Heterogeneous adaptations to climate change: evidence from cattle ranching in the Brazilian Amazon

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Abstract

Deforestation is extending the dry season in the Amazon by as much as 0.6 days per year (Teixeira Leite-Filho et al., 2019; Butt et al., 2011). A longer dry season makes the "accordion effect," in which animals gain weight during the rainy season and lose weight during the dry season, more costly. I use a fixed effects model and rainfall shocks to show that ranchers adapt by selling animals prior to the dry season when they anticipate a severe dry season, whether due to current rainfall signals or recently experiencing a prolonged dry season.

Even without economies of scale to adaptation, adoption is scale related. All but the smallest-volume properties responded to current rainfall signals, but only the top 50% of properties adapted in the medium-run. Moreover, only small-volume properties continue to be negatively impacted by prolonged drought in the following year. This furthers concern that climate change will have disproportionate effects on vulnerable groups.

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1 Introduction

Deforestation is changing the regional climate in the Amazon and extending the dry season by as much as 0.6 days per year (Teixeira Leite-Filho et al., 2019; Butt et al., 2011). While the "accordion effect," in which animals gain weight during the rainy season and lose weight during the dry season, has always been a factor in the region's pasture-fed beef industry, a longer dry season makes this effect more dramatic and more costly. Animals left in pasture during an extreme dry season may require expensive feed, be sold at a low price in a distress sale, or die for lack of food and water.

Ranchers can cope with the dry season without investing in production methods on their own property. Instead, ranchers can prepare for the dry season by selling animals before or at the early stages of the dry season. "Destocking," or reducing herd size by selling animals, is a common response to drought (Wilmer et al., 2016). Destocking during a drought leads to large financial losses, as the rancher must sell animals at a low price and low weight and try to rebuild their herd when prices have recovered. In contrast, destocking prior to the drought allows ranchers to sell animals at a higher weight and price.

Strategic destocking is possible because, unlike agricultural crops, which must be harvested at maturity, animals may be sold before they are ready for slaughter. Properties with improved pasture or confinement operations that are drought-resilient can purchase animals for fattening and assume the cost of fattening during the dry season. Thus, while not all ranchers can invest in drought resistant production methods, every ranch should be able to adapt to the changing climate by selling animals at the onset of the dry season (Bryan et al., 2009).

I develop a theoretical model of fattening decisions under rainfall uncertainty to draw testable hypotheses. I model whether ranchers sell cattle for fattening prior to the dry season based on their expectations of the dry season and whether this strategy is heterogeneous based on property sales volume. I test the hypotheses of the model by linking data on a decade of all cattle transactions in the Brazilian state of Rondônia with municipal-level data on daily rainfall. The results of a fixed effect model confirm the theoretical model.

Ranchers make short-run selling decisions for the dry season based on current rainfall, but they also make medium-run changes based on previous dry season experiences. Statewide, my results correspond to an additional 65,000 heads transferred for fattening between April and June in response to a one standard deviation increase in days without rain in March and April (the end of the current rainy season). Additionally, a one standard deviation delay in the rainy season leads to an additional 130,000 heads transferred for fattening two and three years later. This response is over and above the 160,000 increase in head sold per fattening per year that occurred through the period for other reasons, such as market development.

Although the adaptation does not incur any fixed cost, which should reduce economies of scale, adoption is still dependent on volume. The response to current rainfall and previous dry season experiences are increasing in average sales volume, and the smallest-volume properties do not respond to signals at all. Moreover, only small-volume properties are negatively impacted by a prolonged dry season in the following year. Thus, small-volume properties are already the most harmed by climate change, and that is likely to continue as they do not adopt the same mitigation techniques as higher-volume properties.

A large literature studies how climate change affects agricultural production and economic outcomes more broadly.[1] My work expands on previous work in four key ways.

First, I provide the first industry-wide property-level study of adaptation to climate change. My rich data provides a census of cattle transactions over nine years and allows me to study adaptation at the property level. Previous work has tested effects at the county level (Hornbeck, 2012; Hidalgo et al., 2010) or relied on a representative sample of farmers (Taraz, 2017; Kurukulasuriya and Mendelsohn, 2008).[2]

Next, while most studies use variation in weather to draw conclusions about how producers will respond to climate change, there is debate over whether studies on the weather fully capture the effect of climate change (Hsiang, 2016). The Amazon provides an important case study for adaptation to climate change, as deforestation is rapidly changing the regional climate, but individuals do not determine the climate on their own property. I therefore identify responses to current climate change, which offer insights into how producers will respond as global climate change progresses.

To my knowledge, I am the first to directly estimate adaptation in livestock production, which offers a number of unique opportunities and challenges compared to crop production. Currently, more than 1.3 billion people worldwide rely on livestock production for income, and the industry uses one third of global cropland and freshwater (Herrero et al., 2013). Whether and how livestock producers adapt to climate change has implications for future food supply, environmental outcomes, and the welfare of billions of people. As the world's largest beef producer, Brazil plays a pivotal role in determining this future (United States Department of Agriculture (USDA), 2019).

Finally, I contribute to the literature on the importance of variability and timing of rainfall on agriculture. While the popular conception of climate change is that the world will become "warmer and wetter," this phrase masks a third and critical change: an increase in the variability of rainfall (Stocker et al., 2013). While models predict increased production in parts of the world due to the

[1]See Auffhammer and Schlenker (2014) for a review of the literature on agricultural production and weather and (Dell et al., 2014) for an excellent review of work on weather and economic outcomes.

[2]Hornbeck (2012) shows that in the aftermath of the American Dust Bowl farmers reallocated land to hay, which is less sensitive to soil erosion, and left regions with high erosion. Taraz (2017) finds evidence of both crop switching and increased irrigation in response to the Indian monsoon. Kurukulasuriya and Mendelsohn (2008) find that farmers choose crops based on current weather. Hidalgo et al. (2010) use rainfall as an instrument for rural income and find that lower rural incomes increase land invasions and conflict in Brazil.

increase in total rainfall, accounting for variability reduces these gains or even results in net losses (Fishman, 2016). I test two measures of rainfall that represent local perceptions, which have been shown to capture detail and phenomena that traditional measures of rainfall quantity miss (Sánchez-Cortés and Chavero, 2011; Marin, 2010; Orlove et al., 2000).

The paper proceeds as follows: section 2 describes the climate and cattle production in Rondônia, section 3 presents the theoretical model, section 4 presents the data, section 5 details the estimation strategy, section 6 presents results, and section 7 concludes.

2 Background

2.1 Study area

I study the Brazilian state of Rondônia, which is located in the southwestern Amazon and encompasses 240,000 km^2. The state experienced large influxes in population during the colonization of the Amazon. In 1970, the state had 0.49 people per km^2, and today it has 6.58; this remains far below the national average of 22.43 people per km^2 (Instituto Brasileiro de Geografia e Estatística (IBGE), 2019). Colonization was characterized by deforestation, and 60,400 km^2 have been cleared in Rondônia since the arrival of non-indigenous Brazilians in the 1960s (Instituto Nacional de Pesquisas Espaciais (INPE), 2020). These changes were accompanied by increased agricultural production; the state's cattle production rose from 41,030 heads in 1974 to 14,367,161 in 2018 (Instituto Brasileiro de Geografia e Estatística (IBGE), 2018).

Cattle production is an important part of the economy of Rondônia. In 2018, cattle production accounted for 16% of state GDP, and the state's cattle herd was more than 14 million heads (Instituto Brasileiro de Geografia e Estatística (IBGE), 2018; Governo do Estado de Rondônia, 2019). Rondônia's cattle industry as outpaced the rest of the country's in growth over the last two decades. The state was the fifth largest producer of cattle in Brazil in 2018, compared to the eighth largest in 2008 and tenth in 1999 (Instituto Brasileiro de Geografia e Estatística (IBGE), 2018, 2008, 1999).

