Occupational Choices: Economic Determinants of Land Invasions[*]

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Abstract

This study estimates the effect of economic conditions on redistributive conflict. We examine land invasions in Brazil using a panel dataset with over 50,000 municipality-year observations. Adverse economic shocks, instrumented by rainfall, cause the rural poor to invade and occupy large landholdings. This effect exhibits substantial heterogeneity by land inequality and land tenure systems, but not by other observable variables. In highly unequal municipalities, negative income shocks cause twice as many land invasions as in municipalities with average land inequality. Cross-sectional estimates using fine within-region variation also suggest the importance of land inequality in explaining redistributive conflict.

Keywords: land conflict, inequality, redistribution, rainfall, political economy, development, social movement, collective action

JEL codes: D74, Q15, D3, O17, P16

1 Introduction

Conflict over land is endemic to many rural economies. In environments marked by a highly skewed distribution of property, incomplete land and credit markets, poorly or unevenly enforced property rights, and weak political institutions, agents often resort to extralegal means to improve their economic positions. The poor frequently invade private properties and occupy them until either forcibly expelled or granted official titles. Land conflict, which is prevalent in many countries such as Brazil, South Africa, Uganda and Venezuela, may distort the allocation of resources in the agricultural sector away from productive uses and thereby contribute to the persistence of rural poverty. How do economic conditions affect this redistributive conflict?

This paper explores this question using a rich municipal-level dataset of 5,299 land invasions from 1988 to 2004 in Brazil. We follow Miguel, Satyanath and Sergenti [2004] by using rainfall as a source of exogenous variation to study the relationship between income and conflict, and find that adverse economic shocks cause the rural poor to invade large landholdings. This effect exhibits considerable heterogeneity by land inequality and land tenure systems. In highly unequal municipalities, negative income shocks cause twice as many land invasions as in municipalities with average land inequality. The effect of income shocks is even stronger in highly polarized municipalities, as measured by the degree of bimodality in the land distribution. Cross-sectional estimates using fine within-region variation also suggest the importance of land inequality in explaining redistributive conflict. We also find that income shocks cause significantly more land invasions in municipalities with a greater proportion of land under fixed-rent contracts. By contrast, we find no evidence of heterogeneity on a range of other political and socioeconomic variables, including political competition, sharecropping, police expenditures and social welfare spending.

Recent microeconometric studies have examined two channels by which economic factors can cause conflict: (1) lowering the opportunity cost of engaging in conflict, and (2) increasing the returns to violence. With respect to opportunity costs, in a study of the Colombian civil conflict, Dube and Vargas [2006] present evidence that steep declines in coffee prices reduced workers' wages and increased their propensity to join armed groups. Similarly, Do and Iyer [2006] analyze community-level data from Nepal and find that civil conflict is strongly correlated with poverty and lower levels of human capital, which they consider to be proxies for opportunity costs. With respect to returns to violence, Angrist and Kugler [2008] present evidence on economic factors that increase the rents of engaging in armed conflict in Colombia. They find that increases in the price of coca act as a type of "resource curse" that leads to more violence as people are drawn into the illegal drug trade. Deininger [2003] also finds some support for this latter channel in a study of the Ugandan civil war, observing a positive correlation between expropriable agricultural assets (coffee plants) and violence, though he argues that this channel may be less important than suggested by the cross-country literature.

Consistent with previous findings about the opportunity-costs channel, our paper finds evidence that rural productivity shocks, such as droughts, lower the returns to agricultural labor and thus increase conflict. This study, however, is the first to show that the effect of income shocks exhibits heterogeneity in ways consistent with economic theories of conflict as well as with qualitative evidence. Previous papers have been unable to examine many plausible sources of potential heterogeneity because of data limitations. By contrast, our panel dataset, which includes over 50,000 municipality-year observations, enables testing of various interactions. Another important contribution is that we examine conflicts that are explicitly redistributive, whereas other studies predominantly consider civil wars, which are often fought for a variety of economic and non-economic reasons.

While the predicted effect of income shocks on conflict is relatively straightforward, the relationship between inequality and conflict is more ambiguous.[1] At first glance, the link between land inequality and land invasions may appear obvious. High land inequality concentrates property in relatively few landholdings, so the returns to invading the largest properties increase. In addition, high land inequality typically is associated with a higher percentage of the population that is land-poor, which may heighten sensitivity to economic shocks and thus increase land invasions.

However, numerous scholars [e.g., Grossman and Kim 1995; Esteban and Ray 1999, 2002; Acemoglu and Robinson 2001, 2006] argue that the relationship between inequality and redistributive conflict is nonmonotonic. For example, Acemoglu and Robinson [2006] argue that in situations with extremely high asset inequality, the rich may be more willing to expend resources on repression in order to deter revolution. Moreover, it may be easier for a smaller landholding class to over-come the collective action problem of contributing to the protection of private property [Esteban and Ray 2002]. Hence, areas with the highest levels of land inequality may well experience less conflict.

The effect of land inequality on redistributive conflict through political channels is also ambiguous. High land inequality, for example, may be associated with enduring patron-client relations [Baland and Robinson 2003], which could potentially decrease land invasions if the poor fear losing employment, credit, or future access to land owned by the rich. Historically high inequality may also make political institutions less representative [Engerman and Sokoloff 2001], thereby leading the poor to resort to extralegal action for land redistribution. Given such diverse predictions that operate through both economic and political channels, we explore the relationship between land inequality and redistributive conflict empirically. We use numerous measures of land inequality, as well as other political and economic variables, to explore the various mechanisms that theories suggest may connect the distribution of land to conflict.

Our study also contributes to the literature on land tenure systems. The large literature on agricultural contracts suggests that they are risk allocation mechanisms between landowners and the land-poor [see Bardhan and Udry 1999]. Under fixed-rent contracts, the land-poor are not only residual claimants of the returns from farming, but also bear all risk from agricultural shocks such as rainfall [Stiglitz 1974; Otsuka and Hayami 1988]. If land invasions respond to transitory variation in income, then land tenure systems that better insure the land-poor would be expected to mitigate the effect of income shocks on land invasions. Therefore, theory predicts that rainfall shocks would cause more land invasions in municipalities with a high degree of fixed-rent contracts, conditional on the distribution of land.[2] We explore this prediction in our specifications below.

In addition to literature on political economy, this paper also contributes to a longstanding debate in the fields of political science and sociology: when do the rural poor become politically active? Studies of political change have highlighted the important historical role of agrarian class conflict in institutional transitions [Moore 1966; Huntington 1968]. Many examine the role of poverty and inequality in rural class conflict [e.g., Scott 1976; Popkin 1976], and some suggest that different systems of land tenure foster or inhibit peasant mobilization [Wolf 1969; Paige 1975]. This literature is generally based on in-depth case studies, and the few studies that are quantitative [e.g., Paige 1975; Markoff 1996] are not sensitive to the problems posed by endogeneity. Our paper advances this overall debate by using panel data.

2 Overall Context

Brazil has the eighth-most unequal distribution of land in the world [FAO 2005]. The concentration of property in Brazil is so skewed that the largest 3.5 percent of landholdings represent 56 percent of total agricultural land. The Gini coefficient of land inequality remained stable between 1967 and 1998, measuring 0.84 in both the beginning and end of the period.[3] Some regional differences exist, but land inequality in all regions is high when compared internationally [Hoffmann 1998].

Efforts to reduce Brazil's land inequality have been hamstrung by political constraints. During the presidency of Getúlio Vargas (1930-45), proposals for land reform emerged but were quickly sidelined because Vargas relied on continued support from landed elites [Morissawa 2001, p. 81]. In the early 1960s, President João Goulart initiated modest land reform measures but was soon ousted by the military coup of 1964. Land reform stagnated during the twenty-year military dictatorship. The authoritarian regime expropriated only eight properties per year on average, and instead attempted to placate rural peasants through colonization projects, which typically entailed resettlements to government land in the Amazon [Alston, Libecap and Mueller 1999, pp. 135-6]. Even since Brazil's transition to democracy in 1985, land reform has been limited. Just over 100,000 families received land from 1985 to 1994, despite the government's stated goal of resettling 1.4 million families in the first five years.

Amidst limited formal land reform, many landless Brazilians have invaded private estates and public lands, squatting in an attempt to appropriate land. Over three million people participated in land invasions in the Brazilian countryside between 1988 and 2004 [CPT 2004]. By invading large properties, poor Brazilians have placed the issue of land redistribution on the national political agenda, pressuring the government to expropriate land. Their efforts have been successful: due in large part to these land invasions, land reform trebled under Fernando Henrique Cardoso (1995-2002), reaching nearly 260,000 families during his presidency [INCRA 2005].

Land invaders are the principal beneficiaries of land redistribution. There are no comprehensive data on how often land invaders successfully obtain official titles. However, case studies examining various communities suggest that 60 to 80 percent of redistributed land is received by individuals who previously invaded the properties [Lopes 1999; Heredia et al. 2002; Wolford 2003]. For example, a study of 37 redistributed properties in Santa Catarina found that only seven had not involved land invasions [Wolford 2003, p. 515]. Recipients of redistributed land also become eligible to receive several forms of government support, providing an additional incentive to invade properties. Upon receiving the land, invaders can obtain government credit for the purchase of food, equipment, and housing through the "Implantação" program administered by INCRA, the national land reform agency. Hence, land invasions have the potential to yield substantial benefits for those who participate.

These land invasions, also termed "land occupations" in Brazil, are large undertakings, each involving an average of 156 families. While systematic data on the socioeconomic profile of participants are unavailable, case studies suggest that invaders are typically farmers (renters or squatters) or landless agrarian workers, although relative proportions vary regionally [Wolford 2004*b*]. A 1996 survey of recipients of land through government redistribution showed that 53 percent were previously farmers and eight percent were salaried agricultural workers [Viero Schmidt, Marinho and Rosa 1997].[4]

In practice, land invasions are highly complex. First, the poor must identify rural properties that are likely to be expropriated by the federal government following an invasion—in particular, underutilized land that does not fulfill its "social function."[5] Once a target property is identified, participants must secretly develop plans for invasions, gather food and materials for housing, and arrange caravans of buses and cars [Paiero and Damatto 1996]. Land invasions involve tense and often violent struggles—in 2003 alone, 55 land invaders were killed, 73 were physically attacked, and 155 received death threats [CPT 2003]. Landowners routinely seek to regain possession of their land through both extralegal and legal means; for example, by hiring private militias while simultaneously obtaining expulsion orders from local judges enforceable by the military police [De Janvry, Sadoulet and Wolford 2001, p. 16]. If invaders manage to remain on occupied properties, INCRA may recognize their claim if it deems the occupied land to be "unproductive." INCRA then estimates the value of the land and offers a sum to the owner in exchange for expropriation.[6]

Because the poor face considerable obstacles when invading land, the coordination of efforts is crucial. Many land occupations are facilitated by social activists. Most significantly, those affiliated with the Landless Workers Movement (*Movimento dos Trabalhadores Rurais Sem Terra*, commonly known as the MST)—Latin America's largest social movement—aided 57 percent of all families invading land in Brazil between 1996 and 1999 [Comparato 2003, p. 104]. Many studies in the fields of political science and sociology focus on how the MST and other organizations mobilize the poor to invade rural properties in Brazil.

