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Abstract

We study how weather shocks affect the farm-size distribution and agricultural productivity. Using survey data from several developing countries, we document new empirical patterns in farm-size dynamics and the effect of weather shocks. Drawing on unique administrative data from Colombia with land-transaction records, census-based farm sizes, and household surveys on consumption and investment, we show that shocks intensify land market activity and increase the number of small farms, reducing average farm size within regions. We calibrate a heterogeneous-agent model that endogenizes the farm-size distribution and use it to study mechanisms and the dynamic effects of weather shocks and climate change.

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1 Introduction

In low- and middle-income countries, a large share of households rely on small, low-productivity farms as their main source of income (Restuccia et al., 2008; Gollin et al., 2014; Herrendorf et al., 2014). Mounting evidence shows that the prevalence of small farms in these settings constrains aggregate productivity (Adamopoulos and Restuccia, 2014; Foster and Rosenzweig, 2022). At the same time, because households lack insurance, the occurrence of weather shocks shapes production decisions and triggers asset sales—including land—to smooth consumption (Rosenzweig and Wolpin, 1993; Kazianga and Udry, 2006; Krishna, 2010; Donovan, 2021). These observations point to a potential connection between weather shocks, distress land sales, and the predominance of small farms in developing countries. Yet this link remains insufficiently understood, both theoretically and empirically.

This paper studies the impact of weather shocks on the farm-size distribution and its implications for agricultural productivity. We first document new empirical facts on the dynamics of farm size and its relationship with weather shocks across developing countries, using a collection of longitudinal household-level datasets on land use. We then turn to two unique administrative datasets from Colombia—one covering hundreds of thousands of land transactions nationwide and another containing the universe of land registry records—to estimate the effect of weather shocks on land transactions and the farm size distribution. To shed light on mechanisms, we further complement this analysis with two surveys. First, a longitudinal household-level survey that we use to provide reduced-form evidence on land transactions as a consumption-smoothing response to adverse shocks. Second, a nationwide survey we conducted with rural community leaders to characterize who buys land following an adverse shock. Finally, we build a dynamic, heterogeneous-agent model in which the farm-size distribution is endogenous, shaped by agents' occupational choices and landholding decisions. We calibrate the model to Colombia's economy to uncover the mechanisms consistent with our reduced-form patterns and to simulate counterfactual scenarios with alternative distributions of weather shocks, including scenarios linked to climate change.

We begin by documenting a set of new empirical facts on the relationships between farm-size growth and exit dynamics across developing countries. In contrast to a static view of the farm-size distribution, we uncover substantial changes over time, with patterns that resemble those documented in the firm-size distribution literature for manufacturing (e.g., Jaimovich et al. (2023); Clementi and Palazzo (2016)). First, we find greater churning among households operating smaller farms: these farms are more likely to exit agriculture, yet those who stay experience faster farm size growth than surviving large farms. Second, we find that when a region experiences adverse weather shocks, incumbent farmers are more likely to exit and operate no land. In stark contrast, after such shocks, landless households are more likely to enter farming and operate some land. This asymmetry indicates that the incentives underlying the decision of being a farmer after adverse shocks differ sharply between landless households and incumbent farmers.

Motivated by these initial patterns, we next turn to Colombia, where detailed administrative records on land transactions and farm size—together with a longitudinal household survey and a qualitative survey we conducted with rural community leaders— offer a unique opportunity to study how adverse weather shocks shape the farm-size distribution and the mechanisms underlying this relationship. Using these data we present three sets of results. First, based on administrative data on land transactions, we show that an increase in adverse weather shocks in a municipality leads to a substantial increase in land market activity.[1] Both the number of farm sales—full and partial—and the number of mortgage contracts rise following such shocks. Notably, much of this increase in sales is driven by purchases made by buyers who did not previously own land in the region, consistent with our previous finding that weather shocks induce entry among households that previously operated no land.

Second, using administrative census data that are collected regularly, we find that, in a municipality, weather shocks reduce the mean and median farm size and increase the number of farmers. This last result indicates that the entry of new farmers following adverse shocks more than offsets the exit of existing ones. Examining changes across the farm-size distribution, we find that this increase is driven primarily by a rise in the number of small farms. Specifically, while adverse weather shocks have a large impact on the number of small farms, they have little to no detectable effect on the number of large farms. These patterns imply not only that there are more farmers overall—thereby reducing the average farm size—but also that the new entrants tend to operate small farms. Moreover, these results indicate that large farms are not expanding or absorbing small farms, as they are themselves adversely affected by the shock and less able to acquire additional land.

Third, using a household panel survey from rural Colombia, we show that adverse weather shocks lead to declines in both income and consumption, with a larger drop in income. Also, households are more likely to migrate to another municipality and to sell land, livestock, and durable assets, such as televisions and refrigerators. These results are consistent with the increases in land sales observed in the administrative data. Moreover, a larger fall in income than consumption, together with a higher likelihood of migration and the sale of a broad range of assets, suggests that land sales are part of a consumption-smoothing strategy.

These reduced-form results are robust to an extensive set of checks, including different

[1] Colombia is divided into 32 *departamentos* (departments) the largest administrative unit, and roughly 1,100 municipalities, the second-level administrative units.

measures of weather shocks, alternative farm size and sample definitions, and alternative sets of controls that account for competing mechanisms. We also account for institutional factors, such as differences in land regulation and the degree of contiguity between small and large farms within municipalities. Our main findings remain largely unchanged across this broad battery of tests.

To further characterize the agents who enter farming after a shock, we conducted an original survey of rural community leaders from across the country. Their responses corroborate that distress land sales are common in rural areas, and that a substantial share of buyers —especially during distressed times—includes landowners from other municipalities as well as landless individuals coming from both within and outside the municipality.

After documenting these empirical patterns, we develop a quantitative heterogeneous-agent model with three objectives in mind. First, to explain the economic incentives that can quantitatively generate the reduced-form patterns observed in the data. Second, to examine the implications of weather shocks for aggregate agricultural productivity and for the economy's dynamic adjustment. Third, to use the model to simulate how increases in the frequency of adverse weather shocks—for example, those related to climate change—affect the farm-size distribution and aggregate agricultural output.

The basic structure of our model is as follows. Agents can be either farmers or non-agricultural workers and must choose their occupation each period. Those who choose to farm decide, before the harvest season, how much land to buy for production. Those who choose to work sell all their land—if they have any—and earn wages. Agents are heterogeneous in their initial landholdings as well as in their productivity in agricultural and non-agricultural activities. These productivities are subject to idiosyncratic shocks, introducing uncertainty into the maximization problem. Reflecting the institutional context of rural markets in developing countries, households lack access to both agricultural insurance and land rental markets. In this environment, land serves a dual role: it is both a productive asset accumulated by agents and a consumption-smoothing device. When agents experience adverse shocks, they can sell land to smooth consumption. Consequently, the farm-size distribution emerges endogenously from agents' joint decisions over land accumulation and occupational choice.

We calibrate the model so that its stationary distribution matches several statistics of the farm-size distribution in Colombia, and, importantly, so that the evolution of consumption in the economy after a weather shock matches the reduced-form patterns uncovered above. In the stationary equilibrium, we target, among others, the mean and variance of farm size, the share of households engaged in agriculture, and the exit rates of farmers across the farm-size distribution. With the calibrated model in hand, we first examine the potential efficiency losses that arise in equilibrium because decisions are made under uncertainty about future idiosyncratic productivity and because land serves as a consumption-smoothing device. Our calibration indicates substantial misallocation: less productive farms hold more land than optimal. We find that an efficient economy—where the marginal product of land is equalized across farmers—would feature a greater share of large farms and an agricultural output that is 42 percent higher.

To study the dynamic and aggregate effects of weather shocks on the economy, we model them as aggregate disturbances to agricultural total factor productivity (TFP) and conduct two types of analyses. First, starting from the stationary equilibrium, we examine the economy's impulse response to a weather shock with a magnitude equal to one standard deviation of the empirical distribution and persistence matching the empirical autocorrelation. We find large and persistent effects. Following the shock, the average farm size falls by 0.12 percent. It remains 0.06 percent below its pre-shock level even twenty years later, despite aggregate TFP returning to its steady-state value within a decade. This persistence also manifests in agricultural output: both output per farm and average idiosyncratic productivity decline. Because the number of farms increases, output per unit of land rises—consistent with the common empirical observation that regions with smaller farms tend to exhibit higher yields—but output per worker decreases.

Our model simulations reveal a natural explanation for the striking asymmetry in the effects of weather shocks on incumbent farmers versus landless households—and for the resulting increase in the total number of farmers after an adverse shock. On the supply side, adverse weather shocks induce farmers to sell land to smooth consumption. On the demand side, the key lies in the shock's short-run nature. If the shock is sufficiently transitory—i.e., if it has low autocorrelation—it does not affect the present value of becoming a farmer. Therefore, the expected future value of becoming a farmer remains unchanged for landless households, while land becomes cheaper due to the supply expansion. As a result, landless agents are induced to purchase land, crowding out potential expansion by incumbent farmers whose incomes are adversely affected by the shock.

In contrast, when the shock is sufficiently persistent, it reduces the future value of becoming a farmer, hindering demand from landless agents and allowing incumbent large farmers to absorb the small farms. Indeed, when we simulate alternative scenarios with more persistent shocks than those observed in our data, the qualitative result reverses: the total number of farmers declines and the average farm size increases. To the best of our knowledge, this is the first paper to emphasize how the degree of persistence of productivity shocks shapes their effects on production with qualitatively different outcomes.

After analyzing the economy's response to a single weather shock, we follow the approach proposed by Auclert et al. (2021) and Boppart et al. (2018) to study the evolution of a stochastic economy subject to a sequence of such shocks. Specifically, we modify the distribution of our weather-shock variable—defined as the number of atypical temperature days over the previous two years—by raising the probability of an atypical temperature day occurring. We find that even small increases in the frequency of atypical days can lead to substantial aggregate effects: a 3 percent increase reduces aggregate output by 5.5 percent. Because farm size also declines as the frequency of shocks rises, output per worker falls by roughly twice as much. Our results highlight a new mechanism through which changes in the frequency of weather shocks can have large effects——a point emphasized in recent work on the macroeconomic impacts of climate change (Bilal and Känzig, 2024).

Related Literature. This paper contributes to growing research on the causes and consequences of the farm size distribution in developing countries. Previous studies have explored various driving factors, including frictions in land and labor-markets (Foster and Rosenzweig, 2022; Acampora et al., 2025), land institutions (Bolhuis et al., 2021; Adamopoulos and Restuccia, 2020, 2014; Adamopoulos et al., 2022; Chen et al., 2022), and market access to urban centers (Gáfaro and Pellegrina, 2022; Pellegrina, 2022; Rao et al., 2022; Madhok et al., 2022). We make three contributions to this line of work. First, we document new facts about the dynamics of the farm-size distribution across developing countries, drawing a parallel to the literature on firm size distribution in the manufacturing sector. Second, while previous studies have documented the occurrence of distress land sales with survey data from developing countries (Cain, 1981; Deininger and Jin, 2008; Musyoka et al., 2021), to the best of our knowledge, we are the first to link income shocks and the resulting land-market responses to the overall farm-size distribution. Third, we adopt a dynamic perspective that uncovers how agricultural shocks differentially affect landless households and farmers, highlighting the central role of shock persistence in shaping their responses.

In further relation to this strand of the literature, our results emphasize that low agricultural productivity can be exacerbated by the aggregate consequences of individual responses to uninsured risk. By documenting how uninsured weather shocks lead to a more fragmented farm-size distribution, our findings illustrate a new mechanism explaining the notoriously low productivity of agriculture relative to the non-agricultural sectors of developing economies (Gollin et al., 2014; Restuccia et al., 2008; Caselli, 2005). Notably, our results show that short-term shocks can have very persistent effects on the economy.

Our paper also contributes to the literature on heterogeneous-agent models building on the seminal work of Hopenhayn (1992) and Aiyagari (1994). In particular, we add to a growing line of research that applies this class of models to the agricultural sector in developing economies. Brooks and Donovan (2020) examine the effects of risk reduction induced by bridge construction; Manysheva (2022) and Gottlieb and Grobovšek (2019) analyze how communal land systems shape aggregate agricultural productivity; Peralta-Alva et al. (2023) quantify the costs of raising tax revenue in low-income countries with large agricultural sectors; and Mazur and Tetenyi (2024) study the macroeconomic implications of agricultural input subsidies. Relative to these papers, our key contribution is to fully endogenize the farm-size distribution—treating it as an equilibrium outcome determined by households' occupational and landholding decisions.[2] Specifically, our paper is the first to study the effects of weather shocks in a model where the farm-size distribution is the central equilibrium object. Moreover, whereas existing studies typically focus on the stationary equilibrium, our work emphasizes the transition dynamics of the economy following economic shocks and how different types of shocks shape aggregate results.[3]

Finally, we contribute to a rich literature in development economics examining the effects of income shocks on agricultural households. A substantial body of work has documented the various strategies households employ to smooth consumption when faced with negative income shocks (Paxson, 1992; Townsend, 1994; Udry, 1994; Morduch, 1995; Dercon, 2002). Closer to our work, some studies show that negative productivity shocks often force poor landowners to liquidate assets to smooth consumption (Deaton, 1989; Rosenzweig and Wolpin, 1993; Carter and Zimmerman, 2003; Kazianga and Udry, 2006). Beyond asset depletion, other work has highlighted a broader set of behavioral responses—including adjustments in labor and input use, loan repayment, crop choice, migration, and investment in human capital (Jayachandran, 2006; Jessoe et al., 2018; Colmer, 2021; de Roux, 2021; Jagnani et al., 2021; Aragón et al., 2021). In particular, consistent with our findings, Kaboski et al. (2022) show that farmers in Uganda invest in land when they win a large lottery. We add to this literature by documenting that land sales constitute an important margin of adjustment for farmers facing negative productivity shocks. Because land is a key asset for most farmers in developing economies, land sales can have strong, long-lasting effects on their future income. In addition, because climate change increases the severity and frequency of adverse weather shocks (Burke et al., 2015; IPCC, 2021), our results highlight an additional mechanism through which these changes can deepen the agricultural performance gap between poor and rich economies.

[2] Our approach to landholding choices is analogous to models of firm investment under adjustment costs, e.g., Khan and Thomas (2008).

[3] In solving for these dynamics and simulating the stochastic economy, our work benefits from recent methodological advances in the solution of heterogeneous agent models, including Auclert et al. (2021) and Boppart et al. (2018).

2 Farm Size Dynamics, Weather Shocks, and Rural Land Markets in Developing Countries

This section provides an overview of farm-size dynamics and the impact of weather shocks in developing countries. To that end, we bring in household-level longitudinal data from eleven countries—three in Latin America and eight in Africa—each with information of at least two survey rounds conducted approximately three years apart. For each country, we construct a panel using two survey rounds, which we merge with region- and year-specific measures of weather shocks. Throughout the analysis, we define farm-size as the land operated by the household.[4] Given our focus on Colombia in subsequent analysis, when the data allows, we present the empirical patterns separately for that country. We conclude this section by discussing key characteristics of land markets in developing countries, which serve as the foundation of the model developed in Section 5.1. Details about the surveys used in this section are provided in Appendix OA.

2.1 Farm size Dynamics and the Impact of Weather Shocks

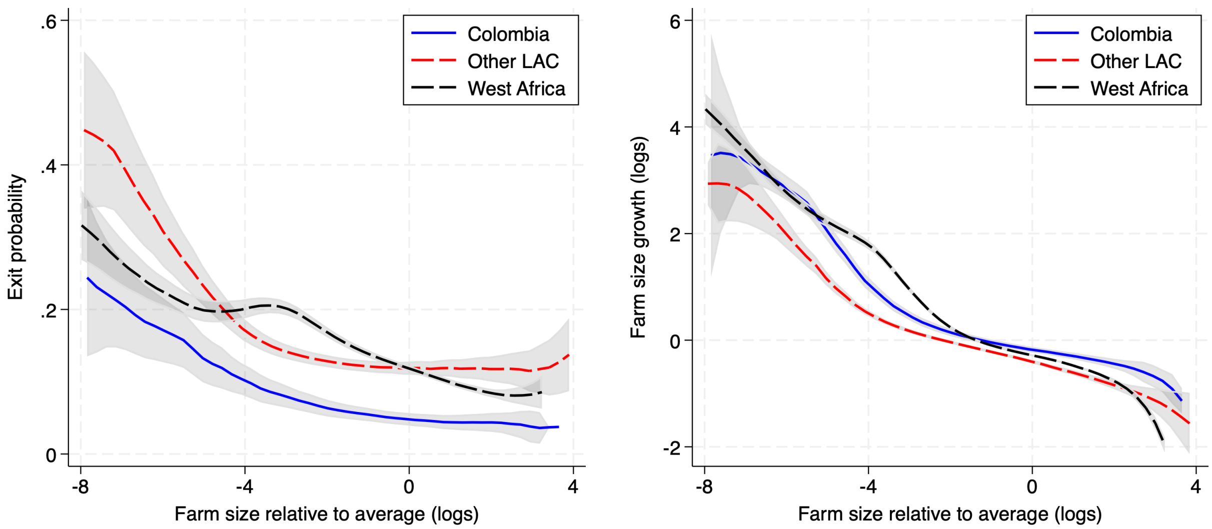
Farm Size Dynamics. We document two patterns related to farm-size dynamics that parallel empirical regularities observed in firms —see for example Jaimovich et al. (2023) and Clementi and Palazzo (2016). Figure 1 shows results from local polynomial regressions in the sample of households that operated some land in the first survey round. In Panel (a), the outcome is a dummy equal to one if the household does not operate any land in the second survey round. In Panel (b), the sample is further restricted to households that also operate land in the second period, and the outcome is the log growth rate of farm size between periods. In both panels, the right-hand-side variable in the regression is farm size in the first period relative to the average farm size in the country.[5] Panel (a) shows that smaller farmers are more likely to exit farming and operate no land. The magnitudes are relevant: in Colombia, within the three-year period between surveys, farmers operating below the average farm size are on average 75 percent more likely to exit (a probability of 0.07 versus

[4] By focusing on operated land, we avoid issues related to land ownership. In particular, we are agnostic about how farmers change their operating status—for example, through land transactions, communal land redistribution, within-family reallocation, or land rentals. Our qualitative patterns do not hinge on these institutional characteristics. We provide a detailed discussion of the institutional features of land markets in developing countries later in the section.

[5] In the Colombian data, not operating land is strongly associated with moving. Between 2010 and 2013, 18 percent of households that show up without land operations in 2013 moved to the urban area of their municipality, compared to virtually 0 percent of those that continue operating land. Likewise, 30 percent of households with no land operations in 2013 moved out (to an urban area or another municipality), versus only 1 percent among those still farming.

Figure 1: Farm Size Dynamics across Countries

(a) Exit Probability (b) Farm Size Growth



Notes: This figure shows results from local polynomial regressions (bandwidth = 1). Panel (a) uses households that operated land in the first survey round; the outcome is an exit indicator equal to 1 if the household operates no land in the second period. Panel (b) restricts the sample to households that also operate land in the second period; the outcome is the log of the ratio of farm size between periods. In both panels, the right-hand-side variable is farm size in the first period relative to the country's average (in logs), which is also shown on the x-axis. The data cover Colombia, Mexico, and Peru in Latin America, and Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo in Africa. Survey rounds are 2010–2013 for Colombia, 2002–2005 for Mexico, and 2018–2021 for West Africa. For Peru, the data come from an annual rotating panel (2007–2023); we use households observed three years apart.

one of 0.04). In West African countries, farmers below the average farm size are twice as likely to exit as those above (0.16 versus 0.08). The patterns for the other Latin American Countries in our sample are similar.

Panel (b) shows that small farms tend to grow, whereas large farms tend to shrink.[6] In Colombia, farms below the average farm size grow by a factor of 12, whereas those above the average grow by about 5 percent; patterns for the other Latin American countries are similar. In West Africa, farms below the average grow by a factor of about 13, while those above the average shrink by roughly 30 percent. Much of the large growth among small farms comes reflects the extremely low base: In the West African countries in our sample the average farm size is 3.5 hectares, whereas in Colombia it is 2.6.[7]

[6] A small proportion of surviving farmers experience no change in operated farm size between survey rounds: about 6% show exactly no change, and 11% percent show a change smaller than 10 percent.

[7] As discussed in Section 3, the Colombian household survey data used in these exercises are only representative of small farms in a few regions of the country. For comparison, we note that in the 2014 agricultural census, the average farm size in the country is 5.8 hectares.

Weather Shocks Effects. We estimate the impact of weather shocks on farm-size dynamics using the following specification:

$$y_{h,t} = \beta_1 \, TempShocks_{i(h),t} + \beta_2 \, TempShocks_{i(h),t} \times \mathbb{1}\{\text{Landless}\}_h + \beta_3 \, TempShocks_{i(h),t} \times \mathbb{1}\{\text{Small Farm}\}_h + \alpha_h + \gamma_{r(h),t} + \varepsilon_{h,t}, \tag{1}$$

where h indexes households, $i(h)$ denotes the municipality of household h, and $t \in \{1, 2\}$ indexes survey waves. The dependent variable $y_{h,t}$ equals one if household h operates any land in period t. The terms α_h and $\gamma_{r(h),t}$ denote household and region–year fixed effects, respectively, where regions represent one level of geographic aggregation above municipalities. $TempShocks_{i(h),t}$ denotes weather shocks, defined as the total number of atypical temperature days (in hundreds) over the previous two years.[8] The indicator $\mathbb{1}\{\text{Landless}\}_h$ identifies households that did not operate any land in the initial period ($t = 1$), while $\mathbb{1}\{\text{Small Farm}\}_h$ identifies those whose operated area was below the median farm size in their respective region. $\varepsilon_{h,t}$ denotes the error term, which we cluster at the municipality (i) level. We exclude Colombian households from this estimation because the rural household survey focuses on landowning households in $t = 1$, preventing us from accounting for entry into farming from landless households.

