Temperature Shocks and Land Fragmentation: Evidence from Transaction and Property Registry Data*

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Preliminary. Please do not circulate.

Abstract

This paper studies the effect of weather shocks on rural land sales and the farm size distribution. Using a unique administrative dataset with transaction-level information and a land registry covering most of Colombia's farmland, we show that extreme temperature events increase the frequency of land sales and decrease the average farm size within municipalities. These results are driven by small farms being subdivided and purchased by previously landless owners, with no evidence of weather shocks leading to the consolidation of small farms into larger holdings. The effects of extreme temperature on land sales are stronger in poorer and more isolated municipalities, where landowners are also less likely to take out land mortgages after a shock. To explain these patterns and explore how they can be exacerbated by underdevelopment, we develop an intertemporal, two-sector model where agents face a subsistence consumption constraint. Our findings highlight how climate-induced distress land sales are a relevant margin of adjustment that can have large distributional and efficiency implications for the agricultural sector of developing economies.

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1 Introduction

Large shares of the population in low and middle-income countries are employed in small, low-productivity farms (Restuccia et al., 2008; Adamopoulos and Restuccia, 2014; Gollin et al., 2014). The prevalence of small farms can constrain technological progress and limit potential economies of scale and productivity gains, hindering poverty reduction and development (Foster and Rosenzweig, 2022). Understanding the determinants of the farm size distribution is therefore a first-order concern.

This paper studies a potential determinant of land fragmentation that is particularly salient in low and middle-income countries, uninsured risk. In these settings, agricultural production is highly exposed to income fluctuations related to weather and commodity price variability and coping mechanisms like insurance and credit are scant (Jayachandran, 2006; Colmer, 2021; Fafchamps, 1992; Cole et al., 2017; Carter et al., 2017).[1] In the event of a negative productivity shock, poor land owners may have to sell a fraction of their landholdings in order to smooth consumption, affecting in turn the farm-size distribution (Rosenzweig and Wolpin, 1993; Carter and Zimmerman, 2003; Kazianga and Udry, 2006).[2] Using two unique administrative data sets with information on hundreds of thousands of land sale transactions and information on a land registry covering most of the country of Colombia, we show that temperature shocks cause land sales and lead on average to smaller-sized farms. We show that this reduction in farm size is entirely driven by the entry of new landholders that operate relatively small farms, and find no evidence of shocks leading to the consolidation of larger holdings. To explain these patterns we develop a general equilibrium, heterogeneous-agent model where agents face an intertemporal consumption decision bound to a subsistence constraint. The model illustrates how the occurrence of negative productivity shocks can lead to the exit of incumbent farmers from the agricultural sector, while also causing new, previously landless agents to buy land. Both our empirical and theoretical results document how climate-induced distress land sales are a relevant margin of adjustment that can have important distributional and productivity implications. The results shed light on an additional, potentially large, negative consequence of climate change, given that the intensity and frequency of extreme weather events are bound to increase in the coming decades (IPCC, 2021).

[1] Unsubsidized agricultural insurance coverage rates in high income countries are on average 41.7% while coverage rates for lower-middle income and low income countries are, respectively, 8% and 0.5% (Mahul and Stutley, 2008).

[2] According to a longitudinal survey of rural Colombian households, between 2013 and 2016, nearly 65% of households who reported selling land did so in order to pay for household expenses or cover outstanding debts, pay for a medical treatment, or pay for education fees. These figures come from the ELCA survey described in more detail below.

To study the relationship between extreme weather events, land transactions and farm size, we use a unique administrative dataset containing official records of land transactions between 2000 and 2011 involving plots allocated by the Colombian government to private farmers throughout the 20th century. These plots comprise about 50% of all rural land currently held by private individuals in the country and are evenly distributed across regions. With information on nearly 500,000 land transactions we construct a yearly balanced panel with the number of full and partial land sales both at the municipality level and at the *vereda* level, Colombia's smallest rural administrative unit. We complement this data with information collected from the National Land Registry, a census of properties covering most of Colombia's farmland. This dataset allows us to measure yearly changes in the number of land owners and the distribution of plot sizes at the municipality level. Because land rental markets in Colombia are thin –data from a national representative survey of farms shows that in 2019 only 9% of farms operated rented land–,[3] these measures of plot size are a good representation of farm size and farm operational scale.

We combine both datasets with high-resolution meteorological data from Copernicus Climate Change Service (C3S). Our preferred measure of temperature shocks identifies days of atypically high or low temperatures by constructing distributions that are specific to the vereda (or the municipality) and to the calendar quarter. This accounts for seasonality and for differences across regions in weather patterns. We exploit both within-vereda and within-municipality variation in weather shocks to identify the causal effects of interest under the standard assumption in the literature (e.g., Dell et al. (2014)) that, conditional on time and geographical unit fixed effects, temperature shocks are uncorrelated with other time-varying factors affecting land sales.

First, we show that extreme temperature shocks induce distress land sales. In particular, 100 additional days of atypical temperature in a two-year period increase the number of land sales in the municipality by 7.6%. These temperature shocks also induce land fragmentation as average farm size decreases by 1.2%. The latter is driven by the entry of new owners with land holdings in the lowest quintiles of the initial size distribution. The effect of weather shocks on land sales is stronger in less densely populated municipalities, located farther away from urban markets. While land owners in wealthier, better connected municipalities are more likely to respond to negative temperature shocks by taking out mortgages on their land. This suggest that better access to credit can mitigate the need for distress sales. We complement our main findings using data from a 3-wave longitudinal household survey and show that following an adverse temperature shock, rural households have lower consumption,

[3]National Agricultural Survey (ENA), carried out by the National Statistical Agency (DANE); 2019-1 bulletin.

are more likely to migrate, are less likely to hold land, and are more likely to reallocate their labor to the non-agricultural sector. These effects are consistent with the use of distress sales as a consumption smoothing mechanism.

This paper contributes to the literature that explores the determinants of farm size in developing countries. Recent literature on this topic has focused on institutional factors that distort farm sizes and induce misallocation (Adamopoulos and Restuccia, 2020; Chen et al., 2022), or on the changes to the distribution of farm sizes induced by variations in urban labor demand (Rao et al., 2022; Madhok et al., 2022). We add to this literature by providing evidence on the effect of negative productivity shocks on farm size. While a standard heterogeneous-agent model with credit market imperfections would predict that the expansion in land supply due to distress sales should lead to the consolidation of small farms into larger landholdings, we show that the opposite effect, land *fragmentation*, takes place.

Our results also emphasize that low agricultural productivity can be exacerbated by the aggregate consequences of individual responses to uninsured risk. By documenting how the aggregate exposure to adverse weather shocks leads to a more fragmented farm size distribution, our findings point to another mechanism explaining the notoriously low productivity of agriculture relative to the non-agricultural sector in developing economies (Gollin et al., 2014; Restuccia et al., 2008; Caselli, 2005). While some previous studies have documented the occurrence of distress land sales with survey data in several developing countries (Cain, 1981; Deininger and Jin, 2008; Musyoka et al., 2021), our use of administrative data allows us to estimate the aggregate effects of distress sales on the farm size distribution.

Finally, this paper contributes to the literature exploring the effects of weather shocks on agriculture. This literature has shown that farmers' responses to weather shocks include adjustments in labor and intermediate inputs use, changes in crop choice, migration, or investment in human capital (Jayachandran, 2006; Jessoe et al., 2018; Colmer, 2021; Jagnani et al., 2021; Aragón et al., 2021). We complement this literature by documenting that land sales constitute an important margin of adjustment for farmers facing negative productivity shocks. Because land is the main financial asset of most farmers in developing economies, land sales can have strong, long-lasting effects on farmers' future income. As climate change intensifies, our results highlight an additional mechanism through which increases in the severity and frequency of adverse weather shocks can deepen the wedge in the performance of agricultural sectors between poor and rich economies (Burke et al., 2015; IPCC, 2021).

The rest of this paper is organized as follows. In the next section, we describe the historical and institutional context and our main sources of data. Section 3 gives the details of our empirical strategy and in Section 4 we present our main results. Section 5 sketches the theoretical model that we develop to rationalize our results, and Section 6 concludes.

2 Context, Data, and Descriptive Statistics

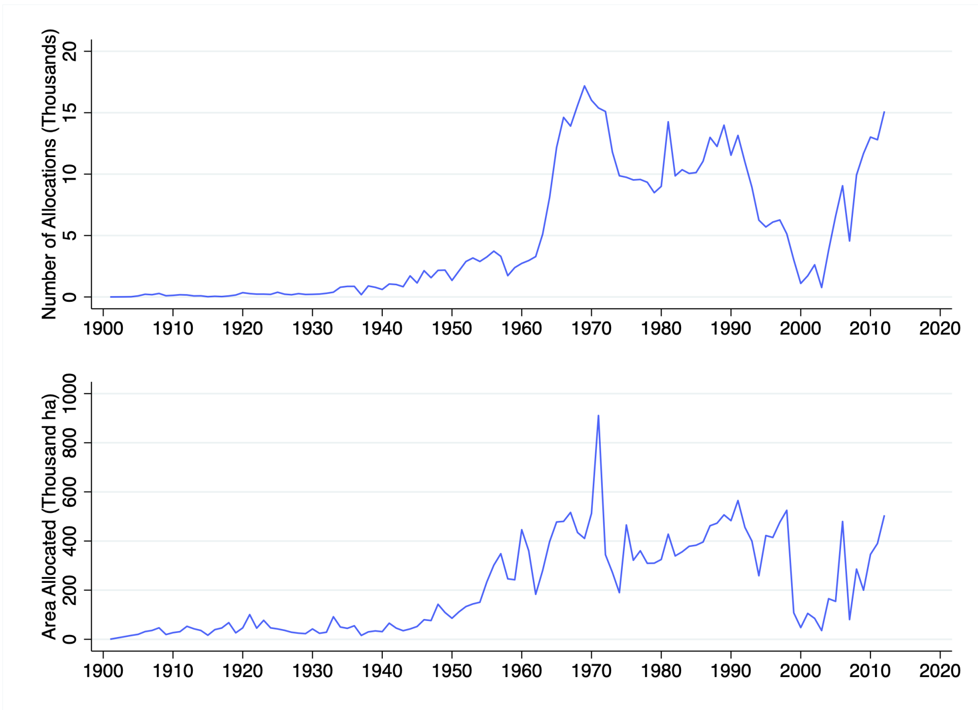
Studying the relation between land market transactions, land fragmentation, and weather shocks requires information with special characteristics. First, we need information at the transaction level spanning a long time period and a large geographical area. Second, assessing land fragmentation requires a registry of plot information that allows for characterizing the complete distribution of the size of farms for a given geographical unit. Third, we need measures of weather shocks that are homogeneous across time and space and that can be linked to the transaction and land registry data at some fine geographical level. In this paper, we use two unique administrative data sets that allow us to study the relations of interest at an extremely granular level. The first one contains information on plots that were originally granted to owners in the context of the Colombian public land distribution program. The second contains information from land property registries. In this section, we provide an account of the institutional and historical context associated with land redistribution in Colombia and describe the different data sets that we use.

