source: Author's elaboration with data provided by the CHIRPS project and *CadÚnico* with the QGIS software.

4.3 A Standardized Historical Precipitation Measure

We build on Bobonis et al. (2022); Hidalgo et al. (2010) a standardized precipitation measure based on historical precipitation in the grid (area) of interest - the region where a household's address is located, for each month of the year. Differently from them, however, we develop this historical precipitation assessment at the smallest area possible, the grids of size 0.05° by 0.05° from the CHIRPS datasets.[13]

This historical assessment is important to ensure meaningful comparisons across areas with differing climatic conditions. As Bobonis et al. (2022), extreme natural events are

[13]We exploit two distinct phenomena with the precipitation index based on the heterogeneous effects of rainfall on agricultural and urban areas. The first case is analyzed in this paper; the second one exploits high volumes of rainfall in short periods of time. The latter has is forthcoming with preliminary title "Resilience in Adversity: How Social Policies Amend Labor and Capital Mobility in the Face of Extreme Weather Events" in collaboration with the UNU-WIDER and IMDS.

measured as the difference between the current period's precipitation index and the historical mean of precipitation in the grid during identical periods of time, divided by the grids' historical standard deviation of precipitation for a given period of time.

Following Corbi et al. (2024), we use two measures of weather shock. The first relies on the cumulative rainfall during crop growing season in Brazil, between Spring (November) and Autumn (April), a vital period of rainfall for agricultural output.[14] The other uses yearly cumulative rainfall over an area. The standardized index is computed as follows:

$$\text{Standardized Precipitation}_{g,t} = \frac{(Precipitation_{g,t} - \overline{Precipitation}_{g,t})}{\sigma_{g,t}}$$

where $Precipitation_{g,t}$ refers to precipitation in grid g in time period t (a Growing Season or year); $\overline{Precipitation}_{g,t}$ refers to the average historical precipitation in grid g and time period t; and $\sigma_{g,t}$ is the historical standard deviation of precipitation in grid g and time period t.

This measure is useful to assess the extent to which the precipitation index over the Growing Season GS or year y was historically extreme. It's important to note that our standardized index is based on historical deviations for each grid and time period. For longer periods, we employ a similar strategy by calculating the cumulative precipitation for the same months across different years. For example, the cumulative precipitation in grid g is derived from the sum of precipitation between years t and t-1.

5 Migration decisions

We begin the analytical section of this paper by presenting a simple model of individual migration decision-making. Migration decisions in the context of climate change involve

[14] The growing season (GS) is very similar for different regions of Brazil. We use the months between November and April as an approximation:

$$Precipitation_{g,GS} = \sum_{m \epsilon [Nov,Apr]} Precipitation_{g,m}$$

a complex interplay of political, socioeconomic, and behavioral factors (Black et al., 2011; Martin et al., 2014). Nevertheless, migration remains one of the most common strategies for vulnerable individuals to cope with the impacts of extreme natural events (Berlemann and Steinhardt, 2017; Hunter, 2005; Ober, 2019). Economic hardship, along with direct income and wealth losses resulting from these events, is identified as a primary driver of migration, particularly for households facing climate and economic vulnerability. Consequently, social protection policies hold significant potential for enabling vulnerable individuals to adapt and develop resilience strategies in response to climate shocks. (Cattaneo et al., 2019; Premand and Stoeffler, 2020).

We outline a locational choice model where the migration decisions is a function of both financial and non-financial factors, along with a random shock component, as follows:

$$\text{Migration Decision}_{i,t} = f(I_i, S_i, C_i, \varepsilon_{i,t})$$

where $MigrationDecision_{i,t}$ is the individual i decision to migrate or not assessed in time t. This assessment is a comparison between financial factors, as income I and social benefits S, and non-financial factors, as community links C. A key component for our analysis is the random shock ε, such as an extreme natural event. We are mostly interested in understanding the relationship between the random shock component and financial factors on migration decisions.

6 Empirical Strategy

The migration model presented in 5 is applied to the migration decision-making of vulnerable agricultural households exposed to extreme weather events. Take a scenario where crop output, highly dependent on precipitation, is the main income source of a vulnerable family firm;[15] they are beneficiaries of social programs, such as the BFP; preferences

[15] Rainfall indices are vastly used as proxies for rural household's income in the literature, as seen in (Hidalgo et al., 2010; Jayachandran, 2006; Dell et al., 2014).

for non-financial factors are fixed over short periods of time; and they are subject to the occurrence of extreme weather events.

We rely on the hypothesis that extreme negative deviations from the historical precipitation over a grid/residence are quasi-random events. Consequently, exposure to high instances of drought is considered an unanticipated negative shock to agricultural productivity. To reinforce this assumption, we also account for longer periods of cumulative precipitation up to years *t*-1 and *t*-2.