While such groups clearly play an important role in mobilizing the poor, they offer an incomplete explanation for when and where land invasions occur. Figure 1 shows that the prevalence of land invasions varies greatly across municipalities in Brazil. Furthermore, qualitative research on land conflict in Brazil underscores the importance of transitory income shocks and the concentration of land ownership [Palmeira and Leite 1998; Medeiros 2003; Wolford 2004*a*]. For example, Wolford [2004*a*] offers a detailed case study of Água Preta, a municipality with high land inequality (land Gini = 0.935) in the northeastern state of Pernambuco. In the early 1990s, sugar plantation workers faced a substantial income shock due to drought, declines in international sugar prices, and cuts in government subsidies. As Wolford explains, landless workers became easier to mobilize for land invasions as wage earnings from sugar plantations fell.[7] This study explores whether economic factors help to explain the conditions under which the rural poor choose to invade land.

3 Data

3.1 Land Invasions

We employ municipal-level data on land invasions provided by Brazil's Pastoral Land Commission (*Comissão Pastoral da Terra* – CPT) and Dataluta (*Banco de Dados da Luta pela Terra*). This dataset provides one of the largest samples on redistributive conflict in the world, covering 5,299 land invasions. The data consist of the number of distinct land invasions per year in each Brazilian municipality between 1988 and 2004.[8] Additionally, our data include the number of families participating in each land invasion. The CPT, a church-based NGO active since 1976, collects these data from various sources.[9]

There may be concerns with the coverage of the reports: for example, they may be systematically biased towards underreporting conflict in remote areas. All of our results are qualitatively similar when we restrict our sample to only municipalities that have reported invasion activity. There may also be systematic measurement error due to journalistic bias towards overreporting the size of a land invasion. For this reason, we focus on the number of invasions, which is relatively less vulnerable to such bias than reported size of invasions. However, for comparison we also provide results for the number of families involved in land invasions. In addition, we examine a binary measure of whether conflict occurred in a municipality-year, as this measure may be less prone to measurement error.

3.2 Agricultural Income

Our primary independent variable of interest is agricultural income, which is measured by crop revenue. Data on crop production are from statistics on municipal agriculture production (*Produção Agrícola Municipal*) from Brazil's national census bureau (*Instituto Brasileiro de Geografia e Estatística* – IBGE). For each muncipality-year, we take a revenue-weighted sum of the log crop yields (tons per hectare) as a measure of log agricultural income [Jayachandran 2006; Kruger 2007]. This calculation includes the eight most important crops in Brazil, which are cotton, rice, sugar, beans, corn, soy, wheat and coffee [Helfand and Resende 2001, p. 36].[10] We assume that municipalities take crop prices as given in domestic and international markets. Given the difficulties of ongoing data collection in rural areas, crop data are subject to numerous sources of measurement error. Macroeconomic conditions, including periods of hyperinflation, may also contribute to measurement error. Because measurement error in our data may be nonclassical, the direction of the resulting bias is ambiguous, highlighting the need for an instrument.

3.3 Rainfall

We use rainfall as a source of exogenous variation in agricultural income. Daily rainfall data from 2,605 weather stations across Brazil for the 1985-2005 period are from the Brazilian National Water Agency (*Agência Nacional de Águas* – ANA). In order to derive a municipal-level measure of rainfall, we match municipalities to the nearest weather station within 50 kilometers. Municipalities without a weather station within this matching radius were excluded. All of our results are robust to changing the acceptable matching radius to values between 20 and 100 kilometers.

Raw rainfall totals would be inappropriate to use in this context given the wide range of climatic variation in a country the size of Brazil. A 10-centimeter drop in annual rainfall may be expected to have different economic effects in arid regions of the Northeast than in the temperate South. In order to measure comparably the effect of rainfall on agricultural productivity, we transform the rain data as follows. Monthly rain totals are first standardized by station-month, then summed across the twelve months of the year. These annual totals are then standardized by station-year. Standardizing by month accounts for seasonal patterns and may more accurately identify aberrant rainfall years [Mitchell 2003]. Standardization also makes rainfall measurements comparable across municipalities since agricultural production is likely to be adapted to the average level and variance of rainfall in each municipality.

The primary measure of rainfall used here is the absolute value of standardized rainfall because the relationship between rainfall and income changes is nonmonotonic. As shown below, both drought and flooding are negatively correlated with agricultural income. Formally, the primary measure is given by:

$$z = \left| \frac{x_{it} - \overline{x}_i}{s_i} \right| \tag{1}$$

where rain observations x for every rain measuring station i and year t pair are standardized by the mean $\overline{x}_i$ and standard deviation s_i of the rain data from each rain station's 21-year (1985-2005) time-series.[11] For this rainfall measure, x_{it} is the annual sum of standardized monthly rainfall, given by:

$$x_{it} = \sum_{m=1}^{12} \frac{x_{imt} - \overline{x}_{im}}{s_{im}} \tag{2}$$

For robustness, we also examine additional measures of rainfall. A second rainfall measure is squared rain deviation, given by:

$$z = \left(\frac{x_{it} - \overline{x}_i}{s_i} \right)^2 \tag{3}$$

As a third rainfall measure, we use the absolute value of standardized annual rainfall, without first standardizing by month. This more coarse measure is given by Equation 1, where x_{it} is now the measured rainfall for each station-year.[12]

We also examined various alternative rainfall measures, including non-standardized measures, higher-order polynomials, and dummies for various rain thresholds. These alternative measures of rainfall are not employed as instruments because they are not as highly correlated with agricultural income.

3.4 Land Inequality and Land Tenure

Municipal-level data on the distribution of land in 1992 and 1998 were calculated from INCRA's land registry by Rodolfo Hoffmann [Hoffmann 1998]. In addition to Gini coefficients of the land distribution, these data contain the number of properties within given size brackets in each municipality. Because the land Ginis were calculated based only on landowners, we adjusted them using the share of population that is landless in each municipality, taken from the 1995/96 IBGE Agricultural Census. To reduce measurement error and increase the sample size, we average the 1992 and 1998 observations where both are available, and take the available observation from 1992 or 1998 otherwise. Endogeneity of inequality to land invasions is not a concern given how persistent land inequality is over time, with a correlation coefficient of 0.86 between Hoffmann's 1992 and 1998 observations.

Because our dependent variable is a measure of redistributive conflict, we also construct a measure of economic polarization [Esteban and Ray 1994; Duclos, Esteban and Ray 2004].[13] This measure, while closely linked to the Gini coefficient, captures the degree of bimodality in the distribution of land. Esteban and Ray [1999] argue that polarization is a better predictor of conflict than the Gini coefficient.

Data on three types of land tenure—rental, ownership, and sharecropping—also come from the 1995/96 IBGE Agricultural Census. Landholding is classified as rental if the tenant pays the owner a fixed amount of money in rent, or if the tenant must meet a production quota. Sharecropping, on the other hand, refers to properties in which tenants pay owners a certain share (a half, quarter, etc.) of the harvest. When a landowner engages in production, land is classified in the "ownership" category.[14] We measure these variables as the fraction of a municipality's arable land under each land contract system.

3.5 Other Variables

Data on rural population, poverty rates, income Gini coefficients and per capita income are from the 1991 and 2000 national censuses.[15] Data on agricultural workers and the quality of land come from the 1995/96 Agricultural Census. IBGE administers both the national and agricultural censuses, and also provides land area data. Annual population data and municipal budget data are from the Institute for Applied Economic Research (*Instituto de Pesquisa Econômica Aplicada* – IPEA), a Brazilian government agency. Data on municipal elections come from the Supreme Electoral Court (*Tribunal Superior Eleitoral* – TSE). All analysis is restricted to municipalities with more than 10 percent rural population (averaged for the 1991 and 2000 census years); results are robust to different thresholds.

Table 1 lists summary statistics for the variables included in the fixed-effects specifications. The top half of the table describes data used in the 14-year panel with annual crop data, and the bottom half describes census data we use as a robustness check. We add 0.01 before calculating log families, resulting in a negative mean for the variable. The political competition variable is defined as the difference in vote share received by the top two mayoral candidates in the last mayoral election (mayors were elected in 1996, 2000, and 2004).[16]

4 Identification Strategy

Endogeneity is an important issue when estimating the relationship between economic conditions and conflict. In our study, there may be reverse causation because land invasions may reduce agricultural income by preventing harvesting. Another potential source of bias is that agricultural income may be correlated with omitted variables that covary with land invasions. Although we use municipality and year fixed effects, there may also be municipality-specific, time-varying omitted variables such as the number of activists in the area or the responsiveness of local judges to landowners' complaints. One important potential confounder is differential trends across municipalities, such as urbanization and the expansion of education, that are correlated with income growth, but that also facilitate collective action [Putnam, Leonardi and Nanetti 1994; Miguel, Gertler and Levine 2006]. This phenomenon would bias OLS estimates towards 0: while rising income would diminish the incentive to invade land, increasing organizational capacity, for example, would simultaneously make it less costly. The measurement error concerns discussed above may also bias our estimates, and may be exacerbated by the inclusion of fixed effects.

Our identification strategy uses rainfall as an instrument for rural income. For many years, rainfall has been used as an instrument to study various empirical questions [e.g., Paxson 1992; Jayachandran 2006], including the relationship between income and conflict [Miguel, Satyanath and Sergenti 2004]. Rainfall is a particularly good instrument for this study because land invasions occur in rural municipalities, which are sensitive to weather variation. Below, we show that rainfall is strongly correlated with municipal-level agricultural income, and then discuss possible violations of the exclusion restriction. Our first-stage equation models the relationship between rainfall and agricultural income:

$$y_{it} = D_1 Z_{it} + D_2 X_{it} + \delta_i + \delta_t + \mu_{it} \tag{4}$$

In this equation, rainfall deviations (Z_{it}) instrument for agricultural income (y_{it}) in municipality i in year t. We control for other municipality characteristics (X_{it}). Municipality fixed effects (δ_i) are included in all specifications to control for omitted, time-invariant characteristics of municipalities that may be related to both agricultural income and land invasions, such as total land area and soil type. We also include year fixed effects (δ_t) in all specifications to control for time-varying, national-level trends, as discussed in Section 2. The term μ_{it} is an error term, clustered at the municipal level. Clustering on rain station and micro-region yield qualitatively similar results.[17] Results are broadly comparable, though weaker, when using lagged rainfall as an instrument for agricultural income.

The first-stage relationship between rainfall deviation and agricultural income is strongly negative and significant at over 99 percent confidence (Table 2). This result is robust to all three transformations of rainfall discussed in Section 3.3. The strength of the first-stage relationship using all three measures is remarkable, with F-statistics for the excluded instruments of approximately 86 for the absolute value measures (Columns 1 and 3) and 70 for the squared rainfall (Column 2). By contrast, cross-country studies that use rainfall as an instrument for GDP [e.g., Miguel, Satyanath and Sergenti 2004] have suffered from weak instrument problems [Bound, Jaeger and Baker 1995; Staiger and Stock 1997]. Possible reasons for this difference may include our use of agricultural income instead of GDP and our much greater sample size.

As a falsification exercise, we regress agricultural income on future rainfall, controlling for time and municipality fixed effects. Column 4 presents a specification that includes rainfall at time $t+1$ as well as at t. Future rainfall does not predict present agricultural income: the coefficient on future rainfall is very small and statistically insignificant.

To justify our choice of using the absolute value of the standardized rainfall measure, Figure 2 shows a nonparametric graph of agricultural income on the standardized rainfall measure. This strong relationship is clearly nonmonotonic, approximately exhibiting an inverted-U shape. Given the slight asymmetry around zero in the nonparametric plot, we also tried using an indicator for rain shocks greater than two standard deviations as an instrument for income. This instrument, however, was not as strongly correlated with agricultural income as is the continuous rainfall deviation measure.