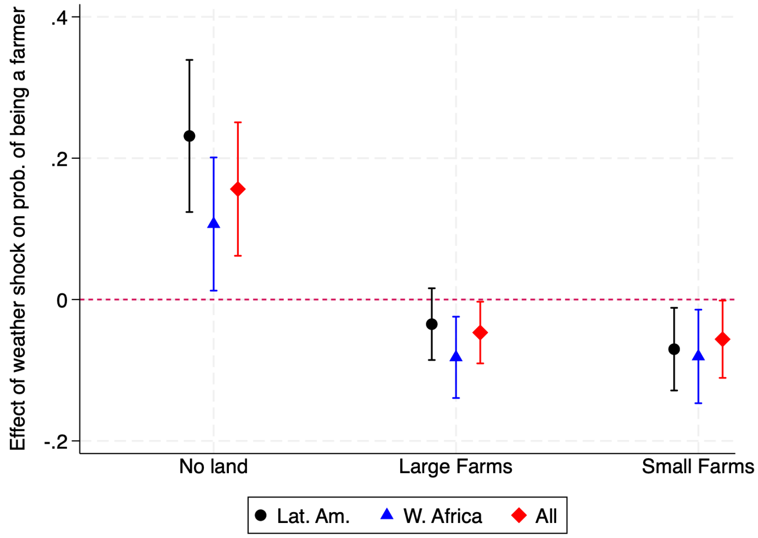
Figure 2 plots the estimated coefficients from equation (1), and Appendix Table O.1 reports the regression results along with estimates from specifications that include additional fixed effects. Across all regions, weather shocks reduce the likelihood that both small and large farmers operate any land —with slightly larger effects for small farms—while increasing the probability that landless households begin operating land. This figure illustrates that the incentives to engage in farming after a weather shock differ sharply between landless households and incumbent farmers. Later in Section 5.1, we provide an economic explanation for this pattern, which relates to short-run nature of the weather shocks. Before turning to the empirical results using the Colombian administrative data, we next discuss key characteristics of land markets in developing countries.

2.2 Rural Land Markets in Developing Countries

Three additional facts guide the interpretation of our reduced-form findings and the design of our model. First, land rental markets in developing countries are generally thin, and farm operation usually coincides with land ownership. In Colombia, according the National Agricultural Survey (DANE, 2019), about 85% of plots are operated by owners, and only

[8] A detailed description of the weather data and the construction of our weather-shock measures is provided in Section 3.

Figure 2: Effects of Weather Shocks on Farmers' Exit and Entry



Notes: This figure shows the impact of weather shocks on households' probability of operating land. We plot the estimates $\hat{\beta}_1$ (large farmers), $\hat{\beta}_1 + \hat{\beta}_2$ (landless households), and $\hat{\beta}_1 + \hat{\beta}_3$ (small farmers) from equation (1) and their 95% confidence intervals. Standard errors are clustered at the geographic administrative level at which the weather shock is measured. The sample contains 24,074 household-year observations for LAC and 85,584 for West Africa.

9% of farmers operate rented land. These figures are similar to those reported by Acampora et al. (2025), who find that the proportion of households renting land in Kenya is 4% and ranges between 0% and 5% in six other countries in six countries in sub- Saharan Africa. This stands in contrast to the U.S and the European Union, where the share of farmland operated under a rental agreement is about 40% and 46%, respectively.[9] These statistics suggest that the patterns documented in Figure 1 likely reflect changes in land ownership.[10]

Second, the adoption of agricultural insurance is extremely low in developing countries. Unsubsidized agricultural insurance coverage rates in high-income countries average 41.7%, compared to 8% and 0.5% in lower-middle-income and low-income countries, respectively (Mahul and Stutley, 2008). In Colombia, according to DANE (2019), the share of farmers with any form of agricultural insurance is below one percent. In the absence of insurance, farmers facing adverse shocks may be forced to sell their assets to smooth consumption.

Third, the Colombian household survey indicates that distress land sales are common and that farmers sell land when experiencing financial distress to smooth consumption. For example, between 2013 and 2016, nearly 65% of households who reported selling land did so to pay for household expenses or cover outstanding debts, pay for medical treatment, or

[9] USDA Economic Research Service (2024) and Eurostat (2020).

[10] Communal land tenure systems persist in some regions of developing countries. In our sample, the average share of communal land across African countries is 30%, ranging from 70% in Burkina Faso to 10% in Niger. Below, we study changes in land ownership originating from land market transactions in Colombia. However, similar patterns may arise from non-market communal land allocation.

pay for education fees. Section 4.5 returns to this point using the original survey that we conducted with rural community leaders from across the country. The use of land sales as a consumption smoothing device is also documented by Krishna (2010) in Africa.

These empirical regularities motivate the basic structure of our model in Section 5.1. To capture the relationship between farm growth and farm size shown in Figure 1, we introduce idiosyncratic productivity shocks that induce farmers to expand or shrink their operations. Additionally, agents make occupational choices, in which they can either buy land and become farmers or sell their entire property and exit agriculture. These choices are made in an economic environment with uninsured risk and no land rental markets.

Next, we turn our attention to Colombia, where we assemble a comprehensive longitudinal dataset on land transactions and farm sizes. We use it to uncover a set of complementary facts that highlight the mechanisms behind the effects of weather shocks on the farm-size distribution.

3 Data from Colombia

Our Colombian dataset is structured at two levels of disaggregation: municipality and farm. At the municipality level, it contains annual information on land transactions, moments of the farm-size distribution, and weather shocks for 864 municipalities.[11] At the farm-level, it provides detailed information on household consumption, asset ownership, and investment decisions. Here, we provide a brief description of our datasets, relegating details to Appendix OA. Appendix Table O.2 present descriptive statistics of the different estimation samples. After presenting our data, we turn to the reduced-form effects of weather shocks in Section 4.

Land Transactions. We obtained administrative, property-level transaction information from the *Superintendencia de Notariado y Registro.* (SNR, National Superintendence of Notaries)—the government agency that regulates and oversees Colombia's notarial and public-registry system. Beyond recording real-estate transactions, it supervises notaries and registry offices and guarantees the legal validity of property titles. For each property-level transaction, we observe the buyer, the seller, and whether the transaction was a partial property sale, a full sale, or a mortgage.[12] These data cover all the properties that were once part of a *baldío*—publicly owned vacant land—and were subsequently allocated to private owners.

[11] We exclude from our final sample of municipalities large metropolitan areas and municipalities with very few rural properties (i.e. below the 1st percentile). Our final sample encompasses 85.3% of the rural population in the country.

[12] We do not observe the price or the size of the properties.

By 2014, they summed to to 23 million hectares—more than half of the currently privately-held land in the country (Sánchez and Villaveces, 2016; Arteaga et al., 2017). These data contain all transactions dating back to the early 1900s, but we focus on the period 2000-2011 when our other datasets are available. We construct a balanced panel at the municipality-year level with the number of full and partial sales, and the number of mortgage transactions. For complementary analyses, we split the number of sales into those involving buyers who previously owned land and those involving first-time owners in the *departamento*. Appendix OB.3 provides details about the identification of these buyers in the data.[13]

Farm Size Distribution. Our farm-size distribution data come from the national cadastre managed by the *Instituto Geográfico Agustín Codazzi* (IGAC, National Geographical Institute of Colombia). This land registry contains information on the universe of farm properties in Colombia.[14] We obtained municipality-level aggregate information from all properties 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, comparable in size to Germany or California. The data form a yearly panel for 2000–2011 at the municipality level and include the number of farms, the number of owners, and the mean and median farm size for specific size ranges.[15]

Household-Level Data. We use household panel data from the rural sample of the *Encuesta Longitudinal Colombiana* (ELCA), a survey conducted by Universidad de los Andes. The data include a sample of 4,800 rural households interviewed over three survey rounds (2010, 2013, and 2016). The baseline sample covers households in 222 rural communities of 17 municipalities. We have detailed information on land ownership, consumption, income, migration, and assets.

Weather Shocks. We construct our weather shock variables based on temperature information from ERA5 data, provided by the Copernicus Climate Change Service (C3S) of the

[13]We proxy ownership by determining whether the name of the buyer appears in the past in the SNR at the receiving end of a transaction (sale, inheritance, or government allocation) within the same *departamento*. As discussed in Appendix OA, we restrict the search for names within *departamentos* to avoid false matches arising from common names across regions.

[14]The cadastral data-collection process is designed to capture even informal properties that do not have all required formal documentation.

[15]The land registry records rural properties used for agriculture, which we treat as equivalent to farms. In settings with active land-rental markets, property and farm can differ because farmers may operate land they do not own or combine plots from multiple owners. In Colombia land rental is uncommon, so ownership and operation (farm) typically coincide. Consistent with this, land registry data show that owners in a municipality almost always report only one property.

European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset contains global reanalysis information on temperature with a horizontal resolution of $0.25° \times 0.25°$ (≈ 28 km^2) at an hourly frequency since 1979.[16] We first compute the historical quarterly distribution of daily average temperatures by aggregating all municipality-day temperature observations within calendar-quarter throughout the period 1979–2016. That yields four temperature distributions per municipality, one per quarter. We then classify a municipality as experiencing an atypical temperature day if the temperature is below the 20$^{\text{th}}$ or above the 80$^{\text{th}}$ percentile of its corresponding quarterly temperature distribution. Indexing days by d, quarters by q, years by t, and municipalities by i, and denoting the 20$^{\text{th}}$ and 80$^{\text{th}}$ percentiles of quarterly temperature distributions as $\mu^{20}_{i,q(d)}$, and $\mu^{80}_{i,q(d)}$, we define an atypical temperature day in a municipality by

$$AtipicalDay_{i,t,d} = \mathbb{1}(\text{Temperature}_{i,t,d} \leq \mu^{20}_{i,q(d)}) + \mathbb{1}(\mu^{80}_{i,q(d)} \leq \text{Temperature}_{i,t,d}). \tag{2}$$

To define a single shock variable for each municipality i in year t, we face two challenges. First, there may be a lag between farmers' reactions to atypical weather and the registration of land transactions or farm properties in the data. In Colombia, it can take months—or even years—for land transactions to be recorded. Second, the impact of the shock may influence farmers' decisions and outcomes with a lag—for example, atypical days experienced by a farmer at the end of calendar year $t-1$ can have an effect on crop revenues only in t, during the harvest. To address this potential mismatch between the timing of atypical days and economic outcomes, in our preferred specification, we define the shock as the sum of atypical days lagged over the past two years:

$$TempShocks_{i,t} = \sum_{d=1}^{365} AtypicalDay_{i,t-1,d} + \sum_{d=1}^{365} AtypicalDay_{i,t-2,d}. \tag{3}$$

In Appendix OB.1, we present results from alternative specifications in which we include the contemporaneous effect of atypical days within year t, together with lags up to $t-7$. Moreover, Appendix OB reports results using alternative definitions of temperature shocks, including three different ways of defining an atypical day, different formulations of the shock variable with accumulations over various lag lenghts, and an alternative source of weather data. We discuss the results from these robustness exercises in Section 4.4. Our conclusions remain largely unchanged across these different approaches.

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

4 Reduced-form Impact of Weather Shocks in Colombia

This section presents the reduced-form effects of weather shocks in Colombia. We begin with our municipality-level regressions in Section 4.1, which show how land transactions and the farm-size distribution respond to weather shocks. Section 4.2 then provides household-level evidence showing that consumption smoothing operates as a supply-side mechanism underlying land transactions. In Section 4.3, we discuss —and rule out— institutional explanations for the observed farm-size patterns. Finally, Section 4.5 presents results from our survey of community leaders, which we use to validate our interpretation of the results and to characterize new entrants into farming. Section 4.4 discusses robustness checks and alternative specifications.

4.1 Municipality-Level Regressions

We estimate the impact of temperature shocks on land transactions and farm size using:

$$s_{i,t} = \beta TempShocks_{i,t} + X'_{i,t}\delta + \eta_i + \kappa_t + \varepsilon_{i,t}. \tag{4}$$

Here, $s_{i,t}$ represents the number of land transactions (sales or mortgages), the log number of farm owners, or the log average and median farm size in municipality-year pair (i, t). $X_{i,t}$ is a vector that includes time-varying municipality characteristics. Specifically, rainfall in year t and five lags, the cumulative number of land allocations in the municipality up to t, a dummy for cadastral updates, and the total municipal land area recorded in the registry, which accounts for changes in registry coverage. The specification also includes municipality fixed effects η_i to control for time-invariant heterogeneity, and year fixed effects κ_t to capture common shocks to land markets and farm size. Standard errors are clustered at the municipality level.

Equation (4), as well as all subsequent specifications, relies on the identifying assumption that, conditional on the fixed effects and control variables, there are no municipality-specific, time-varying unobservables correlated with temperature shocks. This assumption is standard in the literature (see, e.g., Dell et al. (2014)). Appendix OB.2 shows that our results are robust to specifications that include state-specific time trends, alternative sets of controls, and alternative measures of atypical temperature.

Effects on Land Transactions. Table 1 presents the OLS estimates from equation (4) on different measures of land transactions. Column 1 shows results for the total number of land sales. Columns 2 and 3 separate this into *full* sales (entire-property transfers) and

Table 1: Temperature Shocks and Land Transactions

	Land Sales					
	Transaction Type			Buyer Type		
	All	Full	Partial	Landless	Owner	Mortgages
	(1)	(2)	(3)	(4)	(5)	(6)
TempShocks	2.537***	2.013***	0.523**	1.866***	0.671***	1.046***
	(0.536)	(0.504)	(0.229)	(0.408)	(0.192)	(0.237)
Observations	10,021	10,021	10,021	10,021	10,021	10,021
Adjusted R^2	0.896	0.893	0.600	0.878	0.823	0.733
Mean Dep. Var	12.62	10.83	1.79	9.37	3.25	2.62

Notes: This table presents coefficient estimates from equation (4) in a balanced panel at the municipality-year level. The dependent variable in column 1 is the number of land sales (full + partial), in column 2 the number of full sales, in column 3 the number of partial sales. Columns 4 and 5 separate total sales into those involving buyers who previously owned land in the *departamento* and those involving first-time buyers. Buyer type is identified by checking whether the buyer's name appears in earlier SNR records (sales, inheritances, or government allocations) within the same *departamento*. The dependent variable in column 6 is the number of land mortgages. The independent variable is the total number of atypical temperature days in the past two years divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. See the text for details. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Superintendency of Notaries (SNR). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

partial sales (fractional-property transfers). Column 1 shows that more days with atypical temperature lead to more land sales. In particular, an additional 100 atypical days (roughly two standard deviations) over the previous two years increases the number of land sales by 20%. Columns 2 and 3 show that this effect is driven by a 19% increase in full sales and a 29% increase in partial sales. Column 6 shows that an additional 100 days of atypical temperature in the municipality increase by 38% the number of mortgages. In sum, weather shocks substantially increase land-transaction activity within a municipality.

To better understand whether the observed increase in transactions is driven by purchases made by landless households or by farmers who already own land in neighboring municipalities, we make use of transaction data reporting both the buyer and the seller in each land sale. We use this information to construct a list of individuals who own any land within each *departamento* (the administrative unit above the municipality, of which there are 28) at the start of every year, and match it to the list of land buyers in each municipality during the following two years. This allows us to determine whether buyers already owned land in any of the municipalities within the *departamento*. Details on the construction of these lists, the matching process between them, and alternative approaches to data construction are discussed in Appendix OB.3.

We decompose the estimated impact of weather shocks on total land sales into sales made to landless buyers and sales made to farmers who were already landowners at the time of the sale. Columns 4 and 5 of Table 1 show that extreme temperatures increase land purchases

Table 2: Temperature Shocks and Average Farm Size

	Number of Owners (logs) (1)	Mean Farm Size (logs) (2)	Median Farm Size (logs) (3)
$TempShocks$	0.015***	-0.015***	-0.021*
	(0.005)	(0.005)	(0.012)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974

Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution. Dependent variables are the log number of land owners in the municipality (column 1), log average farm size (column 2), log median farm size (column 3). The independent variable is the total number of atypical temperature days in the past two years divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

made by both types of buyers, but effects are larger among landless buyers, who on average account for 74% of the weather-driven land purchases. These results indicate that, although a substantial share of transactions occurs among existing farmers, weather shocks also trigger sales to households that previously owned no land in the municipality.

Effects on the Farm Size Distribution. Table 2 presents the results of estimating equation (4) on the number of owners and different moments of the farm-size distribution.[17] A higher number of atypical-temperature days in a municipality during the previous two years leads to an increase in the number of landowners (column 1). Importantly, this indicates a *net* increase in landowners—some landowners might leave, but overall there must be more entry than exit. Column 2 shows that both the average and the median farm size fall. An additional 100 days of atypical temperature over a two-year period increases the number of landowners by 1.5% and reduces average and median farm size by 1.5% and 2.1%, respectively. Weather shocks therefore lead to land fragmentation instead of land consolidation.

Table 2 does not provide information on which types of farms drive the decline in average farm size. This decline could arise from the division of large estates into medium-sized properties without any change in the number of small farms, or from small farms fragmenting into even smaller plots, without affecting larger properties. To investigate this, we estimate effects in the number of owners within fixed farm-size bins over time. We begin by splitting each municipality's farm-size distribution in 2000—the first year of the sample—into quantiles.[18] We then compute, for each subsequent year, the number of owners in each fixed-size

[17]Farm size is defined based on the registered size of the plots. Since some farmers might own more than one plot, the average farm size can differ from the ratio of total land to the number of owners.

[18]97% of municipalities have registry information in that year. For the remaining municipalities, we use

bin. Consider J quantiles in municipality i, denoted by $\{q_i^1, ..., q_i^J\}$.[19] Let $AreaOwned_{o,i,t}$ denote the total landholdings of owner o in municipality i and year t. For each year, we then compute the number of owners whose total landholdings fall within each of these fixed-size bins as:

$$NumOwners_{i,t}^j \equiv \sum_{o \in i} \mathbb{1} \cdot [AreaOwned_{o,i,t} \in (q_i^{j-1}, q_i^j)], \tag{5}$$

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

$$\log(NumOwners_{i,t}^j) = \gamma^j \; TempShocks_{i,t} + X_{i,t}' \xi^j + \mu_i^j + \kappa_i^j + \omega_{i,t}^j, \tag{6}$$

where the right-hand variables are the same as in equation (4).

Figure 3 reports estimates of γ^j for $j = 1, \ldots, 10$. Extreme temperature shocks cause a sizable increase in the number of owners with farms in the lower five deciles of the initial distribution, but close to zero and statistically insignificant effects on the number of owners in the top five deciles.[20] This shows that weather shocks increase the number of smaller farms but do not affect the number of large farms, suggesting that the decline in average farm size is driven by new owners acquiring parcels subdivided from small farms. This is inconsistent with small farmers being solely absorbed by larger farms.

4.2 Household-Level Regressions

We now examine the effects of temperature shocks using information from the three survey waves of the ELCA household survey. Our goal is to assess whether the household-level responses align with the aggregate patterns in land sales and farm size, and whether they support our interpretation of land sales as a consumption-smoothing device. Similar to Section 2, we estimate:

$$y_{h,t} = \alpha \; TempShocks_{v(h),t} + X_{v(h),t}' \tau + \iota_h + \kappa_t + \psi_{h,t}, \tag{7}$$

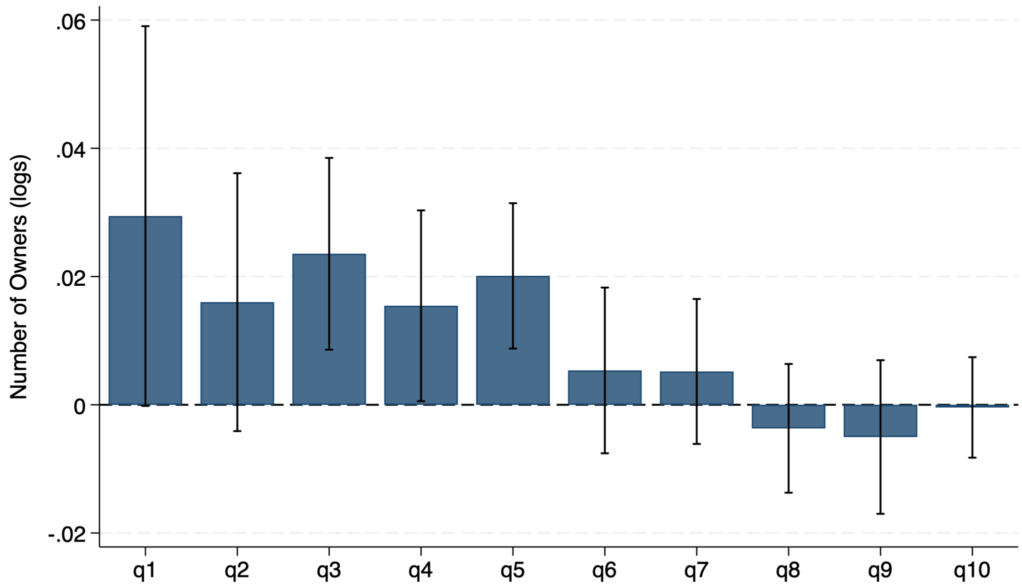
where $y_{h,t}$ denotes an outcome for household h in survey round $t \in \{2010, 2013, 2016\}$. The temperature-shock variable, $TempShocks_{v(h),t}$, is analogous to the municipality-level

the first year in which they appear in the land-registry dataset.

[19]For example, if we consider deciles, $J = 10$, and farms with areas in $(0, q_i^1]$ are those is the lowest decile in municipality i.

[20]Regression results are presented in Appendix Table O.12. Appendix Figure O.9 shows analogous estimates for alternative partitions of the initial farm-size distribution ($J = 5$ and $J = 20$).