We estimate the reduced-form equation of the relationship between being a social program beneficiary and exposure to extreme natural events in a panel of vulnerable agricultural individuals between the baseline year *t* and the following periods *t*+1 and *t*+2, as follows:

$$
\begin{aligned}
y_{i,t+n} = \alpha_{i,t} + \theta Income_{i,t} + \beta \, (\text{BFP Beneficiary}_{i,t} * \text{X\% Drought Exposure}_{i,t}) \\
+ \gamma \text{ BFP Beneficiary}_{i,t} + \eta \, (\text{X\% Drought Exposure})_{i,t} + \\
+ \omega_1 \, (\text{Cumulative Historical Neg. Std. Precipitation})_{i,t} + \\
+ \omega_2 \, (\text{Cumulative Historical Neg. Std. Precipitation})_{i,t-1} + \\
+ \omega_3 \, (\text{Cumulative Historical Neg. Std. Precipitation})_{i,t-2} + \\
+ X'_{i,t} \, \Delta_1 + HH'_{i,t} \, \Delta_2 + M'_{i,t} \, \Delta_3 + O'_{g,t} \, \Delta_4 + \phi_i + \rho_t + \epsilon_{i,t}
\end{aligned}
$$

where $y_{i,t+n}$ is a dummy variable that assumes the value of 1 if the individual i migrated any time in the following period, *t*+*n* years, measured as a probability;[16] The coefficient of interest β conveys the association between the individual being a beneficiary of the BFP and their exposure to extreme drought instances as a dummy variable (in quantiles of the historical rainfall distribution) in year *t*. Thus, the variables $\text{BFP Beneficiary}_{i,t}$ and $\text{X\% Drought Exposure}_{i,t}$ are individual components of the mentioned interaction, respectively. $\text{Cumulative Historical Neg. Std. Precipitation}_{i,t}$ and the cumulative rainfall for *t*-1

[16] Migration is assessed cumulatively for one, two, or three years after the baseline year *t* if the geographic coordinates of the address registered in each year for each individual in the *CadÚnico* changed.

and t-2 are continuous variables in Standard Deviations of the Distribution of the negative precipitation index historically assessed for a grid unit. $X_{i,t}$ the matrix of time-varying controls containing the individual characteristics in year t, including, for instance, education level and individual income; $HH_{i,t}$ the matrix of time-varying controls containing the household characteristics in year t, including, for instance, average income and residence characteristics; $M_{i,t}$ the matrix with information on any natural disasters acknowledge by the federal authorities from the S2iD dataset; $O_{g,t}$ the matrix of time-varying controls containing average characteristics of the households located in the same geographic coordinates of origin g in year t; ϕ_i the individual fixed effects; ω_t the year fixed effects; and $\epsilon_{i,t}$ the idiosyncratic error term. All estimations are clustered at the panel unit of analysis, individuals.

We should expect that β is a robust estimate of the causal effect of social policy benefits and exposure to climate change's effects on migration decision, given the quasi-random occurrence of extreme natural events. Exposure to drought is measured at both the intensive and the extensive margins, based on historical conditions for each grid/area. As a result, farmers cannot predict the extent of drought exposure in any given year. This uncertainty helps explain why half of our sample migrates in the first year following a major drought event. At the same time, the comparison groups are very similar vulnerable households registered in the *CadÚnico* for social benefits. Beneficiaries and non-beneficiaries of the BFP differ by a small margin given the program's eligibility criteria.

7 Observed Units

For the empirical analysis we wanted to observe as close as possible the universe of vulnerable agricultural producers in Brazil, their households' addresses and exposure to extreme natural events. We have special interest in the small, family units, the most exposed to negative income shocks, stemming from effects of climate change. After observing that the occupational information from family-members registered in the *CadÚnico* was not optimal for such,[17] we managed to link the *CadÚnico* datasets with the DAP/Pronaf, a registry of vulnerable agricultural household producers maintained by the Ministry of Agrarian Development and Family Agriculture. Notwithstanding, we were able to find all of the benefit holders in DAP/Pronaf between 2015 and 2020 also in the *CadÚnico* by using their social security number (CPF) as the key. This way, we secured a match between the universe of social program beneficiaries that are vulnerable agricultural producers. All other datasets were merged by individual and/or administrative territory for the analysis, with close to perfect matching results.