Figure 3 displays the first-stage relationship using the absolute value of rainfall deviation, which is clearly downward sloping. Note that droughts and floods are both associated with lower agricultural income in Brazil. This result differs from recent studies in Africa [Miguel, Satyanath and Sergenti 2004] and India [Besley and Burgess 2002], which find that floods increase crop yields.

The second-stage equation estimates the impact of agricultural income on different measures of land conflict (C_{it}):

$$C_{it} = \beta_1 y_{it} + \beta_2 X_{it} + \delta_i + \delta_t + \epsilon_{it} \tag{5}$$

With respect to the exclusion restriction, a potential problem could be that rainfall directly affects the decision to invade land. By using rain *deviations* as our instrument, we mitigate this concern. It is relatively improbable that both droughts and floods similarly reduce (or increase) the probability of invading land except through their effect on income.

5 Basic Results

Negative income shocks, instrumented by rainfall, cause an increase in land invasions across all three of our dependent variables: a dichotomous indicator of whether or not a land invasion occurred, a count of the number of invasions, and the log of the number of families participating in land invasions.

Table 3 presents linear probability model specifications, in which the dependent variable is dichotomous. Municipality and year fixed effects are included in all specifications but are not shown. The OLS estimate of the effect of agricultural income on land invasions is not statistically significant, possibly due to the biases discussed above (Section 4).

Columns 2 through 4 present coefficient estimates and t-statistics for the IV-2SLS specifications using each of our rain measures. Results are stable across all three instruments: all are statistically significant at 99 percent confidence. A one standard deviation drop in agricultural income increases the probability of a land invasion by 17 percentage points when instrumenting with the absolute monthly standardized rainfall measure (Column 2). The effect is 20 percentage points for the yearly standardized measure (Column 4), and 24 percentage points when using squared standardized rainfall (Column 3). As a benchmark, Miguel, Satyanath and Sergenti [2004, p. 740] find that a standard deviation income shock increases the probability of civil war by 12 percentage points.

Reduced form estimates of the direct effect of rainfall on land invasions are positive and significant at 99 percent confidence (Columns 5-7). Deviations from average rainfall are associated with a higher probability of land invasions. The estimated effects in the reduced form, however, are quite small. A standard deviation increase in the rainfall measure is associated with a 0.28 to 0.35 percentage point increase in the probability of a land invasion.

Table 4 repeats the specifications shown in Table 3 with a count measure of land invasions (Panel A) and the log of the number of families participating in land invasions (Panel B) as dependent variables. Results are consistent with the linear probability model. OLS estimates of agricultural income on both dependent variables are small and statistically insignificant (Column 1). In the IV-2SLS estimates, however, the coefficients are negative and significant at 99 percent significance on both dependent variables. A standard deviation drop in agricultural income increases the number of land invasions by between 0.35 and 0.51, depending on the choice of rainfall instrument (Panel A, Columns 2-4). Examining Columns 2-4 in Panel B, a 10 percent decrease in agricultural income causes a 11 to 16 percent increase in the number of families participating in land invasions. Columns 5-7 of Table 4 present OLS reduced form specifications of the effect of three rainfall measures. Rainfall coefficient estimates are significant at 99 percent confidence or greater for all specifications, using either dependent variable. As with the linear probability model estimates, the magnitudes of the coefficients are small.

We run several robustness checks to test our research design and data quality. First is the test using future rainfall, described above. Second, we use a different measure of income, from the 1991 and 2000 IBGE census. Specifications using only these two years are shown in Table 5. In Column 1, the OLS estimate of the relationship between income and land invasions is negative and statistically significant. Column 2 shows that census income is positively and significantly correlated with our rainfall instrument. Column 3 shows that the IV-2SLS estimate of land invasions on census income is negative and significant.

Third, we test the effect of rural unemployment on land invasions, another channel by which economic shocks may affect redistributive conflict. Specifications using unemployment are shown in Columns 4-6 of Table 5. As expected, Column 4 finds a positive coefficient on census unemployment, statistically significant at 95 percent confidence. However, as shown in Column 5, rainfall is weakly correlated with unemployment and is thus an inadequate instrument for unemployment. Hence, the IV-2SLS estimate in Column 6 of the effect of rural unemployment on land invasions is not statistically significant. Column 7 reports the OLS reduced-form regression of rainfall on land invasions in the two census years, further confirming our baseline results in this much smaller sample.

Fourth, another potential source of bias is a selection effect in the reporting of land invasions, i.e. remote municipalities may be underreported. To check for this bias, we restrict the sample to the 1028 municipalities with at least one land invasion in the 1988-2004 period. IV-2SLS estimates of the effect of agricultural income on land invasions, shown in Table 6, are significant at 99 percent confidence. Coefficient estimates are over three times larger in magnitude than those estimated using the full sample. These findings suggest that our results are not driven by selectivity in land invasion reporting. Furthermore, agricultural income shocks affect the intensity of rural conflict, not just the outbreak of conflict.

6 Exploring Heterogeneity

In this section, we examine whether the effect of income shocks on land invasions varies across municipalities with different levels of land inequality, land tenure systems, and other characteristics. By examining different dimensions of heterogeneity, we may gain additional insight about the motivations and characteristics of land invaders. For example, if income shocks increase conflict more in municipalities with the greatest share of land owned by the top decile of landowners, this evidence might suggest that the concentration of land in a few large properties provides greater incentives to invade land. Alternatively, if income shocks increase conflict more in places with a high degree of landlessness, this evidence might suggest that a lack of alternative sources of income and assets—and perhaps poverty more generally—helps to explain the prevalence of land invasions.

6.1 Identification

Identification of heterogeneous effects is difficult without truly exogenous (i.e., random) variation. Given the vast number of historical and contemporaneous factors that may mediate the relationship between a municipality's economic conditions and agrarian conflict, we cannot rule out all other possible sources of heterogeneity in our estimates. We attempt to mitigate this problem by looking at characteristics of municipalities that do not exhibit much temporal variation, as well as by considering a large number of alternative covariates. Even so, it should be clear that the estimated heterogeneous effects are not as well identified as the income effects, for which rainfall is a clearly excludable instrument. Nevertheless, our findings regarding heterogeneity are suggestive and represent an advance over previous studies in the literature.

To explore the heterogeneous effects of income shocks, we estimate the following second-stage equation of the impact of agricultural income, interacted with a set of time-invariant covariates (G_i), on different measures of land conflict (C_{it}):

$$C_{it} = \beta_1 y_{it} + \beta_2 (G_i \times y_{it}) + \beta_3 X_{it} + \delta_i + \delta_t + \epsilon_{it} \tag{6}$$

For covariates for which we have annual data, the second-stage specification is

$$C_{it} = \beta_1 y_{it} + \beta_2 (G_{it} \times y_{it}) + \beta_3 G_{it} + \beta_4 X_{it} + \delta_i + \delta_t + \epsilon_{it} \tag{7}$$

We instrument income (y_{it}) with rainfall (Z_{it}), as described above, and instrument the interaction of the covariate and income ($G_i \times y_{it}$) with the interaction of that covariate and rainfall ($G_i \times Z_{it}$).

In order to assess the strength of these first-stage relationships, we examine Anderson-Rubin statistics for the joint significance of the multiple endogenous regressors. The Anderson-Rubin statistic is an F-statistic that is robust to weak instruments and optimal in the just-identified case [Moreira 2006]. While Anderson-Rubin statistics are not formal tests of weak instruments, they are cluster-robust tests of the significance of endogenous regressors that are valid even in the presence of weak instruments. The Anderson-Rubin tests show that the coefficients in Tables 8–10 (discussed below) are jointly significant even if the instruments are weak.[18]

In terms of identification, the use of fixed effects, as well as the standardization of the rainfall measure (subtracting the mean and dividing by the variance, by municipality) helps to control for the parameters of the municipal-specific stochastic process governing rainfall, and eliminates much of the covariance between annual fluctuations in rainfall and relatively time-invariant characteristics of municipalities other than land tenure systems. However, fixed effects do not rule out the possibility that our interaction estimates merely reflect a higher-order outcome of rainfall patterns. If land tenure systems are an outcome of rainfall patterns, and agricultural output shocks are also an outcome of rainfall patterns, then the interaction could be yet another outcome (at a higher order) of rainfall patterns. If this were the case, the interaction regression may only be identifying a non-linear effect of rainfall, rather than the effect of land distribution.

To explore this possibility, Table 7 shows the results from cross-sectional specifications to check for potential endogeneity of land inequality and tenure to the permanent patterns of rainfall (mean, standard deviation, and coefficient of variation, over the sample period) in a municipality. The results for mean rainfall are mixed, with the coefficients only significant when micro-region fixed effects are not included. However, when micro-region fixed effects are included, the coefficient magnitudes fall by an order of magnitude and lose statistical significance. Neither the standard deviation nor the coefficient of variation of rainfall are robustly significant even without micro-region fixed effects, though the coefficient of variation appears to be slightly more correlated with the land inequality and tenure measures. Hence, average rainfall patterns are not robustly correlated with land inequality and tenure in our sample, suggesting that the land inequality and tenure interactions estimated below do not simply indicate non-linear rainfall effects. Nevertheless, to control for possible confounding nonlinearities in rainfall, we conservatively include interactions of agricultural income with the mean and coefficient of variation of rainfall in all of our interaction specifications. Results are qualitatively unchanged by the exclusion of these rainfall interactions.

6.2 Land Inequality

The effect of income shocks on land invasions is heterogeneous by land inequality. Table 8 displays estimated coefficients for specifications of interactions between land inequality and agricultural income. In Column 1, the coefficient on the interaction is negative and significant, while the coefficient on agricultural income is now positive and significant. The effect of income at the mean levels of land inequality, average rainfall, and coefficient of variation of rainfall is still negative (-0.362) and similar to our previous estimates. In municipalities with high inequality, negative income shocks have a greater positive effect on land invasions. The estimates on the interaction imply that at the 90th percentile of the land Gini distribution (and at the mean of average rainfall and coefficient of variation), a one standard deviation fall in agricultural income increases land occupations by 1.04. This is twice as large as the effect at the mean level of inequality, where a standard deviation drop in income causes 0.50 more invasions.

When applying these estimates to the high variation in state-level land inequality across Brazil, substantially different effects of income shocks are predicted. In municipalities with land Ginis at the levels of highly unequal states, such as Amazonas (land Gini = 0.93) and Pará (land Gini = 0.86), a one standard deviation fall in income would result in 1.17 and 0.94 more land invasions, respectively. By contrast, in municipalities with land Ginis of states with much lower levels of land inequality, such as Santa Catarina (land Gini = 0.60) and São Paulo (land Gini = 0.64), the predicted increase in occupations would be only 0.01 and 0.15, respectively.

We also examine a measure of polarization, developed by Esteban and Ray [1994] and Duclos, Esteban and Ray [2004], interacted with agricultural income (Column 2). The coefficient on this interaction is negative, significant, and larger in magnitude than the corresponding coefficient in Column 1. At the 90th percentile of the polarization distribution, a standard deviation drop in income increases land invasions by 1.49. Column 3 shows the "horse-race" regression of the two inequality interactions and finds that the land-Gini interaction is statistically insignificant when the land polarization interaction is included. This finding supports the theoretical predictions of Esteban and Ray [1999], who argue that polarization better predicts conflict than the Gini coefficient.