Figure 3: Temperature Shocks and Number of Owners by Deciles of Initial Distribution



Notes: This figures reports estimates of γ^j for $j = 1, \ldots, 10$ from equation (6). A separate regression is run for each of the ten quantiles of the initial municipality-level distribution of farm sizes. The outcome is the log number of owners whose farm sizes fall within the corresponding decile. The independent variable is the number of atypical temperature days in the past two years, divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Error bars indicate 95% confidence intervals. Standard errors are clustered at the municipality level.

measure described in Section 3, but here we use the finer geographic information available in the survey to compute shocks at the*vereda* v level, a smaller administrative unit than the municipality.[21] Vector $X_{v(h),t}$ includes controls for log aggregate rainfall in the community at time t and its five lags. ι_h and κ_t denote household and year fixed effects, respectively. Finally, $\psi_{h,t}$ denotes the error term, which we cluster at the *vereda* v level.

Table 3 reports the estimates.[22] We find that temperature shocks reduce both the likelihood that households own any land and the average farm size (columns 2 and 4). Consistent with these results, the share of farmers reporting land sales increases. The adverse effects of temperature shocks, however, extend beyond land transactions: we observe higher sales of livestock and a decline in the principal-component index of asset ownership, which aggregates household durables such as appliances, vehicles, and other assets. Appendix Table O.9

[21]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).*

[22]To maintain a consistent estimation sample across outcomes, the results presented in Table 3 impute land-ownership values as zero for households that either migrate to urban areas or do not respond to the agricultural module of the survey. Results that restrict the sample to households that completed the agricultural module yield qualitatively similar but slightly stronger patterns and are reported in Appendix Table O.4.

Table 3: Temperature Shocks and Household Decisions

	Household Migrated (1)	Household Has Land (2)	Household Sold Land (3)	Farm Size (Hectares) (4)	Consumption (logs) (5)	Income (logs) (6)	Sold Animals (7)	Asset Index (8)
TempShocks	0.089***	-0.055*	0.029***	-0.481*	-0.111***	-0.465***	0.046***	-0.112***
	(0.033)	(0.030)	(0.010)	(0.272)	(0.038)	(0.069)	(0.016)	(0.028)
Observations	13,442	13,442	13,442	13,442	13,442	12,773	12,634	12,596
R^2	0.532	0.564	0.412	0.605	0.707	0.647	0.932	0.585
Mean Dep. Var	0.14	0.83	0.03	2.36	2.80	2.06	0.67	-0.00

Notes: This table shows estimates of the effects of temperature shocks on household decisions using a three-wave panel survey of rural households (2010, 2013, 2016). The dependent variables, from left to right, are: a dummy indicating whether the household migrated between survey waves; a dummy indicating whether the household owns any land; a dummy indicating whether the household sold any land; log farm size; log per-capita consumption; log per-capita income; a dummy indicating whether the household sold any livestock; and a principal-components asset index based on household assets and durable goods. Values for the land-ownership variables (columns 2–4) are imputed as zero for households that did not answer the survey's land module. All monetary values are expressed in 2016 Colombian pesos (in millions). All regressions control for log aggregate rainfall at t and its five lags and include household and time fixed effects. *Mean Dep. Var.* reports the sample mean of the untransformed dependent variable. Standard errors clustered at the *vereda* level are reported in parentheses. Data from ELCA survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

disaggregates these results and shows that the decline is driven by lower ownership probabilities across a broad range of assets. Column 1 further shows that affected households are more likely to migrate, consistent with Ibáñez et al. (2022) for El Salvador. Temperature shocks also have a sizable impact on consumption—a 12% decline per 100 additional atypical-temperature days, according to column 5—and an even larger negative effect on income.

The larger decline in income relative to consumption, combined with the sale of land, livestock, and other assets, suggests that households rely on land sales and land-backed credit (as observed in Table 1) to smooth consumption after negative income shocks. Nonetheless, the remaining decline in consumption shows that these strategies only partially succeed, and smoothing remains incomplete.

4.3 Institutional Factors and the Lack of Land Consolidation

Our results so far suggest that weather shocks increase the share of households seeking to sell their land to smooth consumption. The rise in partial land sales further indicates that this strategy may contribute to land fragmentation. This land-market dynamic does not appear to induce consolidation by large farms; instead, it brings landless households into farming. Section 5.1 develops a model that rationalizes these findings by focusing on farmers' lack of insurance and agents' entry and exit decisions. Here, we discuss and discard three alternative mechanisms related to the institutional context that might also explain the lack of land consolidation.

First, we consider whether limited contiguity between large and small farms might constrain the expansion of larger farms following adverse shocks. To test this hypothesis, we construct a measure of contiguity between large and small farms in each municipality using 2017 land-registry maps. Within each municipality, we calculate the share of farms below the 10th percentile of the size distribution that are contiguous to at least one farm above the 90th percentile. Municipalities with a share above the national median are classified as having high contiguity. Second, we explore whether the observed decreases in farm size are driven by the conversion of agricultural land into residential or recreational uses, which is more likely near major cities. We classify municipalities as having high distance from large cities if they lie farther than the national median distance. To test these hypothesis, we estimate the effect of temperature shocks on the number of owners and on mean and median farm size (as in Table 2), adding interaction terms that allow these effects to differ in municipalities with high contiguity or with high distance to large cities.

Table 4 presents results that offer limited support for either alternative explanation. Panel (a) adds an interaction term for high contiguity. Column 3 provides weak evidence that contiguity may interact with the shock, but the coefficients are small and statistically insignificant for both the number of owners and average farm size. Moreover, Appendix Table O.11 shows that the median farm size result is not robust when using an alternative contiguity measure based on GPS coordinates from the 2014 National Agricultural Census. Panel (b) includes an interaction term for municipalities located farther than the median distance from large cities. The estimates in columns 2 and 3 are statistically insignificant, and—contrary to what this mechanism would predict—we find a larger increase in the number of farmers in municipalities farther from major urban centers.

Finally, as a third possible explanation, we consider institutional factors related to Colombia's land regulations. In particular, Law 160 of 1994 established municipality-specific land ceilings that limit the amount of government-allocated land any individual can own. Appendix OB.4 re-estimates equation (4), adding an interaction term for municipalities with an above-median share of government-allocated farmland—where the ceiling is most likely to binding—and shows that this policy does not drive our results.

4.4 Alternative Specifications

Appendix OB shows that our reduced-form results are robust across a wide set of alternative specifications and variable definitions. We first address the concern that our findings may be driven by the specific choice to aggregate atypical temperature days over years $t-1$ and $t-2$. To do so, we estimate a flexible-lag specification that allows the timing of the response to vary with respect to the onset of the shock. This specification—described in

Table 4: Temperature Shocks and Farm Size - Heterogeneous Effects

	Number of Owners (log)	Mean Farm Size (log)	Median Farm Size (log)
	(1)	(2)	(3)
	Panel A: Land Registry Map - Contiguous Plots		
$TempShocks$	0.012**	-0.014**	-0.032**
	(0.005)	(0.006)	(0.014)
$TempShocks \times High$	-0.004	0.004	0.024*
	(0.005)	(0.006)	(0.013)
Observations	9,499	9,499	9,499
R^2	0.991	0.993	0.973
	Panel B: Distance to markets		
$TempShocks$	0.010*	-0.013**	-0.027*
	(0.006)	(0.006)	(0.015)
$TempShocks \times High$	0.011*	-0.006	0.007
	(0.006)	(0.006)	(0.012)
Observations	9,683	9,683	9,683
R^2	0.991	0.993	0.974

Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution, allowing for heterogeneous effects by plot contiguity and distance to a large city. Dependent variables are the log number of land owners in the municipality (column 1), log average farm size (column 2), log median farm size (column 3). The independent variable is the total number of atypical temperature days in the past two years divided by 100. *High* in Panel A denotes a dummy equal to one for municipalities with an above-median share of farms below the 10th percentile of the size distribution that are contiguous to at least one farm above the 90th percentile in the 2017 land-registry map. In Panel B, it denotes a dummy equal to one for municipalities whose driving distance to the nearest major city is above the national median. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

equation (O.1)—estimates separate coefficients for shocks occurring in each year from $t - 7$ through t, and we apply it to all key outcomes: land sales, mortgages, the number of owners, and mean and median farm size. Appendix Figures O.7 and O.8 show that extreme temperature events have effects that persist for several years and that our main results do not depend on any particular choice of lag structure.

Our second set of concerns relates to the definition of atypical temperature days. Three issues arise. First, the thresholds we use—the 20$^{\text{th}}$ and 80$^{\text{th}}$ percentiles of the temperature distribution—might drive our results. Second, to construct these distributions, we rely on temperature realizations from 1979–2016, which extend more than two decades before our sample period (2000–2011). Given climate change, the distribution of temperatures may have shifted over time, raising the question of whether earlier data remain appropriate for defining atypical conditions during our sample years. Third, we rely on ERA5 reanalysis data, and it is important to verify that our results are robust to alternative climate datasets and alternative measures of weather shocks. We address these concerns in Appendix Tables O.5 and O.6, which report estimates from equation (4) using multiple alternative definitions of temperature shocks. Panels A and B redefine atypical temperature days using thresholds at the 5th and 95th percentiles and at the mean ± 1.5 standard deviations of the temperature distribution. Panel C maintains the same thresholds as in the main specification but recalculates the temperature distributions using data from 1990–2011. Panels D and E replace our atypical-day measure with shocks defined using the SPEI index.[23] Across all these specifications, our conclusions regarding the effects of weather shocks on land transactions, the number of owners, and mean and median farm size remain essentially unchanged.

Finally, Appendix Tables O.7 and O.8 present additional robustness exercises. Panel A adds *departamento*-specific time trends to account for the possibility that regional trends in temperature shocks may be spuriously correlated with our outcomes. Panels B and C include controls for forced displacement and homicide rates to capture the influence of violent conflict, motivated by evidence that weather shocks can increase conflict (see, e.g., Miguel et al. (2004)) and by the possibility that conflict may, in turn, affect land markets and land allocation. Panel D re-estimates our main specification but clusters standard errors at both the municipality and *departamento* $\times$ year levels, allowing for potential correlation in the errors across larger spatial units than the municipality. Our results remain robust across these specifications.

4.5 Complementary Evidence from Survey Responses

The reduced-form results presented above show that land sales rise following weather shocks and that many buyers are individuals who previously did not own land in the *departamento*. Before introducing the formal model that accounts for these patterns, we present complementary evidence from an original qualitative survey that we collected to validate our interpretation and provide insight into the characteristics of land buyers. The survey was conducted by telephone in September 2025 with 151 rural community leaders representing more than 7,000 farmers across 30 municipalities in 18 *departamentos*. It gathers information on local land market dynamics, communities' exposure to different types of shocks, and how

[23] The SPEI (Standardized Precipitation–Evapotranspiration Index) is a drought indicator based on the balance between precipitation and evapotranspiration, where evapotranspiration reflects the amount of water that returns to the atmosphere through soil evaporation and plant transpiration. The index is standardized so that unusually dry periods can be identified consistently across space and time. The SPEI is built using climate variables from the CRU TS 4.07 dataset, a global monthly gridded record produced by the Climatic Research Unit of the University of East Anglia (Harris et al., 2020). When using the continuous SPEI measure, we multiply negative values by −1 so that larger numbers correspond to more severe droughts, and in a separate specification we define a drought indicator equal to one when monthly SPEI falls below −2, a common threshold for extreme dry conditions.

these shocks affect land sales.

The main findings are reported in Table 5. The survey results corroborate that distress land sales are common in rural communities: roughly one third of respondents report that income-reducing shocks lead farmers to sell land, and 35% of those experiencing weather shocks also report distress sales. The results also show that although local incumbent farmers do purchase land after distress sales, outside buyers also play an important role. Among respondents who report land sales following an adverse shock, 35% of responses identify buyers as landholders from other municipalities, 19% as landless buyers from other municipalities, and 10% as landless buyers from within the municipality. These buyers are likely acquiring land in the smallest deciles of the distribution, as shown in Figure 3, thereby contributing to the lack of land consolidation after the shocks.

We find these qualitative patterns to be consistent with our reduced-form estimates and to provide further evidence against characterizing land markets as shallow, highly segmented, and active only in the upper tail of the farm-size distribution. Our findings suggest that land markets can draw participants from outside the local area or the agricultural sector, implying substantial spatial integration and mobility among buyers of small farms.

5 A Quantitative Model of Farm Size Dynamics

In this section, we develop a quantitative model of farm-size dynamics with three goals. First, we provide an economic rationale for the reduced-form effects of weather shocks on the farm-size distribution documented in Sections 2 and 4. Second, we use the model to recover the effects on agricultural productivity and the dynamic implications of the shock. Finally, we simulate the model to study how shifts in the underlying distribution of weather shocks—such as the projected temperature changes due to climate change—affect the farm-size distribution and agricultural productivity.

Our model, presented in Section 5.1, endogenously generates the farm-size distribution through agents' land acquisition decisions and their entry and exit from farming, which together determine the total number of farmers in equilibrium. Section 5.2 defines a stationary equilibrium in an economy with a fixed level of aggregate agricultural productivity—that is, an economy without aggregate weather shocks.

Section 5.3 describes how we simulate the evolution of a stochastic economy subject to a sequence of weather shocks, building on Boppart et al. (2018) and Auclert et al. (2021). We then describe the model's calibration in Section 5.4 and discuss the its fit Section 5.5. Finally, in Section 5.6 we study the quantitative implications of risk for agricultural productivity implied by the calibrated model, and in Section 6 we perform counterfactual the analyses.

Table 5: Survey Results on Land Sales and Income Shocks

Panel A: Land Sales and Shocks	**Frequency**
(1) Land sales occur in the community	68.20%
(2) Weather shocks impacted farmers' income in recent years	53.60%
Among respondents who report ocurrence of land sales:	
(3) Shocks of any type lead farmers to sell land	33.10%
Among respondents ocurrence of land sales and weather shocks:	
(4) Weather shocks lead farmers to sell land	35.80%
Panel B: Types of Land Buyers	
In normal times land is bought by:	
(5) Landholders from the municipality	41.38%
(6) Landholders from outside the municipality	29.66%
(7) Non-landholders from the municipality	12.41%
(8) Non-landholders from outside the municipality	16.55%
During distress sales land is bought by:	
(9) Landholders from the municipality	36.25%
(10) Landholders from outside the municipality	35.00%
(11) Non-landholders from the municipality	10.00%
(12) Non-landholders from outside the municipality	18.75%

Notes: This table presents results from the survey "Funcionamiento de los Mercados de Tierras Rurales en Colombia". Frequencies in Panel A correspond to the share of respondents answering "yes" to each question. Questions 1 and 2 were asked of all respondents. Question 3 was asked only of respondents who reported land sales in the community in previous years. Question 4 was asked only of respondents who reported both land sales and weather shocks affecting farmers' income. Frequencies in Panel B correspond to the distribution of selected response categories, as respondents could choose more than one option. The questions under *"In normal times"* (5 to 8) were asked of respondents who reported land sales in the community, whereas the questions under *"During distress sales"* (9 to 12) were asked only of respondents who reported that shocks (of any type) lead farmers to sell land.

5.1 The Model

The economy represents a municipality that operates in discrete time, indexed by t. Each period corresponds to one year and includes a single harvest season. The economy is endowed with a fixed supply of land L and a mass of heterogeneous agents N. There are two sectors: agriculture (a) and non-agriculture (n). Aggregate productivity in agriculture is denoted by Z_t^a, which will later be subject to weather shocks in our simulations. Wages in the non-agricultural sector, w_t, are exogenously given.

Agents. Agents live forever and their preferences are described by their long-life utility $U(c) = \mathbb{E}\left[\sum_0^\infty \beta^t u(c_t)\right]$, where c_t is consumption and $u\left(c_t\right)$ is their utility function. They are heterogeneous in their land ownership, ℓ_t, their idiosyncratic agricultural productivity, s_t^a, and their idiosyncratic non-agriculture productivity, s_t^n. We characterize each agent by a triple $\phi_t = (s_t^a, s_t^n, \ell_t)$. Agents with positive land holding ($\ell_t > 0$) are referred to as farmers and earn farm income at the end of each season, while those without land ($\ell_t = 0$), are workers whose income comes from wages in the non-agricultural sector.

In each period, agents face an exogenous discontinuation shock: with probability δ, they are forced to sell all the land they own and transition to work in the non-agricultural sector in period $t+1$. If they are not hit by this shock, they make occupational and land-purchasing decisions in two stages. In the first stage, agents choose whether to be a farmer or a worker in period $t+1$—a *discrete choice* between $\ell_{t+1} > 0$ and $\ell_{t+1} = 0$. This decision depends on the value of becoming a farmer, $V^a(\phi_t)$, or a worker ,$V^n(\phi_t)$, in $t+1$ given ϕ_t, plus idiosyncratic preference shocks for each occupation, ν_t^a and ν_t^n. In the second stage, conditional on choosing to farm, agents decide how much land to acquire ahead of the harvest season in $t+1$—a *continuous choice* over $\ell_{t+1} > 0$. At this point, they choose consumption and land purchases to maximize current utility, $u(c_t)$, plus the expected value of owning ℓ_{t+1} in $t+1$, and entering the next period with state ϕ_{t+1}, $V(\phi_{t+1})$, subject to their budget constraints.

Production. Agents with land earn income from farming, while those without land earn income from working in the non-agricultural sector. The earnings function is given by:

$$\pi(\phi_t) = \begin{cases} Z_t^a \left(s_t^a\right)^{1-\gamma} \left(\ell_t\right)^{\gamma} & \text{if } \ell_t > 0 \\ w_t^n s_t^n & \text{if } \ell_t = 0 \end{cases} \tag{8}$$

where γ is the share of land in production.[24]

Distributional Assumptions. For agents who own land ($\ell_t > 0$), agricultural productivity s_t^a follows a AR(1) stochastic process, $\log s_t^a = \rho \log s_{t-1}^a + \sigma^a \epsilon_t^a$, where $\epsilon_t^a \sim \mathcal{N}(0,1)$ is an innovation shock, $\rho \in (0,1)$ is a persistence parameter, and $\sigma^a > 0$ is the volatility of ϵ_t^a. We denote by $g^a\left(s_{t+1}^a | s_t^a\right)$ the transition probability that results from this stochastic process. Agents without land ($\ell_t = 0$) draw their idiosyncratic agricultural productivity from the stationary distribution of s_t^a, denoted by $\tilde{g}^a(s_t^a)$. Every agent also draws a non-agriculture skill from the distribution $\tilde{g}^n(s_t^n)$. Finally, preference shocks for each sector, ν_t^a and ν_t^n, are drawn independently from an extreme value type I distribution (EVT1) with dispersion parameter κ and mean normalized to zero.

Timing. The sequence of events within each period t unfolds as follows. First, agents observe their productivities, s_t^a and s_t^n, their preference shocks, ν_t^a and ν_t^n, and a fraction δ of them are hit by the discontinuation shock. Second, conditional on these realizations,

[24]We adopt this formulation for simplicity and parsimony. Appendix OC, shows how variable labor and capital can be incorporated, without affecting our main results.

agents choose their occupation for the next period $t+1$. Third, agents earn income, consume, and buy or sell land. Finally, they transition to period $t+1$.

Optimal Choices. Agents' optimization problem can be written in recursive form. At the start of each period, they choose their occupation based on the value function:

$$V(\phi_t) = (1-\delta)\max\{V^a(\phi_t) + \nu_t^a, V^n(\phi_t) + \nu_t^n\} + \delta V^n(\phi_t) \tag{9}$$

where the value of choosing to be a farmer is

$$\begin{aligned} V^a(\phi_t) &= \max_{c_t,\,\ell_{t+1}>0} \{u(c_t) + \beta\,\mathbb{E}\left[V(\phi_{t+1}) \mid \phi_t\right]\} \\ \text{s.t.} \quad & c_t = \pi(\phi_t) + p_t(\ell_t - \ell_{t+1}) \end{aligned} \tag{10}$$

and the value of becoming a worker is

$$\begin{aligned} V^n(\phi_t) &= u(c_t) + \beta\, V_0(\phi_t) \\ \text{s.t.} \quad & c_t = \pi(\phi_t) + p_t\,\ell_t \end{aligned} \tag{11}$$

We denote by $\ell^*(\phi_t)$ the optimal land purchase choice for ℓ_{t+1}. The term $V_0(\phi_t)$ is the exogenous value of becoming a worker, defined as $V_0(\phi_t) = V_0^a$ if $\ell_t > 0$ and $V_0(\phi_t) = V_0^n$ if $\ell_t = 0$.[25] Our interpretation is that, once an agent chooses not to farm, she accesses an outside option that is not affected by local weather shocks—such as the local urban center or employment in another municipality. She may even become a farmer in another rural area, but for simplicity we refer to all such outside options as non-agricultural work throughout this section.[26]

Evolution of distributions. Let $g(\phi_t)$ denote the density of agents of type ϕ_t at time t. We now describe how this density evolves into $g(\phi_{t+1})$. In period t, the mass of agents of type ϕ_t who choose to become farmers in period $t+1$ is

$$h^a(\phi_t) = \mu_t(\phi_t)\, g(\phi_t) \tag{12}$$

[25]This formulation captures, in a parsimonious way, the possibility that farmers and workers perceive different values of entering non-agriculture, for example due to sectoral relocation costs.