2.1 The Public Land Allocation Program and the Transaction Data

The Colombian government has carried out free allocations of public idle lands (*baldíos*) to private individuals uninterruptedly since the beginning of the twentieth century. This allocations have become the largest and most consequential land reform policy instrument employed by the national government (Albertus, 2015). Formally, a *baldío* allocation is an administrative resolution issued by the national government to transfer state-owned vacant land to a private party. This allocation process has mostly consisted of a combination of frontier-settlement schemes where unused public lands are granted to poor smallholders, and of programs focused on the titling of state-owned lands that might have been previously informally occupied (Ibáñez and Muñoz, 2010).

The bulk of government-owned land allocations began in the midst of the US *Alliance for Progress* program with the enactment of the Social Agrarian Reform Act (Law 135) in 1961, which established the land reform agency (INCORA, later renamed as INCODER, and currently the National Land Agency, ANT). During the second half of the twentieth century, land allocation laws were amended on three occasions (Law 01 of 1968, Law 30 of 1988, and Law 160 of 1994) but the explicit objective of the policy always remained that of reducing land inequality and giving land to landless farmers (CNMH, 2016). Figure 1 shows the evolution of baldíos allocations since 1901, the vast majority of which were granted between 1960 and 1990. In terms of the number of beneficiaries and the amount of land allocated, the scale of the policy has been vast. More than 550,000 land plots have been granted to private individuals in 1,034 of the 1,122 existing municipalities. These plots account for 23 million hectares –more than half of the currently privately-held land in the country (Sánchez and Villaveces, 2016; Arteaga et al., 2017).

Figure 1: One Century of Land Allocations - 1901–2012



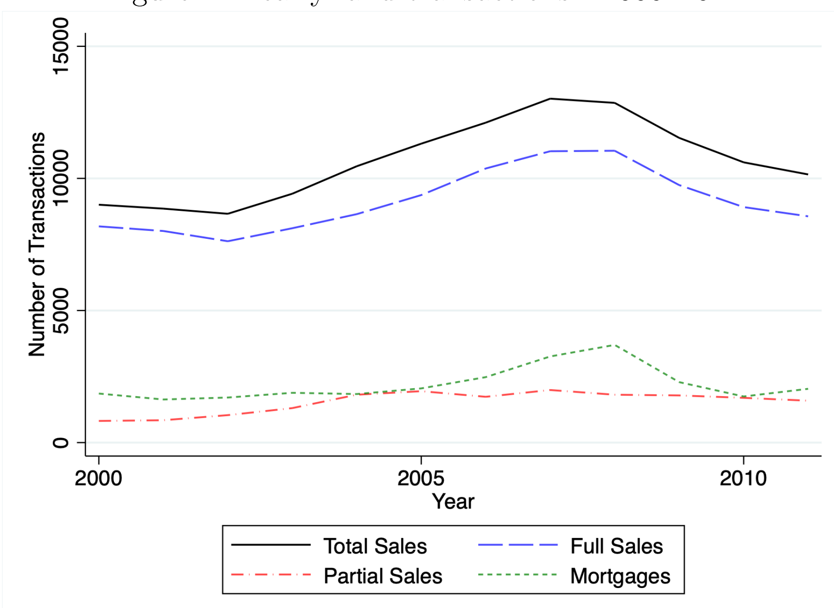
Notes: Data from the System of Information for Rural Development (SIDER)

Land petitioners undergo an administrative process with the national land agency to determine if they fulfill the legal requirements to become a beneficiary. While the requirements have changed in time, the most important conditions petitioners must fulfill involve owning no other land and having an income below a given threshold. Under the current legislation, the process formally consists of nine steps, which include the placement of an ad announcing the allocation in a local newspaper, and a physical inspection of the plot to be granted. Although on paper this procedure should take 60 days, allocation processes are generally much lengthier and some can take years (Gutiérrez Sanín, 2019). Appendix Figure A1 shows the evolution of the average and median size of allocated plots since 1960. The overwhelming majority of land allocations made throughout 1961–2014 period consisted of relatively small land plots, with a median allocation size across municipalities of 6.6

hectares. Importantly for this paper, Law 160 of 1994 established a ceiling on the amount of government-allocated land to which a single individual can claim ownership. This limit, defined by the municipality-specific Agricultural Family Unit (UAF), restricts the capacity of relatively larger farmers to purchase land that was initially government-owned. In appendix section B, we show that these land ceilings are not driving our results.

The universe of land allocations made by the government throughout 1901–2011 period is registered in the System of Information for Rural Development (SIDER) dataset currently maintained by the ANT. After receiving the plot, beneficiaries must register the property in the office of the local public notary, and all formal land transactions carried out over the plot (including mortgages) are henceforth registered and stored in a dataset maintained by the National Superintendence of Notaries (SNR), the government agency that supervises regional notaries and keeps a record of all real estate market transactions held among private parties.[4]

Figure 2: Yearly land transactions - 2000–2011



Notes: Data from the National Superintendence of Notaries (SNR). The figure shows the national-level yearly number of transactions held over plots originally granted by the national government.

Our main source of data is the transaction history of all baldío allocations whose beneficiaries registered their property with the notary thus finalizing the process to obtain a formal property right.[5] We mainly focus on land purchase transactions, which can be either

[4]The history of the transactions carried out over a plot, named the Certificate of Liberty and Tradition (*Certificado de Libertad y Tradición*) is public information that can be consulted by paying a small fee for any property with a real estate registration number on the web page of the SNR.

[5]While the registration process was not automatic and a non-negligible number of beneficiaries failed to follow this last administrative step (Faguet et al., 2020), Appendix Figure A2 in the appendix shows

the transfer of an entire property from one individual to another, or the subdivision and sale of only a fraction of the original plot. We refer to these types of transactions as *full sales* or *partial sales* respectively. We also study mortgages, as they could constitute an important adjustment margin when coping with negative productivity shocks. For each transaction held between two parties, we have access to information on the plot's location, the date in which it occurred, and the type of transaction. Figure 2 shows the yearly evolution of full and partial sales, along with the number of mortgages originated. Most of the sales in the land market are full sales, with partial sales representing a relatively small fraction of total transfers.

We match the location of the plot in the SNR dataset to the official list of Colombian municipalities and veredas provided by DANE, Colombia's National Statistical Agency.[6] We construct a balanced yearly panel both at the municipality and at the vereda level with information on the number of full and partial land sales, mortgages, and government land allocations. While we can match each of the land plots in the SNR data to their corresponding municipality, not all properties have information on the vereda, and we are able to identify it for only 63% of the properties in the SNR data. Figure 3 shows the ratio of total land sales to total allocations for the sample of plots matched to a vereda between 1980 and 2010. The map shows that there is substantial variation in the amount of land sales across space and in the veredas for which we observe transactions.

When deciding on the adequate level of data aggregation we face a tradeoff between the coarser municipality level and the finer, but potentially selected, vereda sample. We estimate the effects of weather shocks on land transactions using both samples and present the results in Section 4. Reassuringly, the choice of sample does not affect the sign or statistical significance of the results.

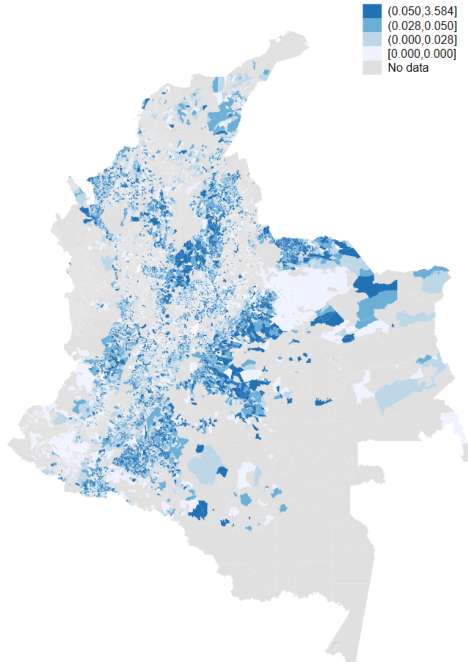
2.2 The Land Registry

For over 50 years, the National Geographical Institute of Colombia (IGAC) has collected information on land use and ownership and keep land valuations up to date. Law 14 of 1983, instituted a plot-level information collection system (the 'Ficha Predial' system) which has been implemented and maintained by IGAC since then. This system is meant to

that allocations and real estate registrations follow each other closely across time, suggesting that the great majority of land plots allocated did end up being registered.

[6]Municipalities are the smallest official administrative division in Colombia. For some administrative purposes, rural areas within municipalities are further divided into veredas. Veredas operate under the executive power of municipalities' mayors but have their own democratically elected Community Action Boards (*Juntas de Acción Comunal).* There are approximately 30,000 veredas in Colombia and 1,123 municipalities.

Figure 3: Ratio of Land Sales to Number of Allocations



Notes: Data from the National Superintendence of Notaries (SNR). The figure shows the proportion of plots sold in each vereda to the total number of plots allocated by the government between 1980 and 2011.

collect information on the location, size, and economic purpose of all real properties in every Colombian municipality with the exception of the state of Antioquia, which runs its own, independent, cadastral information system (Ibánez et al., 2012).

This information system is meant to be an up-to-date census of land ownership for the whole country, and the law stipulates that IGAC must carry out cadastral updates in every municipality every five years. Information is not, however, updated on a regular basis and the amount of time between cadastral updates varies significantly across municipalities.[7] Martinez (2019) shows that IGAC updates are not driven by changes in economic conditions of the municipalities (e.g. property booms).

In our study, we use municipal-level aggregate information from all plots in IGAC's cadastre that are i) privately owned, and ii) categorized as having an agricultural economic purpose. This amounts to roughly 40 million hectares of land. We use a yearly panel of municipalities with the number of plots, the number of owners and average plot size within size ranges as calculated by (Ibánez et al., 2012). The data from the land registry is only

[7]There are currently 80 municipalities across the country in which IGAC has not yet established the census-level cadastral information system. These municipalities have, instead, a self-reported information system ('Catastros Fiscales') in which landowners voluntarily register their properties in regional IGAC offices.

available for the period 2000-2011 and so we restrict our analysis to this time period. We exclude from our final sample of municipalities (both for the transaction-level data and for the land registry data) large metropolitan areas and municipalities with very few (i.e. below the 99^{th} percentile) properties registered. Our final sample is made up of 927 municipalities, which encompass 85.3% of the rural population in the country.

2.3 Weather Data and Temperature Shocks

We define temperature shocks that are specific to each geographical unit (either municipality or vereda) in order to account for the very large variation in climatic conditions across Colombian rural areas. The shocks are defined based on the unit's specific distribution of weather realizations, which we compute using long-run daily weather measurements (similar, for example, to Kaur (2019)). While this approach contrasts with weather shock definitions based on a fixed temperature threshold, which might be more suitable for the analysis of a specific region or crop (see, for example, Ibáñez et al. (2022)), we show that our results are robust to measures such measures of shocks that use using fixed thresholds.