We took a few steps to select our final sample. Firstly, we restricted the *CadÚnico* sample for only household units with “active” entries, so we guarantee the record is up-to-dated and with reliable information.[18]. Then, we compiled the information in DAP/Pronaf by observing any individual, benefit holder of secondary, who was ever registered between 2012 and 2020.[19] Given the household structure of benefits, we kept in our sample any individual member of households in which at least one member was listed in DAP/Pronaf. Finally, we keep in our analysis only individuals observed in the resulting dataset for more than one year in our panel, in order to observe migration by comparing their addresses over time.[20]

8 Summary Statistics

The sample of individuals in vulnerable agricultural households has 55,213,451 observations of 14,362,945 unique individuals across the years 2015 and 2020, which 76% were beneficiaries of the BFP. Of those, 26,793,027 observations were from the 6,661,156 unique individuals

[17]For instance, we should be able to observe with variable “ind_parc_mds_fam” agricultural and agrarian reform households. However, many of those are not listed as agricultural producers in the corresponding occupation variables “cod_agricultura_trab_memb” and “cod_principal_trab_memb”.

[18]This is important to observe only those actively receiving social benefits and with non-missing address information, which were, on average, less than 1% over the 2015-2020 years.

[19]We use the information back to 2012, because the DAP/Pronaf dataset contains only the stock of information ever registered in the system and entries were updated on a biannual basis.

[20]Notice that we are not able to observe individuals who left the *CadÚnico* over the years. This could lead to censored-data bias to our estimates. However, we observe an average migration rate similar to that of the Brazilian Census and to what is found in the literature (Oliveira and Chagas, 2018).

directly found in DAP/Pronaf as main benefit holders.[21] Notice that we can only observe the migration status of individuals in t+1 years between 2015 and 2019; in t+2 years between 2015 and 2018; and t+3 years between 2015 and 2017.

Moreover, one of the main contributions of our analysis is to observe individual migration across the territory, not restricted to administrative areas. Table 3 presents the average share of individuals in our panel who migrates in t+1, t+2, and/or t+3 years after the baseline year t,[22] when exposure to extreme drought is assessed. We constructed three outcome variables as migration assessments: "Migrated", which compares the geographical coordinates of individual's household addresses between time periods; "Within": compares the geographical coordinates of individual's household addresses conditional on belonging to a same municipality; and "Between": compares the geographical coordinates of individual's household addresses conditional on belonging to different municipalities. It is striking to observe that migration within a municipality's territory is five times higher than longer-distance ones to a different municipality.

Table 3: Individual migration of vulnerable agricultural producers between t and t+n, panel 2015-2020

Migrated between t and:	t+1			t+1 / t+2			t+1 / t+2 / t+3		
Address changed	Migrated	Within	Between	Migrated	Within	Between	Migrated	Within	Between
				any member of the family					
Share of ind. (in %)	7%	6%	1%	14%	12%	2%	20%	17%	3%
N of ind. (in millions)	3.81	3.21	0.60	6.18	5.27	0.91	6.68	5.74	0.94
				benefit holder					
Share of ind. (in %)	6%	5%	1%	12%	10%	2%	18%	15%	3%
N of ind. (in millions)	1.63	1.38	0.25	2.68	2.28	0.40	2.92	2.51	0.41

Source: Authors, with data from the CadÚnico and DAP/PRONAF. Migration of individuals in vulnerable agricultural-producer families between 2015 and 2020. The columns stand for "Migrated": addresses with different geographical coordinates between time periods; "Within": different geographical coordinates within a same municipality; and "Between": different geographical coordinates in different municipalities.

Although individuals more frequently migrate to areas of better socioeconomic and infrastructure than their places of origin, the same cannot be taken for granted for those displaced by extreme weather events. Table 4 presents the average characteristics of areas of origin and destination of vulnerable individuals exposed to the 1% and 10% highest

[21]There was missing information for some individuals among those who migrated between and within municipalities in very few instances.

[22]We take the cumulative instances of migration over the years.

instances of drought and beneficiary of the BFP in our sample. We can observe that among those who migrated, they have indeed chosen places of better characteristics than of their places of origin. However, the 1% most affected by drought instances have migrated to places only slightly better than their origins; while those affected by the 10% highest instances of drought have chosen destination places slightly better, comparatively. Moreover, we are presented with how vulnerable these population are, with close to half of them having access to public water and trash collection only; while less than a quarter of them, on average, have access to public sewage system.

Table 4: Test of the difference in means between the average characteristics of the locations of origin and destination of individuals who migrated between 2015 and 2020 - Beneficiaries of the BFP affected by extreme drought (1% and 10% of the distribution))

Drought Instance	1% Highest			10% Highest		
Average of households	Destination	Origin	Difference (t-test)	Destination	Origin	Difference (t-test)
average per capita income (in BRL)	209.96	182.62	27.34***	190.60	166.41	38.71***
monthly household expenses (in BRL)	402.74	362.02	40.72***	376.95	338.25	38.70***
house with finished floor (share)	0.86	0.83	0.03***	0.89	0.87	0.02***
house with concrete finished walls (share)	0.49	0.48	0.01***	0.57	0.55	0.02***
access to public water provision (share)	0.48	0.47	0.01***	0.53	0.51	0.02***
access to public sewage system (share)	0.14	0.13	0.01***	0.17	0.15	0.02***
access to trash collection (share)	0.46	0.43	0.03***	0.47	0.43	0.04***
access to public energy system (share)	0.75	0.75	0.00**	0.80	0.79	0.01***
N of individuals	36,554	36,554		352,291	352,291	

Source: Authors, with data from the CadÚnico and DAP/PRONAF. Comparison of origin-destination average characteristic of households located in a same geographical point for those in areas with the highest instances of drought, 1% and 10% most severe.