Next, we disaggregate the land distribution. Column 4 shows the share of land owned by the top 10 percent and bottom 50 percent of landowners, as well as the fraction of the population that is landless. Only the interaction between the fraction of landless and agricultural income is significant, which may suggest that the landless are the most likely to invade land in response to a negative income shock. This finding may imply that the heterogeneity in the income effect associated with land inequality is linked to economic vulnerability of the land-poor; the targeting of large properties may be of secondary importance at best.

Columns 5-8 repeat these specifications with a different dependent variable, the log of the number of families involved in land invasions. Results are broadly consistent. In Column 5, the effect of income shocks on the number of families engaging in land invasions is twice as large in highly unequal municipalities than the average. A 10 percent drop in agricultural income causes 16 percent more families involved in land invasions at the mean level of the land Gini, while causing 35 percent more families to invade at the 90th percentile of the land Gini distribution. Similarly, Columns 6-8 display coefficient estimates consonant with those in Columns 2-4, respectively.

The interactions of mean rainfall and rainfall variability with agricultural income are significant at the 10 percent level in many of the specifications, reflecting either a higher-order effect of rainfall, or that the climate of a municipality is associated with other factors that mediate the effect of an income shock on conflict. Municipalities with equally concentrated landownership may sustain different forms of agricultural activity based on the climate's suitability. For example, the average level of rainfall might be associated with sugarcane production, which may be vulnerable to land conflict for reasons besides land inequality or land tenure, such as poor political institutions stemming from the historical use of slave labor in sugar cultivation. In the absence of additional data, we cannot explore the heterogeneous effects of local climate in more detail, except by controlling for observable channels that plausibly modify the relationship between income shocks and land conflict.

Figure 4 graphically depicts the heterogenous effect of income by land inequality. The plot represents the nonparametric reduced form regression of land invasions on rainfall and the interaction between rainfall and the land Gini, after netting out municipality and year fixed effects. As the plot shows, the effect of rainfall on conflict is negligible in low inequality municipalities, but increases dramatically with the land Gini. Contrary to some theories discussed above, there appear to be no nonmonotonicities in the interaction between rainfall and inequality. Overall, this nonparametric result is consistent with the estimates from the instrumental-variables specifications with land-inequality interactions.

6.3 Land Tenure

The effect of income shocks on land invasions is also heterogeneous by land tenure. We investigate three systems of land contracts—rental, ownership, and sharecropping. In the theory of agrarian contracting under uncertainty, it is well known that under fixed-rent contracts, tenants bear the full effect of productivity shocks. Thus, we would expect that in municipalities with a large share of renters, income shocks would cause more land invasions.

Table 9 shows model specifications that include interactions with land tenure variables in addition to the interaction between land inequality and agricultural income.[19] Columns 1 through 3 display coefficient estimates for the interactions of the three land contract variables, measured as a fraction of arable land, with agricultural income, each entered separately. Column 4 includes all three interactions together, and Columns 5 through 7 replicate Columns 1 through 3 but with the addition of a triple interaction of land tenure, land Gini, and income, instrumented by the interaction of land tenure, land Gini, and rainfall.

The sign on the land rental interaction in Column 1 is negative and statistically significant with 90 percent confidence, indicating that income shocks cause more land invasions in municipalities with a relatively greater share of land under rental contracts. If the interaction of permanent rainfall patterns are excluded, this coefficient decreases (i.e., increases in magnitude) from -2.97 to -4.01, and is significant at 99 percent confidence (not shown). While higher order rainfall interactions may be partially correlated with the land tenure interactions, as discussed above, the effect remains significant even while controlling for permanent rainfall patterns. This effect is robust to the inclusion of the other tenure variables, as shown in Column 4, and to the addition of a triple interaction (Column 5).[20] The triple interaction indicates that municipalities with high land inequality and a high percentage of land under fixed-rent contracts experience more land invasions with a decrease in income. In contrast, neither the landownership interactions (Columns 2, 4, and 6) nor the the sharecropping interactions (Columns 3, 4, and 7) are significant in any specification.

There are several explanations for these results, but our aggregate data do not enable us to distinguish among them. It may be that fixed-rent tenants have a greater knowledge of farming, and thus stand to gain the most from invading land. It may also be that land renters are more exposed to risk than other farmers, as suggested above, because they bear the full productivity shock and cannot use their land for collateral—unlike landowners—to borrow during poor seasons. Regardless of which particular interpretation is correct, our specifications suggest that the effect of income shocks on redistributive conflict is heterogeneous by land tenure.

These results should be interpreted with caution, however, because land tenure may be endogenously time-varying, as well as correlated with permanent rainfall patterns as discussed above. Locations with higher variance in rainfall may choose land contracts that better allocate risk between land-owners and workers. In addition, land contracts could be renegotiated following a productivity shock, leading the choice of land contract to be correlated with income. Unfortunately, we do not have multiple observations of land tenure systems within the sample period. Nevertheless, other data suggest that land tenure systems are relatively stable over time in Brazil. The fraction of land under rental contracts in the 1995/96 Agricultural Census is substantially correlated with the 1985 Agricultural Census observation ($r = 0.60$); intertemporal correlations on the other tenure variables are comparable. Our results suggest that land contracts may play an intervening role in the relationship between income and conflict; future research should further investigate this relationship.

6.4 Other Interactions

We also inspect whether other mechanisms mediate the effect of income shocks on land invasions. Coefficient estimates for specifications with these interactions, none of which are statistically significant, are shown in Table 10. First, we examine municipal expenditures on public security, which may increase the costs of invading land and thus dampen the effect of income shocks on land invasions. The coefficient is small and insignificant (Column 1).[21]

Second, we consider a number of factors that could mute the impact of income shocks by providing rural workers with income insurance or alternatives to land invasions. For one, we examine public social expenditures, which actually may increase or decrease the effect of income shocks on land invasions. While social programs may offer a substitute to land occupations, they may also serve a complementary role. If the poor use social programs as a substitute for invading land when faced with income shocks, then higher public social expenditures may reduce land invasions. But if invaders can draw on social programs while occupying land, then higher government social expenditure may reduce the cost of land invasions and thereby increase their frequency. Column 2 interacts municipal social expenditures with agricultural income and finds a small and insignificant effect.

We next interact the number of banks in a municipality with agricultural income; the coefficient is small and insignificant (Column 3). Given that asset ownership is typically essential for securing a bank loan in Brazil, it is not surprising that the presence of banks does not moderate the effect of income shocks on land invasions—the landless cannot borrow to smooth their consumption during a bad growing season. In Column 4, we interact agricultural income with the share of local GDP coming from non-agricultural sectors. One could expect that the presence of economic opportunities outside of agriculture may mitigate the effect of extreme weather shocks. However, coefficient estimates are not significant.

Third, we explore whether properties of the income distribution mediate the effect of income shocks. We do so tentatively because the rural income distribution is likely to be time-varying and correlated with mean agricultural income; therefore, identification results depend on the strong assumption that the time-variation and correlation with agricultural productivity does not affect the level of conflict. In any case, neither the interaction of the income Gini (Column 5) nor the interaction of the extreme poverty rate with agricultural income (Column 6) are statistically significant. This may suggest that while income shocks have a greater effect on invasions in places where many are asset-poor (i.e., landless), the same may not be true for the income-poor. Landless agricultural workers depend on agricultural productivity and are thus vulnerable to extreme weather shocks. These asset-poor workers may not fall under the extreme poverty threshold under normal conditions, when work is available. In addition, because some individuals in extreme poverty may be among those excluded from the rural labor force, they may be less affected by agricultural productivity shocks.

Finally, as the rest of the table shows, neither the fraction of unused arable land (Column 7) nor political competition (Column 8) significantly affect the relationship between income shocks and land conflict. We also interacted numerous other variables with agricultural income including agricultural capital intensity (number of tractors), the presence of FM or AM radio stations, urbanization rates, the distance of municipalities from their state capital, and the political party of the mayor. None of these interactions were significant (not reported).

In sum, these interactions explore the mechanisms linking income shocks and land invasions. Factors that increase the vulnerability of rural workers to income shocks—in particular, a high concentration of landownership and the prevalence of tenant farming—may serve to exacerbate the income-shock effect. Asset poverty, and not income poverty, is associated with a greater effect of income shocks. Landless agricultural wage workers and tenant farmers may be particularly likely to suffer from weather-induced income shocks because regardless of current income flows, they possess few assets ensuring future income.

While we cannot examine every potential source of heterogeneity, our data allow us to rule out many of the most obvious. To show that the land inequality and tenure effects are robust, we have attempted a large number of additional interactions. None of these interactions are significant even if the land Gini interaction is excluded. In addition, it is unlikely that the land inequality and tenure variables respond substantially to transitory shocks. Land inequality is relatively stable in most developing countries [Deininger and Squire 1996]; as we note above, the intertemporal correlation of the land Gini in Brazil was 0.86 between 1992 and 1998. With respect to land tenure, while certain aspects of land contracts may well be adjusted after productivity shocks, overall land tenure relations tend to be the outcome of long-held norms and local custom [Young and Burke 2001]. Nevertheless, there may be underlying, unobserved variables that both affect the joint distribution of income and conflict and that are associated with land inequality or land tenure; these may bias our estimates.

7 Land Inequality in the Cross-Section

We now explore the between-variation in land invasions. As above, three dependent variables are examined: the number of land invasions, a dummy indicating the presence of at least one land invasion, and the log of the number of families participating in land invasions. For this section, each of these variables were aggregated for each municipality over the 1988-2004 period. For our independent variables, we take the earliest measurement available during the sample period. Census data covariates are from 1991, while Agricultural Census data are from 1995/96. Descriptive statistics for the cross-section are provided in Table 11. We estimate OLS regressions using the following specification:

$$C_i = \beta X_i + \delta_j + \epsilon_i \tag{8}$$

where X_i denotes a vector of independent variables, δ_j denotes a micro-region j fixed effect, and ϵ_i is an error term. Micro-regions are defined by IBGE as contiguous municipalities in a given state that share an urban center and have similar demographic, economic, and agricultural characteristics. All standard errors are clustered by micro-region. Coefficient estimates and t-statistics are reported in Table 12.

Land inequality is positively associated with land invasions across all specifications in Table 12. In Column 1, which does not include micro-region fixed effects or clustering, land Gini and the land tenure variables, as well as numerous other independent variables, are statistically significant. However, when we control for micro-region fixed effects and cluster the standard errors (Column 2), only land inequality and average rainfall remain statistically significant. The coefficient magnitude for the land Gini remains fairly stable, increasing from 2.71 to 2.92 when including micro-region fixed effects. Altogether, these estimates imply that a one standard deviation increase in land inequality is associated with an increase of .35 to .38 land invasions. Given that the mean number of land invasions across municipalities is 0.95, these coefficients represent a large shift relative to the mean. We also fit a negative binomial model (Column 3), which also yields highly significant results.[22]

Looking at the binary dependent variable, Column 4 shows that land inequality and average rainfall remain the only statistically significant independent variables when micro-region fixed effects are included. Results are consistent when using log families as a dependent variable (Column 5). These coefficients imply that a one standard deviation increase in land inequality is associated with 7.2 percent increase in the probability of a land invasion and a 79 percent increase in the number of families participating in land invasions. The difference of these magnitudes suggests that the effect of land inequality on land invasions operates substantially more on the intensive margin than the extensive margin. However, these cross-municipality specifications may suffer from the omitted variables bias mentioned above.