These increases in output have been accompanied by changes in the production system. While the number of heads slaughtered rose 25% from 2008 to 2016 (1.7 million to 2.2 million head) (figure 2), the number of head moved for fattening more than doubled over the same period (2.6 million to 5.4 million) (figure 2).

2.2 Cattle production in the Brazilian Amazon

Ranchers can adopt a number of technologies to improve their pasture productivity during the dry season, including agroforestry, pasture rotation, and mixed legume-grass pasture (Ermgassen et al., 2018). Additionally, ranchers can invest in semi-confinement or confinement production, which rely on stored feed rather pasture; ranchers may also confine animals in a "sacrificed" pasture area during drought to minimize broader pasture losses (Mackay, 2007). In the Amazon, properties increasingly specialize in calving (*cria*, birth to weaning), rearing (*recria*, weaning to final fattening), or final fattening (*engorda*, the ninety days prior to slaughter). Some properties produce for the full cycle (birth to slaughter) or for a combination of these phases.

Because livestock are mobile, the life cycle can take place on multiple specialized properties. For example, "grass fed, grain finished" beef refers to animals that spend the beginning of their lives (*cria* and *recria*) in pasture and the end of their lives (*engorda*) in these confinement operations.

2.3 The relationship between deforestation and rainfall

Rainfall in Rondônia is characterized by a rainy season and a dry season. Rain peaks at more than 30 centimeters per month in January - March, and falls to less than 5 centimeters per month from May - September (figure 1a). Between these extremes are two transition periods: the offset of the rainy season in April and May and the onset in September and October. The offset is characterized by increasingly sporadic rainfall; on average there were 10.5 days without rain in March and 14.7 in April, compared to 9.1 in February. Appendix figures 5 and 6 map the rainfall across the state in each year from 2005 to 2016. There is a large degree of spatial correlation in rainfall across the state, which I will discuss further in section 5.

Deforestation in the Amazon is changing hydrological processes in the region. Cleared land, such as pasture and cropland, has a drier atmosphere and lower latent heat flux than forested land. Rainfall is therefore less likely to be triggered in deforested areas (Teixeira Leite-Filho et al., 2019). In southern Amazonia, a region with a characteristic rainy and dry season, this results in early offset and delayed onset of the rainy season (Butt et al., 2011; Debortoli et al., 2015; Teixeira Leite-Filho et al., 2019). During the rainy season, the conditions favor rain so strongly that the change in land cover is unlikely to alter rainfall patters; similarly rainfall is so unlikely in the dry season that the land cover has little impact. In transition months, however, the conditions are such that a change in the land cover can be the determining factor in whether or not rain occurs.

Leite-Filho, Pontes, and Costa (2019) find between a 0.12 and 0.17 day increase in the onset of the rainy per percent increase in deforestation across Amazonia. In Rondônia, Butt et al (2011) find the 0.60 day increase in the onset of the rainy season per year across 25 years. The relationship between rainfall and deforestation is found at the meso-region, but is not evident at the micro-region.[3] Khanna et al (2017) show that deforestation in Rondônia between 1988 and 2008 resulted in a shift to a dynamic

[3]Leite-Filho, Pontes, and Costas' results are strongest at the largest scale they test, 30 square kilometers, while Debortoli et al (2016) find evidence of correlation between rainfall and deforestation at the 30 - 50 square kilometer scale but not at the 1 - 15 square kilometer scale.

convective regime, which is characterized by increased rainfall downwind of deforested areas and decreased rainfall upwind of deforested areas.

Rainfall in Rondônia is also affected by El Niño Southern Oscillation (ENSO), as precipitation in the southern Amazon is negatively correlated with sea surface temperature. Droughts were therefore present in ENSO years of 1983, 1995/1995, 1997/1998, 2005, and 2010 (Molinier et al., 2009; Yoon and Zeng, 2010; Coelho et al., 2012; Debortoli et al., 2015). However, global climatic changes do not fully explain the changing rainfall patterns in the Amazon (Khanna et al., 2017). The region therefore presents an important case study for adaptation to climate change, as changes are regionally influenced by local behavior, but individuals do not determine the climate on their own property.

2.4 Seasonality of the cattle market in Rondônia

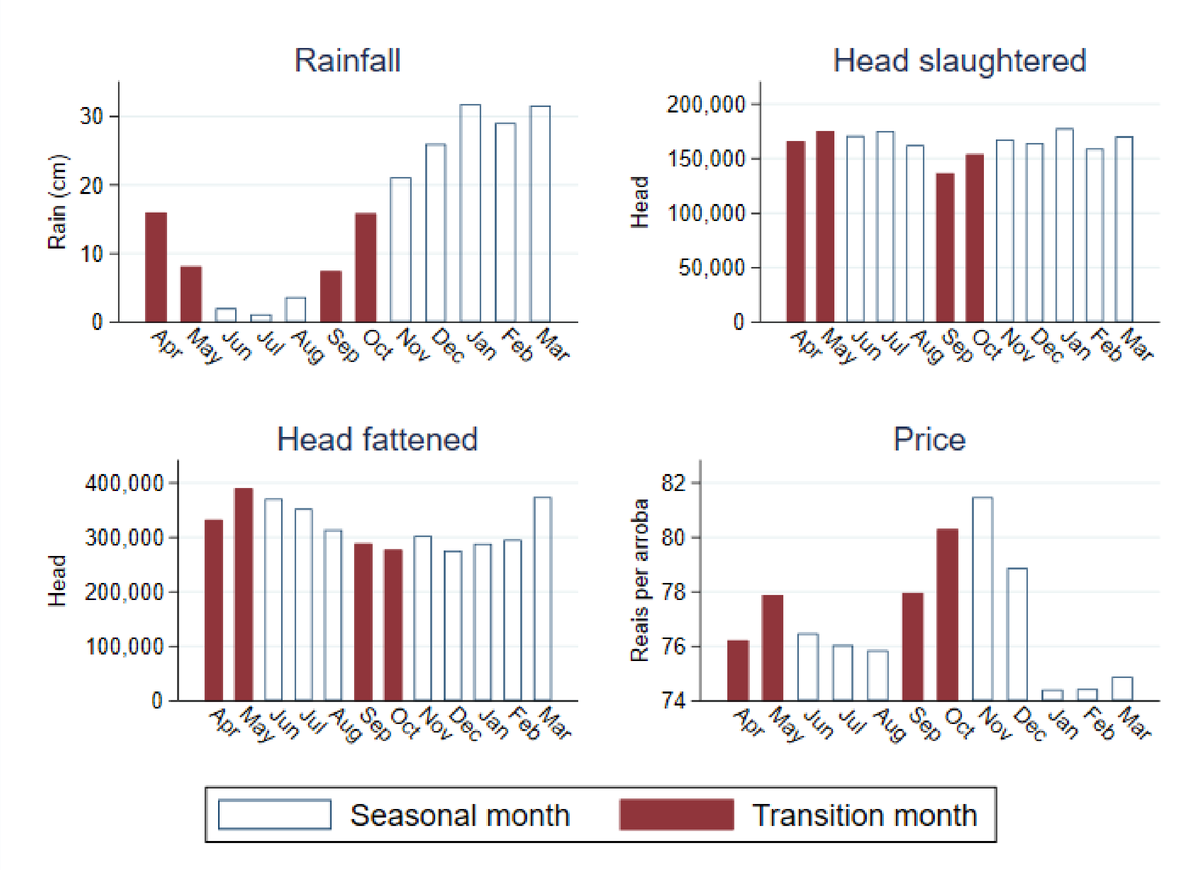
The cattle market in Rondônia is also seasonal. Figure 1c shows that the number of cattle sold for fattening is highest in March and May, as the dry season approaches, and sales remain high in June and July.[4] The volume of sales of cattle for slaughter is more stable throughout the year, although sales for slaughter are lowest in September and October (figure 1b). This dip in the number of sales likely reflects the "accordion effect" that ranchers describe, as animals gain weight through the rainy season and subsequently lose it during the rainy season. Thus, most animals are at their lowest weight immediately following the dry season and ranchers do not sell them for slaughter.