We construct measures of temperature shocks using the ERA5 data set, provided by the Copernicus Climate Change Service (C3S) of the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset contains global reanalysis information on temperature with a horizontal resolution of 0.25×0.25 degrees (approximately 28 km^2 depending on the longitude) at an hourly frequency.[8] We use the temperature of the atmosphere two meters above the surface (in degrees Kelvin) from 1979 to 2016 in ERA5 for pixels in mainland Colombia. For each pixel in the data, we compute the average temperature for each day d, and obtain the average daily temperature of each vereda-day (or municipality-day) pair (v, d) by taking a weighted average of the pixels in the vereda using as weights the area of the pixel relative to the total area of the vereda. We compute the historical quarterly distribution of daily temperatures by considering all temperature measurements for pairs v, d in calendar-quarter q throughout the period 1979–2016. For each vereda this results in four distributions, one per quarter. We compute the 20^{th} and 80^{th} percentiles of each distribution and define the average temperature of a given vereda-day as atypically high if it is above the 80^{th} percentile of the corresponding distribution of average daily temperatures of v, q. Analogously, we define a day as having atypically low temperatures if it is below the 20^{th} percentile of the corresponding distribution.

Finally, for each year y, we sum the number of atypically high or low temperature days in each quarter. In our baseline specifications, we estimate the effect on outcomes measured

[8]Reanalysis weather information from the ERA5 results from the combination of climate models and observational data from satellites and ground sensors.

at the vereda-year (v, y) frequency and use as our preferred measure of weather shock the total number of days with atypical temperatures over the past two years (i.e. $y-1$, $y-2$). Figures A3 and A4 in the appendix show the spatial and temporal variation of the resulting temperature shock measures across veredas. This definition of temperature shocks has two advantages. First, it takes into account seasonality at the calendar quarter level since the distribution is specific to q. For example, since some calendar quarter of the year are typically hotter, we only consider a day as atypically hot if the temperature is high relative to the historical temperature of that quarter. Second, the measure is specific to the vereda (or municipality) and takes into account that an absolute temperature might be atypically high and have a negative consequence in one place but not in another.

In the empirical exercises below we also control for total rainfall. To construct this measure we use the ERA5 monthly precipitation reanalysis data with resolution 0.1×0.1 degrees (approximately 9 km^2 depending on the longitude) and use the conversion factor provided C3S to obtain a measure of total monthly precipitations in cubic milliliters for each pixel. We then obtain a weighted average across the pixels in the vereda to obtain monthly average rainfall. Again, we use as weights the size of the pixel relative to the size of the vereda. For a given year, we add across months to obtain a measure of total precipitation in the pair vereda-year v, y. We take an analogous average of the pixels that compose a municipality to obtain measures of total yearly rainfall in a municipality.

Linking the weather data with the SNR land sales vereda-level panel yields a data set with 12,472 veredas across 782 municipalities. Panel A of Table 1 shows descriptive statistics of this sample. In a given vereda year, there are, on average, 18 accumulated adjudications, 0.55 sales –0.47 full sales and 0.07 partial sales–, and 0.11 mortgages. These numbers are low but there is considerable variation across veredas. On average there are 281 days of atypical temperature days in the two previous years. Linking weather data to the panel of yearly sales at the municipality level (Panel B of Table 1) yields a sample of 866 municipalities. On average there are 12.3 land sales on each municipality-year (10.6 full sales; 1.8 partial), and 2.6 mortgage originations. The average municipality-year observation had 277.2 days with atypical temperatures during the two past years, with a standard deviation of 56.3 days.

Finally, linking the temperature shock measures with the land registry panel yields a sample of 927 municipalities. In the average municipality-year, there are 2516 owners, 2519 farms, the size of the average farm is 29.4 hectares, and there were 277 days of atypical temperature in the past two years. Data in all samples is restricted to the 2000–2011 period.

Table 1: Descriptive Statistics

	Panel A: SNR - Vereda (N = 12,472)			
	Mean	Std. Dev.	Min	Max
Total number of sales	0.55	2.07	0	133
Number of full sales	0.47	1.80	0	132
Number of partial sales	0.07	0.64	0	61
Number of Mortgages	0.11	0.56	0	29
Days of atypical temperature	281.38	55.18	96	560
Days of atypical high temperature	158.42	93.46	0	508
Days of atypical low temperature	122.96	87.65	4	560
Number of total allocations	18.56	55.36	0	2,376
Accumulated precipitation	3,272.2	2,370.8	374.6	33,533
	Panel B: SNR - Municipality (N = 866)			
Total number of sales	12.38	24.56	0	292
Number of full sales	10.63	21.46	0	281
Number of partial sales	1.75	5.98	0	133
Number of Mortgages	2.57	7.48	0	172
Days of atypical temperature	277.24	56.38	96	566
Days of atypical high temperature	157.52	93.52	0	496
Days of atypical low temperature	119.72	90.29	0	564
Number of total allocations	436.52	675.85	0	6,550
Accumulated precipitation	3,539.9	2,836.1	372.2	42,287
	Panel C: Land Registry - Municipality (N = 927)			
Number of owners	2,516.2	2,151.27	18	18,768
Number of plots	2,518.6	2,347.8	17	21,482
Average farm size (ha.)	29.4	94.5	0.65	1,543.5
=1 if land registry update	0.07	0.25	0	1
Registered area (1000 ha.)	39,273.7	84,443.3	170.8	1,465,761
Days of atypical temperature	277.14	56.16	96	566
Days of atypical high temperature	157.68	93.43	0	496
Days of atypical low temperature	119.46	89.67	4	564
Accumulated precipitation	3,488.3	2,804.3	372.2	42,287
	Panel D: ELCA - Household N = 3200			
=1 if HH migrated	0.13	0.33	0	1
=1 if HH has land	0.89	0.31	0	1
=1 if farm size < 3 ha	0.78	0.41	0	1
Farm size (ha.)	2.49	5.54	0	118
Days of atypical high temperature	436.93	165.09	163	816
Days of atypical low temperature	67.03	62.45	0	254
Accumulated precipitation	3792.29	2625.24	720.06	21969.01

Notes: Summary statistics for each estimation sample. Panel A describes the variables used for vereda-level estimations. Total number of sales includes full sales and partial sales during the year. Full sales correspond to sales where the entire property is transferred to another owner. Partial sales correspond to sales that transfer only a fraction of the initial property to a new owner. Number of total allocations corresponds to the cumulative sum of government-allocated plots in the vereda from 1901 until the year of observation. Panel B includes the same information but at municipality level. Panel C summarizes data used for estimations on land distribution at municipality-year level. It takes number of owners, number of plots, average farm size, total registered land and the indicator for land registry update from the national land registry carried out by IGAC. Panel D summarizes data used for estimations at the household-year level. This data comes from 3 rounds (2010, 2013 and 2016) of ELCA, a panel of rural households collected by Universidad de los Andes. Climate data used to compute the number of days with shocks and the accumulated precipitation comes from the Copernicus Climate Change Service (*C3S*). Days with atypical temperature shows the aggregate number of days across the two prior years ($y-2$, $y-1$) with either abnormally high or low temperatures. Accumulated precipitation is the volume of rain in milliliters for year y.

2.4 Longitudinal Household Survey and Additional Data Sources

We complement the previous data sources with data from a household panel that we use to analyze how farmers' decisions change in response to temperature shocks. In particular, we use the Colombian Longitudinal Survey conducted by the Universidad de los Andes (ELCA). The ELCA includes a sample of 4,800 rural households interviewed over three survey rounds (a baseline collected in 2010 and two follow-ups in 2013 and 2016). The rural sample of the ELCA is representative of small agricultural producers in four micro-regions: Atlantic, Central, Coffee-Growing, and South. Within each region, municipalities and veredas were randomly chosen. The baseline sample includes 17 municipalities and 224 veredas. In the follow-up rounds enumerators resurveyed all households and, if the household had split off or migrated, tracked the household head, spouse, and children under nine in 2010. The attrition rate after three waves in 2016 was 13.5%. The household questionnaire collected detailed information on land ownership and migration of household members which we use to complement our empirical analysis. We are interested in how migration, farm size, land ownership, and household consumption change in response to temperature shocks. Panel D of 1 contains descriptive statistics of the ELCA panel. On average, 13% of households migrated, 89% had any land and the average size of the plot was 2.5 hectares, 78% of farms are smaller than 3 hectares.

Finally, we study if effects are heterogeneous according to different measures of income and economic conditions of the municipalities. The availability of financial tools like credit access should allow households to smooth consumption without having to sell their property. Similarly, buffer savings and relatively high initial consumption levels (i.e. sufficiently away from a subsistence threshold) should allow households to cope with shocks without having to liquidate their landholdings. Therefore, we expect our results to be stronger in places with higher poverty rates, that are less connected to markets, and that are more isolated and less densely populated. To test this we use municipal-level information collected from CEDE at Universidad de los Andes which consist of a multidimensional poverty measure (the index of Unmet Basic Needs, UBN), a measure of driving distance to the nearest wholesale market, and a rurality index based on measures of population density.[9]

3 Empirical Strategy

The empirical strategy uses the spatial and temporal variation in the occurrence of adverse weather to estimate the effect of negative productivity shocks on land transactions and the

[9]We define municipalities as highly rural if they have a population below 25,000 inhabitants and have a population density below 100 inhabitants per squared kilometer. These thresholds are used by the Colombian government to categorize the 'rurality degree' of municipalities in Colombia. Under this definition close to 63% of municipalities are classified as highly rural.

farm size. In our first specification we estimate the following equation:

$$s_{v,y} = \beta TempShocks_{v,y} + X'_{v,y}\delta + \eta_v + \kappa_y + \varepsilon_{v,y}, \tag{1}$$

where, $s_{v,y}$ is the log number of land sales or mortgages in vereda or municipality v in year y, and $X_{v,y}$ represents a vector of time-varying characteristics composed by rainfall levels in the last three years (y, $y-1$, and $y-2$) and the cumulative number of plots allocated in v from 1901 up to year y. This controls the availability of land for which we can observe transactions.[10] The model includes vereda (or municipality) fixed effects, η_v, that control for time-invariant unobservables, and yearly fixed effects, θ_y, time specific shocks to land markets common to all municipalities. As discussed in section 2.3, we define our measure of adverse weather shocks as the sum of days with atypical temperatures (denoted as $AtypicalDay_{v,d}$) in the two years prior:

$$TempShocks_{v,y} = \sum_{s=y-2}^{y-1} AtypicalDay_{v,s}. \tag{2}$$

Both the model in equation (1) and all subsequent specifications rely on the identifying assumption that there are no vereda- or municipality-specific, time-varying unobservable characteristics correlated to the occurrence of atypical weather events, i.e., conditional on the set of fixed effects the occurrence of temperature shocks is as good as random; a standard assumption in the literature (see e.g., Dell et al. (2014)). In section 4.2, we show that our result are robust to specifications that include in addition state-specific time trends and to alternative measures of atypical temperature computed using fixed thresholds. We cluster standard errors in all regressions at the municipality level.

To measure the effect on the distribution of farm sizes we first estimate a model analogous to the one in equation (1) above but using the land registry data. We estimate for municipality m and year y, the model:

$$n_{m,y} = \rho TempShocks_{m,y} + X'_{m,y}\nu + \mu_m + \kappa_y + \epsilon_{v,y}, \tag{3}$$

where, $n_{m,y}$ is either the log number of land plots or land owners, or the log average or median areas of plots and areas per owner in municipality m in year y.[11] The vector of controls $X_{m,y}$ contains rainfall levels in the past three years, a dummy indicating if there was

[10] Regressions where the dependent variable is instead defined as the number of sales divided by cumulative allocations yields qualitatively identical results.