Finally, Figure 5 presents further evidence that the relationship between asset inequality and conflict is monotonically increasing. The figure shows the nonparametric regression of the total number of land invasions in the 1988-2004 period on the level of land inequality, as measured by the Gini coefficient, conditional on micro-region fixed effects. The relationship is increasing over the full range of Gini values. We find no evidence that high levels of inequality decrease the amount of open conflict by increasing the incentive for asset holders to invest in the coercive means to protect their property, contrary to certain theories.[23]

8 Conclusion

Our estimates show that adverse economic shocks, instrumented by rainfall, cause the rural poor to occupy large landholdings. Moreover, in highly unequal municipalities, negative income shocks cause twice as many land invasions as in municipalities with average land inequality. This effect appears to be monotonic. We find even stronger effects using a measure of land polarization instead of the land Gini. In addition, municipalities with relatively more land under rental contracts are more likely to have a land invasion following a poor crop. Cross-sectional specifications are consistent with our finding that land inequality is an important factor in explaining land invasions, and also suggest a monotonic relationship. Our results are consistent with extensive qualitative research on how economic conditions affect redistributive conflict in rural contexts.

This paper highlights an understudied cost of inequality: open, extralegal redistributive conflict. Land inequality may be associated with poor political institutions, thereby channeling redistributive pressures into extralegal social-movement activity. Furthermore, by creating incentives to engage in costly land invasions and by exposing a larger fraction of the population to the risk of income shocks, land inequality may lead to a suboptimal allocation of resources. De Janvry, Sadoulet and Wolford [2001, p. 293] warn that land invasions are "a road of access to land that is increasingly difficult to implement . . . and in conflict with the need to secure property rights in order to attract capital-intensive investments in the modernization and diversification of agriculture."

Despite these and other potential negative effects, it remains unclear whether land invasions are on balance detrimental for overall welfare. For example, land invasions may result in a more equitable distribution of land, which might in turn enhance future economic growth. Alternatively, given a lack of formal insurance mechanisms, land invasions may represent an optimal response by the poor to a negative income shock. These and other issues are important to consider when weighing different policy options in response to land invasions, such as allowing invasions to continue, engaging in formal land reform, or expanding income insurance mechanisms.

Additional research would help to further clarify the policy implications of our findings. For example, we find no evidence that formal insurance mechanisms would reduce land invasions—our tests suggest that alternative sources of income such as municipal government spending, credit and urban employment do not attenuate the effect of income shocks on land conflict. However, given that it is plausible that none of these variables effectively provides income insurance to rural workers, further research could explore whether more effective insurance mechanisms would be likely to reduce the prevalence of land invasions.

Empirical research on the economic determinants of conflict is relatively new. This paper has contributed to the literature by examining the effect of economic conditions on land invasions. Future research would ideally use individual-level panel data in order to test directly whether shocks to individual income cause participation in land invasions. Finally, while this paper has largely looked at the demand-side determinants of land occupations, another challenging area of research is on the supply side. Identifying strong research designs for examining the role of social movements and organization on redistributive conflict is an important future task.

Notes

[1]Using cross-country regressions, scholars have suggested a positive association of inequality with political conflict. [Alesina and Perotti 1996; Keefer and Knack 2002]. In addition, while many emphasize how redistributive pressures can undermine economic growth [Alesina and Rodrik 1994; Persson and Tabellini 1993], our findings provide evidence in the other causal direction: contractionary periods can increase some forms of redistributive pressures.

[2]In a previous version of the paper, we included a model formalizing this argument.

[3]High land inequality dates back to the initial European partitioning of the New World. During the colonial period, the Portuguese monarchy divided Brazil's territory into twelve captaincies. By bestowing these massive properties to individuals, the Portuguese established a land structure based on *latifúndios*, or large rural landholdings [Bethell 1987].

[4]Because the government also redistributes land to some individuals who do not participate in land invasions, the population of invaders and recipients is not the same. These figures, nonetheless, should be considered as suggestive.

[5]The concept of the "social function" of property has existed as a legal concept since the 1964 Land Statute and has since been incorporated into the 1988 constitution. If INCRA determines that the occupied land is "productive," then no expropriation is legally possible.

[6]Alternatively, in some cases, government officials bargain with the invaders, offering property on government-owned land in exchange for dismantling camps [Ondetti 2002, p. 71].

[7]Our data for this municipality corroborate Wolford's ethnography. In 1993, Água Preta experienced a dramatic decline in rainfall (1.95 standard units), and crop yields fell as a result. The municipality experienced a land invasion that year—its first in the 1988-2004 period—as well as another in the following year.

[8]The CPT defines land occupations as "collective actions by landless families that, by entering rural properties, claim lands that do not fulfill the social function" [CPT 2004, p. 215, authors' translation].

[9]The CPT compiles information on land invasions from a range of data sources, including local, national and international news articles; state and federal government reports; reports from various organizations such as churches, rural unions, political parties and NGOs; reports by regional CPT offices; and citizen depositions [CPT 2004, pp. 214-26]. When data sources conflict, reports from regional CPT offices are used. In 2004, the CPT collected land invasion data from 171 sources. Repeated invasions of the same property in a given year are only counted once.

[10]Helfand and Resende also include oranges, which are missing from our data.

[11]While our agricultural income and land invasions data are limited to a shorter panel, we use this 21-year rainfall data series for standardization in order to attain a better measure of the local rainfall conditions.

[12]Additional details on the rain data and the handling of missing observations are available upon request.

[13]Polarization is calculated using discrete distribution data by the formula

$$\sum_i \sum_j \pi_i^{(1+\alpha)} \pi_j |\mu_i - \mu_j|$$

where π is the fraction of landowners in group i or j, and μ is the share of land owned by the corresponding landowners, for all pairs of i and j [Esteban, Gradín and Ray 2005]. In this study, we let $\alpha = 0.5$.

[14]These three categories, as shares of arable land, do not sum to one because the Agricultural Census has a fourth category of land, land that is "occupied," or invaded. We exclude this category due to obvious endogeneity concerns with the dependent variable, not to mention the fact that it is probably more time-variant than the other three types of land tenure.

[15]Our primary measure of agricultural income is discussed above (Section 3.2). Census data on per capita income are used as a robustness check in Section 5.

[16]Mayors were also elected in 1988 and 1992, but electoral data are incomplete for this period, so we cannot compute the degree of political competition. We thank David Samuels for sharing with us the partial data he compiled for this earlier period.

[17]As discussed below, micro-regions are defined by IBGE as contiguous municipalities in a given state that share an urban center and have similar demographic, economic, and agricultural characteristics.

[18]How to test for weak instruments directly when there are multiple endogenous regressors and heteroskedastic or autocorrelated standard errors is currently an open area of research. Stock and Yogo [2005] suggest the Cragg-Donald statistic, but limit analysis to the homoskedastic case; it is unknown whether this continues to be valid when there is heteroskedasticity or within-cluster autocorrelation in the error terms [Stock and Yogo 2005, p. 33]. The Cragg-Donald statistics for the specifications in Tables 8–10 (assuming homoskedastic errors, not shown but available upon request) are above the critical values for rejecting a larger than 10 percent size distortion from weak instruments in the IV-2SLS estimates (at 95 percent significance). Note that these conservative critical values are calculated using the procedure in Stock and Yogo [2005], who do not provide critical values for specifications with more than 3 endogenous regressors.

[19]Substituting the land polarization measure for the land Gini in the interactions shown in Table 9 yields broadly similar results on the land tenure variables. Results are also consistent when the land Gini interaction is excluded.

[20]The distribution of the tenure variables are clustered around 0 (renting and sharecropping) and 1 (ownership), with long, narrow tails. Excluding the extreme 1 percent of outlying observations yields nearly identical results, suggesting that outliers are not driving this result.

[21]Note that most security spending is at the state level in Brazil. The Polícia Militar is controlled at the state level, and only some larger municipalities have significant police forces of their own. The interaction of state public security expenditures and agricultural income (not reported) is also insignificant.

[22]For situations in which the incidence of an event increases the probability that another event will occur, as we assume to be the case for land invasions, negative binomial regression is more appropriate than Poisson regression for event counts [Long 1997, pp. 230-6].

[23]The nonparametric regression of land invasions on land inequality without micro-region fixed effects (not shown) also finds a strictly increasing relationship.