[26]We also assume that the probability of returning to local agricultural after exiting is sufficiently low, ensuring that the value of the outside option is not influenced by changes in the local value of becoming a farmer.

where $\mu_t(\phi_t)$ is the probability that an agents of type ϕ_t becomes a farmer in $t+1$. Conversely, the mass of agents who become a worker in $t+1$ is

$$h^n(\phi_t) = [1 - \mu_t(\phi_t)]g(\phi_t). \tag{13}$$

Given the properties of the EVT1 distribution and the discontinuation probability δ, the probability that an agent of type ϕ_t becomes a farmer in period $t+1$ can be written as

$$\mu_t(\phi_t) = (1-\delta)\frac{\exp(\kappa V^a(\phi_t))}{\exp(\kappa V^a(\phi_t)) + \exp(\kappa V^n(\phi_t))} \tag{14}$$

Using equation (12), the density of agents who become farmers in period $t+1$ is

$$g(\phi_{t+1}|\ell_{t+1} > 0) = \int_{\phi_t} \mathbf{1}[\ell_{t+1} = \ell^*(\phi_t)]\, g\left(s^a_{t+1}|s^a_t\right)\tilde{g}^n\left(s^n_{t+1}\right)h^a(\phi_t)\,d\phi_t, \tag{15}$$

where $\mathbf{1}[\ell_{t+1} = \ell^*(\phi_t)]$ equals 1 when $\ell_{t+1} = \ell^*(\phi_t)$ and 0 otherwise. Similarly, using equation (13), the density of agents who become workers in period $t+1$ is

$$g(\phi_{t+1}|\ell_{t+1} = 0) = \int_{\phi_t} \tilde{g}^a\left(s^a_{t+1}\right)\tilde{g}^n\left(s^n_{t+1}\right)h^n(\phi_t)\,d\phi_t. \tag{16}$$

Resource Constraints and Market Clearing. To define the equilibrium, we specify the resource constraints. First, the land market must clear in every period t: aggregate land supply L must equal aggregate land demand,

$$L = \int \ell^*(\phi_t)\,h^a(\phi_t)\,d\phi_t. \tag{17}$$

Second, occupational choices must be consistent with the evolution of the population measure. The total mass of agents N is conserved across periods,

$$N = \int_{\phi_t} [h^a(\phi_t) + h^n(\phi_t)]\,d\phi_t, \tag{18}$$

which simply restates the conservation of agents implied by the law of motion for $g(\phi_t)$.

5.2 Stationary Equilibrium

Given distributions $\{g^a, \tilde{g}^a, \tilde{g}^n\}$, a mass of agents $\{N\}$, a land endowment $\{L\}$, a production parameter $\{\gamma\}$, a discontinuation probability $\{\delta\}$, a dispersion parameter for preference shocks $\{\kappa\}$, aggregate agricultural productivity $\{Z^a\}$, and a non-agricultural wage $\{w^n\}$, a stationary competitive equilibrium consists of optimal land and consumption choices $\{\ell^*(\phi), c^*(\phi)\}$, a land price $\{p^*\}$, and an invariant distribution $\{g^*(\phi)\}$ such that: land and consumption choices are optimal and satisfy (9) to (11); optional occupational choices and the discontinuation probability satisfy (14); the stationary distribution is consistent with (12), (13), (15) and (16); and the resource constraints in (17) and (18) hold.

5.3 Stochastic Economy

We now characterize the evolution of an economy subject to a sequence of weather shocks, following the approach of Boppart et al. (2018) and Auclert et al. (2021). To this end, we first parametrize how weather shocks ω_t influence aggregate agricultural productivity:

$$Z^a(\omega_t) = \bar{Z}\frac{2}{1+\exp(\xi\omega_t)}. \tag{19}$$

Here, ξ governs the sensitivity of agricultural productivity to weather shocks, and $\bar{Z}$ is a scale parameter. We assume that ω_t follows an autoregressive AR(1) stochastic process, $\omega_t = \rho^\omega \omega_{t-1} + \sigma^\omega e_t^\omega$, where e_t^ω is distributed normal $\mathcal{N}(0, 1)$. This specification implies that ω_t has mean zero. Note also that our parametric form implies $Z^a(\omega_t = 0) = \bar{Z}$. For simplicity, we assume that the non-agriculture sector is not affected by weather shocks, so the wage w_t^n remains fixed. This assumption is consistent with evidence showing that agriculture is more sensitive to climate variation than non-agricultural sectors—see, for example, Nath (2025).

To simulate the evolution of an endogenous variable y_t in an economy exposed to a sequence of weather shocks, we compute

$$dy_t = \sum_s \widehat{dy}_s \, \omega_{t-s}, \tag{20}$$

where dy_t denotes the change in y_t, $\widehat{dy}_s$ is the model-implied response of y_t in period s to a one-time (MIT) at time 0, and ω_{t-s} is the realized weather shock in period $t-s$.[27] The change in y_t at time t is thus obtained by summing the effects of all past shocks, each weighted by the corresponding dynamic response of the economy estimated from the MIT experiment. In other words, dy_t reflects the accumulated effects of the entire history of shocks, with each shock contributing according to the strength of the economy's response s periods after it

[27] We compute the fully non-linear impulse-response to a one-standard deviation shock in ω_t using the sequence-space Jacobian method developed in Auclert et al. (2021). The impulse response function relies on certainty equivalence: agents behave as if uncertain future aggregate variables were equal to their expected values and therefore do not internalize higher moments of the aggregate shock, such as its variance. See Reiter (2018) for a discussion of the advantages and limitations of this approach relative to alternative computational methods. Appendix OC provides further details on the implementation.

occurs. For example, the total change in the number of farms in period T combines the one-period response to the shock in $T-1$, the two-period response to the shock in $T-2$, and so forth.

5.4 Calibration

To simulate the model, we need to assign values to the following parameters: $\{\beta,\ \kappa,\ V_0^a,\ V_0^n,\ N,\ L, \gamma,\ \rho,\ \sigma,\ w^n, \mu^n,\ \sigma^n,\ \delta,\ \bar{Z}^a, \xi,\ \rho^\omega,\ \sigma^\omega\}$. Table 6 summarizes the parameter values used in our simulations. Appendix OD.3 provides additional details on the calibration.

We start by setting the values of a few parameters without solving the model. For preferences, we choose a discount factor of $\beta = 0.96$, following Greenwood et al. (2019), who estimate this parameter in a developing-country context, and we assume log utility. For the production function, we set the share of land to $\gamma = 0.28$, consistent with the estimates of Avila and Evenson (2010) for Colombia. We estimate the persistence of idiosyncratic agricultural productivity, ρ, using farm-level longitudinal data from Colombia (the same data we use in Section 4.2), by computing the autocorrelation of model-implied measures of farm productivity over three years. The weather-shock parameters ρ^ω and σ^ω— the persistence of weather shocks and the variance of their innovations—are estimated directly from our weather-shock data. We set $\delta = 0.02$, based on the exit rate of large farms with properties above the 90 percentile (approximately 8 hectares). Finally, without loss of generality, we normalize $\bar{Z} = 1$, the land endowment to $L^S = 1$, and the wage to $w_t^n = 1$.

For the remaining parameters $\{\kappa,\ V_0^a,\ V_0^n,\ N,\ \sigma, \mu^n,\ \sigma^n\}$, we search for the values that make several model-generated statistics related to the farm-size distribution and the farmer's exit probabilities match their counterparts in the data. First, we adjust κ to match the exit probability of medium sized farms (between 0.1 and 8 hectares) and V_0^a to match the exit probability of very small farms (smaller than 0.1 hectares).[28] Second, we calibrate the total mass of agents, N, to match the average farm size, and we choose the variance of the innovation to idiosyncratic agricultural productivity, σ, to match the variance of farm size in the Colombian agricultural census. We calibrate μ^n to match the average size of new farms, and set σ^n directly from the coefficient of variation of workers income. Finally, we calibrate V_0^n to match the average rural share of the population across *departamentos* in Colombia, which equals 0.37.

After calibrating in its stationary equilibrium, we choose the value of ξ that makes the simulated evolution of the stochastic economy reproduce the reduced-form regression results

[28] We select δ to match the exit rate of very large farms, and κ governs how strongly farmers respond to incentives to exit. When κ is small, the relationship between exit rates and farm-size becomes very steep on the left side, causing the model to understate exit among middle sized farms. See Panel (b) of Figure 4.

Table 6: Summary of Calibration

Parameter	Description	Target/Source	Value
Panel (a): Preferences			
β	Discount rate	Greenwood et al. (2019)	0.96
κ	Dispersion of preference shocks	Exit of medium farms	8.5
V_0^a	Outside option for farmers	Exit of small farms	-97
V_0^n	Outside option for workers	Share of farmers	-12
Panel (b): Technology and Endowments			
N	Total mass of agents	Avg. farm size	0.54
L	Total land supply	Normalized	1
γ	Share of land / Span-of-control	Avila and Evenson (2010)	0.28
Panel (c): Idiosyncratic shocks			
ρ	AR(1) coefficient of s_t^a	Estimated from farm-level data	0.75
σ	Variance of shock to s_t^a	Variance of farm-size distribution	2.6
w_t	Wages	Normalization	1
μ^n	Average of draws of s_t^n	Average farm-size of entrants	0.51
σ^n	Variance of draws of s_t^n	Income dispersion of workers	0.53
δ	Exogenous exit probability	Exit rate of large farms	0.02
Panel (d): Aggregate Productivity			
$\bar{Z}$	Agricultural TFP shifter	Normalized	2
ξ	Impact of ω_t on TFP	Reduced-form impact on consumption	0.61
ρ^ω	AR(1) coefficient of ω_t	Estimated from temperature shocks	0.41
σ^ω	Standard error of shock to ω_t	Estimated from temperature shocks	0.2

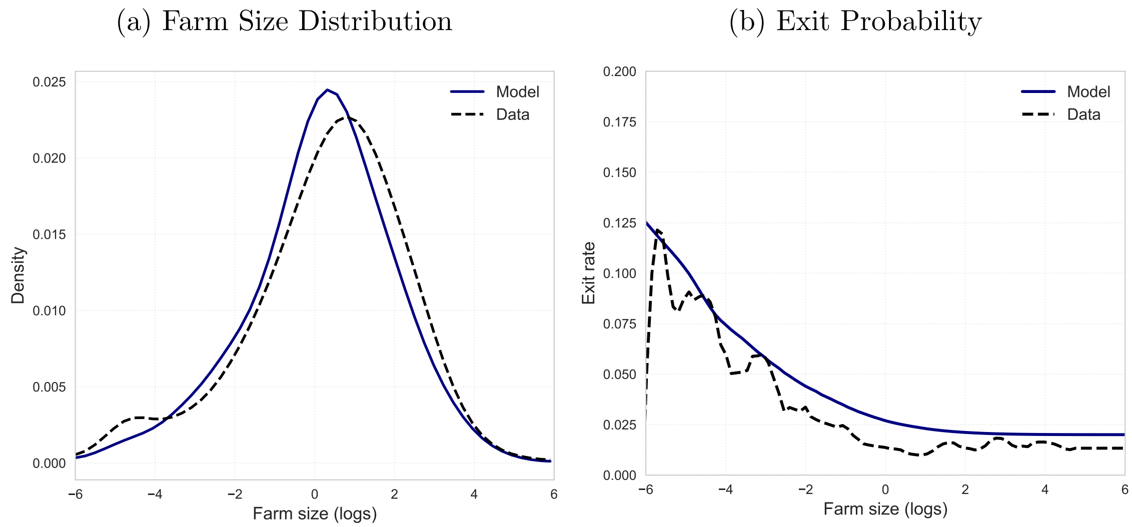
of log of consumption on weather shocks estimated in the data. Specifically, we target a value of -0.11, reported in column (5) of Table 3.

5.5 Fit of the Model

Focusing on the stationary equilibrium, Panel (a) of Figure 4 shows that the model generates a farm-size distribution that closely tracks the empirical one. The model-implied distribution is slightly shifted to the left, as it cannot fully reproduce the high density of very small farmers observed in the left tail of the data. Panel (b) shows that the model also matches farmer's exit rates across different parts of the farm-size distribution.

Turning to the stochastic economy, Figure 5 reports the reduced-form effects of weather shocks on key variables of interest. The first two bars show that, given our calibration of ξ, the model exactly replicates the observed decline in consumption in the data. Reassuringly, beyond this targeted moment, the model also reproduces several key patterns consistent with the mechanisms emphasized in our analysis. In particular, it broadly matches the observed changes in average farm-size and captures the fact that most of this adjustment is driven by smaller farmers (those below the median).

Figure 4: Farm Size Distribution and Exit Rate of Farmers (Model vs. Data)



Notes: This figure shows the farm-size distribution generated by the model and the distribution observed in the data. It also reports the exit rate by farm size in the model and in the data. Appendix OD explains how we estimate annualized exit rates across the farm-size distribution in the data.

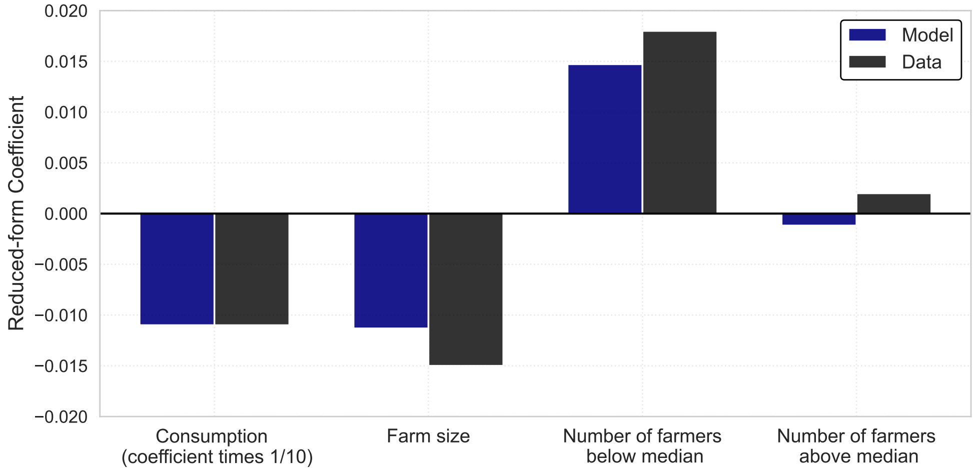
In brief, our model can quantitatively reproduces key features of the dynamics of the farm-size distribution observed in the data. First, it matches both the empirical farm-size distribution and the exit rates across farms of different sizes. Second, it captures how consumption and the farm-size distribution respond to weather shocks. Given the model's ability to replicate these patterns, we next use it to simulate alternative shocks to better understand the underlying mechanisms and to assess the effects of changes in the distribution of weather shocks, ω_t.

5.6 Risk and Agricultural Productivity

Before turning to our counterfactual simulations, we examine how uninsured risk contributes to land misallocation. In an efficient economy, the marginal product of land would be equalized across farmers. In our model, however, two forces prevent this equalization. First, farmers choose how much land to purchase before observing their realized farm productivity, s_t^a. This timing friction creates a mismatch between the period of land choice and the period in which productivity is realized—a constraint that a central planner allocating land prior to the realization of idiosyncratic shocks would face. Second, because farmers rely on land sales to smooth consumption, exposure to risk distorts their land holdings. A central planner able to fully insure farmers would eliminate this channel and the associated misallocation.

In an efficient economy, the marginal product of land would be equalized across farmers,

Figure 5: Reduced-form Impact of Weather Shocks (Model vs. Data)



Notes: This figure shows the impact of weather shocks in the Colombian data and the impact generated by simulating the stochastic economy in the model. We divide the consumption coefficient by 10 for ease of visualization. Our calibration sets ξ to match the reduced-form effect of weather shocks on consumption estimated from the Colombian longitudinal data. The remaining coefficients are not directly targeted in the calibration.

and farm size would be proportional to farm productivity, s_t^a.[29] Appendix Figure O.10 (a) compares the optimal and actual farm-size distributions. The optimal distribution is substantially more dispersed, with a larger mass of both small and very large farms and a correspondingly smaller share of medium-sized farms. In our model, small farms are larger than under the efficient allocation because they accumulate land for precautionary motives. Larger farmers, by contrast, operate less land than optimal because the higher precautionary demand for land among smaller farmers crowds them out. Quantitatively, the standard deviation of the actual farm-size distribution is about 20 percent lower than that of the optimal distribution. Panel (b) shows that more productive farmers have a higher marginal product of land in equilibrium; thus, the efficient allocation would reallocate land away from less productive toward more productive farmers. Under our baseline calibration, implementing the efficient allocation would increase aggregate output by 42 percent.

6 Counterfactual Analysis of Weather Shocks

With the model calibrated, we conduct two counterfactual exercises. First, we examine the economy's response to a single weather shock by evaluating the impulse-response functions.

[29] Specifically, the amount of land operated by a farmer with productivity s_t^a would be $\ell(s_t^a) = \frac{s_t^a}{\int s_t^a dG(\phi_t)} L$.

This exercise serves two purposes. The first is to clarify the economic mechanisms that can rationalize the reduced-form results presented in Sections 2 and 6. The second is to study the dynamic implications of weather shocks and assess how persistent their effects are over time. Second, we study the economy's response to different sequences of weather shocks, drawing on our definition of a stochastic economy in Section 5.3. In this exercise, we consider alternative shock distributions that feature a higher probability of extreme temperatures, as expected under climate change. We then examine how these changes in the distribution of weather shocks affect the farm-size distribution and aggregate agricultural productivity.

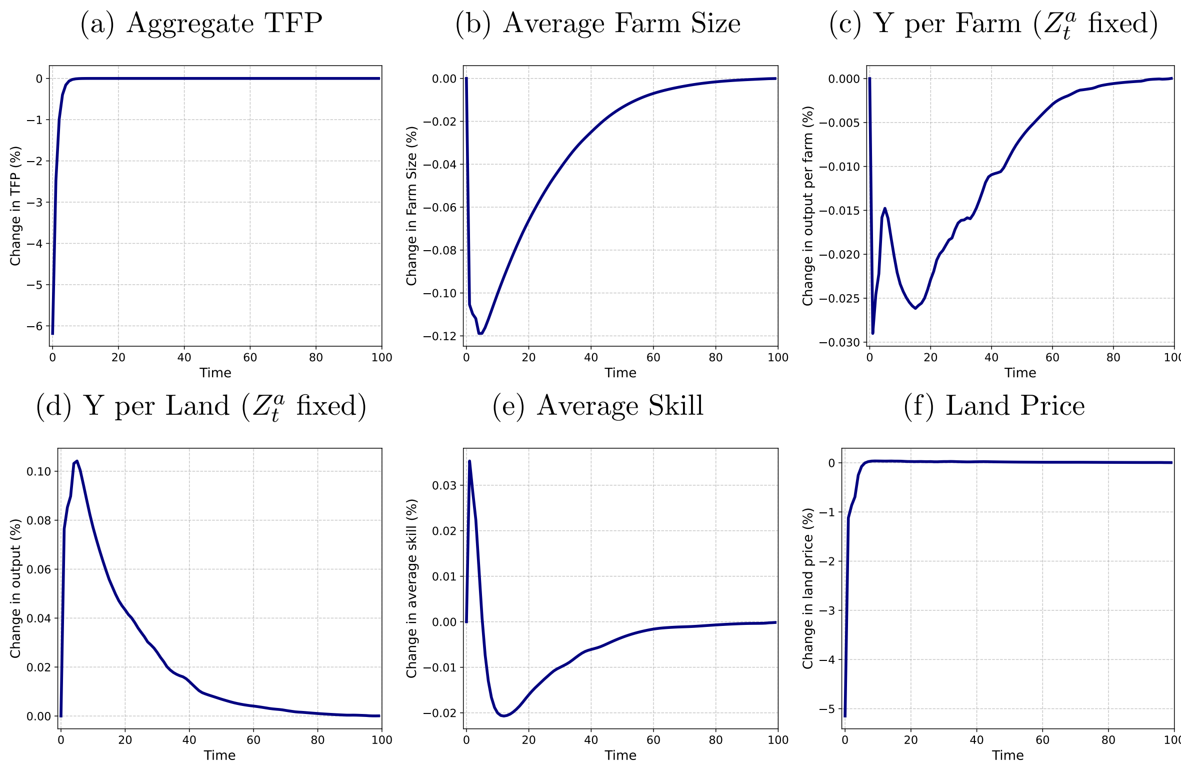
6.1 Weather Shocks and Transition Dynamics

We simulate an economy that experiences a temporary, unexpected shock that increases the weather-shock variable ω_t by one standard-deviation, with an autocorrelation of 0.4—consistent with our estimates from the data. As shown in Panel (a) of Figure 6, this shock generates a large drop in agricultural TFP of about 6 percent at $t = 0$. The impact on TFP is short-lived, however: productivity returns to its average level fewer than ten years.

Effects on farm size and agricultural productivity. In the aftermath of the shock, the average farm size declines by about 0.12 percent, as shown in Panel (a) of Figure 6. This contraction is driven by the entry of new, smaller farmers into agriculture. Although aggregate TFP recovers within a few years, the adjustment in farm size is much slower: even twenty years after the shock, the average farm size remains roughly 0.06 percent below its pre-shock level. The increase in the number of farms leads to a decline in output per farm, above and beyond the direct negative effect of the weather shock on aggregate TFP. Panel (c) of Figure 6 illustrates this by showing the reduction in agricultural output per farm net of TFP changes—that is, isolating the economy's endogenous response. Output per farm falls by about 0.02 percent, and, once again, the recovery is slow.

Panel (d) shows that, despite the decline in output per farm, output per unit of land actually rises once we abstract from the TFP shock. This pattern reflects the entry of additional farmers into agriculture, which raises the marginal product of land while lowering the marginal product of labor. The result is consistent with the common finding that regions with a high concentration of small farms exhibit higher land yields but lower output per worker. Panel (e) shows that, after the initial exit of small and low-productivity farms, the continued inflow of new low-skill entrants reduces average agricultural skill. This occurs because entrants draw their skills randomly from the stationary distribution, whereas incumbent farmers in the stationary equilibrium self-select into agriculture based on their

Figure 6: Transition Dynamics in response to a Weather Shock



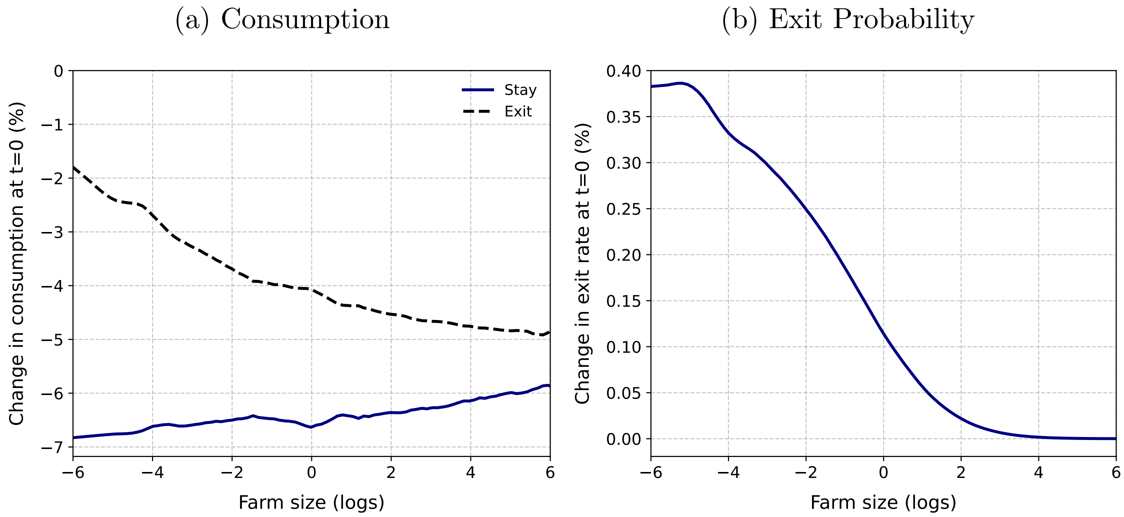
Notes: This figure shows the impulse-response functions of the economy following a one-standard deviation increase in weather shocks. Panel (a) shows the impact on the aggregate TFP term, Z_t^a. Panel (b) shows the transition dynamics of average farm size, Panel (c) the agricultural output per farm, Panel (d) the agricultural output per unit of land, Panel (e) the average skill of farmers at the start of the period, and Panel (f) the land price.

comparative advantage. As a result, incumbents are positively selected on skill, which raises average productivity, while the entry of new farmers weakens this selection process.