[11] We define *plots* as a piece of land with a distinct registry number, an owner can have several –not necessarily contiguous– plots.

a cadastral update in the municipality that year, and the log of total municipal land area recorded in the registry. Municipality and year fixed effects are represented by μ_m and κ_y, respectively.

While the model in equation (3) allows us to estimate how productivity shocks have an effect on different moments of the municipal farm-size distribution, it is not informative on whether these changes are driven by the sale and transfer of farms of a specific size. For example, a reduction in the average farm size within a municipality could be equally driven by the fragmentation of large estates into medium-sized farms without there being any change in the number of small farms, as by the fragmentation of small farms into even smaller ones without having any change in the number of larger properties.

In order to investigate the type of farm size where the effect of negative productivity shocks translates more strongly into property transfers, we estimate how the number of owners within fixed farm-size bins changes across time. We do this by splitting the distribution of farm sizes within each municipality by quantiles, such that each quantile has, in the initial year of our sample, the same number of farm owners.[12] Keeping these quantile thresholds fixed, we then compute for each subsequent year the number of owners within each bin. If, for example, average farm sizes are dropping due to the partition of the largest plots, we would then observe a sharp reduction in the number of owners with landholding areas at the –fixed– top quantile of the initial farm-size distribution.

Denote as $\{q_m^1, ..., q_m^J\}$ the areas defining each of the j quantiles of farm size distribution in municipality m in the year 2000, and denote as $AreaOwned_{i,m,y}$ the total landholdings of farmer i in municipality m on year y. We compute for each year the number of owners with total landholdings within each of these fixed size bins as:

$$NumOwners_{q_m^j,m,y} \equiv \sum_{i \in m} \mathbb{1} \cdot [AreaOwned_{i,m,y} \in (q_m^{j-1}, q_m^j)], \tag{4}$$

where $j = 1, ..., J$, and $q_m^0 = 0$ for all m. We use this variable to estimate independent regressions (one per quantile j) of the form:

$$NumOwners_{q_m^j,m,y} = \gamma^j TempShocks_{m,y} + X'_{m,y}\xi^j + \mu_m^j + \kappa_y^j + \omega_{v,y}^j, \tag{5}$$

where all the right-hand-side variables are the same as in

We finally estimate household-level regressions, using data from the ELCA survey, to investigate the effect of adverse weather shocks on household's decisions. We estimate the

[12] We take the initial distribution to be the year 2000, for which 97% of municipalities have registry information. For the remaining municipalities, we take the initial distribution to be the one observed in the first year in which they appear in the land registry dataset.

model:

$$h_{i,v,y} = \alpha TempShocks_{v,y} + X'_{v,y}\tau + \iota_i + \kappa_y + \psi_{v,y}, \tag{6}$$

where $y = \{2010, 2013, 2016\}$, and $h_{i,m,y}$ is either log per capita consumption, a dummy indicating household migration, different measures of land ownership, or measures of work outside agriculture. $X_{v,y}$ represents rainfall levels in the past three years, ι_i represents household-level fixed effects and κ_y year fixed effects.

4 Results

4.1 Main Results

Table 2 presents the OLS estimates from equation (1) on our four measures of land transactions. Columns 1 and 5 report the effect of weather shocks on all types of land sales within veredas and municipalities respectively, while columns 2 and 6 report the effect on sales that transfer the entire area of a plot to the new owner, which we denote as 'full' sales. Columns 3 and 7 report the effect on partial sales. Increases in the frequency of adverse weather shocks raise the number of land transactions. This result holds regardless of whether the observation unit is set at the municipality or at the vereda level. Land sales caused by adverse shocks are entirely driven by full sales when the unit of observation is set at the vereda level. By contrast, when observed at the municipality level, the effect on partial sales is substantially higher. This disparity in the effect of shocks on partial land sales might be related to unobserved characteristics related to the selected nature of the vereda sample. For example, veredas with better record keeping practices which we are thus better able to match in the data might be also richer or situated closer to urban centers. These characteristics could also be the reason why the effect of shocks on partial sales (and more generally on all types of transactions) is smaller than when compared to the –unselected– municipality sample. Consistent with this hypothesis, results shown in section 4.3 below do indicate that shocks have a stronger effect on transaction frequency in less densely populated and more isolated regions.

Columns 4 and 8 of Table 2 show that adverse shocks lead to a substantial increase in the number of mortgages taken out by farmers against their properties. In the case of the municipality sample, the magnitude of the effect on mortgages is roughly 30% larger than on total sales. While the use of mortgages is uncommon in rural Colombia (our data shows that on average only 2.6 mortgage originations happen in a municipality per year) this result clearly indicates that weather shocks lead farmers to look for ex-post mechanisms that allow

Table 2: Temperature Shocks and Land Sales

	Vereda level panel				Municipality level panel			
	Total (1)	Full (2)	Partial (3)	Mortg. (4)	Total (5)	Full (6)	Partial (7)	Mortg. (8)
$TempShocks_{v,y}$	0.020***	0.022***	0.003	0.022***	0.076***	0.088***	0.116***	0.104***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.021)	(0.023)	(0.028)	(0.020)
Observations	149,664	149,664	149,664	149,664	10,392	10,392	10,392	10,392
R-Squared	0.574	0.561	0.359	0.392	0.912	0.903	0.710	0.793
Mean Dep. Var.	0.55	0.47	0.07	0.11	12.38	10.63	1.75	2.57

Notes: Data from the National Superintendency of Notaries (SNR) records. Columns 1 and 5 show the effect on total (full + partial land sales) columns 2 and 6 show the effect on full sales (when the entire property is transferred to another owner), columns 3 and 7 show the effect on partial sales (when only a fraction of the plot is transferred), and columns 4 and 8 show the effect on mortgage originations. All dependent variables are in log(x+1) transformation. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

them to cope, and that it is in the absence of such mechanisms that land sales might become a last resort measure. Indeed, heterogeneity results shown in section 4.3 show that in richer municipalities mortgages as a response to shocks are roughly twice more likely to occur than sales, while the opposite is true in poorer, more isolated municipalities.

The increases in the frequency of land sales caused by weather shocks further translates into a reduction in average farm sizes. Table 3 presents the results of estimating equation (3) on different measures of municipal land size using the land registry data. More days of atypical temperature in a municipality during the previous two years lead to an increases the number of plots and owners (columns 1 and 2), and thus to lower average farm and plot sizes (columns 3 and 4). Taken together, the magnitudes of these effects are economically important and suggest that the presence of uninsured covariate shocks play an important role in determining land distribution patterns. An additional 100 days of atypical temperature (roughly a two standard deviation increase) throughout a two-year period increase the number of land purchases and mortgage originations in a municipality by 7.6% and 10.4% respectively, while reducing the average farm size by 1.2%.

The results shown in Table 3 suggest that the net effect of weather shocks on land distribution patterns is to increase fragmentation. However it is not possible to know from that estimation alone if there is a specific part of the farm size distribution responsible for the overall decrease in average area owned. In order to investigate this, we estimate equation (5) on 10 quantiles of the initial municipality-level farm size distribution. The coefficients of interest from these regressions are summarized in Figure 4. Negative weather shocks cause a sizable increase in the number of owners with farms on the lower 5 deciles of the initial distribution, but no statistically significant effect on the number of owners in the 5 top deciles.[13] This result shows that the observed reduction in mean farm sizes caused by weather shocks is entirely driven by the subdivision and sale of smaller farms to new owners that did not have any additional landholdings. The fact that there is no noticeable change in the number of owners in the right part of the initial distribution indicates that large landholders are not driven to sell their land after facing a weather shock. This result is not surprising under the presumption that large landholders are more likely to have buffer savings and better access to credit than small farmers. However, these results also show that large landholders fail to use the expansion in land supply caused by adverse weather shocks to increase their own landholdings (a fact shown in Figure 4 but, more generally, evidenced as well in the previous set of results which show that average landholding area falls).

Table 3: Temperature Shocks and Average Farm Size

	Number of Plots	Number of Owners	Mean Plot Size	Mean Area/Owner	Median Plot Size	Median Area/Owner
	(1)	(2)	(3)	(4)	(5)	(6)
$TempShocks_{v,y}$	0.0120**	0.0120***	-0.0120**	-0.0123***	-0.0164	-0.0126
	(0.0048)	(0.0045)	(0.0048)	(0.0046)	(0.0113)	(0.0089)
Observations	10,934	10,934	10,934	10,934	10,934	10,934
R-squared	0.9905	0.9920	0.9935	0.9947	0.9763	0.9881
mean.dep.var	2519	2516	30.50	29.36	15.22	12.88

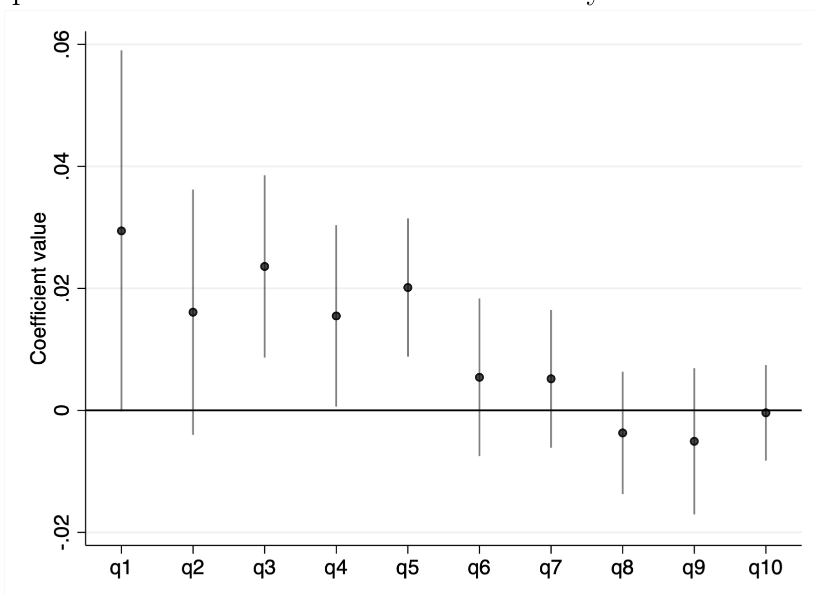
Notes: Data from the National Land Registry (*Catastro Nacional*), mantained by the National Geographical Institute (IGAC). All dependent variables are in logarithms. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

We also use data from the ELCA survey to explore if observed household-level decisions in response to shocks are consistent with the aggregate patterns on land sales and farm size distribution we document. Table 4 presents the results of estimating equation (6) on several household-level variables for years 2010, 2013, and 2016. Column 1 shows that more days of atypical temperature increase the probability that the household migrates, a result that is consistent with Ibáñez et al. (2022), who show that households migrate in el Salvador in response to temperature shocks. Column 2 shows an imprecisely estimated negative effect of shocks on the size of the household farms, but columns 3 and 4 do show evidence that shocks lead households to liquidate their landholdings and increase the likelihood that the household farm has less that 3 hectares of land. Column 5 shows that a 100 day increase in

[13] Regression results in table form are in A1 in the appendix. Appendix Figure A5 shows analogous estimations for alternative partitions ($j = 5$, and $j = 20$) of the initial farm size distribution.

the number of days with harmful temperatures increases the probability of a household head shifting from agricultural to non-agricultural activities by 7.7%, while column 6 shows that there are no statistically significant effects on the probability that the household head works off farm. Finally, column 7 shows that weather shocks have a sizable effect on the monetary value of per-capita consumption –a 12.2% drop per 100 additional days–. This result suggest that households are not able to fully smooth consumption.