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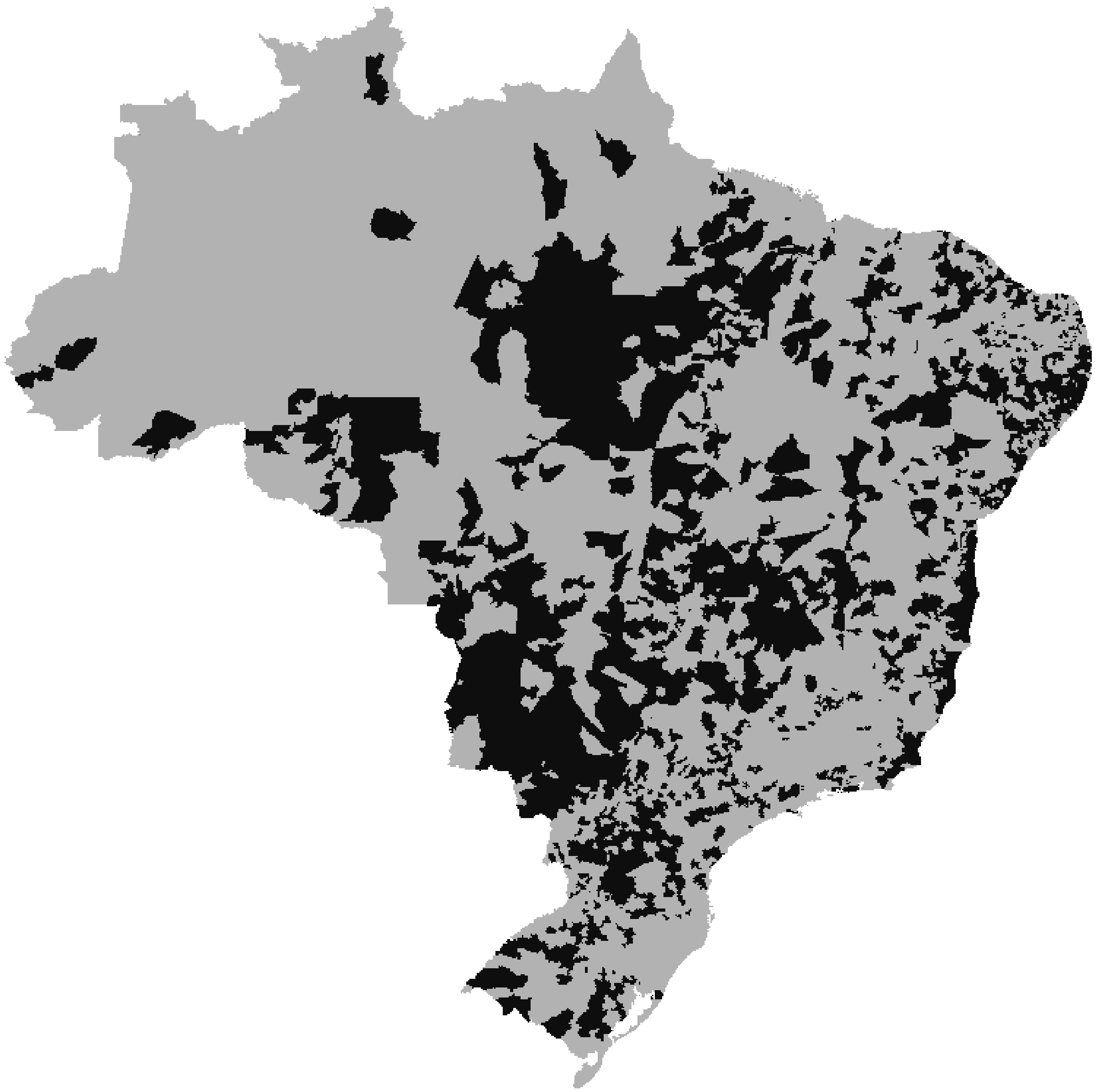
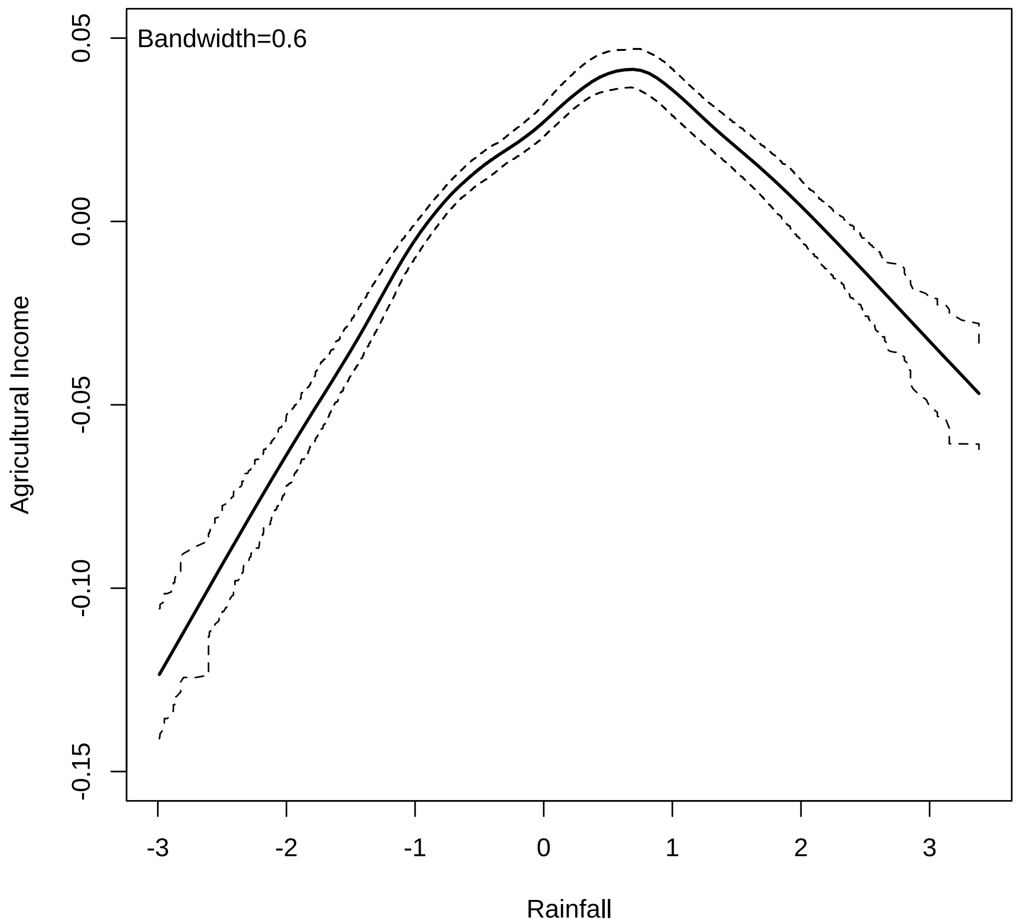
9 Figures

Figure 1: Map of Rural Conflict



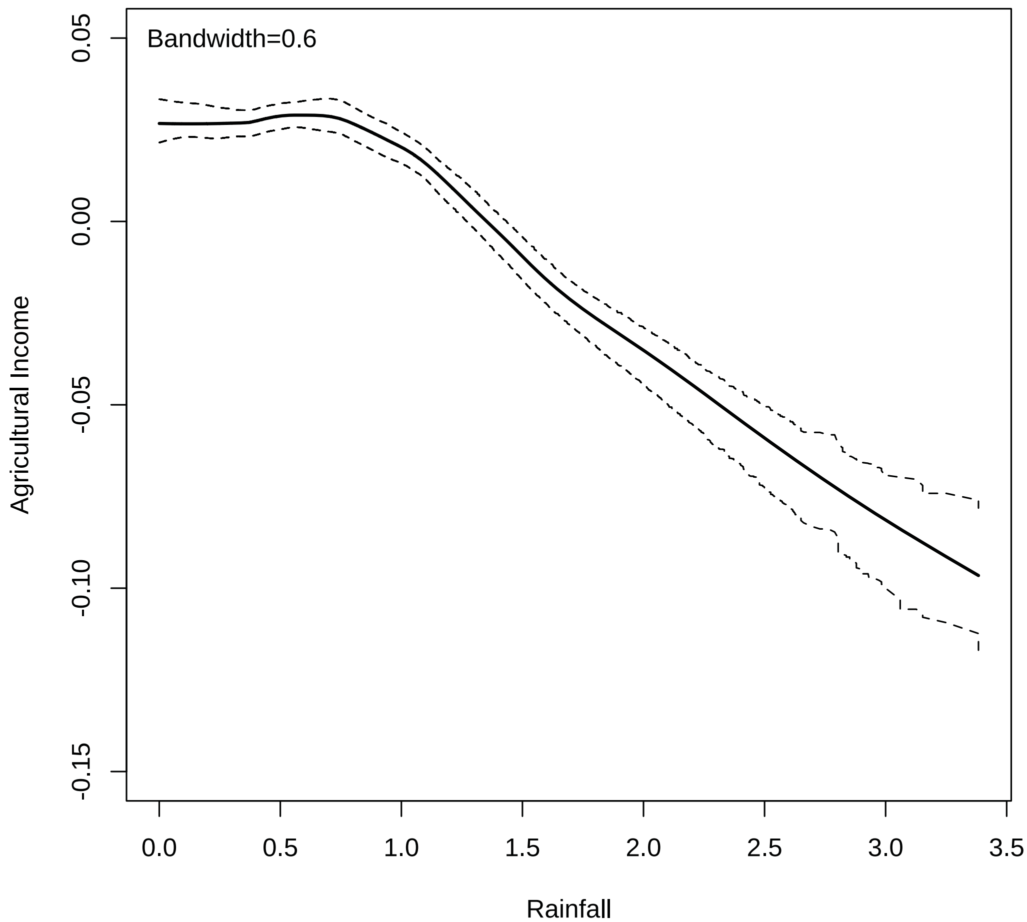
Note: Municipalities that experienced at least one occupation between 1988 and 2004 are shaded black. Non-shaded municipalities did not experience land invasions.

Figure 2: The First Stage: Nonparametric Regression of Agricultural Income on Standardized Rainfall



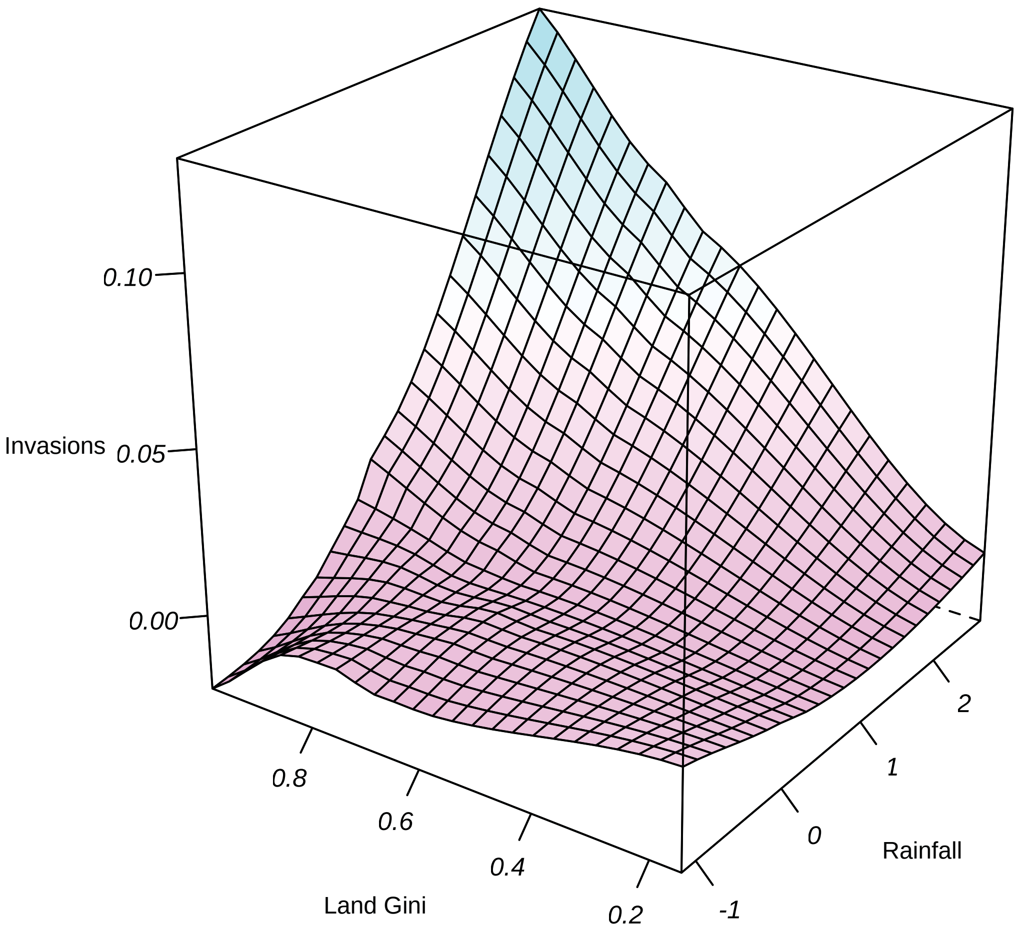
Locally weighted (lowess) regression of agricultural income on monthly standardized rainfall, conditional on municipal and year fixed effects. Dashed lines represent 95 percent confidence bands.