Effects on land prices, consumption, and exit rate. Panel (f) of Figure 6 shows that land prices fall by about 25 percent at $t = 0$ when agents are hit by the shock. This decline occurs because the negative shock leads small farmers to sell land in order to smooth consumption—see Panel (a) of Figure 7. Larger farmers, by contrast, adjust their landholdings only minimally. At higher consumption levels, the marginal utility loss from a negative shock is smaller under concave utility, reducing their incentive to liquidate productive assets. In this sense, wealthier farmers are partially self-insured against shocks.

The change in consumption shown in Panel (a) of Figure 7 highlights the trade-off farmers face when confronted with the shock. Among smaller farms, those who remain in agriculture experience a sharp decline in consumption—between 6 and 7 percent. This reduction is particularly severe given their lower baseline utility, which implies a higher marginal utility of consumption. In contrast, small farmers who choose to sell all their assets and exit agriculture

Figure 7: Exit Rate and Consumption Responses by Farm Size at $t = 0$



Notes: Panel (a) shows the consumption response to the shock for farmers who choose to exit (dashed black line) and for those who remain in agriculture (blue line) at $t = 0$. Panel (b) shows the change in the exit rate at $t = 0$ in response to the shock when farmers learn about it.

face a more modest decline in consumption of about 2–4 percent. The consumption response among larger farms is much smaller. Consequently, the exit probability—shown in Panel (b)—is substantially higher for smaller farms.

Appendix OE provides analytical results showing that higher income dampens the effect of shocks on exit decisions. Two mechanisms drive agents' choices after the shock. First, there is an income effect that operates for agents with positive landholdings: agricultural revenues fall, and this income loss is amplified for smaller farmers due to their lower consumption levels. This mechanism applies only to those who hold land. Second, there is a land-price effect. Lower land prices increase the incentive to remain in agriculture, and unlike the income effect, this mechanism also influences the entry decisions of landless households. We return to these mechanisms below to examine how shock persistence shapes their relative importance.

The role of persistence. Our results indicate that when land prices fall, landless agents become more likely to enter agriculture and buy land. The strength of this response depends on how much land prices decline relative to the value of becoming a farmer. When productivity falls, some farmers sell part of their landholdings and others exit agriculture altogether, putting downward pressure on land prices. For landless households, however, the value of becoming a farmer is only mildly affected, because agricultural productivity returns to its steady-state level shortly after the shock. As a consequence, this reduction land prices—without an equivalent decline in the present value of becoming a farmer— attracts landless agents into agriculture. In contrast, when we simulate a more persistent shock, one with a high autocorrelation, we find a net outflow of farmers and an increase in average farm size. In this case, the decline in land prices is not sufficient to attract households out of non-agricultural activities. Figure 8 illustrates this pattern by comparing the effects of the same shock on farm size under different assumptions about the autocorrelation of the productivity shock.

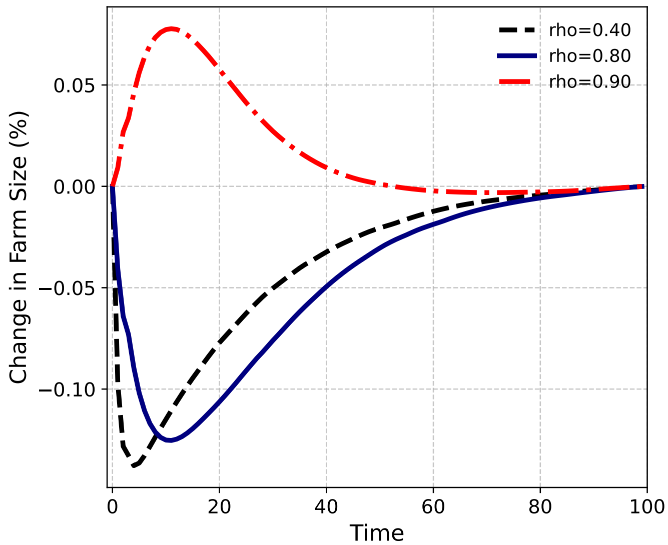
To clarify the underlying mechanisms, it is useful to separate the influence of a decline in the land price p_t from the effect of a decline in aggregate productivity Z_t. Appendix OE provides the analytical results that guide our discussion. We begin by considering a short-term reduction in aggregate productivity Z_t, abstracting from general equilibrium effects on the future value of becoming a farmer versus a worker and on the current land price p_t. In that case, the incentives to remain in agriculture shift in a clear direction: current consumption falls, which widens the utility gap between staying and exiting. With concave utility, a reduction in consumption raises marginal utility, making the consumption smoothing achieved by selling land more valuable. Intuitively, agents move closer to subsistence levels of consumption, so the additional consumption they can finance by selling land becomes more attractive.

When we instead consider a reduction in the land price p_t, abstracting from changes in aggregate productivity Z_t or in the future value of farming and working, the effect on the probability of becoming a farmer becomes ambiguous. On the one hand, agents who already own land become poorer: the value of their asset falls, reducing the amount of consumption they can finance by selling land. As with the decline in Z_t, this operates through decreasing marginal utility—lower consumption raises marginal utility, making the option of exiting more attractive. On the other hand, because land becomes cheaper, agent's purchasing power rises, increasing their incentive to become farmers. Importantly, workers are affected only through this second channel, since they do not own land. Thus, holding everything else constant, a reduction land prices, will unambiguously increase the probability that landless agents enter agriculture.

6.2 Climate Change and Agricultural Productivity

To close our analysis, we simulate a stochastic economy under alternative distributions of weather shocks. We begin by modeling the stochastic process that generates weather shocks in the data. Specifically, we divide each year into 365 days and assume that number atypical days in a year is the outcome of a sequence of Bernoulli trials, where each day is atypical with

Figure 8: Farm Size response to Shocks with Different Persistence Structure



Notes: This figure shows the farm-size response to a one-time, one-standard increase in weather shock w_t at $t = 0$ under different persistence assumptions. We consider three shocks, with autocorrelations of 0.4, 0.8 and, 0.9, as indicated in the figure.

probability 0.4. To match the autocorrelation observed in the data, we allow these Bernoulli trials to be correlated over time, following a Markov process in which the economy transitions between typical and atypical days. We calibrate the persistence of this stochastic process so that the standard deviation of the annual sum of atypical days matches the standard deviation of the weather-shock series in the data. [30] This gives us a sequence of weather shocks that we use as our baseline scenario.

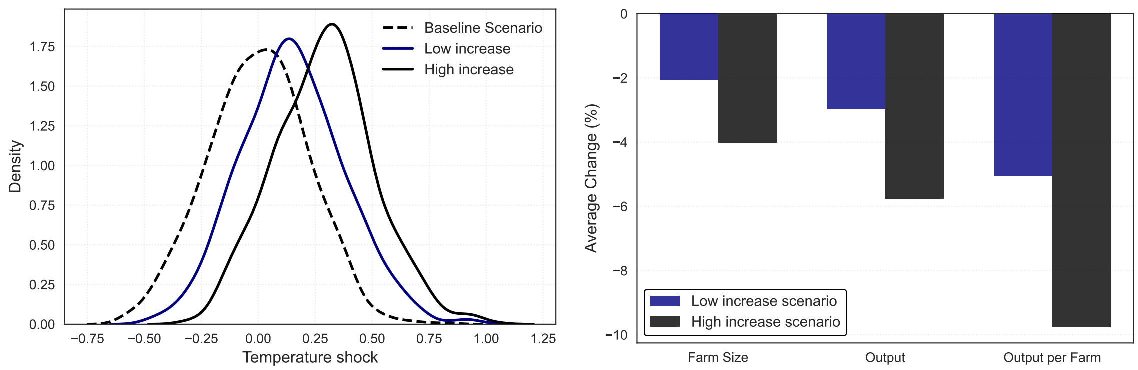
To produce alternative scenarios consistent with climate change, we increase the probability of an atypical day in the underlying stochastic process from 0.4 to 0.42 in the "low increase" scenario and to 0.44 in the "high increase" scenario. The resulting distributions are shown in Panel (a) of Figure 9. Relative to the baseline, the mean of the weather-shock series increases by 0.2 standard-deviation points in the low-increase scenario and by 0.35 standard-deviations points in the high-increase scenario.

Panel (b) of Figure 9 presents the effects of climate change on agricultural output and average farm size. For each scenario, we simulate the full sequence of the economy and compute changes in the variables using equation (20). In the low-increase scenario, agricultural output declines by about 3 percent. Because average farm size also falls—by roughly 2

[30] If atypical days were uncorrelated, we would simply have a sum of Bernoulli trials, which approximates a normal distribution with mean $n \times p$ and variance $n \times p \times (1 - p)$, where n is the number of trials and p is the probability of success. In the data, however, the empirical distribution of weather shocks exhibits a larger variance because atypical days are correlated over time.

Figure 9: Response to a Change in the Distribution of Weather Shocks

(a) Change in Weather Shock Distribution (b) Change in Selected Variables



Notes: Panel (a) shows the distributions of weather-shock sequences generated under alternative probabilities of having an atypical day within a year. The "Low increase" scenario raises this probability from 0.4 to 0.42, and the "High increase" scenario raises it from 0.4 to 0.44. Panel (b) shows the resulting impacts of these different sequences on farm size, output and ouptut per farm.

percent—the reduction in output per farm is amplified to around 5.5 percent. These effects are quantitatively large.

To put them in perspective, the implied elasticity of output per worker with respect to the probability of an atypical weather day is approximately 1.1 percent ($5.5/5 \approx 1.1$). Under the more severe scenario, in which the probability of atypical days rises by 10 percent, the decline in output per worker approaches 10 percent. Taken together, these results indicate that even modest shifts in the distribution of weather shocks can generate substantial aggregate productivity losses in agriculture through the mechanisms highlighted in this paper.

7 Conclusion

This paper brings a dynamic perspective to the analysis of the farm-size distribution in developing countries. Using a collection of datasets from a wide range of countries, we first document substantial movements in the land operated by farmers over time and in exit probabilities across the farm-size distribution—patterns that resemble those observed in the firm-size distribution in manufacturing. We also show that adverse weather shocks reduce farmers' survival probabilities but, in stark contrast, sharply increase the share of landless households that begin to operate a positive amount of land.

To investigate the mechanisms behind these dynamics, we draw on several datasets from Colombia, including administrative records of land transactions and a census of farm plots. We find that weather shocks substantially intensify land-market activity and increase the number of farmers in a region, thereby reducing average farm size and generating a pronounced rise in the number of small farms. We use survey data to further explore the mechanisms driving these changes in land transactions and farm size. On the supply side, we provide household-level evidence consistent with land sales being used to smooth consumption. On the demand side, a survey with community leaders indicates that buyers include not only incumbent local landowners but also landowners from other regions and landless individuals both from within and outside the municipality, all of whom contribute to land fragmentation.

To interpret these findings and quantify the dynamic effects of weather shocks, we develop a heterogeneous-agent dynamic model in which households choose both their occupation and the amount of land to operate. The model endogenously generates a farm-size distribution along with patterns of entry and exit, and we discipline it using data from Colombia and our reduced-form estimates. The model provides a natural explanation for the empirical results: because the shocks are short-lived, small farmers liquidate assets to smooth consumption, yet the value of becoming a farmer in the future remains largely unchanged. Consequently, the option to enter farming becomes cheaper for non-farm households. In contrast, when we simulate more persistent shocks, average farm size increases due to a net exit of agents from agriculture. Additional simulations show that weather shocks generate sizable productivity losses: increasing the frequency of atypical temperature days by just 5 percent reduces aggregate agricultural output by about 3 percent and output per worker by roughly 5 percent.

More broadly, our results point to a new mechanism contributing to low agricultural productivity in developing countries—one linked to uninsured risks and the use of land as a consumption-smoothing device. The dynamics of the farm-size distribution that we identify are consistent with key empirical facts documented by the literature: for example, low output per worker but high output per unit of land in regions dominated by smallholders, and substantial misallocation, reflected in large dispersion in the marginal product of land across farms.

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Online Appendices for "Farm Size Distribution, Weather Shocks, and Agricultural Productivity"

(Not for Publication)

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OA Data

This section describes in detail all the data sources we use. Appendix Table O.2 provides summary statistics for our main datasets.

OA.1 Household Surveys Data

Household survey data for Colombia comes from ELCA, the *Encuesta Longitudinal Colombiana de la Universidad de los Andes*, a longitudinal household survey with three waves (2010, 2013, and 2016), collected by Universidad de Los Andes. The survey is nationally representative for urban areas and representative at the rural level for four agroecological regions. For the estimations in Section 2, we use the 2010 and 2013 rounds, for comparability with other countries. For the rest of the analysis, we include all survey rounds.

Data for Mexico comes from ENNVIH, the *Encuesta Nacional sobre Niveles de Vida de los Hogares* (also known as MxFLS), a nationally representative longitudinal survey conducted in three waves: 2002, 2005, and 2010. We use the 2005 and 2010 rounds in our analyisis. For Peru, we use ENAHO, the *Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza*, a continuous, nationally representative household survey conducted annually since 2007. Its rotating panel structure allows households to be tracked over multiple years. While ENAHO interviews panel households every year, for comparability with other surveys we select households that were interviewed three years apart (i.e., at least four consecutive years) between 2007 and 2023.

Finally, the EHCVM (*Enquête Harmonisée sur le Conditions de Vie des Ménages*) are nationally representative household surveys with two rounds of data (2017-2018 and 2021-2022) for Benin, Burkina Faso, Côte D'Ivoire, Guinea Bissau, Mali, Niger, Senegal, and Togo.

OA.2 Land Transaction Data

Recipients of land in Colombia must register their property with the local public notary, and all formal land transactions involving the estate—including mortgages—must be recorded in the national land registry maintained by the *Superintendencia de Notariado y Registro* (SNR, National Superintendence of Notaries)—the government agency that regulates and oversees Colombia's notarial and public-registry system. Our land-transaction dataset contains the complete transaction history of all land plots granted by the government to private individuals between 1900 and 2010. We match the location of the property in the SNR records to the official list of Colombian municipalities provided by DANE, Colombia's National Statistical Agency.[31] Using this information, we construct a balanced annual panel at the municipality level with data on the number of full and

[31] Municipalities are the smallest official administrative division, of which there are 1,123 in total.

partial land sales, mortgages, and government land allocations.

The Colombian government has carried out the free allocation of public idle lands (*baldíos*) to private individuals continuously since the beginning of the twentieth century. These 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. In practice, this allocation process consisted largely two types of programs: frontier-settlement schemes, through which unused public lands are granted to poor smallholders, and initiatives focused on titling state-owned lands that had previously been occupied informally (Ibáñez and Muñoz, 2010).

The bulk of government-owned land allocations began during the period of the U.S. Alliance for Progress with the enactment of the Social Agrarian Reform Act (Law 135) in 1961, which created 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 consistently remained the reduction of land inequality and the provision of land to landless farmers (CNMH, 2016). Figure O.1 shows the evolution of *baldíos* allocations since 1901, the vast majority of which occurred between 1960 and 1990. In terms of both the number of beneficiaries and the amount of land allocated, the scale of the policy has been substantial: more than 550,000 land properties have been granted to private individuals in 1,034 of the 1,123 existing municipalities. These properties account for 23 million hectares—more than half of the privately held land in the country (Sánchez and Villaveces, 2016; Arteaga et al., 2017).

Land petitioners undergo an administrative process with the national land agency to determine whether they meet the legal requirements to become a beneficiaries. Although these requirements have changed over time, the most important conditions involve owning no other land and having an income below a specified threshold. Under the current legislation, the process formally consists of nine steps, which include placing an announcement of the intended allocation in a local newspaper and conducting a physical inspection of the land to be granted. Although the procedure is officially expected to take 60 days, in practice allocation processes are considerably longer, and some can take years (Gutiérrez Sanín, 2019).

Appendix Figure O.3 shows the evolution of the average and median size of allocated properties since 1960. The overwhelming majority of allocations made during the 1961-2014 period consisted of relatively small land parcels, 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 that a single individual can own. This limit, defined by the municipality-specific Agricultural Family Unit (UAF), restricts the ability of relatively larger farmers to purchase land that was originally government-owned. In Appendix section OB.4, we show that these land ceilings do not drive our results.

The universe of land allocations made by the government during the 1901–2011 period is registered in the System of Information for Rural Development (SIDER) dataset currently maintained by the ANT. After receiving the property, beneficiaries must register it with the local public notary, and all formal land transactions carried out on the property (including mortgages) are subsequently 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 conducted among private parties.[32]

Our main source of data is the transaction history in the SNR for all *baldío* allocations whose beneficiaries registered their property with a notary, thereby completing the administrative process required to obtain a formal property right.[33] We focus primarily on land-purchase transactions, which include either the transfer of an entire property from one individual to another or the subdivision and sale of only a fraction of the original property. We refer to these as *full sales* or *partial sales* respectively. We also study mortgages, as they may serve as an important adjustment margin when households face negative productivity shocks. For each transaction between two parties, we observe the property's location, the transaction date, and the type of transaction.

OA.3 Farm Size Distribution

For more than 50 years, the National Geographical Institute of Colombia (IGAC) has collected and managed the national cadastre. This system records information on the location, size, ownership, and economic purpose of all real estate properties in every Colombian municipality with the exception of the *departamento* of Antioquia, which operates its own independent cadastral system (Ibáñez et al., 2012).

By law, IGAC must conduct comprehensive cadastral updates in every municipality every five years. Between these broad updates, the dataset is updated annually based on new property registrations submitted by landowners, which allows us to measure the annual variation in the farm-size distribution. In practice, however, information is not always updated regularly, and the interval between cadastral updates varies across municipalities.[34] Martinez (2019) shows that the

[32]The history of the transactions carried out over a property, known as the Certificate of Liberty and Tradition (*Certificado de Libertad y Tradición*) is public information and can be consulted —upon payment of a small fee—for any property with a real estate registration number on SNR's website.

[33]Although registration was not automatic and a non-negligible number of beneficiaries did not complete this final step (Faguet et al., 2020), Appendix Figure O.4 shows that allocations and real estate registrations track each other closely over time, suggesting that the vast majority of allocated properties were ultimately registered.

[34]There are currently 80 municipalities in which IGAC has not yet implemented census-level broad updates of the cadastral information system. These municipalities rely instead on a self-reported system (*Catastros Fiscales*), under which landowners register their properties at regional IGAC offices.

timing of IGAC updates is not driven by changes in local economic conditions (e.g., property booms).

In our study, we use municipal-level aggregate information from all farms in IGAC's cadastre that are (i) privately owned, and (ii) classified as having an agricultural economic purpose. This amounts to roughly 40 million hectares of land. We construct a yearly municipal panel with the number of farms, the number of owners, median farm size, and average farm size within size ranges as defined by (Ibáñez et al., 2012). Because data from the land registry is only available for the period 2000-2011, we restrict our analysis to these years. We exclude from our final sample of municipalities (for both for the transaction-level data and the land registry data) large metropolitan areas and municipalities with very few properties registered (i.e. below the 1st percentile). Our final sample consists of 927 municipalities, which together account for 85.3% of the country's rural population.

OA.4 Land Transaction Data - Landless Buyers

The observed increase in the number of landowners per municipality, shown in Figure O.8 and Table 2 indicates that large landowners within the municipality are not expanding their operations by purchasing the small plots sold after the shocks. We cannot rule out, however, the possibility that these plots are being acquired by large landowners from nearby municipalities.

To investigate this possibility, we compile yearly lists of landowners at the *departamento* level using the history of land transactions. We define an individual as a landowner if they appears in the land registry data on the receiving end of a transaction—whether a sale, an inheritance, or a government allocation—and construct a list of current owners for each year in our sample. We then match the names of individuals buying land on a given year with the list of current landowners to determine whether those buyers owned any land in any other municipality of the same *departamento*.

Since we do not have information on the ID numbers of buyers and owners, we match individuals in both lists by first and last name, assuming that all registries under the same name within a *departamento* correspond to the same individual. Because names may contain misspellings or variation in the ordering of first and last names, we implement this matching using several string-matching algorithms that vary in how conservative they are respect to type-I errors, including exact matching, bigram similarity, and Jaro-Winkler distance. We then compare the results across these approaches.

OA.5 Weather Shocks

We define temperature shocks at the level of each administrative unit to account for the variation in climatic conditions across areas. The shocks are based on the unit's own distribution of weather realizations, which we compute using long-run daily weather measurements (similar, for example, to Kaur (2019)). This differs from definitions based on a fixed temperature threshold—more suitable for analyses focused on a specific region or crop (see, for example, Ibáñez et al. (2022)).