Figure 4: Temperature Shocks and Number of Owners by Initial Distribution Quantiles



Notes: OLS estimates of the γ coefficients according to equation (5), for each of the 10 quantiles of the initial municipality-level distribution of farm sizes. Each point estimate corresponds to a separate regression where the main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. The dependent variable is number of owners per quantile and is in logarithms. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions include year and municipality fixed effects. Error bars display 95% confidence intervals for standard errors clustered at the municipality level.

These micro-level responses to weather shocks are broadly consistent with the distribution-wide effects on farm sizes presented above. Note that ELCA was designed to cover and be representative of small agricultural producers, so the fact that we find that these households are migrating and reallocating labor away from agriculture falls in line with the result from Figure 4 showing that it is mostly farmers on the lower tail of the farm size distribution the ones who respond to adverse shocks by asset liquidation.

4.2 Robustness

Appendix tables A2 and A3 present the results of two robustness checks that we perform. First, we estimate our baseline specifications in equations 1 and 3 including state-specific time trends. This allows us to rule out that spurious correlations between regional time

Table 4: Temperature Shocks and Household Decisions

	Household Migrated	Farm Size	Household Has Land	Farm Size $\leq$ 3 ha	Sector Not Agri.	Work off Farm	Consumption per capita
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$TempShock_{v,y}$	0.064***	-0.126	-0.050***	0.049***	0.077**	-0.010	-0.122***
	(0.019)	(0.088)	(0.016)	(0.019)	(0.034)	(0.023)	(0.026)
Observations	12,124	10,756	11,987	12,124	7,523	12,124	10,884
R-squared	0.555	0.779	0.678	0.717	0.767	0.537	0.729
Mean Dep. Var.	0.107	2.875	0.900	0.777	0.242	0.749	2.665

Notes: Data from ELCA. Dependent variables are, from left to right: a dummy indicating if household migrated between survey waves; area owned by the household in hectares; a dummy indicating if household owns any land; a dummy indicating if household's landholdings are below 3 hectares; a dummy indicating if household head works in the non-agricultural sector; a dummy indicating if household head main economic activity happens outside the family farm; value of per capita consumption in 2016 colombian pesos (in millions). All regressions include a control of aggregate rainfall and household-level fixed effects. *Mean Dep. Var.* is the mean of the untransformed variable. Robust standard errors reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

trends of temperature shocks and our variables of interest are driving our results. As shown in Panel A of both tables, the coefficient estimate on land sales (Table A2) and farm size (Table A3) remain unchanged.

Second, we estimate equations 1 and 3 using an alternative measure of temperature shocks. In particular, we follow Aguilar-Gomez et al. (2022), and we compute countrywide temperature thresholds for atypically high and low temperatures. We use the distribution of maximum and minimum daily temperatures across all municipalities over the sample period and define high and low-temperature thresholds as the 95^{th} and the 5^{th} percentiles of maximum and minimum temperatures, respectively. As in our main specifications, we then add the total number of days with temperature above (below) the high (low) threshold over a two-year window. Panel B of tables A2 and A3 show that our main results on land sales and farm size are robust to this alternative definition of temperature shock.

4.3 Heterogeneity

In this section we explore the potential mechanisms that might drive our results on land sales and farm size. Table 2 shows that weather shocks have a sizable impact on the number of landholders that access credit by using their land as collateral. Being able to mortgage property is not likely, however, to be accessible for most landholders in poorer and more isolated economies where credit markets are less developed. Incomplete credit markets could therefore be a potential driver behind our findings. Similarly, if households need to meet a minimum subsistence consumption threshold, the ability to cope with drops in income by cutting back on expenses is more reduced the closer the initial consumption levels are to the subsistence threshold. Faced with a shock, poorer households should be then more likely to be forced to liquidate their assets in order to maintain a minimum consumption level. We would expect households in poorer municipalities to respond more strongly to shocks through land sales and, by contrast, we would expect households in richer municipalities to respond more strongly through mortgage originations.

We show in Table 5 the result of estimating equation (1) with an additional interaction term indicating if a municipality is i) above the median in a multidimensional poverty index calculated by the national government, ii) above the median in the distance required to reach a wholesale market, and iii) above the median in a 'rurality' index measuring low population density. Consistent with the hypothesis of credit constraints, results in column 4 show that the positive effect of shocks on mortgage originations in high poverty municipalities is roughly three times smaller than the size of the effect in low poverty municipalities. Similarly, columns 8 and 12 show that this same effect on mortgages in municipalities with above-median distance to wholesale markets or with low population density is roughly half the size of the effect observed in municipalities with stronger market access and higher population densities. We take these results as suggestive evidence of the potential for credit markets to prevent distress sales.

Table 5: Temperature Shocks and Land Sales - Heterogeneous Effects

	H_i: High Multipoverty Index				H_i: High Distance to Market				H_i: Low Population Density			
	(1) Total	(2) Full	(3) Partial	(4) Mortgage	(5) Total	(6) Full	(7) Partial	(8) Mortgage	(9) Total	(10) Full	(11) Partial	(12) Mortgage
$TempShocks_{v,y}$	0.0894***	0.102***	0.142***	0.169***	0.0727***	0.105***	0.0872***	0.151***	0.0403	0.0574**	0.0946***	0.161***
	(3.66)	(3.96)	(4.47)	(6.82)	(2.96)	(3.99)	(2.84)	(6.29)	(1.56)	(2.04)	(2.86)	(6.52)
$TempShocks_{v,y} \times H_i$	-0.0184	-0.0226	-0.0275	-0.113***	0.00560	-0.0291	0.0502*	-0.0828***	0.0554**	0.0477*	0.0330	-0.0898***
	(-0.77)	(-0.95)	(-0.96)	(-5.01)	(0.24)	(-1.24)	(1.84)	(-3.77)	(2.28)	(1.92)	(1.16)	(-4.03)
Observations	9924	9924	9924	9924	10392	10392	10392	10392	10392	10392	10392	10392
R-Squared	0.913	0.904	0.710	0.794	0.912	0.903	0.711	0.794	0.912	0.903	0.710	0.794

Notes: Data from the National Superintendency of Notaries (SNR) records. Columns 1 and 5 show the effect on total (full + partial land sales) columns 2 and 6 show the effect on full sales (when the entire property is transferred to another owner), columns 3 and 7 show the effect on partial sales (when only a fraction of the plot is transferred), and columns 4 and 8 show the effect on mortgage originations. All dependent variables are in log(x+1) transformation. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). Standard errors clustered at the municipality level reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

The previous results shed light on poverty and credit constraints as potential mechanisms driving distress sales. These, however, do not necessarily imply land fragmentation. For example, it is possible that large landowners, who are likely to be less credit-constrained, buy land from poor farmers after the shock. This, contrary to our findings, could lead to land consolidation. We now explore if transaction costs that result from the lack of contiguity between large and small farms hinder this process of land consolidation and drive the decreases in farm size that we observe in the data.

We construct two measures of contiguity between large and small farms in a municipality. First, we use land registry maps, available for 2017, to compute the share of plots below the 10^{th} percentile of the size distribution in the municipality that are contiguous to at least one plot above the 90^{th} percentile of this distribution. We then classify municipalities with high contiguity as those with a share above the national median. We also carry out the same exercise using as alternative thresholds the 20^{th} and 80^{th} percentiles of the distribution.

Our second measure uses the GPS coordinates of the farms included in the 2013 agricultural census. We compute buffers around this GPS coordinates to simulate 1.2 times the area of each farm and define as contiguous two farms with overlapping buffers. Using this measure, we compute the share of small farms that are contiguous to at least one large farm. As before, we define small farms as those below the 10^{th} percentile of the municipality size distribution and large farms as those above the 90^{th} percentile, and we conduct the same analysis varying these thresholds to the 20^{th} and 80^{th} percentiles respectively.

Table 6 presents the results of estimating equation 3, with the interaction between the temperature shocks and farm contiguity. Panel A presents the results with the measure we compute with the registry maps. Panel B uses the measure of the overlapping buffers. Odd-numbered columns show results for the 90^{th}-10^{th} percentile definition of large and small plots, while even-numbered columns show results for the 80^{th}-20^{th} percentile definition. As shown in both panels, the coefficient estimates for the temperature shocks have the same sign and statistical significance as in our baseline specification. The interaction term is small in magnitude and not statistically significant regardless of the measure of contiguity. This result suggests that transaction costs associated with the lack of contiguity between large and small farms might not be driving land fragmentation in this context.

Table 6: Temperature Shocks and Farm Size - Heterogeneous Effects

	Number of Plots		Numbers of Owners		Mean Plot Size		Mean Area/Owner	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Land Registry Map - Contiguous Plots							
$TempShocks_{v,y}$	0.011**	0.011*	0.010*	0.009*	-0.011**	-0.011*	-0.010**	-0.009*
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
$TempShocks_{v,y} \times High$	-0.005	-0.004	-0.004	-0.002	0.005	0.004	0.004	0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	10,413	10,448	10,413	10,448	10,413	10,448	10,413	10,448
R-squared	0.990	0.990	0.992	0.992	0.994	0.994	0.995	0.995
Mean Dep. Var	2,576.47	2,568.60	2,582.51	2,574.54	30.41	30.40	29.16	29.16
	Panel B: Agricultural Census Coordinates - Overlapping Buffers							
$TempShocks_{v,y}$	0.016***	0.018***	0.016***	0.017***	-0.016***	-0.018***	-0.017***	-0.017***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
$TempShocks_{v,y} \times High$	-0.006	-0.009	-0.003	-0.004	0.006	0.009	0.003	0.004
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	9,402	9,402	9,402	9,402	9,402	9,402	9,402	9,402
R-squared	0.990	0.990	0.992	0.992	0.993	0.993	0.995	0.995
Mean Dep. Var	2,552.60	2,552.60	2,548.64	2,548.64	29.27	29.27	28.23	28.23

Notes: Data from the National Land Registry (*Catastro Nacional*), mantained by the National Geographical Institute (IGAC). All dependent variables are in logarithms. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). Panels A and B use land registry maps and agricultural census data, repsectively, to measure plot contiguity. Odd-numbered columns in both panels show results for the 90^{th}-10^{th} percentile definition of large and small plots, while even-numbered columns show results for the 80^{th}-20^{th} percentile definition. See text for more details. *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

5 Model

To rationalize the reduced-form results in Section 4, we now develop a model of agricultural production in which heterogeneous agents own and transact land. A key feature of the model is that land sales serves as a consumption smoothing device, which is triggered by subsistence consumption motives when the agricultural sector is subject to a negative weather shock. We next present the environment of the model, we then simulate the impact of negative weather shocks in the economy.

5.1 Environment

Consider a small-open economy region with two sectors, agriculture and non-agriculture, that operates over two periods t_1, t_2. There are a measure of agents N who are heterogeneous in terms of their endowments of two distinct assets: land (l_0) and wealth (m_0). In each period, agents choose whether to be a worker in the non-agricultural sector or a farmer.