9 Results

We start by presenting our main results for the social policy effect on individual migration decisions in t+1, t+2, and/or t+3 years after a vulnerable agricultural producer is highly affected by an extreme drought between 2015 and 2020, as presented in Section 6.[23] Subsection 9.1 focus on the migration decisions of any members of the vulnerable agricultural families, given the family-firm characteristics and structure of the social benefits; while 9.2, on the migration decisions of the main benefit holders, as they are, most commonly, the main providers of the family-firm unit.

[23]The results remain robust in our yearly assessment, although the identification is less precise.

Our results reconcile different strands of literature that suggest social policy can serve both as a buffer and a booster of individual migration decisions, depending on the characteristics of the affected units and the severity of the extreme natural event. We find that the relationship between exposure to the 1% most severe drought instances and the CCT social benefits increased individual migration probability in the following periods by 7% in the first year, 9% in the next two years, and 6% in the next three years. While exposure to the 10% highest instances of drought and the CCT social benefits decreased individual migration probability in the following periods by -4% in the first year, -5% in the next two years, and -11% in the next three years. The effects are particularly pronounced among benefit holders and heterogeneous according to individual characteristics.

9.1 Any Members of Agricultural Producer Households

Table 5 presents the results for members of agricultural producer households affected by the 1% most severe drought instances. Notice that the interaction between being a BFP beneficiary and exposure to these severe drought instances has a significant positive effect on individual migration probability across all cases. Similarly, Table 6 shows the results for households affected by the 10% most severe drought instances. Here, the association of interest is significant but reveals a negative relationship between social benefits and exposure to less extreme drought instances, with the exception of migration between municipalities, which shows a positive, though very small, effect in some cases. In both analyses, controlling for time-varying characteristics of individuals and households reveals a significant source of heterogeneity.

The literature supports our findings in two ways. First, the severity of a drought directly correlates with greater crop loss due to an unanticipated shock. While social benefits may encourage migration by providing the financial resources necessary for individuals who are highly exposed or actually displaced, these benefits may also help those less affected by the disaster to build resilience against moderate income losses, such as those resulting from crop damage. Second, the more extreme the natural disaster, the more heterogeneous its effects on individuals. This highlights the non-linear relationship observed at different levels of drought severity and underscores the importance of time-varying controls in understanding these effects.

In fact, we are able to reconcile these two contrasting results in the literature. We believe that our unique identification strategy allows us to precisely observe the effect of climate change on individual units, thereby enabling us to disentangle these heterogeneous characteristics.

Table 5: Migration decisions of members of agricultural producer households in CadÚnico between 2015 and 2020: Effects of droughts by quantile of the distribution of rainfall and benefits of the BFP.

Precipitation in SDs for the Growing Season (Nov to Apr)	Migrated	Migrated	Within	Within	Between	Between
Addresses' geocodes changed between t and t+1						
Interaction BFP * 1% highest drought instance	0.0022	0.0050	0.0006	0.0032	0.0018	0.0019
Relative Effect (Δ % Mean Dep. Var. given β)	**3.1%**	**7.1%**	**0.8%**	**4.6%**	**2.5%**	**2.7%**
Addresses' geocodes changed between t and t+2						
Interaction BFP * 1% highest drought instance	0.0026	0.0062	-0.0001	0.0034	0.0028	0.0030
Relative Effect (Δ % Mean Dep. Var. given β)	**3.7%**	**8.9%**	-0.1%	**4.9%**	**4.0%**	**4.2%**
Addresses' geocodes changed between t and t+3						
Interaction BFP * 1% highest drought instance	0.0039	0.0041	0.0012	0.0015	0.0031	0.0030
Relative Effect (Δ % Mean Dep. Var. given β)	**5.5%**	**5.8%**	1.7%	2.1%	**4.4%**	**4.3%**
FE for individual and year	X	X	X	X	X	X
Individual- and Household-level Controls		X		X		X
Municipality-level natural disaster control (S2iD)		X		X		X
Local-level Controls (Origin)		X		X		X

Source: Authors, with data from the CadÚnico, DAP/PRONAF, and CHIRPS Precipitation. Precipitation in SDs for the Growing Season (Nov to Apr) at the grid level. Migration of individuals in vulnerable agricultural-producer families between 2015 and 2020. The columns stand for "Migrated": addresses with different geographical coordinates between time periods; "Within": different geographical coordinates within a same municipality; and "Between": different geographical coordinates in different municipalities. Relative effects are in bold for those significant at the 1% level.