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 temperature data with a horizontal resolution of 0.25×0.25 degrees (approximately 28 km^2 depending, on the longitude) at an hourly frequency.[35] We use the temperature of the atmosphere two meters above the surface (in degrees Kelvin) from 1979 to 2016 for all ERA5 pixels in mainland Colombia. For each pixel, we compute the average temperature for each day d, and obtain the average daily temperature of each municipality-day pair (m, d) by taking a weighted average of the pixels within the municipality, using as weights each pixel's area relative to the municipality's total area.

We compute the historical quarterly distribution of daily temperatures by considering all temperature measurements for municipality-day pairs (m, d) in calendar-quarter q throughout the period 1979-2016. For each municipality, this results in four distributions—one for each quarter of the year. We compute the 20^{th} and 80^{th} percentiles of each distribution and define the average temperature of a given municipality-day as atypically high if it is above the 80^{th} percentile of the corresponding distribution for m in quarter q. Similarly, we classify a day as having atypically low temperatures if it falls below the 20^{th} percentile that distribution.

Finally, for each year t, we sum the number of atypically high or low temperature days. In our baseline specifications, we estimate effects on outcomes measured at the municipality-year (m, t) level and use as our preferred measure of weather shocks the total number of days with atypical temperatures over the previous two years (i.e., $t - 1$ and $t - 2$). Appendix Figures O.5 and O.6 show the spatial and temporal variation of the these temperature-shock measures across municipalities. This definition of temperature shocks has two advantages. First, it accounts for seasonality at the calendar-quarter level since the underlying distribution is quarter-specific. For example, because some quarters of the year are typically hotter, we classify a day as atypically hot only if its temperature is high relative to the historical distribution for that same quarter. Second, the measure is municipality-specific, recognizing that a given absolute temperature may be atypically high—and harmful—in one location but not in another.

In our estimations we also control for total rainfall. To construct this measure, we use the

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

ERA5 monthly precipitation reanalysis data with resolution 0.1×0.1 degrees (approximately 9 km^2 depending on the longitude) and apply the conversion factor provided C3S to obtain a measure of total monthly precipitations in cubic milliliters for each pixel. We then compute a weighted average across the pixels within each municipality to obtain monthly rainfall, using as weights the pixel's area relative to the municipality's total area. For each year, we sum precipitation across months to construct a measure of total rainfall for the municipality-year pair (m, t).

OA.6 Colombian Household Survey, ELCA

To study how farmers' decisions respond to temperature shocks, 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 in 2010 and follow-ups in 2013 and 2016. The rural sample 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.

In the follow-up rounds, enumerators attempted to reinterview all households and, when a household had split or migrated, tracked the household head, spouse, and children under nine in 2010. The attrition rate after three waves (by 2016) was 13.5%. The household questionnaire collected detailed information on land ownership and migration histories. We focus on how migration, farm size, land ownership, assets, and household consumption respond to temperature shocks. Panel B of O.2 contains descriptive statistics for the ELCA panel. On average, 12% of households migrated, 88% owned some land, and the average size was 2.5 hectares, with 75% of farms smaller than 3 hectares.

OB Additional Reduced-Form Results

OB.1 Flexible Lag Specification

We estimate a flexible-lag specification that exploits the temporal variation in the occurrence of extreme temperature events, allowing us to estimate separate coefficients for the impact of weather shocks occurring in each year between t and $t-7$. This specification accommodates the possibility that households may exhaust alternative coping mechanisms after consecutive years of adverse weather conditions, and that the effects may take time to materialize in land transactions or in the land registry.

Specifically, we estimate a regression of the form:

$$s_{i,t} = \sum_{j=0}^{7} \beta_j AnnualAtypicalDay_{i,t-j} + X'_{i,t}\delta + \eta_i + \kappa_t + \varepsilon_{i,t}, \tag{O.1}$$

where $s_{i,t}$ denotes the number of land transactions (sales or mortgages), the log number of farm owners, or the log average and median farm size in municipality i and year t. Our main variable of interest, $AnnualAtypicalDay_{i,t-j} = \sum_{d=1}^{365} AtypicalDay_{i,d,t-j}$, measures the number of days with atypical temperatures in the municipality i during year $t-j$. We include the contemporaneous value and seven lags of this variable .

The vector $X_{i,t}$ includes time-varying municipality characteristics. In particular, it contains rainfall at t and seven lags; the cumulative number of farms allocated in the municipality up to t, which controls for the stock of land on which we observe transactions; a dummy variable indicating whether a cadastral update occured; and the total municipal land area recorded in the registry, which accounts for changes in registry coverage. The model also includes municipality fixed effects η_i to control for time-invariant heterogeneity across municipalities, and year fixed effects κ_t to absorb time-specific shocks to land markets and farm size that affect all municipalities. The coefficients β_j capture the reduced form effects of contemporaneous and lagged days of extreme temperature on land transactions and farm size. Although distress land sales are likely to occur soon after a negative income shocks, notarizing a transaction and updating the property information in the land registry are the final steps in the land-transfer process and can take several months or even years.[36]

Appendix Figure O.7 presents the coefficient estimates from equation O.1 using the total number of land sales and land mortgages per municipality as dependent variables. The figure shows that increases in the frequency of extreme temperature events lead to a rise in land sales for up to two years after the shock. Extreme temperature events also increase the number of land mortgages, with statistically significant effects persisting up to five years. Appendix Figure O.8 shows the coefficient estimates for atypical temperature days and their lags, with the number of landowners (panel a), and mean and median farm size (panel b) as dependent variables in equation O.1. The figure indicates that atypical temperature days increase the number of landowners and reduce farm size, with statistically significant effects emerging two years after the shock and persisting up to seven years. The longer lag in the effects observed in the registry data is consistent with the fact that land transactions are reported to the land registry only at the final stage of the purchase

[36]In this process, buyers and sellers first sign a transaction agreement that specifies a sequence of payment installments. The signing of the public deed at a notary's office typically occurs upon the final payment. The signed deed is then submitted to the local land registry office to formalize the transfer of ownership. We observe land transactions on the date when the public deed is signed, and we observe changes in average farm size and in the number of owners for the year in which the deeds are submitted to the registry office.

process. Moreover, because the land registry captures the stock of properties, these shocks are likely to have lasting effects, unless offset by subsequent land transactions.

OB.2 Robustness in Farm Size Distribution and Land Transaction

Appendix Tables O.5 and O.6 report estimates from equation (4) using alternative definitions of temperature shocks. Panels A and B define atypical temperature using thresholds based on the 5th and 95th percentiles, and on the mean $\pm$ 1.5 standard deviations of the temperature distribution, respectively. Panel C applies the same threshold as in the main specification, but recalculates the temperature distributions using data from 1990-2011. Panels D and E define shocks using the SPEI index.[37]

Appendix Tables O.7 and O.8 report estimates from alternative specifications to equation (4). Panel A incorporates *departamento*-specific time trends, which helps account for potential spurious correlations between regional trends in temperature shock and our outcomes of interest. Panels B and C add controls for forced displacement and homicide rates to capture any confounding relationship between violent conflict and weather shocks. Panel D presents results from the main specification with two-way clustered standard errors at the municipality level and the *departamento* $\times$ year level.

OB.3 Alternative Methods for Identifying Previous Owners

We show that the results in Table 1—wich distinguish purchases made by landless individuals from those made by buyers who already own some land elsewhere—are robust to the choice of matching algorithm and to the specific sampling properties of the land-transaction data.

First, because the matching of buyers and owners is based on first and last names—which are subject to misspellings—we report results obtained using different string-matching algorithms (exact match, bigram, and Jaro-Winkler). These algorithms vary in how conservative they are with respect to the risk of incorrectly matching two distinct individuals with similar names (type II error) or failing to match the same individual across lists due to spelling variation (type I error). Panels A, B, and C of Table O.3 show that our results do not depend on the choice of matching algorithm.

Second, because the land-transaction data are available only for plots which were at some point allocated by the government to private individuals, it is possible that some landowners who hold other types of land do not appear in our owner lists are therefore incorrectly classified as landless. This omission could bias the coefficient on sales to landless buyers (column 4 in Table 1) upwards. To gauge the severity of this bias, we re-estimate the regressions using only municipalities in which

[37] See footnote 23 in the main text for a description of the SPEI weather data.

the share of private farmland originiating from government allocations is above the median. In these municipalities, the likelihood of incorrectly classifying landowners as landless should be lower, since a larger share of land transactions is observed. Columns 4, 5, and 6 in Table O.3 report the coefficients from this restricted sample. The estimated share of weather-driven land purchases made by landless buyers is nearly identical to that in the full sample, suggesting that any bias arising from this type of misclassification is small.

OB.4 The Land Ceiling Regulation

In this section, we investigate whether our findings on the absence of land consolidation are driven by institutional factors stemming from Colombia's land regulation policies. As discussed in Section 4, Law 160 of 1994 established municipality-specific land ceilings that cap the amount of land originally granted by the government that any private individual can accumulate. This restriction could help explain the lack of land consolidation at the upper end of the farm-size distribution, since it limits the ability of large landholders to acquire additional parcels whose provenance was a government allocation.[38]

To test if these restrictions are driving our results, we re-estimate the model in (4), adding an interaction term between the shock variable and a dummy indicating whether the municipality is above the median in the share of its area that was at some point part of a government allocation. The intuition behind this test is that land ceilings apply only to allocated land, not to other types of farmland. Therefore, if these restrictions were responsible for the land-fragmentation patterns shown in Table 2, we would expect the effects to be concentrated in municipalities where a large share of agricultural land originates from government allocations.

As columns 4-6 in Table O.10 show, adding the interaction term has no effect on the estimated impact of weather shocks on average farm size or on the total number of owners, although we do find some interaction with median farm size. Moreover, including the continuous measure of the share of government-allocated land as a control (columns 1-3) has virtually no influence on the magnitude or precision of the original estimates. We interpret these results as evidence that our main findings of are not driven by the specific institutional features of Colombia's land-regulation system.

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

OC Model Details and Extensions

OC.1 Extension with capital and labor employment

We consider an alternative production function in which farmers choose both capital and labor. The production function is given by:

$$y_t = Z_t^a (z_t^a)^{1-\gamma} (\ell_t^\alpha n_t^\lambda k_t^\rho)^\gamma \tag{O.2}$$

The maximization problem associated with the production function above yields the following expression for the farmer's profits:

$$\pi_t = \left[Z_t^a (z_t^a)^{1-\gamma} (\ell_t^\alpha)^\gamma \left(\frac{\lambda r_t}{\rho w_t} \right)^{\lambda\gamma} \right]^{\frac{1}{1-\gamma(\rho+\lambda)}} \left[\left(\frac{1}{(\rho+\lambda)\gamma} \right)^{\frac{\gamma(\rho+\lambda)}{1-\gamma(\rho+\lambda)}} - \left(\frac{1}{(\rho+\lambda)\gamma} \right)^{\frac{1}{1-\gamma(\rho+\lambda)}} \right] [r_t]^{\frac{\gamma(\rho+\lambda)}{1-\gamma(\rho+\lambda)}} \tag{O.3}$$

The equation above can be rewritten as

$$\pi_t = \tilde{Z}_t^a (z_t^a)^{\tilde{\gamma}} (\ell_t)^{\tilde{\alpha}} \tag{O.4}$$

where we defined

$$\tilde{Z}_t^a \equiv \left[Z_t^a \left(\frac{\lambda r_t}{\rho w_t} \right)^{\lambda\gamma} \right]^{\frac{1}{1-\gamma(\rho+\lambda)}} \left[\left(\frac{1}{(\rho+\lambda)\gamma} \right)^{\frac{\gamma(\rho+\lambda)}{1-\gamma(\rho+\lambda)}} - \left(\frac{1}{(\rho+\lambda)\gamma} \right)^{\frac{1}{1-\gamma(\rho+\lambda)}} \right] [r_t]^{\frac{\gamma(\rho+\lambda)}{1-\gamma(\rho+\lambda)}},$$

$\tilde{\gamma} \equiv \frac{1-\gamma}{1-\gamma(\rho+\lambda)}$, and $\tilde{\alpha} \equiv \frac{\gamma\alpha}{1-\gamma(\rho+\lambda)}$.

OC.2 Solving for the transition dynamics using the SSJ matrix

In Sections 5.3 and 6 of the main text, we simulate the transition dynamics of the economy when it is hit by an unexpected weather shock—that is, an MIT shock. In general, computing the full sequence of endogenous prices that clears markets in every period can be computationally intensive. We therefore follow the approach developed in Auclert et al. (2021), which relies on the sequence-space Jacobian (SSJ) to solve for this sequence of prices more efficiently. We construct the sequence-space Jacobian matrix and use it to update the land price within our algorithm. In our setting, the SSJ is the matrix that maps a change in the price of land in period s into the corresponding change in land demands in period t.

The algorithm used to solve for the path of land prices proceeds as follows. We beging with an initial guess for the sequence of prices $\mathbf{p}^0$, of length T, where T is the number of periods that we consider in the transition dynamics. Given this price sequence and a vector describing the path of aggregate TFP, $\mathbf{Z}$, over that same horizon, we compute the vector of excess land demand in each period t. We denote the resulting vector of excess demand under this initial guess of prices and aggregate TFP as Δ^g. We then update the sequence of land prices using the sequence-space Jacobian as follows:

$$\mathbf{p}^{g+1} = \mathbf{p}^g - \mathbf{J}^{-1} \times \Delta^g$$

where g indexes the iteration and $\mathbf{J}$ is the sequence-space Jacobian matrix. The matrix $\mathbf{J}$ gives the derivative of excess demand in period t (row) with respect to a change in land price in period s (column). In principle, one could compute the Jacobian numerically by evaluating each derivative element-by-element. However, Auclert et al. (2021) show how to construct this matrix much more efficiently by exploiting the structure of the model's backward- and forward-induction steps. Following their approach, we construct

$$F = \begin{bmatrix} Y_0 & Y_1 & \dots & Y_{T-1} \\ E_0^{'} D_0 & E_0^{'} D_1 & \dots & E_0^{'} D_{T-1} \\ \vdots & \vdots & & \vdots \\ E_{T-2}^{'} D_0 & E_{T-2}^{'} D_1 & \dots & E_{T-2}^{'} D_{T-1} \end{bmatrix}$$

where Y_s is the excess demand for land in period $t = 0$ resulting from a shock to land price in period s; E_t is a matrix representing the expected land demand in period t for each agent type present at $t = 0$, assuming all agents follow the stationary-equilibrium land and occupational choices; and D_s is the change in the density of each agent type from period $t = 0$ to period $t = 1$ following a shock to land prices in period s. The matrix F is referred to as the *fake news* matrix because it captures how excess demand responds when agents first learn, at $t = 0$, that land prices will rise in period s, but then discover at at $t = 1$ that this anticipated shock will not occur. Once F has been constructed, we can obtain the sequence-space Jacobian by computing, for each period t and each price change in period s, $J_{t,s} = J_{t-1,s-1} + F_{t,s}$.

Using the sequence-space Jacobian to update prices allows us to find the solution quickly. Under our main calibration, the model converges in fewer than 10 iterations, with the sum of excess demand across periods falling below 10^{-4}—recall that we normalize the land supply one.

OC.3 Simulating the Stochastic Economy

Following Boppart et al. (2018), we compute the evolution of the stochastic economy using equation (20). To do so, we first obtain the impulse response of the economy's endogenous variables to an MIT shock at $t = 0$. Let $\widehat{dy_s}$ denote the corresponding response in period s. We recover $\widehat{dy_s}$ using the sequence-space Jacobian, embedded in an algorithm that solves for the full nonlinear equilibrium path of prices and endogenous variables. This approach allows us to compute impulse responses without relying on the fully linearized general-equilibrium solution of Auclert et al. (2021), which we do not use here.[39]

OD Calibration Details

OD.1 Solving for the Stationary Equilibrium

We solve for the stationary equilibrium using a grid of 300 points for land ownership and 15 points for the idiosyncratic agricultural productivity shock. This gives a 300×15 matrix of non-agricultural income. Similarly, we set a grid of 300 points for the idiosyncratic non-agricultural productivity and 15 points for the idiosyncratic non-agricultural productivity shock.[40] This gives us a matrix of non-agriculture income for landless agents. Having the two matrices with the same dimensions simplifies the solution algorithm. We space the grid of land and wages according to a log-normal distribution and construct the non-agriculture productivity grid using Rouwenhorst's approach, implemented in the companion package distributed with Auclert et al. (2021).

The algorithm follows a standard solution method. Because we have a discrete-choice problem, the agents' problem presents non-convexities that prevent us from applying the endogenous-grid method. We therefore used a simple value function iteration.

OD.2 Estimating Annual Exit Rates from the Data

The household survey data from Colombia spans a three-year window. To estimate the annualized exit rate used to calibrate the model, we proceed as follows. First, we groups farms into size bins and compute the average exit rate within each bin. We then compute the annualized rate using the following formula:

$$\widehat{p}_{survive}(b) = (1 - p_{exit}(b))^3 \tag{O.5}$$

where $\widehat{p}_{survive}(b)$ is the share of farmers in farm-size bin b who survive over a three years period in the ELCA dataset. Using the formula above, we compute $p_{exit}(b) = 1 - [\widehat{p}_{survive}(b)]^{1/3}$, which is the statistic we use in our calibration.

[39] Auclert et al. (2021) develop a complete linearized general-equilibrium solution method.

[40] Because farmers do not earn a wage and workers do not earn farm revenues within each period, we do not need to consider the full matrix of all combinations of non-agriculture skill, agricultural skill, and land ownership.

OD.3 Estimating ρ

To estimate the persistence in the farm productivity shock, we use our longitudinal ELCA survey data, which contain information on total agricultural output per farm and landholdings. Using this information, we construct the following measure of s_{it}

$$\bar{s}_t^a = Z_t^a \left[\frac{\bar{y}_t}{\bar{\ell}_t^{\gamma}} \right]^{\frac{1}{1-\gamma}},$$

where $\bar{y}_t$ and $\bar{\ell}_t$ are our measured values of output and land, respectively. In what follows, we assume that Z_t is not systematically correlated with $\bar{\ell}_t$. We then assume that the farm productivity of farmer i in period t is given by

$$\log \bar{s}_{i,t} = \rho \log \bar{s}_{i,t-1} + \sigma \epsilon_{i,t},$$

where $\epsilon_{i,t}$ is the productivity shock. Since the gap between survey waves in the data is three years, what we effectively observe is

$$\log \bar{s}_{i,t} = \rho^3 \left(\log \bar{s}_{i,t-3} \right) + \sigma \left(\epsilon_{i,t-2} + \epsilon_{i,t-1} + \epsilon_{i,t} \right).$$

We estimate the regression above while adding a control for the probability of exiting during these three years, which we estimate using a logit model with polynomial in initial farm size as the explanatory variable. Our final estimation is

$$\log \bar{s}_{i,t} = \rho^3 \left(\log \bar{s}_{i,t-3} \right) + \beta P \left(\widehat{exit_{i,t-3}} \right) + \sigma \left(\epsilon_{i,t-2} + \epsilon_{i,t-1} + \epsilon_{i,t} \right)$$

where $P \left(\widehat{exit_{i,t-3}} \right)$ is the predicted probability that the farmer exited over the three-year period.[41] This procedure gives us the value of ρ.

OD.4 Alternative Weather Shock distribution

In Section 6.2, we simulate alternative sequences of weather shocks by increasing the probability of extreme events. To do so, we model the data-generating process for our weather-shock variable. Specifically, we treat each day as a Bernoulli draw indicating whether it is atypical, and define the weather-shock variable as the sum of 712 such daily draws (two years). Each day has a baseline probability of 0.4 of being atypical. We introduce serial correlation by assuming that these draws follow a two-state Markov chain. If day t is atypical, the probability that day $t+1$ is also atypical

[41] Controlling for the predicted probability of exit lowers the correlation between shocks, but the resulting change in point estimates is small.

is $1-0.6(1-\zeta)$. If day t is typical, the probability that day $t+1$ is also typical is $0.4(1-\zeta)$. A higher value of ζ implies stronger persistence in weather conditions. The Markov chain is therefore given by:

$$\begin{pmatrix} 1-0.6(1-\zeta) & 0.6(1-\zeta) \\ 0.4(1-\zeta) & 1-0.4(1-\zeta) \end{pmatrix}. \tag{O.6}$$

OE Analytical Results

To better understand how the change in price shapes agents' decision to become a farmer, we study analytically the impact of a small change in land price and the aggregate productivity. We do so using equation (14), ignoring general equilibrium effects related to changes in the distribution and applying the envelope conditions.

OE.1 TFP shock and the probability of becoming a farmer

For a given agent, $\phi_t = (s_t^a, s_t^n, \ell_t)$, the impact of a small change in Z_t^a on its probability of becoming a farmer, $\mu_t(\phi_t)$ is

$$\frac{\partial \mu_t(\phi_t)}{\partial Z_t} = \kappa(1-\delta)\mu_t(\phi_t)\left(1-\mu_t(\phi_t)\right)\underbrace{\left[u'\left(c_t^F(\phi_t)\right) - u'\left(c_t^W(\phi_t)\right)\right]}_{>0}\frac{\partial \pi_t(\phi_t)}{\partial Z_t^a} > 0 \tag{O.7}$$

where $c_t^F(\phi_t)$ is consumption if the agent becomes a farmer, $c_t^W(\phi_t)$ is consumption if the agent becomes a worker, and $u'()$ is the marginal utility of consumption. Notice that, because $\frac{\partial \pi_t(\phi_t)}{\partial Z_t^a} = 0$ for workers, their decision to become farmers is unaffected by the change in aggregate agricultural TFP. Note that $u'\left(c^F(\phi_t)\right) > u'\left(c^W(\phi_t)\right)$, since consumption is always lower when agents buy land. Therefore, a reduction in Z_t^a always reduces the probability that agents become farmers.