Figure 3: The First Stage: Nonparametric Regression of Agricultural Income on Absolute Standardized Rainfall



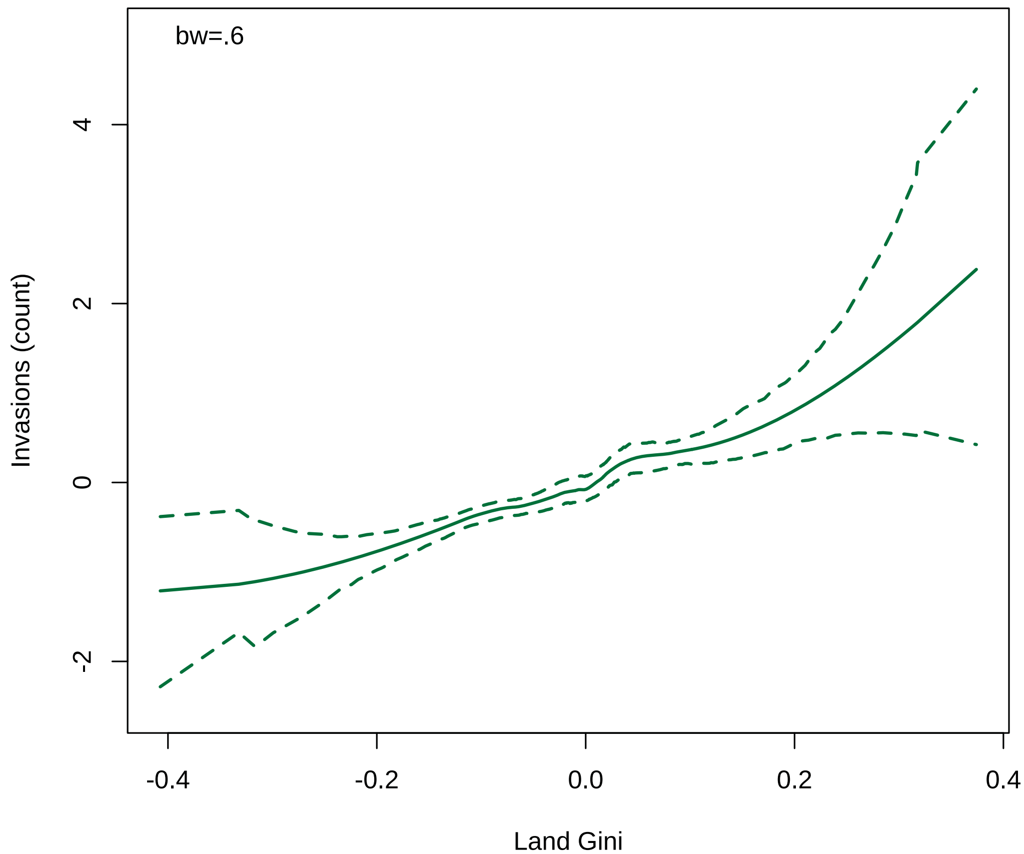
Locally weighted (lowess) regression of agricultural income on monthly absolute standardized rainfall, conditional on municipal and year fixed effects. Dashed lines represent 95 percent confidence bands.

Figure 4: Nonparametric Regression of Land Invasions on Absolute Standardized Rainfall and the Interaction of Rainfall with the Land Gini (Reduced Form)



Locally weighted (lowess) regression of land invasions (count) on monthly absolute standardized rainfall and the interaction between rainfall and the land Gini, conditional on municipal and year fixed effects.

Figure 5: Nonparametric Regression of Land Invasions on Land Inequality (Cross-Section)



Locally weighted (lowess) regression of total land invasions (1988-2004) on land Gini, conditional on micro-region fixed effects. Dashed lines represent 95 percent confidence bands.

Table 1: Descriptive Statistics for the Fixed-Effects Specifications

Variable	N	Mean	SD
	1991-2004		
Land Invasions, Dichotomous	52939	0.040	0.20
Land Invasions, Count	52939	0.064	0.40
Log (Families)	52939	-4.24	1.84
Rain Deviation (Monthly)	52939	0.75	0.55
Rain Deviation (Squared)	52939	0.86	1.16
Rain Deviation (Annual)	50521	0.74	0.56
Average Rainfall (mm/day)	52939	3.81	1.26
SD of Average Rainfall	52939	0.89	0.34
Coefficient of Variation (CV) of Rainfall	52939	0.25	0.10
Agricultural Income	52939	7.69	1.37
Log (Population)	52939	9.22	0.93
Land Gini	49756	0.74	0.14
Polarization	49766	0.59	0.12
Top 10% Landowners' Share	49466	0.53	0.14
Bottom 50% Landowners' Share	49766	0.11	0.06
Landless Population (Proportion)	49768	0.30	0.21
Land with Fixed-Rent Tenure (Proportion)	49768	0.047	0.067
Land with Ownership Tenure (Proportion)	49768	0.89	0.096
Land with Sharecropping Tenure (Proportion)	49768	0.021	0.036
Log (Security Budget)	43968	-0.014	6.51
Log (Social Spending)	43968	11.29	3.84
Banks (Mean, 1991, 1996, and 2000)	52939	1.47	1.90
Non-agricultural Production (Proporiton)	46034	0.61	0.21
Income Gini (Mean, 1991 and 2000)	52939	0.54	0.045
Extreme Poverty (Proportion; Mean, 1991 and 2000)	52939	0.29	0.18
Unused Arable Land (Proportion)	49768	0.048	0.071
Political Competition	34248	0.12	0.11
	1991 and 2000		
Land Invasions, Count	7655	0.056	0.39
Log (Families)	7655	-4.3	1.68
Log (GDP per capita)	7655	4.81	0.56
Rural Unemployment	7654	0.049	0.053
Rain Deviation (Monthly)	7655	0.75	0.58
Log (Population)	7655	9.25	0.92
Income Gini	7655	0.55	0.06
Log (Rural Population)	7655	8.33	0.92
Education HDI	7655	0.72	0.13

Table 2: Rainfall and Income (First Stage); DV: Agricultural Income

	Ordinary Least Squares			
	(1)	(2)	(3)	(4)
Rain Deviation (Monthly)	-0.042			-0.041
	(9.31)***			(8.26)***
(Rain Deviation)^2		-0.017		
		(8.40)***		
Rain Deviation (Yearly)			-0.044	
			(9.26)***	
Rain Deviation (Monthly), $t+1$				-0.007
				(1.43)
Log (Population)	-0.137	-0.138	-0.144	-0.146
	(3.50)**	(3.52)**	(3.57)**	(3.52)**
Observations	52939	52939	50521	48118
# of Municipalities	4221	4221	4114	4221
F-statistic	86.61	70.49	85.66	35.08

Note: All specifications include municipal and year fixed effects and have standard errors clustered at the municipal level. Robust t-statistics in parentheses. F-statistic corresponds to the test of the null hypothesis that the coefficient on the excluded instrument equals zero.
** $p < .01$, *** $p < .001$

Table 3: Agricultural Income and Land Invasions (Linear Probability)

		IV-2SLS			Reduced Form		
	OLS	Monthly	Squared	Yearly	Monthly	Squared	Yearly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agricultural Income	0.0004	-0.126	-0.176	-0.145			
	(0.23)	(3.27)**	(3.70)**	(3.81)**			
Rain Deviation (Monthly)					0.005		
					(3.33)**		
(Rain Deviation)^2						0.003	
						(3.92)**	
Rain Deviation (Yearly)							0.006
							(3.99)**
Log (Population)	0.009	-0.009	-0.016	-0.010	0.009	0.008	0.011
	(0.96)	(0.73)	(1.17)	(0.74)	(0.90)	(0.89)	(1.16)
Observations	52939	52938	52938	50520	52939	52939	50521
# of Municipalities	4221	4220	4220	4113	4221	4221	4114

Note: In columns 2-4, agricultural income is instrumented by rain deviation (monthly), (rain deviation)^2, and rain deviation (yearly), respectively. All specifications include municipal and year fixed effects and have standard errors clustered at the municipal level. Robust t-statistics in parentheses.
** $p < .01$

Table 4: Agricultural Income and Land Invasions; DV: Invasions (Count) and Log (Families)

	OLS	IV-2SLS			Reduced Form		
		Monthly	Squared	Yearly	Monthly	Squared	Yearly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Dependent Variable: Land Invasions (Count)							
Agricultural Income	0.004	-0.252	-0.369	-0.311			
	(1.27)	(3.29)**	(3.76)**	(3.93)**			
Rain Deviation (Monthly)					0.011		
					(3.36)**		
(Rain Deviation)^2						0.006	
						(4.01)***	
Rain Deviation (Yearly)							0.014
							(4.14)***
Log (Population)	0.000	-0.036	-0.052	-0.040	-0.001	-0.001	0.005
	(0.02)	(1.64)	(2.06)*	(1.67)+	(0.08)	(0.09)	(0.31)
Panel B: Dependent Variable: Log (Families)							
Agricultural Income	0.006	-1.108	-1.581	-1.320			
	(0.43)	(3.11)**	(3.58)**	(3.72)**			
Rain Deviation (Monthly)					0.046		
					(3.15)**		
(Rain Deviation)^2						0.028	
						(3.76)**	
Rain Deviation (Yearly)							0.058
							(3.88)**
Log (Population)	0.125	-0.033	-0.100	-0.047	0.119	0.118	0.143
	(1.40)	(0.30)	(0.80)	(0.39)	(1.34)	(1.33)	(1.57)
Observations	52939	52938	52938	50520	52939	52939	50521
# of Municipalities	4221	4220	4220	4113	4221	4221	4114

Note: In columns 2-4, agricultural income is instrumented by rain deviation (monthly), (rain deviation)^2, and rain deviation (yearly), respectively. All specifications include municipal and year fixed effects and have standard errors clustered at the municipal level. Robust t-statistics in parentheses.
+ $p < .10$, ** $p < .01$, *** $p < .001$

Table 5: Income, Unemployment, and Land Invasions; DV: Land Invasions, count

	Income			Unemployment			Reduced
	OLS	1st Stage	IV	OLS	1st Stage	IV	Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (GDP	-0.159		-2.459				
per capita)	(3.51)**		(3.87)**				
Rural				0.340		34.139	
Unemployment				(2.25)*		(1.30)	
Rain Deviation		-0.022			0.002		0.054
(Monthly)		(5.54)***			(1.33)		(5.13)***
Observations	7655	7655	7655	7654	7654	7654	7655
# of Municipalities	4225	4225	4225	4225	4225	4225	4225
F-statistic		30.67			1.76		

Note: In column 2, log (GDP per capita) is instrumented by rain deviation (monthly), while in column 5, rural unemployment is instrumented by rain deviation (monthly). F-statistic corresponds to the test of the null hypothesis that the coefficient on the excluded instrument equals zero. All specifications include municipal and year fixed effects and have standard errors clustered at the municipal level. Robust t-statistics in parentheses. Coefficients for other included controls (Income Gini, Log (Rural Population), Log (Population), and Education HDI score) are omitted.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 6: Rainfall, Income, and Land Occupations in Municipalities with Invasion Activity

	First Stage	DV: Land Invasions		DV: Log(Families)	
		OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)
Rain Deviation (Monthly)	-0.054				
	(5.71)***				
Agricultural Income		0.010	-0.779	0.017	-3.763
		(1.08)	(3.04)**	(0.34)	(3.10)**
Log (Population)	-0.150	0.007	-0.116	0.390	-0.199
	(2.04)*	(0.14)	(1.33)	(1.38)	(0.45)
Observations	13256	13256	13255	13256	13255
# of Municipalities	1028	1028	1027	1028	1027
F-statistic	32.65				

Note: Sample limited to municipalities that experienced at least one land occupation between 1988 and 2004. In columns 3 and 5, agricultural income is instrumented by rain deviation (monthly). F-statistic corresponds to the test of the null hypothesis that the coefficient on the excluded instrument equals zero. All specifications include municipal and year fixed effects and have standard errors clustered at the municipal level. Robust t-statistics in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 7: Rainfall, Land Inequality, and Land Tenure Contracts

	Land Gini				Fixed-Rent Tenure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Rainfall	-0.014	-0.002	-0.018	-0.000	0.006	-0.001	0.005	-0.000
	(6.17)***	(0.37)	(9.16)***	(0.07)	(4.38)***	(0.30)	(4.42)***	(0.26)
SD of Rainfall	0.001	0.006			0.000	0.001		
	(0.13)	(0.62)			(0.03)	(0.25)		
CV of Rainfall			-0.131	-0.002			-0.021	-0.002
			(5.08)***	(0.06)			(1.45)	(0.09)
Log(GDP per capita), 1991	-0.117	-0.019	-0.123	-0.020	0.050	0.026	0.049	0.026
	(6.28)***	(0.83)	(6.64)***	(0.86)	(4.85)***	(1.80)	(4.76)***	(1.78)
Unused Arable Land	-0.255	-0.191	-0.233	-0.190	-0.079	-0.001	-0.075	-0.001
	(8.00)***	(3.67)**	(7.30)***	(3.66)**	(4.44)***	(0.03)	(4.23)***	(0.03)
Extreme Poverty, 1991	-0.004	-0.001	-0.004	-0.001	0.001	0.000	0.001	0.000
	(8.72)***	(1.10)	(8.59)***	(1.12)	(2.05)*	(0.77)	(2.10)*	(0.76)
Micro-region Fixed-Effects Included	no	yes	no	yes	no	yes	no	yes
Observations	3340	3340	3340	3340	3340	3340	3340	3340
R^2	0.29	0.72	0.30	0.72	0.14	0.54	0.14	0.54