The seasonality of both fattening and slaughter sales is more apparent when viewed over the ten year period (figure 2). I divide the year into four seasons. Following the dry season from June to August, I further define seasons as September to November, December to February, and March to May. Movements for fattening clearly spiked every year in March to May. While slaughter is still more stable than fattening, it also exhibits small fluctuations throughout the seasons and typically peaks March to May.

Cattle prices similarly follow seasonal patterns (figure 1d). Prices (per unit weight, in R$ per *arroba*) for finished animals are lowest in January through March. During those months, ranchers hold onto their animals as pasture is rich and animals are reaching their peak rainy season weight. The prices per unit weight of male adults, female adults, and calves all peak in October and November, following the dry season. This corresponds with a low supply of animals for both fattening and slaughter. An animal that lost significant weight during the dry season gains weight rapidly during this period due to the resurgence of rain and pasture. Thus, the premium during these months must be high to match the high marginal benefit of an additional day in pasture for ranchers whose animals lost significant weight during the dry season.

[4] The state sanitation agency holds their semiannual vaccination campaign in April; this likely accounts for the dip in April transactions compared with March and May.

Figure 1: Monthly averages of (a) rainfall (b) heads sold for slaughter (c) heads sold for fattening (d) cattle price



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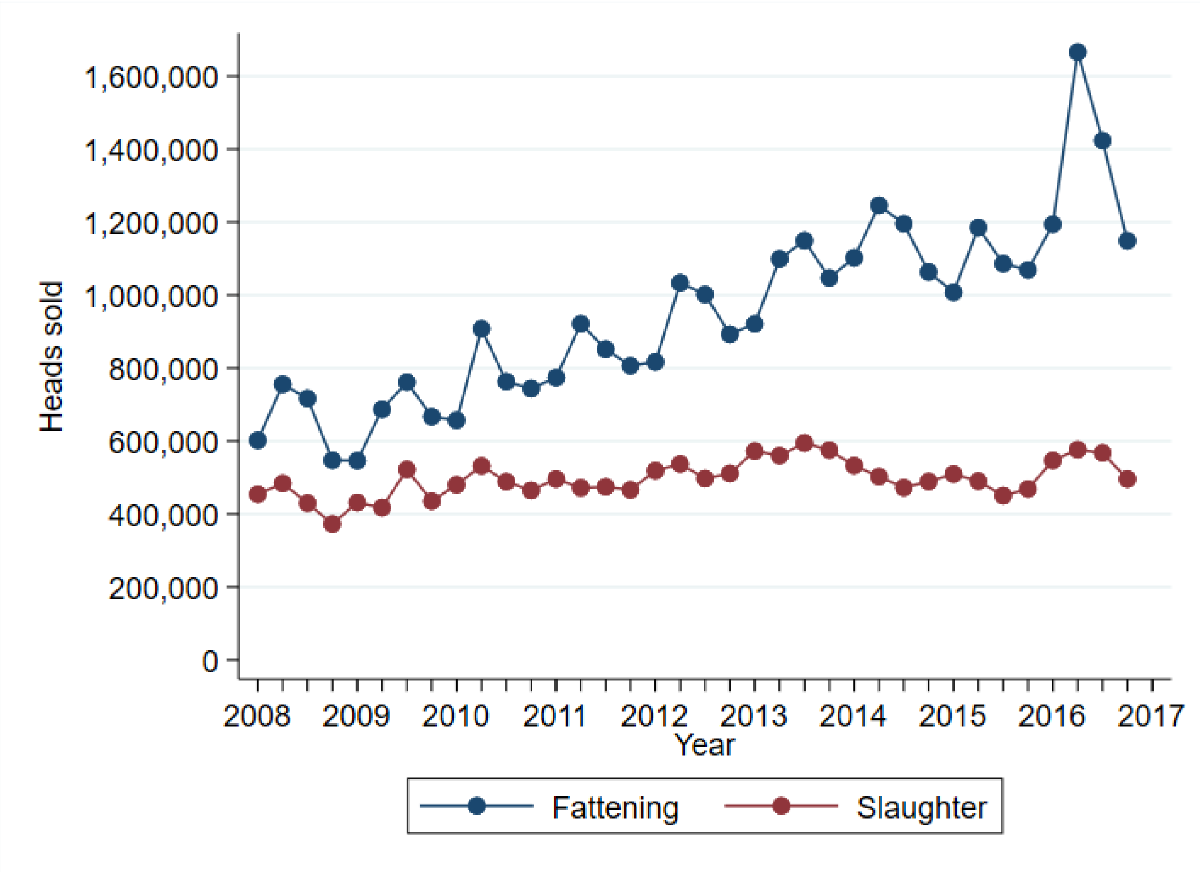
However, a rancher who could continue fattening animals through the dry season could earn a R$6 / arroba (8%) premium by selling animals in October and November. This demonstrates the profitability of improved pasture or confinement techniques that insulate animals from the low availability of pasture in the dry season.

For ranchers that do not invest on their property to allow for efficient dry-season fattening, cattle profits are higher in May and June than in July and August. Prices per unit weight are modestly higher in May and June than in July and August, but this difference does not capture the full difference in profit a rancher makes by selling prior to dry season, rather than under duress during a drought. Leaving an animal in pasture during a drought could lead the animal to lose weight or could require expensive inputs to maintain weight. Both of these losses are avoided by preemptively selling the animal at the onset of the dry season.

Figure 2: Heads sold for fattening and slaughter by season over ten years



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3 Theoretical Model

I now turn to the question of the role of rainfall in the changes outlined in section 2. I start with a model of how cattle ranchers decide to sell animals for fattening at the onset of the dry season based on their expectations of the upcoming season.

3.1 Set up

I model ranchers deciding how to produce cattle during the dry season. At the end of the rainy season, they have Q_C animals that they raised from calves. Ranchers can continue raising animals themselves and sell the animals for slaughter when they are fully fattened, or they can sell animals to a fattening operation and forego all fattening work themselves. The level of rainfall during the upcoming dry season is unknown, but ranchers have belief $\pi(R)$ of the probability of R for every value in the set of potential rainfalls $\mathbf{R} = (0, \bar{R}]$.

I denote the number of animals that the rancher chooses to sell at the beginning of the dry season as Q_S. The rancher cannot sell more than Q_C animals. Animals that are sold at the beginning of the dry season earn a price P_0 per head.[7] This price is constant regardless of the number of animals sold.

When ranchers fatten animals through the dry season and sell them after the dry season, they earn a price $P_1(R) = P_0 + \frac{a}{R^2}$ per head. This assumption is borne out in the data, as prices after the dry season (October - December) are higher with a later onset of the rainy season (i.e. a more extreme dry season). For simplicity, I assume that ranchers do not have time preferences.

The total number of animals the rancher fattens on ranch during the dry season is $Q = Q_C - Q_S$. Ranchers face a cost function $c(Q, R)$ for fattening animals during the dry season:

$$C_Q = \frac{log(Q)}{R}. \tag{1}$$

Thus, cost is decreasing in R and there are economies of scale. The price premium based on rainfall is smaller than the effect of rain on cost.

3.2 Profit Maximization

Ranchers maximize profit during fattening according to

$$Max_{\{Q_S\}} \quad \Pi = P_0 Q_S + \int_{\mathbf{R}} \pi(R) \left(\left(P_0 + \frac{a}{R^2} \right)(Q_C - Q_S) - \frac{log(Q_C - Q_S)}{R} \right) dR + \lambda(Q_C - Q_S). \tag{2}$$

[7] The price for adult cattle is paid per *arroba*, or 15 kilogram. By imposing a price per head, I am implicitly imposing that the animal is sold at the same weight whether it is sold before or after the dry season.