Output in the agricultural sector employs land:

$$y_t(l) = a_t l$$

where $y_t(l)$ is the total output, a_t is the productivity of land and l is the employed land. The productivity parameter a_t is subject to two weather conditions, high a_H and low L ($a_L > a_H$). If agents choose to be a farmer, they earn the agricultural output of their landholdings $y_t(l)$. If they choose to become a worker, they earn wages $w_t = w$. Moreover, in each period, agents earn the returns from their wealth $r_t m_t(\omega)$, where we assume an exogenous return $r_t = r$. Preferences are Stone-Geary:

$$U = \sum_{t=\{1,2\}} \log\left(c_t - c_S\right)$$

where c_S is a subsistence consumption level. Budget constraints for each period are:

$$f_t\left[a_t l_t\right] + (1 - f_t)\left[w_t\right] + r_t m_{t-1} = c_t + m_t + p_t\left(l_t - l_{t-1}\right)$$

where f_t is an indicator function equal to 1 if the agent choose to be a farmer and 0 otherwise. On the left hand side we have the earnings of the agent in period t. On the right hand side we have the expenditure of agents. Agents choose how much to consume (c_t), how much wealth to acquire (m_t), and how much land to own (l_t). If they choose to own more land than the one inherited from $t-1$—i.e., if $l_t - l_{t-1} > 0$—, they must purchase land by a price p_t. Conversely, they can sell land and collect $p_t\left(l_t - l_{t-1}\right)$—if $l_t - l_{t-1} < 0$. We impose two borrowing constraints:

$$0 \leq l_t$$
$$0 \leq m_t.$$

In other words, agents are unable to sell more land than they inherited. In addition, agents are unable to borrow wealth.

The timing of the model is as follows. First, agents observe the weather conditions for the next two periods, their initial endowments of land l_0 and wealth m_0, and choose whether to become a worker or a farmer. (For simplicity, we assume that agents can choose only one occupation for the two period, so that $f_1 = f_2$.) Then, in each period t, they collect their earnings from work (w_t), from land ($a_t l_t$), and from accumulated wealth ($r_t m_{t-1}$), and choose how much to consume.

5.2 Equilibrium

We define the market equilibrium as follows. Given a distribution of land and wealth endowments $\{l_0,\ m_0\}$, a total land a sequence of weather events $\{a_t\}$, wages $\{w_t\}$, and returns to wealth $\{r_t\}$, the market equilibrium is a sequence of consumption, wealth, land ownership and land prices, $\{c_t^*, l_t^*, m_t^*, p_t^*\}$ such that all agents make optimal choices and the following market clearing condition holds

$$\int l_t(\omega) dF(\omega) = \int l_{t-1}(\omega) dF(\omega)$$

where ω indexes an agent and $F(\omega)$ is the distribution of agents.

5.3 Land transactions under adverse weather shocks

To observe any land transaction between agents, it must be the case that the wealth asset has an intermediate rate of return that lies in-between the low agricultural productivity a_L in $t = 1$ and the high productivity a_H in $t = 2$. We thus impose the conditions: $r_1 \geq a_L$, and $r_2 < a_H/(p_1 - a_L)$. Under these conditions agents who decide to become farmers will hold all of their wealth in land, and conversely agents who decide to become non-farm workers will hold all of their wealth in the alternative asset.[14]

Optimal input demands for farmers are then:

$$\begin{aligned} l_{1,F}^* &= \frac{1}{2(p_1 - a_L)} \left[(2a_L - p_1) l_0 + r_1 m_0 + \frac{(p_1 - a_H - a_L)}{a_H} c_S \right] \\ m_{1,F}^* &= 0, \end{aligned}$$

[14] The knife-edge case where $r_2 = a_H/(p_1 - a_L)$ does allow for agents simultaneously demanding positive amounts of both assets. For ease of exposition we abstract away from this case.

which yields utility

$$U_F^* = \log\left(a_L l_0 + r_1 m_0 - (p_1 - a_L)\, l_{1,F}^* - c_S\right) + \log\left(a_H\left(l_0 + l_{1,F}^*\right) - c_S\right).$$

For their part, optimal input demands for workers are:

$$\begin{aligned} l_{1,W}^* &= -l_0 \\ m_{1,W}^* &= \frac{1}{2r_2}\left[r_1 r_2 m_0 + r_2 p_1 l_0 + (1-r_2)(c_S - w)\right] \end{aligned}$$

with utility

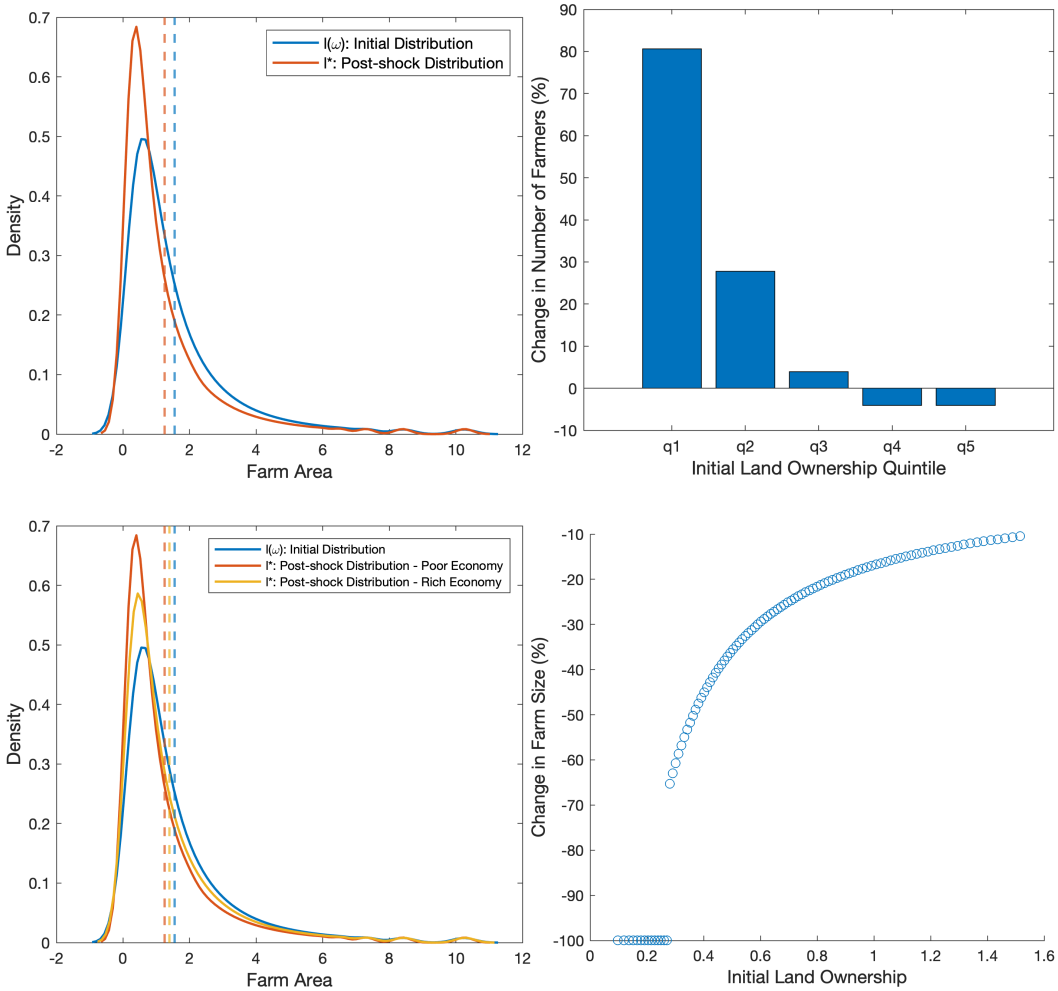
$$U_W^* = \log\left(r_1 m_0 + w - m_{1,W}^* - c_S\right) + \log\left(w + r_2 m_{1,W}^* - c_S\right).$$

An agent chooses to become a farmer if $U_F^* \geq U_W^*$.

5.4 Simulation Results

We simulate the economy described above and document the changes in the equilibrium farm size distribution with respect to initial endowments. Results from this exercise are shown in Figure 5. The simulated economy is able to replicate the main reduced-form results presented in Section 4. First, as shown in the upper-left panel of Figure 5, the initial shock to productivity in $t = 1$ induces a net increase in the number of agents occupied in the agricultural sector and a decrease in the average size of individual farms. Second, also consistent with our empirical findings, the upper-right panel of the same figure shows that this result is almost entirely driven by the increase in the number of agents operating smaller-sized farms, with almost no variation in the number of landholders operating farms in the upper quintiles of the initial size distribution. Third, the bottom-right panel of the figure also shows how, despite an observed net-increase in the number of farmers, the productivity shock does lead a fraction of the smallest initial landholders to exit agriculture altogether. Finally, the bottom-left panel shows that the observed effects of the shock on the farm size distribution are more pronounced in underdeveloped economies, where we parameterize an economy to be 'poorer' if it has a relatively higher subsistence constraint.

Figure 5: Change in Farm Size Distribution - Simulation Results



Notes: Simulated distribution of equilibrium farm sizes with respect to initial endowments. The simulated economy consists of 300 agents with asset endowments drawn from a log-normal distribution with mean = 0 and standard deviation = 1. Top Left Panel: Blue solid line shows the distribution of land endowments before trade occurs. Red solid line shows the equilibrium farm size distribution in $t = 2$. Dashed lines represent average farm sizes. Top Right panel: Percentage change in the number of agents occupied in agriculture by quintiles of the initial land distribution. Bottom Left Panel: Blue solid line shows the distribution of land endowments before trade occurs. Red solid line shows the equilibrium farm size distribution in $t = 2$ for a ''poor' economy parameterized as having a high subsistence constraint $c_S = 0.45$. Yellow solid line shows the equilibrium farm size distribution in $t = 2$ for a 'rich' economy parameterized as having a low subsistence constraint $c_S = 0.15$. Dashed lines represent average farm sizes. Bottom Right Panel: Percent change in landholdings after trade for agents initially endowed with land. Additional parameter values: $a_L = 1$; $a_H = 5$; $r_1 = 1$; $r_2 = 1$; $c_S = \{0.45, 0.15\}$; $w = 0.5$

5.5 Discussion

A key result of the model is that a fraction of agents initially endowed with land will exit agriculture despite the absence of uncertainty, and the fact that all agents are aware that productivity will be higher in the second period. This behavior is driven instead by the fact that agents with the lowest land endowments run against the subsistence consumption constraint and are forced to forego higher consumption in the future to achieve minimum consumption levels in the present. This need to smooth consumption across periods leads to an increase in aggregate land supply and an initial depression of land prices. Faced with the opportunity to acquire relatively cheap assets, both large farmers and agents not initially endowed with land have incentives to increase their landholdings. Under similar conditions, any version of a farm-production model that lacks a non-farm sector will necessarily yield as a result the consolidation of small farms into larger holdings and an increase in average farm size. By contrast, the model presented above is capable of yielding land fragmentation as a result due to the fact that the non-farm sector is unaffected by the initial slump in productivity. Being isolated from the shock, and thus becoming richer relative to landholders, agents endowed with large amounts of the alternative 'wealth' asset are able to outbid large landholders for the excess land supply and enter the soon-to-be more profitable agricultural sector.