Table 6: Migration decisions of members of agricultural producer households in CadÚnico between 2015 and 2020: Effects of droughts by quantile of the distribution of rainfall and benefits of the BFP.

Precipitation in SDs for the Growing Season (Nov to Apr)	Migrated	Migrated	Within	Within	Between	Between
Addresses' geocodes changed between t and t+1						
Interaction BFP * 10% highest drought instance	-0.0045	-0.0026	-0.0044	-0.0026	-0.0002	-0.0001
Relative Effect (Δ % Mean Dep. Var. given β)	**-6.5%**	**-3.7%**	**-6.3%**	**-3.7%**	**-0.4%**	**-0.2%**
Addresses' geocodes changed between t and t+2						
Interaction BFP * 10% highest drought instance	-0.0056	-0.0036	-0.0064	-0.0046	0.0007	0.0009
Relative Effect (Δ % Mean Dep. Var. given β)	**-8.0%**	**-5.2%**	**-9.2%**	**-6.5%**	**1.0%**	**1.3%**
Addresses' geocodes changed between t and t+3						
Interaction BFP * 10% highest drought instance	-0.0060	-0.0080	-0.0069	-0.0088	0.0013	0.0011
Relative Effect (Δ % Mean Dep. Var. given β)	**-8.6%**	**-11.4%**	**-9.9%**	**-12.5%**	**1.8%**	**1.6%**
FE for individual and year	X	X	X	X	X	X
Individual- and Household-level Controls		X		X		X
Municipality-level natural disaster control (S2iD)		X		X		X
Local-level Controls (Origin)		X		X		X

Source: Authors, with data from the CadÚnico, DAP/PRONAF, and CHIRPS Precipitation. Precipitation in SDs for the Growing Season (Nov to Apr) at the grid level. Migration of individuals in vulnerable agricultural-producer families between 2015 and 2020. The columns stand for "Migrated": addresses with different geographical coordinates between time periods; "Within": different geographical coordinates within a same municipality; and "Between": different geographical coordinates in different municipalities. Relative effects are in bold for those significant at the 1% level.

9.2 Benefit Holders in Agricultural Producer Households

Now, the analysis focus on the individual migration decision among social benefit holders. These individuals are typically the primary providers for their households, placing them in a key position to make migration decisions. Table 7 presents the results for members of agricultural producer households exposed to the 1% highest drought instances; while Table 8 presents the results for migration decisions of individuals exposed to the 10% highest drought instances. The results are very similar to those including all family members, but present greater magnitude for migration decisions between municipalities and smaller within municipalities.

These results can be understood through the lens of our migration model, where benefit holders may migrate longer distances in search of better economic opportunities, while other family members may prefer shorter-distance migrations.

Table 7: Migration decisions of the main benefit holders of agricultural producer families in DAP/PRONAF and *CadÚnico* between 2015 and 2020: Effects of droughts by quantile of the distribution of rainfall and benefits of the BFP.

Precipitation in SDs for the Growing Season (Nov to Apr)	Migrated	Migrated	Within	Within	Between	Between
Addresses' geocodes changed between t and t+1						
Interaction BFP * 1% highest drought instance	0.0025	0.0058	0.0011	0.0041	0.0015	0.0018
Relative Effect (Δ % Mean Dep. Var. given β)	**4.0%**	**9.4%**	2.1%	**7.9%**	**14.9%**	**17.8%**
Addresses' geocodes changed between t and t+2						
Interaction BFP * 1% highest drought instance	0.0034	0.0074	0.0004	0.0043	0.0029	0.0032
Relative Effect (Δ % Mean Dep. Var. given β)	**2.7%**	**5.9%**	0.4%	**4.1%**	**14.5%**	**16.0%**
Addresses' geocodes changed between t and t+3						
Interaction BFP * 1% highest drought instance	0.0036	0.0037	0.0008	0.0010	0.0029	0.0029
Relative Effect (Δ % Mean Dep. Var. given β)	**2.0%**	**2.1%**	0.5%	0.7%	**10.4%**	**10.4%**
FE for individual and year	X	X	X	X	X	X
Individual- and Household-level Controls		X		X		X
Municipality-level natural disaster control (S2iD)		X		X		X
Local-level Controls (Origin)		X		X		X

Source: Authors, with data from the CadÚnico, DAP/PRONAF, and CHIRPS Precipitation. Precipitation in SDs for the Growing Season (Nov to Apr) at the grid level. Migration of individuals in vulnerable agricultural-producer families between 2015 and 2020. The columns stand for "Migrated": addresses with different geographical coordinates between time periods; "Within": different geographical coordinates within a same municipality; and "Between": different geographical coordinates in different municipalities. Relative effects are in bold for those significant at the 1% level.