Note: Coefficients for micro-region fixed effects and controls (Income Gini, log(Population), log(Rural Population), log(Land Area), and Education HDI) omitted. Standard errors clustered at the micro-region level in columns 2, 4, 6, and 8. Robust t-statistics in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 8: Land Inequality Interactions

	IV-2SLS							
	DV: Invasions, count				DV: Log (Families)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agricultural Income	3.022	4.047	4.098	1.652	14.397	19.567	19.824	5.428
	(2.34)*	(2.45)*	(2.38)*	(1.16)	(2.42)*	(2.54)*	(2.46)*	(0.88)
Land Gini	-2.551		2.219		-11.883		12.178	
× Agricultural Income	(3.17)**		(0.92)		(3.19)**		(1.06)	
Polarization		-4.278	-7.006			-20.394	-35.341	
× Agricultural Income		(2.85)**	(1.68)+			(2.91)**	(1.77)+	
Top 10% Landowners' Share				0.215				4.011
× Agricultural Income				(0.18)				(0.68)
Bottom 50% Landowners' Share				4.018				25.408
× Agricultural Income				(1.40)				(1.71)+
Landless Population				-2.159				-9.136
× Agricultural Income				(2.61)**				(2.51)*
Average Rainfall	-0.257	-0.321	-0.323	-0.327	-1.276	-1.597	-1.609	-1.610
× Agricultural Income	(1.74)+	(1.87)+	(1.89)+	(1.88)+	(1.88)+	(1.99)*	(2.00)*	(1.99)*
CV of Average Rainfall	-2.087	-2.902	-3.213	-3.177	-9.641	-13.628	-15.322	-14.602
× Agricultural Income	(1.42)	(1.69)+	(1.81)+	(1.74)+	(1.49)	(1.76)+	(1.91)+	(1.81)+
Log (Population)	-0.006	0.009	0.011	-0.004	0.112	0.187	0.196	0.140
	(0.18)	(0.23)	(0.26)	(0.10)	(0.67)	(0.95)	(0.95)	(0.68)
Observations	49755	49765	49755	49455	49755	49765	49755	49455
# of Municipalities	3804	3805	3804	3778	3804	3805	3804	3778
Anderson-Rubin F	6.51	6.17	5.29	5.02	6.44	6.60	5.48	4.85
Mean Effect of Income	-0.362	-0.436	-0.449	-0.475	-1.645	-2.006	-2.085	-2.151

Note: Instrumental-variables regression with municipal and year fixed effects and with standard errors clustered at the municipal level. Instrumental variables are rain deviation (monthly) and rain deviation interacted with the relevant measure of land inequality. Robust t-statistics in parentheses.
+ $p < .10$, * $p < .05$, ** $p < .01$

Table 9: Interactions: Land Contracts; DV: Land Invasions, count

	IV-2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agricultural Income	2.940	2.615	3.180	4.382	2.007	8.070	3.519
	(2.45)*	(1.47)	(2.32)*	(2.21)*	(1.55)	(1.76)+	(0.50)
Land Gini	-2.437	-2.540	-2.658	-2.529	-0.783	-9.899	-4.334
× Agricultural Income	(3.18)**	(3.15)**	(3.18)**	(2.99)**	(0.89)	(1.53)	(0.15)
Fixed-Rent Tenure	-2.968			-3.892	26.112		
× Agricultural Income	(1.87)+			(2.46)*	(1.93)+		
Fixed-Rent Tenure × Land Gini					-38.752		
× Agricultural Income					(1.94)+		
Ownership Tenure		0.381		-1.249		-5.848	
× Agricultural Income		(0.41)		(1.53)		(1.26)	
Ownership Tenure × Land Gini						8.340	
× Agricultural Income						(1.19)	
Sharecropping			-1.753	-1.474			-68.862
× Agricultural Income			(0.72)	(0.61)			(0.06)
Sharecropping × Land Gini							117.333
× Agricultural Income							(0.06)
Average Rainfall	-0.200	-0.242	-0.260	-0.234	-0.279	-0.242	-0.150
× Agricultural Income	(1.42)	(1.53)	(1.74)+	(1.44)	(1.62)	(1.52)	(0.08)
CV of Average Rainfall	-2.302	-2.054	-2.226	-2.594	-2.734	-2.017	-0.688
× Agricultural Income	(1.63)	(1.41)	(1.43)	(1.63)	(1.63)	(1.37)	(0.03)
Log (Population)	-0.006	-0.005	-0.008	-0.012	0.013	0.005	-0.025
	(0.20)	(0.14)	(0.24)	(0.37)	(0.31)	(0.14)	(0.08)
Observations	49755	49755	49755	49755	49755	49755	49755
# of Municipalities	3804	3804	3804	3804	3804	3804	3804
Anderson-Rubin F	5.50	5.34	5.42	4.10	4.88	4.49	4.73
Mean Effect of Income	-0.338	-0.355	-0.367	-0.357	-0.484	-0.388	-0.041

Note: Instrumental-variables regression with municipal and year fixed effects and with standard errors clustered at the municipal level. Instrumental variables are rain deviation (monthly) and rain deviation interacted with the relevant variable. Robust t-statistics in parentheses.
+ $p < .10$, * $p < .05$, ** $p < .01$

Table 10: Interactions: Alternative Opportunities and State Capacity; DV: Land Invasions, count

	IV-2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agricultural Income	3.258	3.290	4.604	6.394	2.741	3.854	3.223	4.037
	(1.78)+	(1.93)+	(1.64)	(0.27)	(2.28)*	(1.82)+	(2.38)*	(2.68)**
Land Gini	-2.636	-2.656	-3.122	-3.613	-2.600	-3.538	-2.605	-4.571
× Agricultural Income	(2.31)*	(2.51)*	(1.95)+	(0.40)	(3.04)**	(2.43)*	(3.19)**	(3.25)**
Log(Security Budget)	-0.014							
× Agricultural Income	(0.30)							
Log(Security Budget)	0.105							
	(0.30)							
Log(Social Spending)		-0.010						
× Agricultural Income		(0.87)						
Log(Social Spending)		0.076						
		(0.86)						
Banks			-0.649					
× Agricultural Income			(0.91)					
Non-agricultural Production				-10.617				
× Agricultural Income				(0.15)				
Non-agricultural Production				78.373				
				(0.15)				
Income Gini					0.648			
× Agricultural Income					(0.40)			
Extreme Poverty						3.223		
× Agricultural Income						(1.57)		
Unused Arable Land							1.803	
× Agricultural Income							(1.57)	
Political Competition								2.501
× Agricultural Income								(0.87)
Political Competition								-19.431
								(0.86)
Average Rainfall	-0.240	-0.236	-0.233	-0.570	-0.263	-0.320	-0.280	-0.322
× Agricultural Income	(1.37)	(1.39)	(1.12)	(0.26)	(1.68)+	(1.45)	(1.81)+	(2.07)*
CV of Average Rainfall	-2.791	-2.600	-4.369	6.839	-2.178	-6.433	-2.668	-1.066
× Agricultural Income	(1.16)	(1.27)	(1.30)	(0.11)	(1.35)	(1.44)	(1.60)	(0.61)
Log (Population)	-0.004	-0.012	0.117	0.790	-0.004	0.026	-0.012	0.001
	(0.09)	(0.32)	(0.81)	(0.14)	(0.12)	(0.53)	(0.36)	(0.01)
Observations	41745	41745	49755	44012	49755	49755	49755	31268
# of Municipalities	3798	3798	3804	3803	3804	3804	3804	3778
Anderson-Rubin F	3.17	3.39	5.32	5.71	5.24	5.37	5.85	5.91

Note: Instrumental-variables regression with municipal and year fixed effects and with standard errors clustered at the municipal level. Instrumental variables are rain deviation (monthly) and rain deviation interacted with the relevant variable. Robust t-statistics in parentheses.
+ $p < .10$, * $p < .05$, ** $p < .01$

Table 11: Descriptive Statistics for the Cross-Sectional Specifications

Variable	N	Mean	SD
Land Invasions (Count), 1988-2004	3340	0.95	2.94
Land Invasions (Dichotomous), 1988-2004	3340	0.26	0.44
Log (Families), 1988-2004	3340	-2.08	4.43
Land Gini	3340	0.75	0.13
Land with Fixed-Rent Tenure (Proportion)	3340	0.046	0.067
Land with Sharecropping Tenure (Proportion)	3340	0.90	0.094
Average Rainfall (mm/day)	3340	3.75	1.28
SD of Average Rainfall	3340	0.89	0.35
Coefficient of Variation (CV) of Rainfall	3340	0.26	0.11
Log (GDP per capita), 1991	3340	4.64	0.53
Unused Arable Land (Proportion)	3340	0.049	0.071
Income Gini, 1991	3340	0.53	0.054
Extreme Poverty (Percent), 1991	3340	32.75	19.30
Log (Population), 1991	3340	9.35	0.89
Log (Rural Population), 1991	3340	8.49	0.87
Log (Land Area)	3340	6.18	1.16
Education HDI, 1991	3340	0.64	0.13

Table 12: Total Land Invasions by Municipality, 1988-2004

	DV: Land Invasions, count			DV: Invasions, dichotomous	DV: Log (Families)
	OLS	OLS	Negative Binomial	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Land Gini	2.711	2.918	5.007	0.552	6.100
	(6.11)***	(3.95)**	(5.81)***	(5.14)***	(5.50)***
Fixed-Rent Tenure	5.626	1.744	-0.634	0.028	0.812
	(5.14)***	(0.88)	(0.52)	(0.15)	(0.42)
Ownership Tenure	1.890	0.403	0.254	0.166	1.423
	(2.56)*	(0.46)	(0.25)	(1.31)	(1.13)
Average Rainfall	0.155	0.343	0.363	0.045	0.494
	(3.10)**	(1.75)+	(3.15)**	(2.80)**	(3.04)**
CV of Rainfall	2.379	0.707	0.727	0.012	0.269
	(3.67)**	(0.66)	(0.96)	(0.09)	(0.20)
Log(GDP per capita), 1991	-1.921	-0.429	-0.133	-0.093	-0.840
	(4.10)***	(0.79)	(0.19)	(0.96)	(0.87)
Extreme Poverty, 1991	-0.069	-0.009	0.002	-0.002	-0.023
	(5.50)***	(0.73)	(0.12)	(0.85)	(0.95)
Unused Arable Land	0.297	1.699	0.197	-0.096	-0.096
	(0.37)	(1.72)+	(0.22)	(0.59)	(0.06)
Observations	3340	3340	3340	3340	3340
R^2	0.10	0.38		0.42	0.44

Note: Coefficients for micro-region fixed effects and controls (Income Gini, log(Population), log(Rural Population), log(Land Area), and Education HDI) omitted. Standard errors clustered at the micro-region level in columns 2-5. Robust t-statistics in parentheses.
+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$