An important feature of this version of the model is that agent heterogeneity is solely driven by differences in initial endowments and not by differences in relative productivity. This entails that, as it stands, all observed changes in asset ownership and on the operational scale of farms have no implications for the aggregate productivity of the economy. A more comprehensive version of this model that allows for heterogeneous productivity across farmers might be able to produce richer predictions related to specific selection effects caused by shocks and the consequences these can have on the aggregate efficiency of the agricultural sector.

More generally, and in order to gauge both the impact of the increasing risk of extreme weather shocks induced by climate change on agricultural productivity, as well as the aggregate impact of the expansion of rural-credit or agricultural insurance programs, we further plan to develop and structurally estimate a model of agricultural production that combines the farm production structure developed in Gáfaro and Pellegrina (2022) with the borrowing frictions modeled in the macro-literature on heterogeneous agent models (Krusell and Smith, 1998; Buera et al., 2011). Our goal will be to inform the behavioral parameters of the model driving agents' decisions to sell and buy agricultural land, and derive a set of results that can indicate under which conditions the model rationalizes the qualitative features of the data. These behavioral parameters should then allow us to estimate policy-relevant counterfactuals of interest that shed light on the potential effects that future increases in weather shock frequency and severity will have on land-distribution patterns and agricultural productivity in developing economies.

6 Conclusion

This paper explores the effect of uninsured weather shocks on distress sales and the farm size in Colombia. Exploiting a unique combination of datasets that include the transaction history of hundreds of thousands of individual plots and a municipal-level census of rural properties we find that shocks lead to an increase in the frequency of land sales and to a reduction in average farm size. This reduction is driven by the smaller farms in the initial farm-size distribution being further subdivided and purchased by previously landless individuals. Consistent with the aggregate patterns we find on land sales and land distribution, we also show that these shocks decrease household consumption and induce rural households to migrate, engage in non-agricultural activities, and operate smaller farms.

Distress sales after a negative covariate productivity shocks might depress land prices. However, a standard heterogeneous-agent model with credit market imperfections would predict that this excess supply of land should lead to the consolidation of many small farms into larger landholdings. Our results are at first glance puzzling since we show that the opposite effect, land *fragmentation*, takes place. We rationalize the results with a model where agents have to make an intertemporal consumption decision while facing a minimum subsistence constraint, and heterogeneity in initial endowments causes some agents to be isolated from the initial negative productivity shock. The combination of the shock and the subsistence constraint induces an expansion of the aggregate supply of land; the presence of relatively wealthier landless agents who find themselves unaffected by the shock and who can profit from the temporary drop in land values then leads to a net increase in the number of agents occupied in agriculture and to lower average farm sizes.

Our empirical findings could be explained by an alternative model where, for example, frictions on land assembly stemming from the potential non-contiguous character of land plots for sale are present (e.g. Brooks and Lutz (2016)). Identifying the specific mechanisms that prevent land from becoming endogenously consolidated would greatly improve our understanding on the organization of economic activity in the agricultural sector of much of the developing world. The evidence that we present in this paper suggests that uninsured weather shocks constitute a substantial barrier for productivity improvements in the agricultural sector of developing countries. Given that extreme temperature shocks are expected to increase in frequency and severity in the near future, these findings have important policy implications related to the expansion of financial tools designed for risk management in rural settings.

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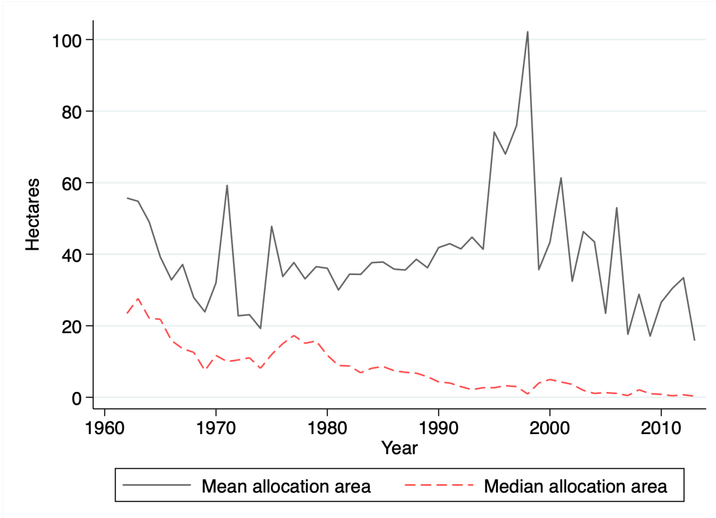
APPENDIX
(for online publication)

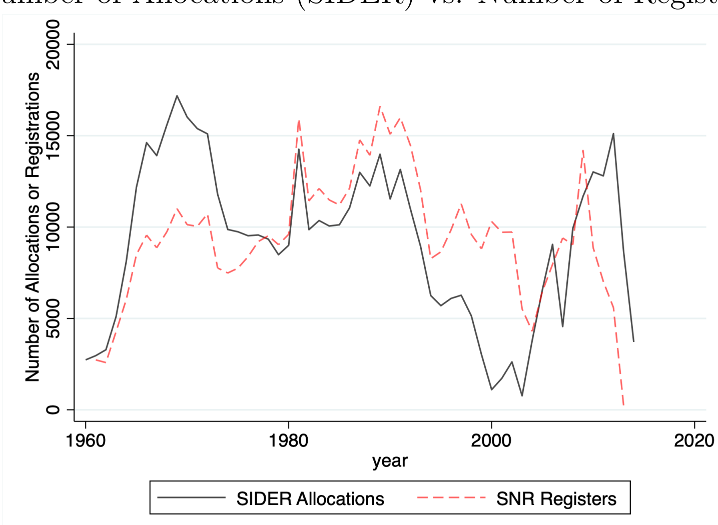
Appendix A Additional Tables and Figures

Figure A1: Mean and Median Allocation Size - 1961–2012



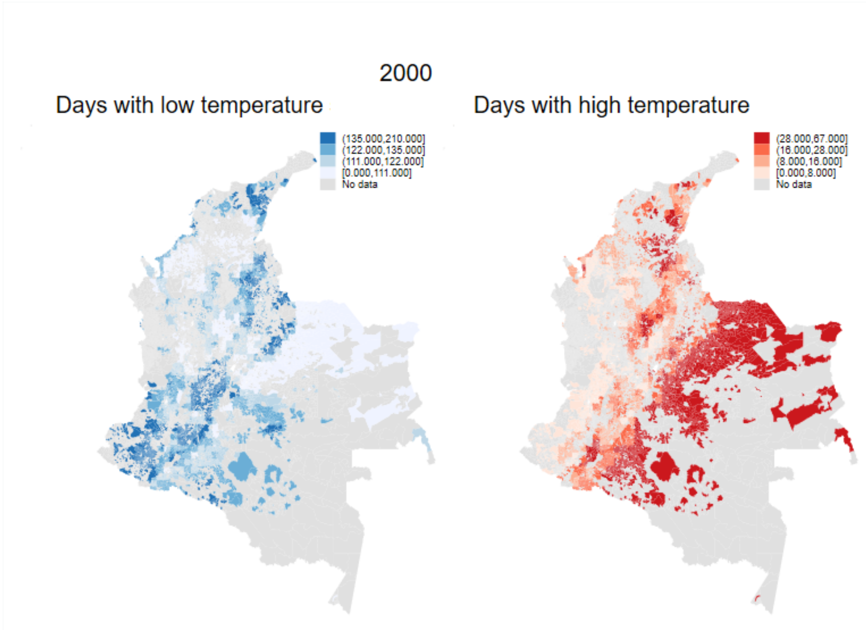
Notes: Data from the System of Information for Rural Development (SIDER). National-level yearly average area of land plots granted by the government as part of the public-land allocation program.

Figure A2: Number of Allocations (SIDER) vs. Number of Registrations (SNR)

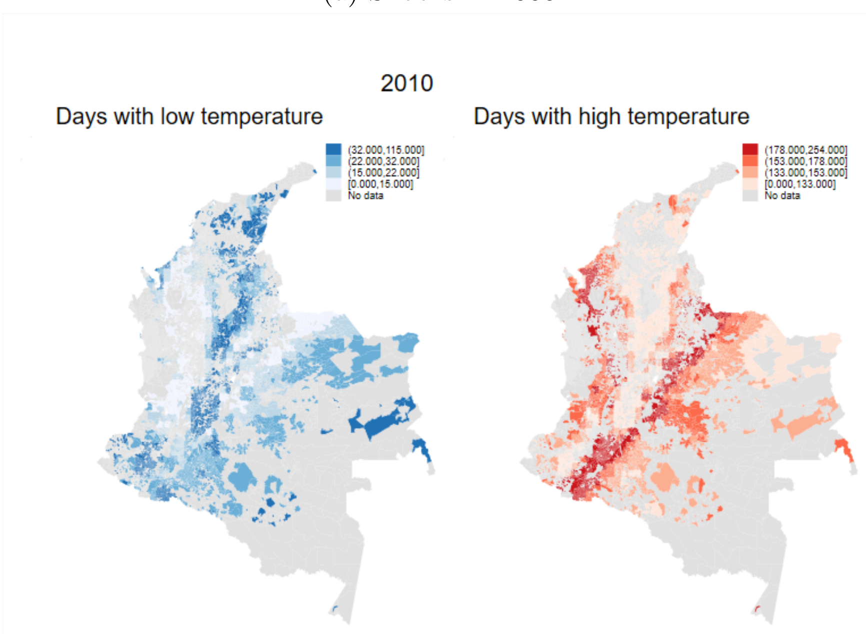


Notes: Data from the System of Information for Rural Development (SIDER) and from the National Superintendency of Notaries (SNR). The figure compares the number of land plots allocated by the government as part of the public-land allocation program with the number of properties registered at local public notary offices as received by the government. Property registration constitutes the final step to finalize the allocation process and ensures the formal property right of the beneficiary over the granted plot of land.

Figure A3: Temperature Shocks Across Space - 2000 and 2010



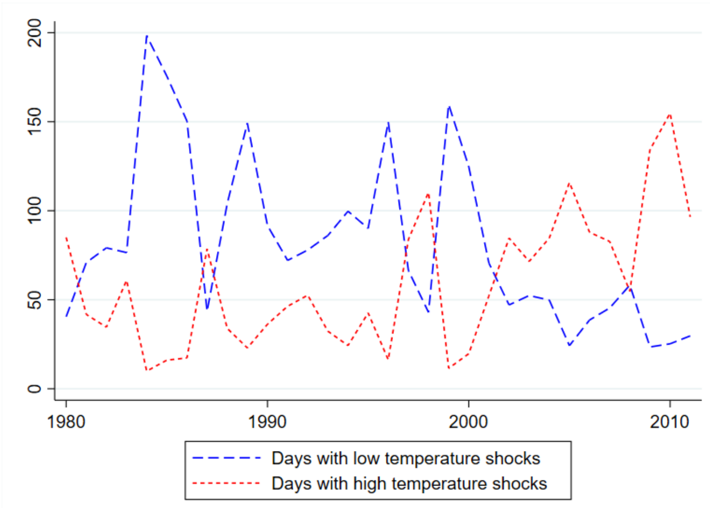
(a) Shocks in 2000



(b) Shocks in 2010

Notes: Data from the Copernicus Climate Change Service (C3S). The figure shows the average number of days with extreme heat (red) and cold (blue) across veredas in our sample in 2000 and 2010.