The FOC is

$$\frac{\partial \Pi}{\partial Q_S} = P_0 - (P_0 + aE\Big(\frac{1}{R^2}\Big) + \frac{1}{Q_C - Q_S}E\Big(\frac{1}{R}\Big) - \lambda. \tag{3}$$

Simplifying,

$$aE\Big(\frac{1}{R^2}\Big) + \lambda = \frac{1}{Q_C - Q_S}E\Big(\frac{1}{R}\Big). \tag{4}$$

The rancher buys additional cattle until the expected marginal profit from fattening animals is equal to the expected marginal cost of buying animals, conditional on the constraint being met. Solving this for Q_S^*:

$$Q_S^* = Q_C - \frac{E\Big(\frac{1}{R}\Big)}{aE\Big(\frac{1}{R^2}\Big) + \lambda} \tag{5}$$

Proposition 1: *Q_S^* is decreasing in $E(R)$. When ranchers expect rainfall will be high, they can fatten cattle cheaply and earn a price premium at the end of the dry season. When rainfall is expected to be low, the cost of fattening through the dry season is high and is not justified by the higher price, P_1 after the dry season.*

Proposition 2: *Q_S^* is increasing in Q_C. Ranchers with a larger initial stock, Q_C will sell a higher number of animals when the expectation of rainfall is low.*

Since $R > 0$, when $E(R) \rightarrow \infty$, then $E\Big(\frac{1}{R^2}\Big) \rightarrow 0$ and $E\Big(\frac{1}{R}\Big) \rightarrow 0$, but $\frac{E\left(\frac{1}{R}\right)}{aE\left(\frac{1}{R^2}\right)+\lambda} \rightarrow Q_C$ and $Q_S^* \rightarrow 0$. Conversely, when $E(R) \rightarrow 0$, then $E\Big(\frac{1}{R^2}\Big) \rightarrow \infty$ and $E\Big(\frac{1}{R}\Big) \rightarrow \infty$, but $\frac{E\left(\frac{1}{R}\right)}{aE\left(\frac{1}{R^2}\right)+\lambda} \rightarrow 0$ and $Q_S^* \rightarrow Q_C$. I will test these propositions using data.

4 Data

4.1 Data sources

Data on cattle movement come from the Guide to Animal Transport (GTA, Portuguese *Guia de Transporte Animal*). The GTA is used to verify the vaccination of animals and track movement of livestock in order to maintain herd health and prevent disease outbreaks. Farmers are required to register every animal movement under Federal Law 12.097 and Decree 7.623, which were passed to maintain international trade (Bowman et al., 2012). The data is stored by state sanitation agencies; the Agency of Agricultural Sanitation Defense of the State of Rondônia is responsible for the GTA in Rondônia. The GTA is publicly available under Law 12.527 and can be downloaded in full using computer algorithms.

It is considered reliable, although some misrepresentation occurs (Klingler et al., 2018). This misrepresentation would be most likely take the form of ranchers not registering movement for fattening, which would bias my results downward.

My data consist of GTA records for fattening or slaughter in Rondônia between 2008 and 2017.[8][9] This results in 4,259,797 transactions across the period. Each GTA record includes the name, owner, and municipality of the property of origin; the name, owner, and municipality of the destination property; the number of animals being moved; the age of the animals; the purpose of the movement; and the date. I identify properties in these transactions based on shared property name, owner name, and municipality after first standardizing these values.[10] Similarly, I identify property owners as those sharing standardized values of owner name and municipality. There are 168,459 unique selling properties and 127,447 unique selling owners.

My analysis is measured at the property-year level. Properties are included in the data in the years in which they register a GTA. I focus on selling properties; the primary sample is made of 534,387 selling property-year observations.

Rainfall measures come from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data. CHIRPS is gridded data with a 0.05° resolution and is available to the public for download. Measures of monthly rainfall are constructed using pentad data, and counts of the days without rain are constructed using daily data. I estimate municipal-level (equivalent to county-level) rainfall based on the median rainfall value of all pixels within the municipality.

To match CHIRPS with the GTA, I link the municipality of origin for each sale with municipal-level rainfall. There are 52 municipalities in Rondônia, and they are 4,569 km^2 on average. Climate data often is spatially correlated; analyses using these data must consider the risk that ommitted variables are also spatially correlated (Hsiang, 2016). This is particularly true when gridded data is interpolated between distant weather stations (Dell et al., 2014). Aggregating data to larger scales, particularly to scales at which the natural patterns of climate are less correlated (in this context, the municipality), reduces the spurious correlation, as does clustering standard errors at levels with less spatial correlation (Hsiang, 2016).

4.2 Variable descriptions and summary statistics

I define a set of variables to characterize sales behavior and rainfall patterns. First, I count the number of animals that a property sells for fattening in April through June, a period of transition between the

[8] Cattle may also be moved for reproduction, auction, or other purposes.

[9] I exclude records with an irregular status, primarily "canceled." This corresponds to 7% of transactions during the period.

[10] Input data is standardized to address spelling and punctuation inconsistencies and errors in property databases and the GTA. Both the names of properties and people/companies were capitalized, and sequences of consecutive white space were replaced with a single space. All non-alphanumeric characters were completely removed, as well as leading and trailing white space. Role descriptors (*próprio, sócio*, etc.) were stripped away, and characters like parentheses or dashes were used to remove parts of the string unlikely to contain the actual name. I cannot identify a property for all transactions; 321,818 transactions are not assigned to a property ID and are excluded from property level analyses.

rainy and dry season (Butt et al., 2011; Teixeira Leite-Filho et al., 2019). I construct separate measures for transactions of animals that are less than a year (calves) and more than a year (adult animals). I also count the heads sold to a different owner for fattening in April through June. Owners may move animals between their own properties as a form of pasture management or rotational grazing; requiring the properties have different owners limits the inclusion of this behavior.

Proposition 2 of the theoretical model predicts that the response to rainfall expectations will vary by the stock of cattle on the property. Since it records transactions, the GTA measures flows rather than stocks. Flows should be correlated with this variable of interest, as properties that sell large volumes of cattle are likely to have high stocks. I directly test heterogeneous effects by average annual sale volume (for fattening or slaughter) in each year that they are active in the GTA. This represents the scale of operations and may represent property wealth and capital better than area, given the variation in stocking density in the region. I also divide properties into deciles based on this average sale volume to allow for non-linearity of response.

In focus groups, farmers report that they form their expectations of the severity of the oncoming dry season based on the transition period between the rainy and dry seasons. Ranchers view sporadic rainfall in March and April as a sign that the dry season will be severe. Decreased rainfall in the transition periods directly affects the severity of the dry season by lengthening the period of low rainfall (Butt et al., 2011; Debortoli et al., 2015; Teixeira Leite-Filho et al., 2019). Further, this understanding corresponds to the scientific literature, which shows that rainfall in the region is not decreasing in the driest months, but is rather decreasing in the transition periods.

Farmers reported that measuring rainfall is uncommon, and most have low awareness of the centimeters of rain that fall on their property. Instead, they conceptualize rainfall based on whether a day passes without any rain. I proxy producers' expectations of the coming dry season using the number of days without rain in March and April. This measure, although crude, is borne out in the data, as an increase in the number of days without rainfall is correlated with less rain during the dry season and a delay in the onset of the rainy season (table 1). Local and indigenous methods of measuring climate have been shown to correspond well to formal climate records, and even capture phenomena or fine-scale details that these records do not (Sánchez-Cortés and Chavero, 2011; Marin, 2010; Orlove et al., 2000).