Table 8: Migration decisions of the main benefit holders of agricultural producer families in DAP/PRONAF and *CadÚnico* between 2015 and 2020: Effects of droughts by quantile of the distribution of rainfall and benefits of the BFP.

Precipitation in SDs for the Growing Season (Nov to Apr)	Migrated	Migrated	Within	Within	Between	Between
Addresses' geocodes changed between t and t+1						
Interaction BFP * 10% highest drought instance	-0.0037	-0.0014	-0.0036	-0.0015	-0.0002	0.0000
Relative Effect (Δ % Mean Dep. Var. given β)	**-6.0%**	**-2.3%**	**-6.9%**	**-2.9%**	-2.0%	0.0%
Addresses' geocodes changed between t and t+2						
Interaction BFP * 10% highest drought instance	-0.0068	-0.0045	-0.0075	-0.0054	0.0005	0.0008
Relative Effect (Δ % Mean Dep. Var. given β)	**-5.5%**	**-3.6%**	**-7.1%**	**-5.1%**	**2.5%**	**4.0%**
Addresses' geocodes changed between t and t+3						
Interaction BFP * 10% highest drought instance	-0.0066	-0.0089	-0.0075	-0.0097	0.0012	0.0010
Relative Effect (Δ % Mean Dep. Var. given β)	**-3.7%**	**-5.0%**	**-4.9%**	**-6.4%**	**4.3%**	**3.6%**
FE for individual and year	X	X	X	X	X	X
Individual- and Household-level Controls		X		X		X
Municipality-level natural disaster control (S2iD)		X		X		X
Local-level Controls (Origin)		X		X		X

Source: Authors, with data from the CadÚnico, DAP/PRONAF, and CHIRPS Precipitation. Precipitation in SDs for the Growing Season (Nov to Apr) at the grid level. Migration of individuals in vulnerable agricultural-producer families between 2015 and 2020. The columns stand for "Migrated": addresses with different geographical coordinates between time periods; "Within": different geographical coordinates within a same municipality; and "Between": different geographical coordinates in different municipalities. Relative effects are in bold for those significant at the 1% level.

10 Conclusion

This research finds a significant impact of social policy on the migration decisions of vulnerable agricultural households affected by climate change. Our findings suggest that Conditional Cash Transfer benefits, such as those provided by the Bolsa Família Program, can either buffer or boost the likelihood of migration among individual members of agricultural households facing exogenous income shocks due to extreme drought impacts on crop yields, up to three years after a baseline year. Specifically, for those affected by the most severe 1% of drought events, social benefits generally boost migration, while for those impacted by the top 10% of drought instances, social benefits tend to act as a buffer, reducing individual migration. These effects are especially pronounced among benefit holders.

Our novel methodology allowed us to precisely identify individual migration patterns and exposure to extreme weather events across time and space. We found that 20% of vulnerable individuals migrated at least once between 2015 and 2020. Moreover, migration to nearby areas, within their municipality of origin, are five times greater than long-distance ones, to other municipalities. Those who receive social benefits tend to remain in areas with poorer socioeconomic infrastructure compared to their migrating counterparts.

These results reconcile two branches of the literature that identify both positive and negative effects of social benefits, such as Conditional Cash Transfers (CCTs), on individual migration decisions, depending on the heterogeneous characteristics of the shock and the affected units. While social benefits can encourage migration by providing the financial resources needed for individuals who are highly exposed or displaced, they can also help those less severely affected by the disaster build resilience against moderate income losses, such as those resulting from crop damage. In this way, social policy may play a critical role in enhancing household resilience to the diverse challenges posed by climate change, while also potentially discouraging migration to areas offering better opportunities for social and personal development (Hallegatte et al., 2016).

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A Aditional Tables and Graphs

A.1 Geocoding - Households and Individuals

Table 9: Geocoded household's addresses in *CadÚnico* between 2012 and 2020 - Total unique households

2012-2020	Total		Urban		Rural	
Households	N	%	N	%	N	%
Processed	221.589.840	100%	172.319.551	100%	48.669.601	100%
Geocoded	220.589.026	99.5%	171.877.924	99.7%	48.166.319	99.0%
Not found	1.000.814	0.5%	441.627	0.3%	503.282	1.0%
Quality of Geocoding						
Street or similar	161.739.074	73%	142.859.622	83%	18.316.102	38%
Street with house number	6.554.705	3%	5.502.506	3%	1.045.837	2%
Public areas	11.822.982	5%	6.303.010	4%	4.905.030	10%
Locality:	40.472.265	18%	16.612.252	10%	23.843.883	50%
Postal Code	2.092.723	1%	1.358.438	1%	731.486	2%
District	9.798.051	4%	6.400.533	4%	3.389.824	7%
Municipality	28.581.491	13%	8.853.281	5%	19.722.573	41%
Correct Municipality	210.649.163	95.5%	166.602.550	96.9%	43.458.847	90.2%

Authors, with household data from the *CadÚnico* for Social Programs from 2012-2020. HERE Platform Geocoding API. The quality analysis conveys the information from the output variable retrieved from the HERE Geocoding algorithm. The groups "Urban" and "Rural" as defined by the CadÚnico variable COD_LOCAL_DOMIC_FAM, which we did not use after finding it not reliable by an analysis in the QGis software.