Figure A4: Temperature Shocks Across Time



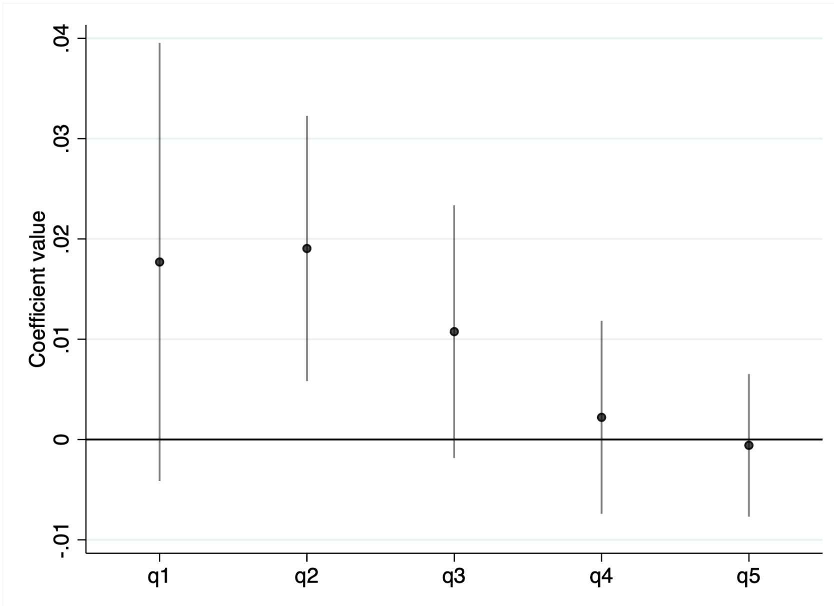
Notes: Data from the Copernicus Climate Change Service (C3S). The figure shows the average number of days with extreme heat (red) and cold (blue) across veredas in our sample for the 1979–2016 period.

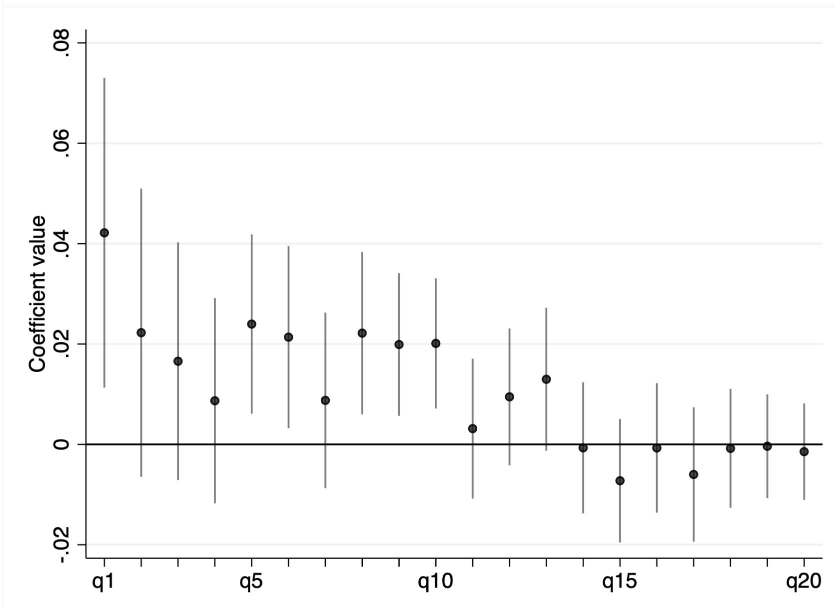
Table A1: Temperature Shocks and Number of owners, by Initial Size Quantile

	Number of owners by initial distribution quantiles (q_m^j)									
	(1) q_m^1	(2) q_m^2	(3) q_m^3	(4) q_m^4	(5) q_m^5	(6) q_m^6	(7) q_m^7	(8) q_m^8	(9) q_m^9	(10) q_m^{10}
$TempShocks_{v,y}$	0.029*	0.016	0.024***	0.015**	0.020***	0.005	0.005	-0.004	-0.005	-0.000
	(0.015)	(0.010)	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)	(0.004)
Observations	10915	10878	10853	10804	10907	10869	10928	10892	10907	10928
R^2	0.942	0.971	0.982	0.983	0.987	0.986	0.986	0.991	0.990	0.993

Notes: Data from the National Land Registry (*Catastro Nacional*), mantained by the National Geographical Institute (IGAC). Dependent variables are number of owners whose farm are is in the corresponding size range defined by the quantiles of the initial farm distribution. Dependent variables are in logarithms. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Figure A5: Temperature Shocks and Number of Owners by Initial Distribution Quantiles - Alternative Partitions





Notes: OLS estimates of the γ coefficients according to equation (5). Top panel: coefficient values for 5 quantiles of the initial municipality-level distribution of farm sizes. Bottom panel: coefficient values for 20 quantiles of the initial municipality-level distribution of farm sizes. Each point estimate corresponds to a separate regression where the main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions include year and municipality fixed effects. Error bars display 95% confidence intervals for standard errors clustered at the municipality level.

Table A2: Temperature Shocks and Land Sales - Alternative Specifications

	Municipality level panel				Vereda level panel			
	Total	Full	Partial	Mortg.	Total	Full	Partial	Mortg.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: State Specific Time Trends							
$TempShocks_{v,y}$	0.076***	0.087***	0.115***	0.103***	0.020***	0.022***	0.003	0.022***
	(0.021)	(0.023)	(0.028)	(0.020)	(0.006)	(0.006)	(0.005)	(0.006)
Observations	10,392	10,392	10,392	10,392	149,652	149,652	149,652	149,652
R-squared	0.912	0.903	0.710	0.794	0.574	0.562	0.360	0.393
Mean Dep. Var	1.54	1.44	0.44	0.64	0.24	0.22	0.04	0.06
	Panel B: Temperature Shocks with Absolute Thresholds							
$TempShocksAbs_{v,y}$	0.070**	0.108***	0.001	0.004	0.015	0.021***	-0.005	0.016*
	(0.028)	(0.029)	(0.029)	(0.031)	(0.009)	(0.008)	(0.007)	(0.009)
Observations	10,392	10,392	10,392	10,392	149,652	149,652	149,652	149,652
R-squared	0.912	0.903	0.709	0.793	0.574	0.562	0.360	0.392
Mean Dep. Var	1.54	1.44	0.44	0.64	0.24	0.22	0.04	0.06

Notes: Data from the National Superintendency of Notaries (SNR) records. Columns 1 and 5 show the effect on total (full + partial land sales) columns 2 and 6 show the effect on full sales (when the entire property is transferred to another owner), columns 3 and 7 show the effect on partial sales (when only a fraction of the plot is transferred), and columns 4 and 8 show the effect on mortgage originations. All dependent variables are in log(x+1) transformation. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). Panel A adds state specific time trends. Panel B uses country level absolute thresholds to identify days of atypical temperature. *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A3: Temperature Shocks and Average Farm Size - Alternative Specifications

	Number of Plots	Numbers of Owners	Mean Plot Size	Mean Area/Owner	Median Plot Size	Median Area/Owner
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: State Specific Time Trends					
$TempShocks_{v,y}$	0.012**	0.013***	-0.012**	-0.013***	-0.017	-0.013
	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)	(0.009)
Observations	10,935	10,935	10,935	10,935	10,935	10,935
R-squared	0.990	0.992	0.994	0.995	0.976	0.988
Mean Dep. Var	2,518.49	2,516.07	30.49	29.36	15.22	12.88
	Panel B: Temperature Shocks with Absolute Thresholds					
$TempShocksAbs_{v,y}$	0.023**	0.016*	-0.023**	-0.020**	-0.032*	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.016)	(0.012)
Observations	10,935	10,935	10,935	10,935	10,935	10,935
R-squared	0.990	0.992	0.994	0.995	0.976	0.988
Mean Dep. Var	2,518.49	2,516.07	30.49	29.36	15.22	12.88

Notes: Data from the National Land Registry (*Catastro Nacional*), mantained by the National Geographical Institute (IGAC). All dependent variables are in logarithms. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). Panel A adds state specific time trends. Panel B uses country level absolute thresholds to identify days of atypical temperature. *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Appendix B The Land Ceiling Regulation

Finally, we investigate if our results on the absence of land consolidation on the part of large landholders in the aftermath of an adverse weather shock is due to institutional factors stemming from Colombia's land regulation policies. As discussed in section 2, Law 160 of 1994 imposed municipality-specific land ceilings that place a cap on the amount of land originally granted by the government that any private individual can accumulate. This restriction could be consistent explanation for the lack of land consolidation on the right part of the farm size distribution, since it restricts the capacity of large landholders to acquire any new land plots whose provenance was a government allocation.[15]

To test if these restrictions are in fact explaining our results, we re-estimate the model in (3) including an additional interaction term between the shock variable and a dummy indicating if the municipality is above the median in the share of the municipality's area that was at some point part of a government allocation. The idea behind this test lies in the fact that land ceilings only apply to allocated land, but not to other land plots. Hence, if restrictions are driving the land-fragmentation results shown in Table 3 we would expect the bulk of the result to be concentrated in municipalities with a high share of their agricultural land coming from government allocations.

As columns 5-8 in Table A4 show, we find no such heterogeneity. Moreover, as shown in columns 1-4, including the continuous value of the share of government-allocated land as a control has virtually no impact on the magnitude or precision of the original estimates. We take these results as evidence that the main findings of our paper are not driven by the specific institutional characteristics of land regulation in Colombia.

[15]The explicit purpose of the land ceilings, as stated in the text of the law, was precisely to prevent land concentration by large landholders.

Table A4: Temperature Shocks, Farm Size, and Share of Government-Allocated Area

	Control: Share Allocated				H_i: Share Allocated			
	Number of Farms	Number of Owners	Mean Farm Size	Mean Area/Owner	Number of Farms	Number of Owners	Mean Farm Size	Mean Area/Owner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TempShocks_{v,y}$	0.0113**	0.0112**	-0.0113**	-0.0115**	0.0134***	0.0116**	-0.0134***	-0.0119**
	(0.0049)	(0.0046)	(0.0049)	(0.0047)	(0.0048)	(0.0046)	(0.0048)	(0.0046)
$TempShocks_{v,y} \times H_i$					-0.0068	-0.0013	0.0068	0.0012
					(0.0092)	(0.0080)	(0.0092)	(0.0080)
Observations	10,934	10,934	10,934	10,934	10,935	10,935	10,935	10,935
R-squared	0.9905	0.9920	0.9935	0.9947	0.9905	0.9921	0.9935	0.9948
mean.dep.var	2519	2516	30.50	29.36	2518	2516	30.49	29.36
Share alloc.	Yes	Yes	Yes	Yes	No	No	No	No

Notes: Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). All dependent variables are in logarithms. The main independent variable is the total number of atypical temperature days in the past two years ($y-1$, $y-2$) divided by 100. Controls are accumulated allocations, accumulated precipitation during years y, $y-1$, and $y-2$. Regressions also include year and geographic fixed effects (vereda or municipality). *Mean Dep. Var.* is the mean of the untransformed variable. Standard errors clustered at the municipality level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.