Ranchers could also update their expectations of the dry season based on the severity of the previous dry seasons. I proxy the severity of the previous dry season using the delay in the onset of the previous rainy season. A later onset of the rainy season is particularly harmful for production as it occurs at a time when pasture has been dry for months and animal weights are low. Ranchers in the Amazon often replant pasture during the transition, so delayed rain also delays or altogether prevents this planting. I follow Teixeira Leite-Filho et al. (2019), who quantify the onset of the rainy season as

Table 1: Rain in the dry season (June - Aug, cm) and the onset of the rainy season (days since September 1st) as a function of the number of days without rain in March and April

	(1)	(2)
	Dry season rainfall	Onset of the rainy season
Days without rain	-0.594***	0.456**
	(0.182)	(0.172)
Observations	520	520

Table 2: Summary statistics of dependent and independent variables

	Mean	SD	Min	Max	N
Rainfall variables					
Onset of rainy season (days after 1 Sep)	55.51	25.69	2	122	468
Days without rain March - April	25.56	6.28	10	43	468
Days with $<$ 5mm March - April	29.73	5.50	15	45	468
Selling variables					
Heads moved per year	87.40	317.16	1	34,098	523,863
Heads sold for fattening April - June	15.70	85.19	0	13,080	523,863
Adult animals ($>$ 12 months)	10.31	69.27	0	13,080	523,863
Calves ($<=$ 12 months)	5.39	33.21	0	4,242	523,863
Heads sold to different owner	9.15	47.34	0	5,840	523,863

Note: Rainfall variables are measured at the municipality-year level, while transaction variables are measured at the property-year level.

the first day with more than 20 millimeters of rain, and then measure the number of days the onset occurs after September 1.

Table 2 lists summary statistics of treatment and outcome variables in the sample. Appendix figures 5 and 6 map the distribution of rainfall treatments across space and time.

5 Estimation strategy

Equation 5 in the theoretical model predicts that low expectation of rainfall increases sales for fattening at the beginning of the dry season. I cannot measure expectations directly, but proxy them using two measures discussed in section 4. I employ a fixed effects strategy to identify the effect of expectations on property level sales decisions. This analysis rests on the assumption that municipal-level rainfall is exogenous to individual behavior on a property. Based on this assumption, the effect of rainfall shocks on cattle production is causally identified by a model with property and year fixed effects.[11] The theoretical model also predicts that ranchers will sell proportionally more animals when they have higher initial stocks.

The model that tests both the main and heterogeneous effects of the ranchers' expectations of rainfall takes the form:

[11] See Hidalgo and Nichter (2008); Da Cunha et al. (2015) for two examples of papers conducting similar analyses in Brazil.

$$F_{it} = \alpha t + \lambda_i + \beta E_{mt} + \nu E_{mt} V_i + \sum_{n=1}^{3} \Big(\gamma_{t-n} D_{m,t-n} + \omega_{t-n} D_{m,t-n} V_i \Big) + \epsilon_{mt} \tag{6}$$

where F_{it} is the sales behavior of property i in year t. As detailed in section 4, the main specification of F_{it} is the number of heads moved for fattening in April through June, but for additional insight I test sales of adult animals and calves. Due to the large distribution of F_{it}, I use the inverse hyperbolic sine (IHS) transformed value of F_{it}. I include a property fixed effect, λ_i.

I test the effect of current rainfall using, E_{mt} the days without rain in March and April municipality m in year t. I test the heterogeneous effects by interacting E_{mt} with V_i denoting the IHS transformed average annual sales volume by property i. Hypothesis 2 predicts that ν and ω will be positive as larger properties will respond to a rainfall shock by purchasing more animals for fattening. I omit these interaction terms when estimating average effects only. I test the effect of previous rainfall using $D_{m,t-n}$, the onset of the rainy season in year $t-n$, measured in days after September 1st. I include three lagged measures of $D_{m,t-n}$. This is important since the previous dry season may directly affect the number of heads that are ready for fattening in the following year, whereas behavior in year $t-2$ and $t-3$ better represents medium-run adaptation. Again, I exclude the interaction terms between $D_{m,t-n}$ and Q_i when estimating the average effect only and include them when testing heterogeneous effects.

In the main specification I use a year trend, t, due to the limited variation in the treatment variable across space. Although there is significant variation in rainfall in the sample, year and municipal fixed effects explain 73% of the variation in the number of days without rainfall in March and April (appendix figure 5). Moreover, the coefficients on the year fixed effects increase over the period, suggesting that a year trend should largely capture the changes in fattening that are occurring for reasons other than rainfall shocks (appendix figure 7). I include the results of a model that uses year fixed effects as a robustness check. Motivated by this correlation in rainfall across space, I cluster standard errors at the municipal level, m.

I use a non-parametric specification to test the heterogeneous effects by dividing properties into deciles by average annual sales volume. This model takes the form:

$$F_{it} = \alpha t + \lambda_i + \beta E_{mt} + \sum_{n=1}^{3} \gamma_{t-n} D_{m,t-n} + \sum_{q=2}^{10} \left(\nu_q E_{mt} Q_{qi} + \sum_{n=1}^{3} \omega_{q,t-n} D_{m,t-n} Q_{qi} \right) + \epsilon_{mt} \tag{7}$$

where Q_{qi} is a dummy variable indicating if property i is in decile q. I expect ν_q and ω_q to be increasing in q.

6 Results

6.1 The effect of rainfall shocks on cattle transactions

Ranchers are selling more cattle for fattening prior to the dry season, and this change is partially driven by rainfall. On average, a one standard deviation increase in the number of days without rain increases the heads moved for fattening per property from April to June by 2.2% (table 3 column 1).[12] This corresponds to 46,000 additional heads sold for fattening, based on the total number of properties and the average number of heads sold for fattening.[13] The individual changes to sales of adult animals and calves were comparable; a one standard deviation increase in days without rain leads the rancher to increase sale of adults by 1.3% calves by 1.4% (columns 3 and 5).

Columns 2, 4, and 6 shows how responses vary by property sales volume. I present the total effects for the 5th percentile, median property, and 95th percentile. The 5th percentile of properties sells 3.4 total head per year and 0.8 head per year for fattening from April to June. The median property sells 27.9 total head per year and 6.3 head for fattening from April to June. The 95th percentile of properties sells 313.1 total head per year and 54.8 head for fattening from April to June. The total effect of additional days without rain is not different from zero at low volumes. The median property responds to a one standard deviation increase in the number of days without rain by increasing sales for fattening by 2.0%, which is comparable to the average effect. At the 95th percentile of volume, however, they increased sales for fattening by 4.9%.

I simultaneously consider the ranchers' response to the timing of the onset of the previous rainy season. Here, a larger value of the treatment variable represents a later onset of the previous rainy season and thereby a longer dry season. I find weak evidence of an overall change in sales for fattening two and three years after a delay in the onset of the rainy season (column 1). On average, properties increase sales for fattening by 2.6% two years after a one standard deviation delay in the onset of the rainy season (significant at the 10% level); the results are not significant in years one or three.[14] However, higher volume properties significantly increase sales for fattening two and three years after a delayed onset (columns 2). The median property increases sales for fattening 2.3% two years later (significant at the 10% level), with no significant change in years one or three. The 95th percentile of properties increases sales by 6.5% two years later and 3.9% three years later.

Notably, I find evidence that small-volume properties decreased sales for fattening the first year after a delay in the onset of the rainy season, although this is not evident for larger-volume properties. The 5th percentile of properties decreases sales for fattening by 2.6% one year after a one standard deviation delay in the onset of the rainy season. A prolonged dry season could result in animals dying

[12]The average municipality had 25.56 days without rain in March and April, with a standard deviation of 6.28.
[13]There were 168,459 active properties and they sold an average of 15.12 head for fattening between April and June.
[14]The average municipality has a 55.51 day delay in onset, with a standard deviation of 25.69

in the field or force ranchers to sell animals at a loss in the dry seasons; either would reduce the size of the herd at the end of the following rainy season. That I only find evidence of this for small-volume properties suggests that these properties are the hardest hit by prolonged dry seasons.