This equation also shows that farm productivity s_t^a and total land ℓ_t have an ambiguous effect on the magnitude of the impact of Z_t^a on the measure of farmers $\mu_t(\phi_t)$. On the one hand, more productive or skilled farmers—those with higher s_t^a and ℓ_t—are more exposed to aggregate shocks because their profits are more sensitive to changes in productivity, implying a larger derivative $\frac{\partial \pi_t(\phi_t)}{\partial Z_t^a} > 0$. On the other hand, these same farmers tend to have higher consumption levels, which reduces the marginal-utility gap between farming and working; that is, $u'\left(c^F(\phi_t)\right) - u'\left(c^W(\phi_t)\right)$ is smaller. Because of the curvature of the utility function, this dampens the response of their occupational choice to aggregate shocks.

OE.2 Price shock and the probability of becoming a farmer.

The impact of a small shock to land prices on the probability of becoming a farmer, $\mu_t(\phi_t)$, is given by:

$$\frac{\partial \mu_t(\phi_t)}{\partial p_t} = \kappa(1-\delta)\mu_t(\phi_t)\left(1-\mu_t(\phi_t)\right)\left[\underbrace{\left[u'\left(c_t^F(\phi_t)\right) - u'\left(c_t^W(\phi_t)\right)\right]\ell_t}_{\text{income effect (+)}} - \underbrace{u'\left(c^F(\phi_t)\right)\ell_t^*(\phi_t)}_{\text{land price effect (-)}}\right] \lessgtr 0. \tag{O.8}$$

In this case, two mechanisms operate in opposite directions. First, there is an income effect: when land prices rise, agents who own more land become richer. This mechanism moves in the same direction of prices, and its influence is stronger when farmers are poorer, since the marginal utility difference $u'\left(c^F(\phi_t)\right) - u'\left(c^W(\phi_t)\right)$ is larger. Notice that agents with no land are not affected by the income effect.

Second, there is a land price effect, which moves in the opposite direction of the income effect. When land prices fall, agents are more likely to enter or remain in farming because they can purchase more land. For agents outside of agriculture, this is the only mechanism that affects their decision, since they do not own land and therefore are not affected by the income effect.

OF Tables and Figures

Table O.1: Effect of Weather Shocks on Households' Entry and Exit from Agriculture

	LatAm (1)	LatAm (2)	W. Africa (3)	W. Africa (4)	All (5)	All (6)
TempShock	-0.035	0.006	-0.082***	-0.095***	-0.047**	-0.035
	(0.026)	(0.023)	(0.029)	(0.031)	(0.022)	(0.023)
TempShock × No Farm	0.266***	0.072*	0.189***	0.132***	0.203***	0.125***
	(0.060)	(0.041)	(0.045)	(0.030)	(0.052)	(0.037)
TempShock × Small Farm	-0.035	0.006	0.001	-0.001	-0.009	-0.000
	(0.023)	(0.028)	(0.016)	(0.014)	(0.017)	(0.017)
N	24074	24074	85584	85584	109658	109658
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Group FE	No	Yes	No	Yes	No	Yes

Notes: This table shows results from estimating equation (1) using data from household surveys in West Africa (EHCVM 2018–2021), and Latin America (ENNVIH 2002–2005; ENAHO 2007–2023).

Table O.2: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)
	Panel A: Municipality (N= 864)			
SNR				
Number of Total Land Sales	12.62	24.75	0	292
Number of Full Land Sales	10.83	21.63	0	281
Number of Partial Land Sales	1.79	6.05	0	133
Number of Mortages	2.62	7.54	0	172
Land Registry				
Number of owners	2,501.13	2,160.43	21	18,768
Mean of farm size	32.06	106.71	1	1,693
Median of farm size	16.15	86.73	0	1,438
Controls				
Number of total allocations	444.68	679.23	1	6,550
=1 if land registry update	0.07	0.25	0	1
Registered area (1000 ha.)	41,255.76	87,792.98	340	1,475,761
Accumulated precipitation	3,516.60	2,647.67	372	21,144
Days of atypical high temperature	120.47	75.50	5	483
Days of atypical low temperature	154.92	72.23	1	401
Days of atypical temperature	275.39	43.56	157	485
	Panel B: ELCA - Household (N= 4,280)			
=1 if HH has land	0.92	0.27	0	1
=1 if farm size $\leq$ 3 ha	0.75	0.43	0	1
=1 if HH migrated	0.10	0.30	0	1
=1 if HH sold animals	0.69	0.46	0	1
Asset index	0.00	0.39	-1	3
Farm size (ha.)	2.65	5.62	0	118
Consumption per capita	2.79	2.52	0	104
Accumulated precipitation	3,617.71	2,457.81	729	22,934
Days of atypical high temperature	264.14	118.34	64	528
Days of atypical low temperature	50.80	43.60	0	176
Days of atypical temperature	314.94	84.67	174	529

Notes: This table presents summary statistics for each estimation sample. Panel A describes the variables used for municipality-level estimations. Total number of sales includes full and partial sales during the year. Full sales correspond to transfers of the entire property to another owner, while partial sales transfer only a fraction of the property. The number of total allocations corresponds to the cumulative sum of government-allocated farms in the municipality from 1901 until the year of observation. Panel B summarizes the data used for estimations at the household-year level. This data comes from three 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 atypical temperature days and the accumulated precipitation come from the Copernicus Climate Change Service (*C3S*). Days with atypical temperature refer to the total number of days across the two prior years abnormally high or low temperatures. Accumulated precipitation is the volume of rainfall in milliliters for year t.

Table O.3: Effect of Temperature Shock on Land sales: matching vs. non-matching buyers

	Full Sample			Above median land share from govt. allocations		
	Total Sales	Landless Buyers	Already Owners	Total Sales	Landless Buyers	Already Owners
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Fuzzy Matching - Bigram					
$TempShock_{i,t}$	2.537***	1.866***	0.671***	3.524***	2.679***	0.845***
	(0.536)	(0.408)	(0.192)	(0.855)	(0.654)	(0.300)
Observations	10,021	10,021	10,021	5,097	5,097	5,097
R^2	0.905	0.889	0.838	0.899	0.877	0.839
Mean Dep. Var	12.62	9.37	3.25	20.91	15.47	5.44
	Panel B: Fuzzy Matching - Jaro Winkler					
$TempShock_{i,t}$	2.537***	1.402***	1.135***	3.524***	2.080***	1.445***
	(0.536)	(0.325)	(0.291)	(0.855)	(0.526)	(0.466)
Observations	10,021	10,021	10,021	5,097	5,097	5,097
R^2	0.905	0.857	0.889	0.899	0.845	0.885
Mean Dep. Var	12.62	6.10	6.52	20.91	10.04	10.87
	Panel C: Exact Matching					
$TempShock_{i,t}$	2.537***	1.780***	0.757***	3.524***	2.546***	0.978***
	(0.536)	(0.412)	(0.190)	(0.855)	(0.663)	(0.297)
Observations	10,021	10,021	10,021	5,097	5,097	5,097
R^2	0.905	0.889	0.837	0.899	0.877	0.839
Mean Dep. Var	12.62	9.62	3.00	20.91	15.90	5.01

Notes: This table presents coefficient estimates from equation (4) in a balanced panel at the municipality-year level using as outcome land sales. Columns (1)–(3) report estimates for the full sample, while columns (4)–(6) restrict the sample to municipalities with an above-median share of land allocated by the government. Within each set of columns, we show results for total sales, sales to landless buyers, and sales to existing owners, respectively. Buyer type is identified by checking whether the buyer's name appears in earlier SNR records (sales, inheritances, or government allocations) within the same *departamento*. Panels present results across alternative matching procedures used to classify buyers (Fuzzy Matching–Bigram, Fuzzy Matching–Jaro Winkler, and Exact Matching). The independent variable is the total number of atypical temperature days in the past two years divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. See the text for details. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Superintendency of Notaries (SNR). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.4: Temperature Shocks and Household Decisions, Excluding Migrant Households

	Household Migrated (1)	Household Has Land (2)	Household Sold Land (3)	Farm Size (Hectares) (4)	Consumption (logs) (5)	Income (logs) (6)	Sold Animals (7)	Asset Index (8)
$TempShocks$	0.089***	-0.101***	0.038***	-0.443	-0.111***	-0.465***	0.046***	-0.112***
	(0.033)	(0.023)	(0.012)	(0.295)	(0.038)	(0.069)	(0.016)	(0.028)
Observations	13,442	11,778	11,778	11,778	13,442	12,773	12,634	12,596
R^2	0.532	0.557	0.428	0.627	0.707	0.647	0.932	0.585
Mean Dep. Var	0.14	0.92	0.03	2.65	2.80	2.06	0.67	-0.00

Notes: This table shows estimates of the effects of temperature shocks on household decisions using a three-wave panel survey of rural households (2010, 2013, 2016). The sample is further restricted to households that responded to the survey's agricultural module (thus excluding households that migrated to non-rural areas), with the exception of the first column, in which we include all households including migrants. The dependent variables, from left to right, are: a dummy indicating whether the household migrated between survey waves; a dummy indicating whether the household owns any land; a dummy indicating whether the household sold any land; log farm size; log per-capita consumption; log per-capita income; a dummy indicating whether the household sold any livestock; and a principal-components asset index based on household assets and durable goods. Values for the land-ownership variables (columns 2–4) are imputed as zero for households that did not answer the survey's land module. All monetary values are expressed in 2016 Colombian pesos (in millions). All regressions control for log aggregate rainfall at t and its five lags and include household and time fixed effects. *Mean Dep. Var.* reports the sample mean of the untransformed dependent variable. Standard errors clustered at the *vereda* level are reported in parentheses. Data from ELCA survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.5: Temperature Shocks and Land Sales - Alternative Shock Definitions

	All	Full	Partial	Mortgages
	(1)	(2)	(3)	(4)
Panel A: Threshold 5, 95				
$TempShocks$	4.290***	3.150***	1.140***	1.922***
	(0.867)	(0.804)	(0.370)	(0.368)
Observations	10,021	10,021	10,021	10,021
R^2	0.906	0.902	0.636	0.757
Mean Dep. Var	12.62	10.83	1.79	2.62
Panel B: Threshold 1.5SD				
$TempShocks$	3.689***	2.765***	0.925***	1.762***
	(0.752)	(0.695)	(0.317)	(0.314)
Observations	10,021	10,021	10,021	10,021
R^2	0.906	0.902	0.636	0.758
Mean Dep. Var	12.62	10.83	1.79	2.62
Panel C: Shorter time window				
$TempShocks$	2.248***	1.887***	0.361	1.004***
	(0.546)	(0.504)	(0.238)	(0.231)
Observations	10,021	10,021	10,021	10,021
R^2	0.905	0.902	0.635	0.757
Mean Dep. Var	12.62	10.83	1.79	2.62
Panel D: SPEI continuous				
$SPEI(-)$	0.859**	0.441	0.418**	-0.349*
	(0.349)	(0.324)	(0.171)	(0.183)
Observations	10,021	10,021	10,021	10,021
R^2	0.905	0.902	0.636	0.756
Mean Dep. Var	12.62	10.83	1.79	2.62
Panel E: SPEI discrete				
Months($SPEI < -2$)	0.846**	0.647**	0.199	0.389***
	(0.348)	(0.322)	(0.160)	(0.121)
Observations	10,021	10,021	10,021	10,021
R^2	0.905	0.902	0.635	0.756
Mean Dep. Var	12.62	10.83	1.79	2.62

Notes: This table presents coefficient estimates from equation (4) in a balanced panel at the municipality-year level, using various measures of land-market activity as outcomes. The dependent variable in column 1 is the total of land sales (full + partial), in column 2 the number of full sales, in column 3 the number of partial sales, and in column 4 the number of land mortgages. The independent variable is the total number of atypical-temperature days in the past two years, divided by 100. Panels A and B, use alternative thresholds to define atypical-temperature days. in Panel A, atypical days are those falling below the 5th or above the 95th percentile of the temperature distribution. In Panel B, the thresholds are defined as *mean ± 1.5 standard deviations*. Panel C constructs the temperature shock following the same procedure as the main specification, but uses the 1990–2011 period to compute the underlying temperature distribution. Panel D uses the negative annual SPEI in the previous two years as the independent variable. Panel E defines a shock as a dummy equal to one when the monthly SPEI is below −2 in either of the previous two years. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. See the text for details. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Superintendency of Notaries (SNR). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.6: Temperature Shocks and Average Farm Size - Alternative Shock Definitions

	(1) Number of Owners	(2) Mean Farm Size	(3) Median Farm Size
	(1)	(2)	(3)
Panel A: Threshold 5, 95			
$TempShocks$	0.024***	-0.028***	-0.036**
	(0.008)	(0.008)	(0.015)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974
Panel B: Threshold 1.5SD			
$TempShocks$	0.016**	-0.018***	-0.027**
	(0.006)	(0.007)	(0.014)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974
Panel C: Shorter time window			
$TempShocks$	0.013***	-0.013**	-0.021*
	(0.005)	(0.005)	(0.012)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974
Panel D: SPEI continuous			
$SPEI(-)$	0.013**	-0.017**	-0.042**
	(0.006)	(0.007)	(0.019)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.975
Panel E: SPEI discrete			
Months($SPEI < -2$)	0.006*	-0.006	-0.012
	(0.003)	(0.004)	(0.009)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974

Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution. Dependent variables are the log number of land owners in the municipality (column 1), log average farm size (column 2), log median farm size (column 3). The independent variable is the total number of atypical-temperature days in the past two years, divided by 100. Panels A and B, use alternative thresholds to define atypical-temperature days. in Panel A, atypical days are those falling below the 5th or above the 95th percentile of the temperature distribution. In Panel B, the thresholds are defined as *mean* $\pm$ *1.5 standard deviations*. Panel C constructs the temperature shock following the same procedure as the main specification, but uses the 1990–2011 period to compute the underlying temperature distribution. Panel D uses the negative annual SPEI in the previous two years as the independent variable. Panel E defines a shock as a dummy equal to one when the monthly SPEI is below -2 in either of the previous two years. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. See the text for details. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.7: Temperature Shocks and Land Sales - Alternative Specifications

	Total (1)	Full (2)	Partial (3)	Mortgages (4)
Panel A: Controls for departamento specific linear trends				
$TempShocks$	2.532***	2.018***	0.514**	1.059***
	(0.535)	(0.502)	(0.224)	(0.241)
Observations	10,021	10,021	10,021	10,021
R^2	0.905	0.902	0.636	0.757
Mean Dep. Var	12.62	10.83	1.79	2.62
Panel B: Controls for displacement				
$TempShocks$	2.524***	2.000***	0.525**	1.049***
	(0.537)	(0.505)	(0.229)	(0.237)
Observations	10,014	10,014	10,014	10,014
R^2	0.906	0.902	0.636	0.757
Mean Dep. Var	12.63	10.84	1.79	2.62
Panel C: Controls for homicide				
$TempShocks$	2.457***	1.938***	0.519**	1.016***
	(0.540)	(0.509)	(0.226)	(0.237)
Observations	10,014	10,014	10,014	10,014
R^2	0.906	0.903	0.636	0.758
Mean Dep. Var	12.63	10.84	1.79	2.62
Panel D: Municipality and departamento × year clusters				
$TempShocks$	2.537***	2.013***	0.523*	1.046***
	(0.786)	(0.732)	(0.284)	(0.388)
Observations	10,021	10,021	10,021	10,021
R^2	0.905	0.902	0.636	0.757
Mean Dep. Var	12.62	10.83	1.79	2.62

Notes: This table presents coefficient estimates from equation (4) in a balanced panel at the municipality-year level, using various measures of land-market activity as outcomes and different econometric specifications. The dependent variable in column 1 is the total of land sales (full + partial), in column 2 the number of full sales, in column 3 the number of partial sales, and in column 4 the number of land mortgages. The independent variable is the total number of atypical-temperature days in the past two years, divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Panel A adds an interaction between the administrative division *departamento* and a linear trend. Panels B and C add controls for the displaced population and the total number of homicides, respectively (each expressed as a proportion of the municipality's 2005 population). Standard errors clustered at the municipality level are reported in parentheses (except in Panel D). Panel D clusters standard errors by municipality and by *departamento*–year. Data from the National Superintendency of Notaries (SNR).

Table O.8: Temperature Shocks and Average Farm Size - Alternative Specifications

	Number of Owners (logs) (1)	Mean Farm Size (logs) (2)	Median Farm Size (logs) (3)
Panel A: Controls for departamento specific linear trends			
$TempShocks$	0.015***	-0.015***	-0.022*
	(0.005)	(0.005)	(0.012)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.975
Panel B: Controls for displacement			
$TempShocks$	0.015***	-0.015***	-0.022*
	(0.005)	(0.005)	(0.012)
Observations	10,014	10,014	10,014
R^2	0.992	0.993	0.974
Panel C: Controls for homicide			
$TempShocks$	0.015***	-0.015***	-0.022*
	(0.005)	(0.005)	(0.012)
Observations	10,014	10,014	10,014
R^2	0.992	0.993	0.974
Panel D: Municipality and departamento $\times$ year clusters			
$TempShocks$	0.015**	-0.015**	-0.021
	(0.006)	(0.007)	(0.013)
Observations	10,021	10,021	10,021
R^2	0.992	0.993	0.974

Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution using different econometric specifications. Dependent variables are the log number of land owners in the municipality (column 1), log average farm size (column 2), log median farm size (column 3). The independent variable is the total number of atypical-temperature days in the past two years, divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. See the text for details. Standard errors clustered at the municipality level reported in parenthesis. Panel A adds an interaction between the administrative division *departamento* and a linear trend. Panels B and C add controls for the displaced population and the total number of homicides, respectively (each expressed as a proportion of the municipality's 2005 population). Standard errors clustered at the municipality level are reported in parentheses (except in Panel D). Panel D clusters standard errors by municipality and by *departamento*–year. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.9: Temperature Shocks and Household Assets

	Refrigerators (1)	Washing Machines (2)	Blenders (3)	Ovens (4)	Microwave (5)	Heaters (6)	Showers (7)	Air-conditioning (8)	Televisions (9)	Radios (10)
$TempShocks$	-0.058**	0.058**	-0.039	-0.015	-0.017	-0.019*	-0.063***	-0.099***	-0.049**	0.008
	(0.027)	(0.026)	(0.027)	(0.013)	(0.013)	(0.010)	(0.017)	(0.031)	(0.022)	(0.031)
Observations	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596
R^2	0.663	0.629	0.550	0.438	0.438	0.402	0.550	0.435	0.524	0.531
Mean Dep. Var	0.63	0.24	0.70	0.04	0.03	0.02	0.05	0.06	0.84	0.53
	Sound Equipment	Video Equipment	Computers	Bikes	Motorcycles	Automobiles	Houses	Office	Lots	Other Goods
$TempShocks$	-0.051**	0.006	-0.043**	-0.007	0.051**	-0.036***	-0.006	0.001	-0.005	-0.160***
	(0.020)	(0.023)	(0.018)	(0.028)	(0.025)	(0.011)	(0.012)	(0.003)	(0.006)	(0.038)
Observations	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596	12,596
R^2	0.574	0.523	0.511	0.594	0.669	0.694	0.512	0.455	0.412	0.478
Mean Dep. Var	0.32	0.25	0.08	0.40	0.31	0.05	0.05	0.00	0.01	0.06

Notes: This table shows estimates of the effects of temperature shocks on household assets using a three-wave panel survey of rural households (2010, 2013, 2016). The dependent variables are dummies corresponding to the options presented to households when asked: *"Does this household own any of the following assets?"* All regressions control for log aggregate rainfall at t and its five lags and include household and time fixed effects. *Mean Dep. Var.* reports the sample mean of the untransformed dependent variable. Standard errors clustered at the *vereda* level are reported in parentheses. Data from ELCA survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.10: Temperature Shocks, Farm Size, and Share of Government-Allocated Area

	Control: Share allocates			H_i: Share allocated		
	Number of Owners	Mean Farm Size	Median Farm Size	Number of Owners	Mean Farm Size	Median Farm Size
	(1)	(2)	(3)	(4)	(5)	(6)
$TempShocks$	0.014***	-0.015***	-0.022*	0.014***	-0.016***	-0.031***
	(0.005)	(0.005)	(0.012)	(0.005)	(0.005)	(0.011)
$TempShocks \times H_i$				0.000	0.004	0.027*
				(0.008)	(0.009)	(0.015)
Observations	10,021	10,021	10,021	10,021	10,021	10,021
R^2	0.992	0.993	0.975	0.992	0.993	0.975

Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution. The dependent variables are the number of land owners in the municipality (columns 1 and 4), the average farm size (columns 2 and 5), and the median farm size (columns 3 and 6). The independent variable is the total number of atypical-temperature days in the past two years divided by 100. Columns 1–3 include the continuous measure of the share of municipal land that originated from government allocations as a control. Columns 4–6 add an interaction between the temperature-shock variable and an indicator for whether the municipality is above the median in the share of its area that was ever part of a government allocation. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral-registry updates. Standard errors clustered at the municipality level are reported in parentheses. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.11: Temperature Shocks and Farm Size - Heterogeneous Effects by Contiguous Plots

	Number of Owners	Mean Farm Size	Median Farm Size
	(1)	(2)	(3)
$TempShocks$	0.019***	-0.019***	-0.022
	(0.006)	(0.007)	(0.015)
$TempShocks \times High$	-0.003	0.005	0.010
	(0.006)	(0.006)	(0.013)
Observations	8,575	8,575	8,575
R^2	0.991	0.993	0.973