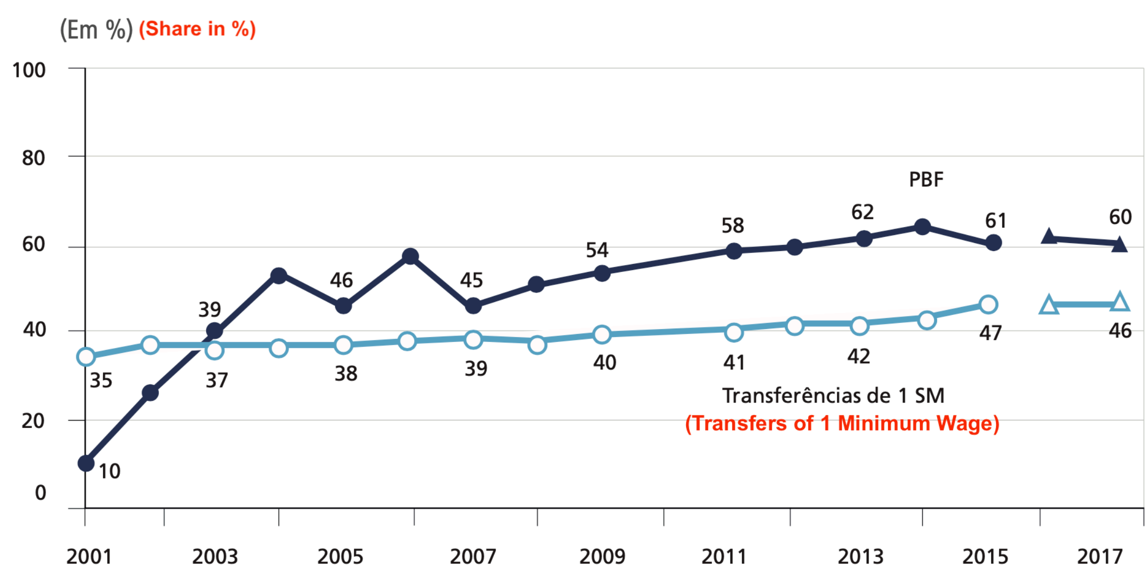
A.2 Summary Statistics - *CadÚnico*

Table 10: Geocoded household's addresses in *CadÚnico* between 2012 and 2020 - Total of individuals, household members

2012-2020	Total		Urbano		Rural	
Individuals	N	%	N	%	N	%
Processed	638.010.358	100%	484.152.545	100%	153.231.864	100%
Geocoded	634.905.909	99.5%	483.103.890	99.8%	151.452.791	98.8%
Not found	3.104.449	0.5%	1.048.655	0.2%	1.779.073	1.2%
Quality of Geocoding						
Street of similar	456.334.451	72%	398.679.647	83%	57.069.555	38%
Street with house number	18.916.071	3%	15.570.319	3%	3.338.894	2%
Public areas	35.383.641	6%	19.836.313	4%	15.532.142	10%
Locality:	124.271.746	20%	48.741.482	10%	75.512.200	50%
Postal Code	6.275.820	1%	3.923.428	1%	2.349.246	2%
District	28.871.333	5%	18.149.450	4%	10.713.703	7%
Municipality	89.124.593	14%	26.668.604	6%	62.449.251	41%
Correct Municipality	604.466.704	95.2%	467.200.567	96.7%	136.654.247	90.2%