The effect on sales of adult animals follows the same patterns as the overall sales for fattening (column 4). There is an overall response to a delayed onset two years prior, but no overall response in years one or three. Larger properties respond more, with a significant increase in sales of adult animals at the median and 95th percentile in year two, but only at the 95th percentile in year three. Again, small volume properties significantly decrease sales for fattening one year after a delayed onset in the rainy season.

I find different effects on sales of calves (column 6). There is little evidence of an increase in sales after a delayed dry seasons, with the exception of the largest volume properties two years later. This likely reflects the different value that calves and adult animals hold. A calf is an asset that a rancher intended to hold for at least another year, and it will gain significant value if a rancher continues to raise it. Thus, selling calves is not a long-run adaptation strategy to the dry season (as responding to previous dry seasons would reflect), but rather a crisis response to an impending dry seasons (as a response to days without rain at the end of the current rainy season would suggest). In contrast, an adult animal is much closer to the end of its life cycle and its final value, and selling them for fattening is a long-run method to mitigate dry season losses.

The year trend shows that the movement of animals for fattening increased significantly over the period, apart from the effect of rainfall. On average, properties increase the head moved for fattening in April to June by 6.3% per year, with an increase of 5.6% for adult animals and 2.9% for calves. This is consistent with evidence of increasing movement of adult animals to finishing operations prior to slaughter (Vale et al., 2019). Thus, the effect of a single rainfall shock is similar in magnitude to the increase in fattening that is occurring annually due to other forces.

6.2 Non-parametric heterogeneity analysis

I confirm that larger-volume properties respond more to rainfall shocks using a non-parametric analysis. I interact nine property decile dummies with each of the rainfall variables and report all coefficients in appendix table 5. Figure 3 graphs the total effect (i.e. main effect and interaction effect combined) on heads sold for fattening based on the property decile of sale volume. I find that higher volume deciles increase sales for fattening in response to more days without rain or two years after a delay in the onset of the rainy season. There is no significant response to any rainfall shocks at lower deciles, and no response at any decile one or three years after a delay in the onset of the rainy season.

Table 3: (IHS transformed) heads transported for fattening in April - June in response to an additional day without rain in March and April and delay in onset of previous rainy seasons

	(1)	(2)	(3)	(4)	(5)	(6)
	All transactions		Adult animals		Calves	
Days without rain	0.0035**	-0.0044***	0.0027**	-0.0040***	0.0028**	-0.0043***
	(0.0015)	(0.0015)	(0.0010)	(0.0013)	(0.0010)	(0.0013)
DWR * volume		0.0019***		0.0016***		0.0017***
		(0.0004)		(0.0004)		(0.0003)
Onset t - 1	0.0001	-0.0020***	-0.0001	-0.0016***	0.0001	-0.0011***
	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
t - 1 * volume		0.0005***		0.0004**		0.0003**
		(0.0002)		(0.0002)		(0.0001)
Onset t - 2	0.0010*	-0.0019*	0.0009**	-0.0014	0.0005	-0.0015**
	(0.0006)	(0.0010)	(0.0004)	(0.0008)	(0.0004)	(0.0007)
t - 2 * volume		0.0007***		0.0005**		0.0005***
		(0.0002)		(0.0002)		(0.0002)
Onset t - 3	0.0005	-0.0012	0.0004	-0.0008	0.0002	-0.0007
	(0.0004)	(0.0010)	(0.0004)	(0.0008)	(0.0003)	(0.0006)
t - 3 * volume		0.0004*		0.0003*		0.0002*
		(0.0002)		(0.0002)		(0.0001)
Total effects: Days without rain						
5th percentile		-0.0007		-0.0010		-0.0011
		(0.0012)		(0.0008)		(0.0010)
50th percentile		0.0032**		0.0024**		0.0025**
		(0.0014)		(0.0010)		(0.0010)
95th percentile		0.0079***		0.0064***		0.0067***
		(0.0021)		(0.0018)		(0.0015)
Total effects: Onset t - 1						
5th percentile		-0.0010**		-0.0009**		-0.0006**
		(0.0005)		(0.0004)		(0.0003)
50th percentile				-0.0001		0.0001
		(0.0005)		(0.0004)		(0.0003)
95th percentile		0.0013		0.0007		0.0008
		(0.0008)		(0.0007)		(0.0005)
Total effects: Onset t - 2						
5th percentile		-0.0005		-0.0003		-0.0006
		(0.0006)		(0.0005)		(0.0004)
50th percentile		0.0009*		0.0008*		0.0004
		(0.0005)		(0.0004)		(0.0003)
95th percentile		0.0025***		0.0021***		0.0016**
		(0.0009)		(0.0008)		(0.0006)
Total effects: Onset t - 3						
5th percentile		-0.0004		-0.0002		-0.0003
		(0.0006)		(0.0005)		(0.0003)
50th percentile		0.0005		0.0004		0.0002
		(0.0004)		(0.0004)		(0.0003)
95th percentile		0.0015**		0.0011*		0.0008
		(0.0007)		(0.0006)		(0.0005)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of observation is the property-year. All models include property-level fixed effects. Robust standard errors are in parentheses and are clustered at the municipality level (N = 52).

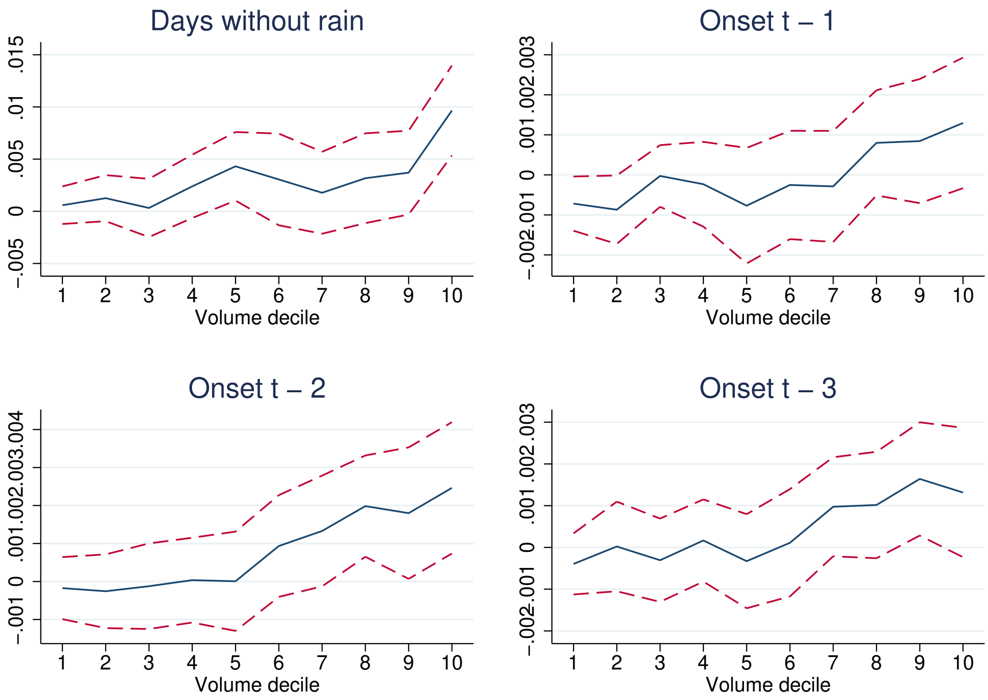

Figure 3: Total effects of rain on fattening early from a non-parametric regression based on volume decile

6.3 Robustness checks

In order to better understand what is driving my results and to address potential threats to identification, I test alternative specifications. I first describe each of these concerns and how I address them, and then fully describe the results.