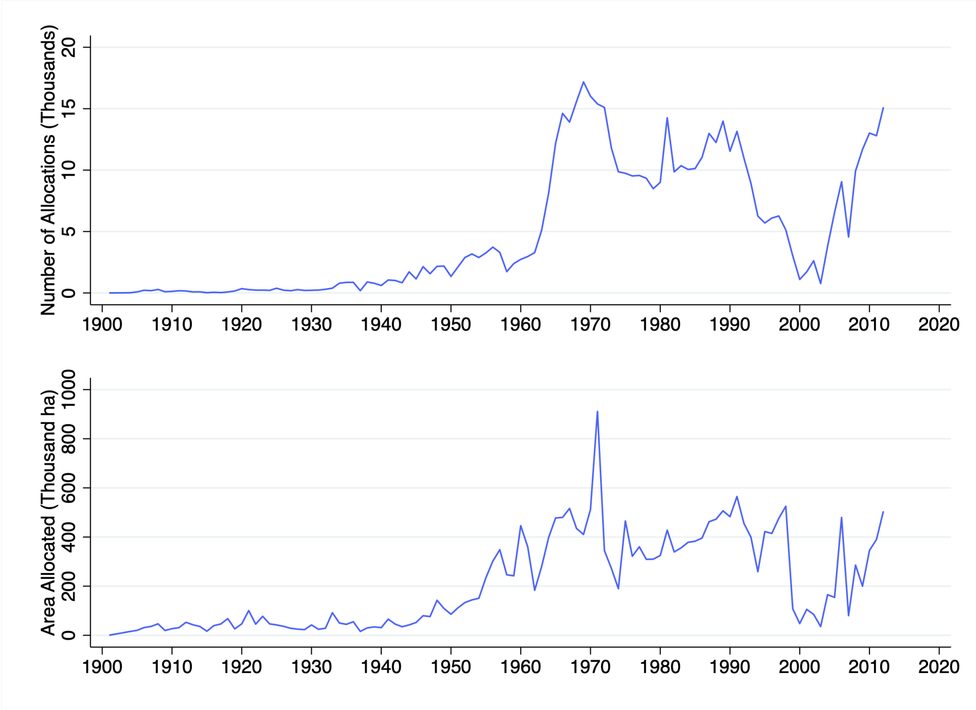
Notes: This table reports the estimated effect of temperature shocks on the farm-size distribution using an alternative measure of contiguity between small and large farms. The dependent variables are the number of land owners in the municipality (column 1), the average farm size (column 2), and the median farm size (column 3). The independent variable is the total number of atypical-temperature days in the past two years divided by 100. The variable *High* indicates municipalities with above-median contiguity as determined from GPS coordinates in the 2014 National Agricultural Census; the interaction term tests whether temperature shocks have differential effects in these municipalities. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral-registry updates. Standard errors clustered at the municipality level are reported in parentheses. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table O.12: Temperature Shocks and Number of owners, by Initial Size Quantile

	Number of owners by initial distribution quantiles (q_m^j)									
	q_m^1	q_m^2	q_m^3	q_m^4	q_m^5	q_m^6	q_m^7	q_m^8	q_m^9	q_m^{10}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$TempShocks$	0.032**	0.017*	0.026***	0.016*	0.022***	0.008	0.006	-0.001	0.001	-0.000
	(0.016)	(0.010)	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.004)
Observations	10,004	9,967	9,942	9,893	9,996	9,958	10,017	9,981	9,996	10,017
R^2	0.940	0.971	0.981	0.982	0.986	0.985	0.985	0.990	0.990	0.993

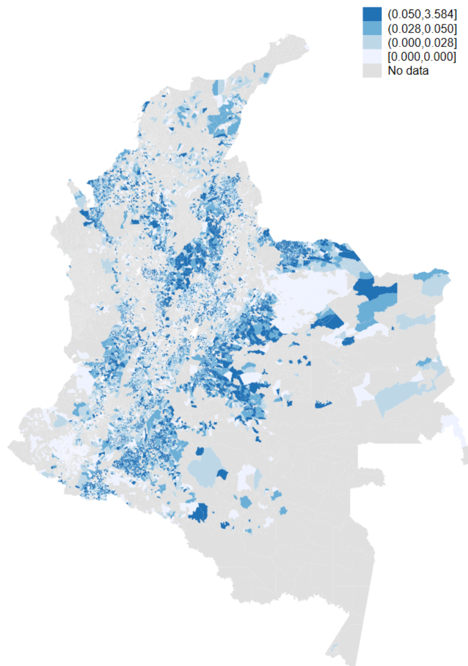
Notes: This table reports the estimated effect of temperature shocks on the number of land owners within fixed segments of the initial farm-size distribution. The dependent variables are the number of owners in municipality–year whose total landholdings fall into each of the ten farm-size bins defined by the municipality's baseline (year 2000) land-distribution deciles. The independent variable is the total number of atypical-temperature days in the past two years divided by 100. Each column corresponds to a different regression. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Standard errors clustered at the municipality level reported in parenthesis. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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



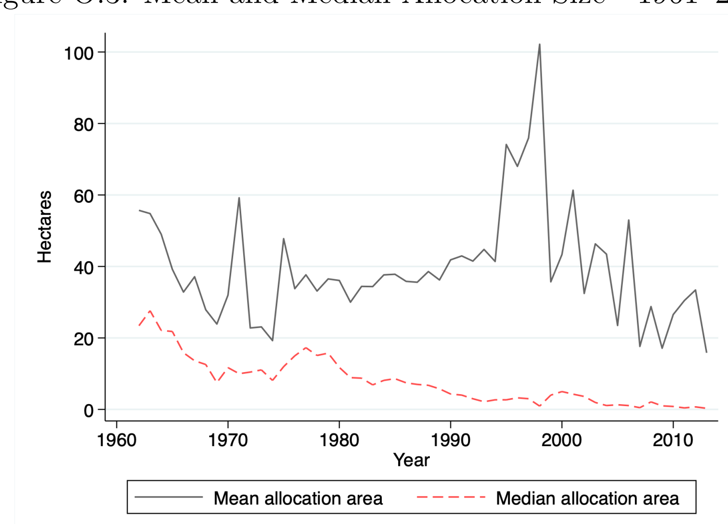
Notes: Data from the System of Information for Rural Development (SIDER)

Figure O.2: Ratio of Land Sales to Number of Allocations



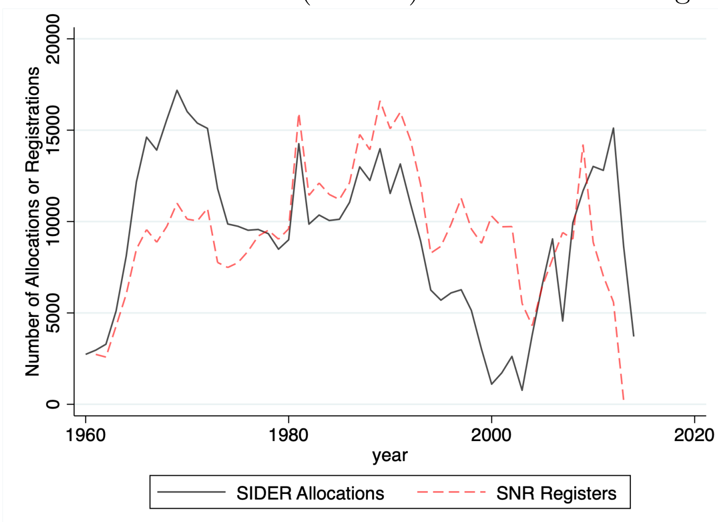
Notes: The figure shows the proportion of farms sold in each *vereda* to the total number of farms allocated by the government between 1980 and 2011. Data from the National Superintendence of Notaries (SNR).

Figure O.3: Mean and Median Allocation Size - 1961–2012



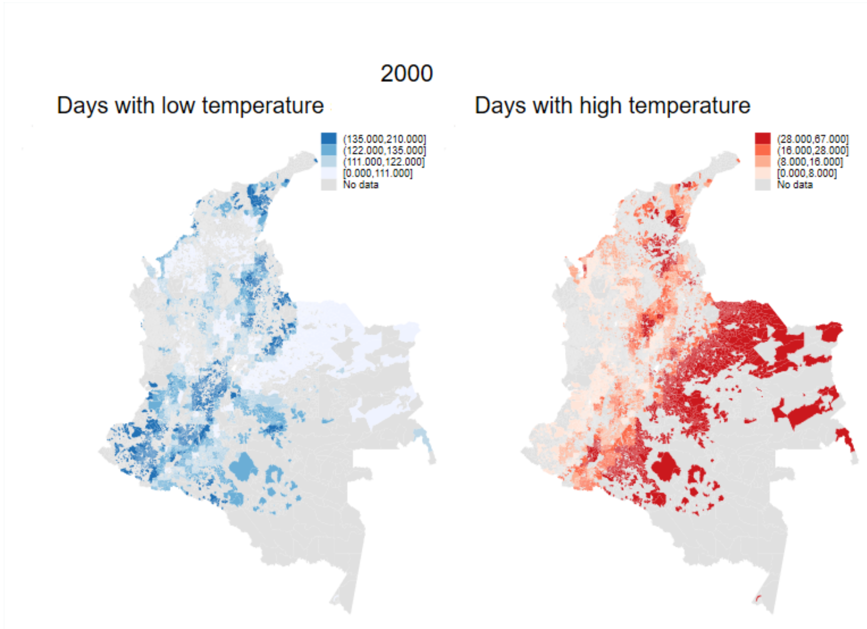
Notes: This figure shows the national yearly mean and median areas of land properties granted by the government through the public land–allocation program. Data from the System of Information for Rural Development (SIDER).

Figure O.4: Number of Allocations (SIDER) vs. Number of Registrations (SNR)

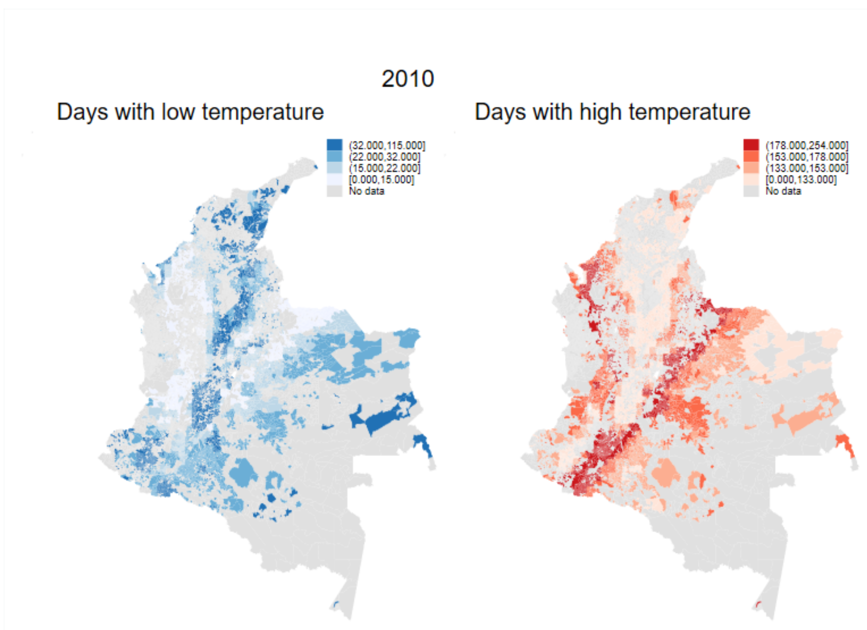


Notes: The figure compares the number of land properties allocated by the government through the public land–allocation program with the number of properties registered at local public notary offices as having been received from the government. Property registration is the final step in the allocation process and establishes the beneficiary's formal property rights over the granted plot. Data from the System of Information for Rural Development (SIDER) and the National Superintendency of Notaries (SNR).

Figure O.5: Temperature Shocks Across Space - 2000 and 2010



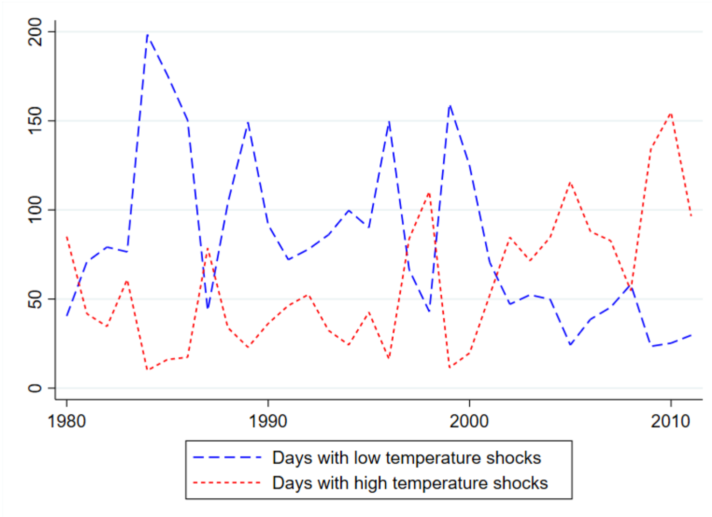
(a) Shocks in 2000



(b) Shocks in 2010

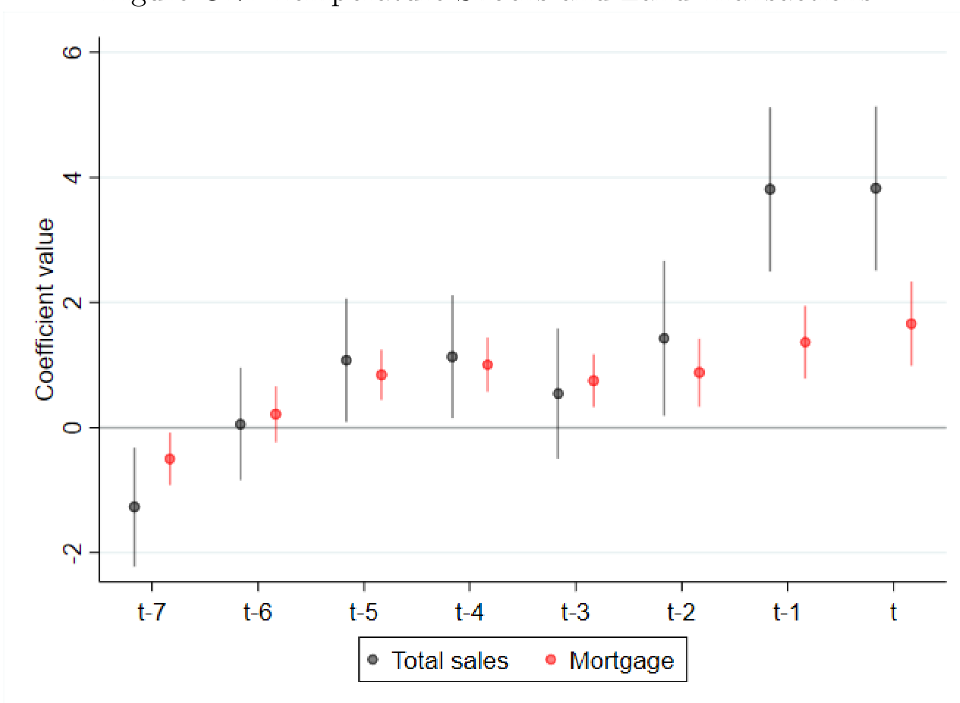
Notes: The figure shows the average number of days with extreme heat (red) and extreme cold (blue) across *veredas* in our sample in 2000 and 2010. Data from the Copernicus Climate Change Service (C3S).

Figure O.6: Temperature Shocks Across Time



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

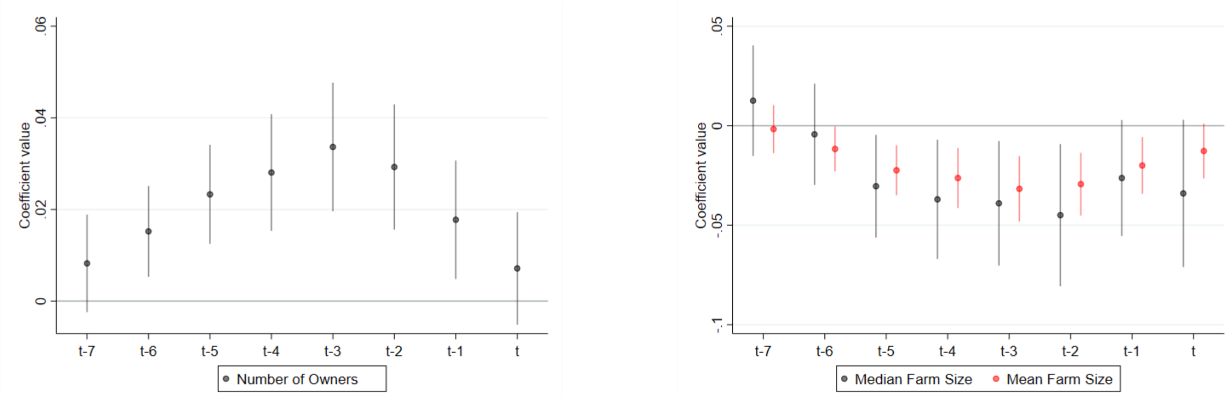
Figure O.7: Temperature Shocks and Land Transactions



Notes: The figure presents the coefficient estimates for the number of days with atypical temperature (divided by 100) and its lags from equation (O.1). The outcomes are the total number of land sales (black) and the total number of land mortages (red). All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Standard errors clustered at the municipality level. Error bars indicate 95% confidence intervals. Data from the National Superintendency of Notaries (SNR).

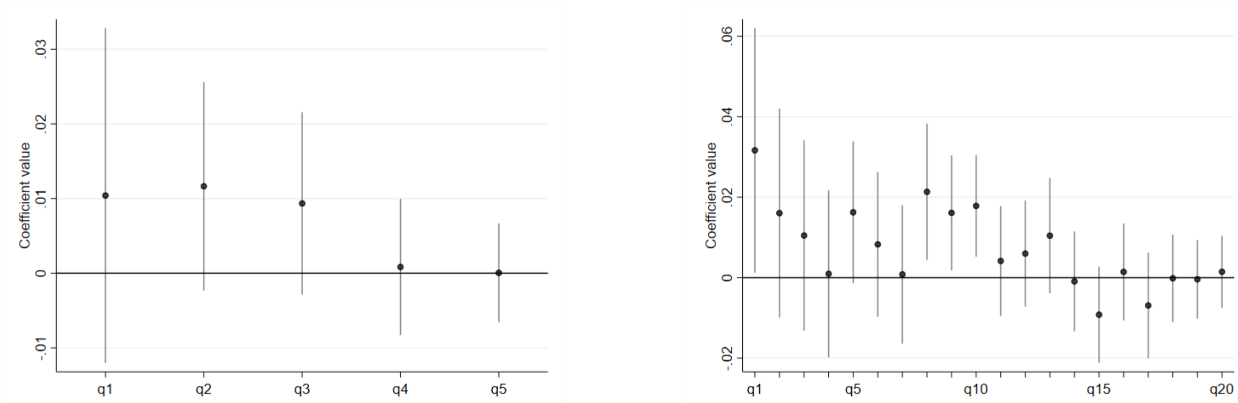
Figure O.8: Temperature Shocks and Farm Size

(a) Owners (b) Area



Notes: The figure presents coefficient estimates for the number of days with atypical temperature (divided by 100) and its lags from equation (O.1). In Panel (a), the outcome is the number of owners, and in Panel (b), the outcomes are mean and median farm size. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral-registry updates. Standard errors are clustered at the municipality level. Error bars indicate 95% confidence intervals. Data from the National Land Registry (*Catastro Nacional*), maintained by the National Geographical Institute (IGAC).

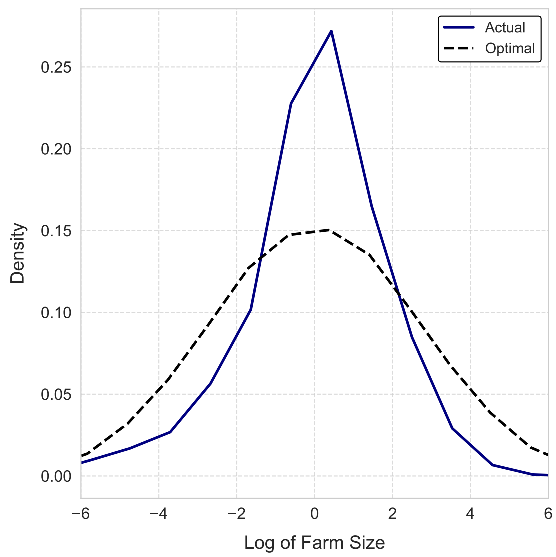
Figure O.9: Temperature Shocks and Number of Owners by Initial Distribution Quantiles - Alternative Partitions



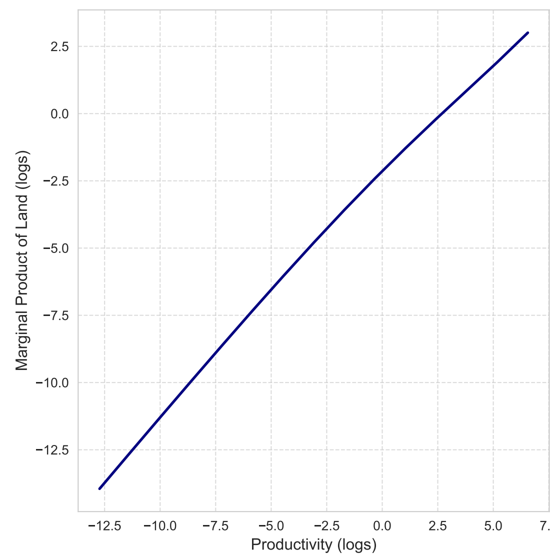
(a) Quintiles (b) Vigintiles

Notes: This figures reports estimates of γ^j for $j = 1, \ldots, 5$ (Panel a) and of f γ^j for $j = 1, \ldots, 20$ (Panel b) from equation (6). A separate regression is run for each of the quantiles of the initial municipality-level distribution of farm sizes. The outcome is the log number of owners whose farm sizes fall within the corresponding quantiles. The independent variable is the number of atypical temperature days in the past two years, divided by 100. All regressions include municipality and year fixed effects, as well as cumulative rainfall and its five lags, the accumulated number of land allocations, the area covered by the land registry, and an indicator for cadastral registry updates. Error bars indicate 95% confidence intervals. Standard errors are clustered at the municipality level.

Figure O.10: Optimal Farm Size Distribution



(a) Optimal vs. Actual Farm Size



(b) Marginal Product of Land

Notes: This figure shows the farm-size distribution generated by the model and the implied distribution if the marginal product of land equalized across farmers, as would occur under fully functioning rental markets. The optimal farm size is computed as $\ell(s_t^a) = \frac{s_t^a}{\int s_t^a dG(\phi_t)} L$, assuming the stationary distribution of farm productivity.