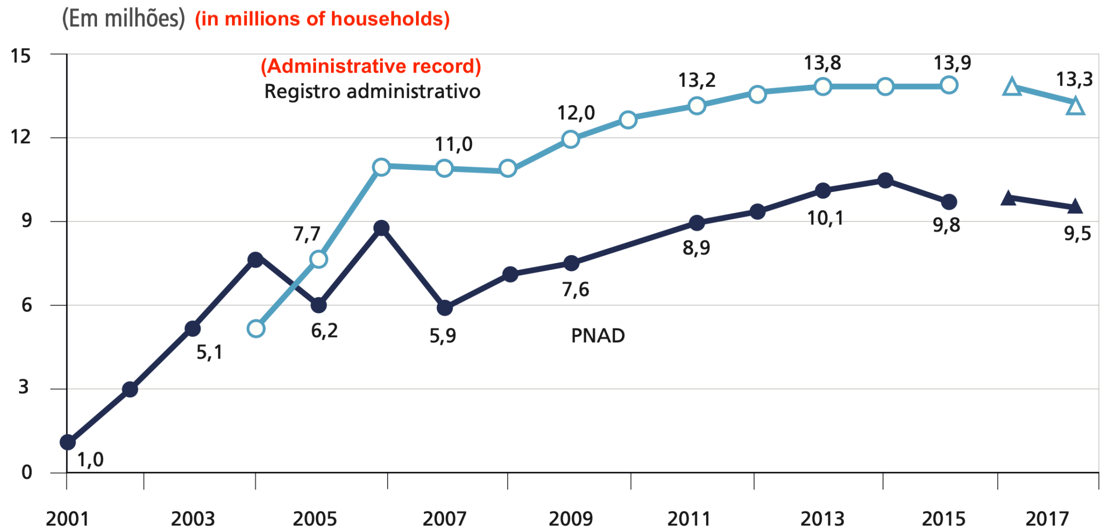
Authors, with household data from the *CadÚnico* for Social Programs from 2012-2020. HERE Platform Geocoding API. The quality analysis conveys the information from the output variable retrieved from the HERE Geocoding algorithm. The groups "Urban" and "Rural" as defined by the CadÚnico variable COD_LOCAL_DOMIC_FAM, which we did not use after finding it not reliable by an analysis in the QGis software.

Figure 3: Coverage of the Bolsa Família Program (BFP) and transfers equivalent to one minimum wage (Previdência and BPC) among the poorest 20% according to PNAD surveys (2001-2017)



Source: Adapted from (Souza et al., 2019), graph 3, page 15. Created using data from PNAD surveys (2001-2015), Continuous PNAD surveys (2016-2017).
Note: PNAD information includes the predecessor programs of the BFP and excludes rural areas of the Northern states (except Tocantins) until 2003. The population among the poorest 20% was defined based on the net per capita household income of each benefit.

Figure 4: Households benefiting from the BFP in administrative records and PNAD surveys (2001-2017)



Source: Adapted from (Souza et al., 2019), graph 1, page 11. Created using data from PNAD surveys (2001-2015), Continuous PNAD surveys (2016-2017), and data from the Social Information Matrix of the Secretariat for Evaluation and Information Management (SAGI/MCidadania).
Note: PNAD information includes the predecessor programs of the BFP and excludes rural areas of the Northern states (except Tocantins) until 2003. Information from administrative records includes only the BFP and refers to September (2001-2015) and June (2016-2017).

Table 11: Distribution of households/households according to registration status

households	2019	2018	2017	2016	2015	2014	2013	2012
Number of Obs.	53,187,644	48,770,064	44,112,029	40,015,875	37,612,900	35,439,014	32,897,119	30,243,128
	Number of observations per registration status code (cod_est_cadastral_fam)							
in registration	13,663	42,970	53,378	19,001	21,474	30,052	42,670	31,483
without civil registration	951	1,368	2,197	3,200	2,921	2,579	1,915	1,410
registered	28,884,068	26,913,965	26,950,657	26,457,577	27,326,122	29,172,487	27,200,920	25,069,565
excluded	24,288,962	21,811,761	17,105,797	13,536,097	10,262,383	6,233,896	5,651,614	5,140,670

Source: Own elaboration with data from the Unified Registry for Social Programs of the Federal Government and the Payroll of the Bolsa Família Program, from the Ministry of Citizenship/Social Development.

Table 12: Distribution of individuals according to registration status

Individuals	2019	2018	2017	2016	2015	2014	2013	2012
Number of Observations	175,995,622	165,016,862	153,645,158	143,935,709	136,994,748	130,429,631	123,179,294	115,543,894
	Number of observations per registration status code (cod_est_cadastral_memb)							
in registration	21,344	57,641	70,109	28,182	39,751	41,850	64,146	44,659
without civil registration	8,997	11,678	18,794	26,150	31,310	30,985	23,474	13,384
registered	76,415,223	73,570,482	76,464,300	77,829,966	80,793,612	88,181,943	84,291,806	81,296,980
excluded	99,118,459	90,957,954	76,731,894	66,002,780	55,969,699	41,979,054	37,949,178	34,083,210
awaiting NIS attribution	2,141	64,957	75,444	48,630	56,600	38,418	19,617	9,425
awaiting characterization change	0	0	0	0	103,775	157,376	768,224	66,185

Source: Own elaboration with data from the Unified Registry for Social Programs of the Federal Government and the Payroll of the Bolsa Família Program, from the Ministry of Citizenship/Social Development.