6.3.1 Inclusion of time fixed effects

A year trend could introduce bias in my identification if the trend failed to control for other factors that simultaneously influenced rainfall and fattening in a single year; the inclusion of year fixed effects would account for this. I test the model using year fixed effects rather than a year trend and find that my results are largely consistent, and the coefficients of the year fixed effects support the use of a year trend.

Columns 1 and 2 of table 4 shows how the results change with the inclusion of time fixed effects. First, the main effect on heads transported for fattening is no longer significant (column 1). Additionally, the main effect of days without rain is negative and significant when I include an interaction term, although the interaction term between days without rain and volume remains positive and significant. The fifth percentile of properties reduced sales for fattening by 1.1% in response to a one standard deviation increase in days without rain. There total effect for the median or 95th percentile of properties

Table 4: Alternative specifications of (IHS transformed) heads transported for fattening in April - June in response to an additional day without rain in March and April and delay in onset of previous rainy seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Year FE		Different owner		Alternative rainfall		Limited sample	
Days without rain	-0.0018	-0.0094***	0.0027**	-0.0026*	0.0022	-0.0059**	0.0038**	-0.0053***
	(0.0033)	(0.0026)	(0.0012)	(0.0015)	(0.0018)	(0.0022)	(0.0015)	(0.0020)
DWR * volume		0.0018***		0.0013***		0.0020***		0.0021***
		(0.0004)		(0.0003)		(0.0006)		(0.0004)
Onset t - 1	-0.0006	-0.0027***	0.0000	-0.0011*	0.0001	-0.0020***	0.0000	-0.0023***
	(0.0004)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0008)
t - 1 * volume		0.0005***		0.0003*		0.0005***		0.0005***
		(0.0002)		(0.0001)		(0.0002)		(0.0002)
Onset t - 2	0.0007	-0.0020**	0.0008*	-0.0013*	0.0010*	-0.0019*	0.0011*	-0.0017
	(0.0005)	(0.0009)	(0.0005)	(0.0007)	(0.0006)	(0.0010)	(0.0006)	(0.0012)
t - 2 * volume		0.0007***		0.0005***		0.0007***		0.0006**
		(0.0002)		(0.0002)		(0.0002)		(0.0003)
Onset t - 3	0.0007*	-0.0009	0.0005	-0.0008	0.0006	-0.0013	0.0004	-0.0014
	(0.0004)	(0.0009)	(0.0004)	(0.0007)	(0.0004)	(0.0009)	(0.0005)	(0.0011)
t - 3 * volume		0.0004*		0.0003*		0.0005**		0.0004
		(0.0002)		(0.0002)		(0.0002)		(0.0002)
Year			0.0625***	0.0624***	0.0870***	0.0869***	0.0903***	0.0902***
			(0.0056)	(0.0056)	(0.0069)	(0.0069)	(0.0068)	(0.0068)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of observation is the property-year. All models include property-level fixed effects. Robust standard errors are in parentheses and are clustered at the municipality level (N = 52).

is not significant.

In contrast, the response to a delay in the onset of the rainy season is robust to the inclusion of fixed effects. The 5th percentile experiences a significant decrease in sales one year after a prolonged drought but show no change two or three years later. The median property increases sales for fattening by 1.7% three years after a one standard deviation delay in the onset; the top 95% of properties increase sales for fattening by 5.7% and 2.3% two and three years after a delay, respectively.

As I discussed in section 4, year and municipal fixed effects explain 73% of variation in days without rainfall. Thus, including fixed effects leaves very little variation in this treatment variable. Instead, this model identifies off of a limited set of variations in rainfall, specifically, cases where municipalities experienced rainfall shocks that differed from that year's overall weather patterns. Municipal and year fixed effects only explain 34% of the variation in delay in the dry season, so there is more variation in this treatment variable after the inclusion of fixed effects. Notably, the individual year dummies are increasing over the period (figure 7). I take this as evidence that a year trend accounts for the increase in fattening over the period while still leaving variation in both treatment variables.

6.3.2 Multiple property ownership by ranchers

Property arrangements in the Amazon are often complex, and ranchers may own multiple properties (Rausch and Gibbs, 2016). Because all movements of cattle must be registered, my results might be driven by ranchers moving animals between their own properties; in this case, my results would capture cattle movement rather than cattle sales. I limit the analysis to cattle movements between two distinct owners and find that cattle are sold to different owners in response to days without rainfall (table 4 columns 3 and 4).

Columns 3 and 4 of table 4 shows that the effects are consistent although smaller when I limit to sales to a different owner. This is to be expected, as I am reducing the set of adaptative behavior I consider. A standard deviation increase in the number of days without rain increases the number of heads sold for fattening to a different owner by 1.7% overall, compared to 2.2% when I consider heads sold to any owner (column 3). The median property increased sales for fattening by 1.6%, the 95th percentile increased by 3.5%, and the 5th percentile of properties did not respond. (column 4). I find a 2.1% overall increase in fattening sales to a different owner two years after a one standard deviation delay in onset of the rainy season; this compares to a 2.6% increase in the main specification. The 5th percentile has no response in any years, the median property increases fattening by 1.9% two years later, and the 95th percentile increased fattening by 5.1% and 3.1% two and three years later, respectively.

6.3.3 Robustness to definition of the treatment

I confirm that my results are not overly sensitive to my definition of rainfall using an alternative specification of late-rainy season rainfall (table 4 columns 5 and 6). I count the number of days with less than five millimeters of rainfall (rather than zero) to ensure my results are not overly sensitive to rainfall measurements at zero. The coefficient on the average effect of days without rainfall is similar in magnitude (0.22 vs 0.27) to the main specification but no longer significant. However, the interaction term between volume and days without rain is positive and significant. The total effect for the median property is no longer significant, although the increase for the 95th percentile is still positive and significant (3.7% vs 4.9%. The decrease in magnitude and significance is expected as the coefficient is now less precise than the binary measure (rain or no rain) that farmers report using to interpret rainfall signals.

The coefficients on the onset of the previous rainy seasons are similar in both magnitude and significance (column 5).

Throughout the analysis, I impose a linear relationship between my rainfall variables and cattle sales; here I relax this assumption. I test whether the response to changes in days without rain is nonlinear by measuring days without rainfall using six dummies corresponding to a five day range, compared to the omitted category of zero to fourteen days without rain. I graph the values of these dummies in figure 4. For the onset of the previous rain season, I use six dummies to measure the response corresponding to a ten day range, compared to the omitted category of a zero to twenty-nine day delay. Ranchers sell more total animals, adult animals, and calves both two and three years after a fifty to seventy day delay in onset (table 6). This range corresponds to an above average delay

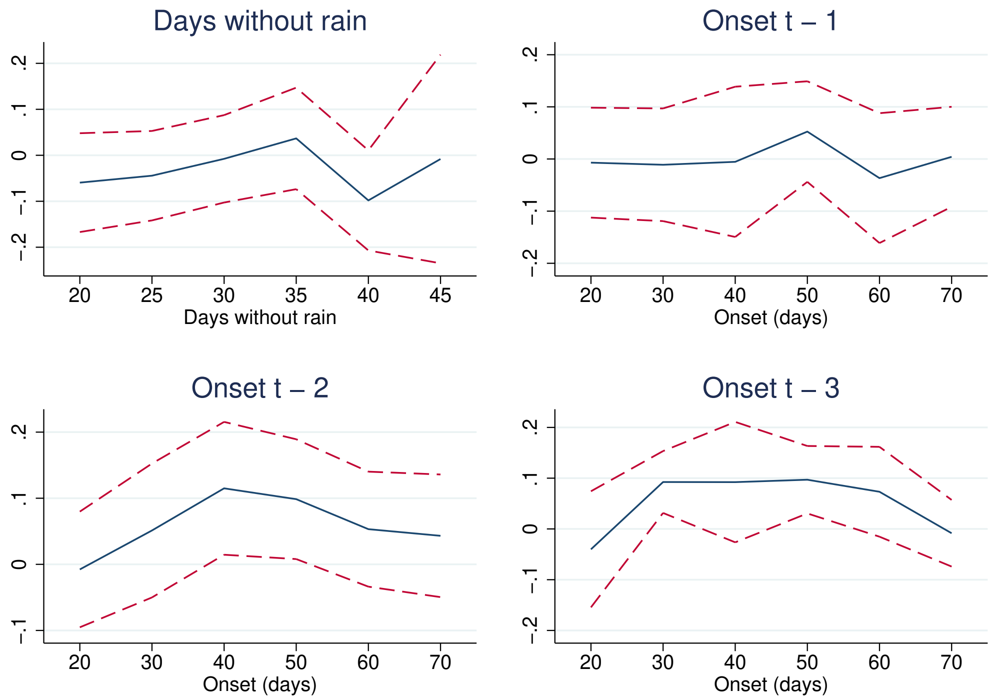

Figure 4: Nonlinear effects of rain on fattening early

in onset.[15] Notably, the dummies for more than a seventy day delay are not significant; a drought this extreme may have long-lasting effects on herd size (i.e. loss of animals to starvation or forced destocking) and farm finances that continue to affect sales two and three years later.

However, I do not find evidence of a non-parametric response to days without rain. This may be due to the lack of balance between groups for the days without rain. There are 13,485 and 9,714 observations in the lowest and highest categories, respectively, compared to 151,365 and 171,292 for the third and fourth categories, respectively. In this case, a continuous measure of the variable better captures the variation and responses than binary categories that overweight observations at the extremes.

6.3.4 Analysis limited to "active" properties

Finally, although the GTA is a reliable data source and my method of identifying individual properties and owners is rigorous, very low-activity properties may not accurately represent active cattle ranchers. First, these properties could be engaged in small- scale production as a hobby or for other reasons, and would therefore not use the same decision making framework as a typical rancher. Second, I may be classifying transactions as originating on a separate property when someone other than the usual owner registers the GTA. This is because I identify distinct properties based on the property name, municipality name, and the owner name listed in the GTA. For example, a property where the husband usually registers the GTA, but the wife occasionally does so, would therefore appear as two

[15]The sample mean is a 55.5 day delay.

separate properties. To reduce this concern of misrepresentation of properties, I run the analysis excluding the least active properties. I define properties to be active if they registered a GTA in three or more years and had six or more transactions. This should eliminate properties that are not engaging with the market frequently as well as cases where another person filed a GTA very rarely.

Columns 7 and 8 of table 4 show that there is an increase in heads sold for fattening when I exclude inactive properties, and the size of the effect increases compared to the full sample. On average, active properties sell an additional 2.8% head for fattening in response to a one standard deviation increase in days without rain compared to 2.2% in the full sample. The heterogeneity analysis shows that, even after excluding inactive properties, the smallest-volume properties did not respond to rainfall signals, but larger-volume properties did. On average, there was a 2.8% increase in fattening two years after a one standard deviation delay in the onset of the rainy season compared to 2.6% in the full sample. The 5th percentile of properties decreased sales one year after a one standard deviation in delay in the rain season, the median property increases fattening two years later, and the 95th percentile increases both two and three years later. I therefore conclude that mischaracterization of properties is not driving my results, including the lack of response by small-volume properties.

7 Conclusion

Cattle ranchers in the Amazon are adapting to climate change by increasing their strategic sales of cattle for fattening rather than sustaining the costs of holding the cattle during the dry season. I show that ranchers sell animals prior to the dry season when they anticipate a severe dry season and that their expectations are based on the number of days without rainfall at the end of the rainy season as well as their previous dry season experiences. A one standard deviation increase in the days without rain in March and April leads to an additional 65,000 heads transferred for fattening between April and June, while a one standard deviation delay in the rainy season leads to an additional 130,000 heads transferred for fattening over two years. These results are significant after controlling for the long-term increase in sales for fattening; fattening increased by an average of 160,000 head per year for other reasons, such as market development. Response to rainfall signals varied by property-volume, with all but the smallest properties responding to current rainfall signals as the dry season approached, but only the top 50% of properties adjusting based on a delay in the dry season two or three year prior.

My results present a puzzle, as selling for fattening should be a highly accessible adaptation technique for small and medium-volume producers. Compared to many adaptation strategies, such as irrigation, chemical inputs, and new crops varieties, selling cattle for fattening does not require a lump-sum investment that might be prohibitive for smaller producers. Thus, this strategy should be accessible and beneficial strategy for smallholders faced with climate change. Instead, I find that large-volume properties respond more strongly to rainfall shocks. Additionally, only large-volume properties respond to the previous dry seasons, which suggests that medium-volume properties are not making medium to long-run changes, but only responding to immediate signals.

There are several potential explanations for this. First, there are transaction costs for any sale, and these costs might be larger than the potential gain for ranchers with a small numbers of animals to sell for fattening. Second, livestock are a form of savings. Small-volume ranchers report a fear that if they sell their animals prior to a severe dry season they will be unable to afford the same number of heads after the dry season, as they will face other financial losses during the dry season. Inflationary concerns due to previous experience may also lead small-volume ranchers to only sell animals, which store value, until a point at which they can immediately purchase replacements. Large producers may have alternative methods to protect against inflation, including investing in other currencies.

Finally, adopting fattening sales every year at the end of the rainy season requires a seasonal structure to the production cycle in which births, sales, and slaughter happen according to a schedule. Small-volume ranches may not already use a structured production model, so adopting fattening sales as a long-term strategy represents a major change to their production. Lack of information, awareness, or willingness to change production is well documented in the technology adoption literature, with a lower adoption observed on smaller farms (Foster and Rosenzweig, 2010; Mwangi and Kariuki, 2015). Choosing which aspects of a "modern" production system to adopt requires an analysis of the economic benefits that Embrapa (2018) argues is challenging for many producers. They suggest the transition to modern cattle production can rarely be achieved without a consultant, thereby adding to the cost of intensification and leading low-capital ranchers to ultimately stay with the status-quo.

My work presents the first industry-wide measure of adaptation to climate change. Unlike analyses that rely on responses to weather to gain insight on climate change, I estimate responses to climate change due to the rapid local changes in rainfall in the Amazon. I add to the understanding of how variation in rainfall, rather than absolute rainfall, matters for agriculture, and present a measure of how rainfall affects expectations. Finally, I offer insight into adaptation across the supply chain using a census of cattle transactions over nine years and show that adaptation is not evenly distributed.

Several questions should be addressed in future work. First, while confinement operations play an important role in the increased transactions for fattening, the data does not currently reliably identify confinements. Future work should identify these properties and address whether they are developed in response to the dry season and how many of the additional sales that I identify are destined for confinements. Next, further work could quantify property-level stocks to better test the theoretical model. Finally, household data can confirm whether transaction costs or credit constraints are the cause of the lack of response by small volume properties.

This paper demonstrates that cattle ranchers are adapting to a changing climate via the supply chain. My results suggest that cattle sales at the beginning of the dry season will increase as the dry season becomes more severe, but these changes will be strongest on large properties. This will lead to a more segmented supply chain, as well as a supply chain that relies on a limited number of properties to withstand droughts. As policy makers and agricultural actors anticipate the effects of climate change, they will need to include supply chain restructuring in their considerations. The lack of response by small properties has implications for the distributional consequences of climate change. Even in this setting, where there are no economies of scale to adaptation, adoption is scale related. This raises concern for how smallholders will be able to adapt to climate change, and suggests that the effects of climate change will be high for this already vulnerable group.

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A Variation in rainfall across time and space

Figure 5: Variation in days without rain in March and April in each year

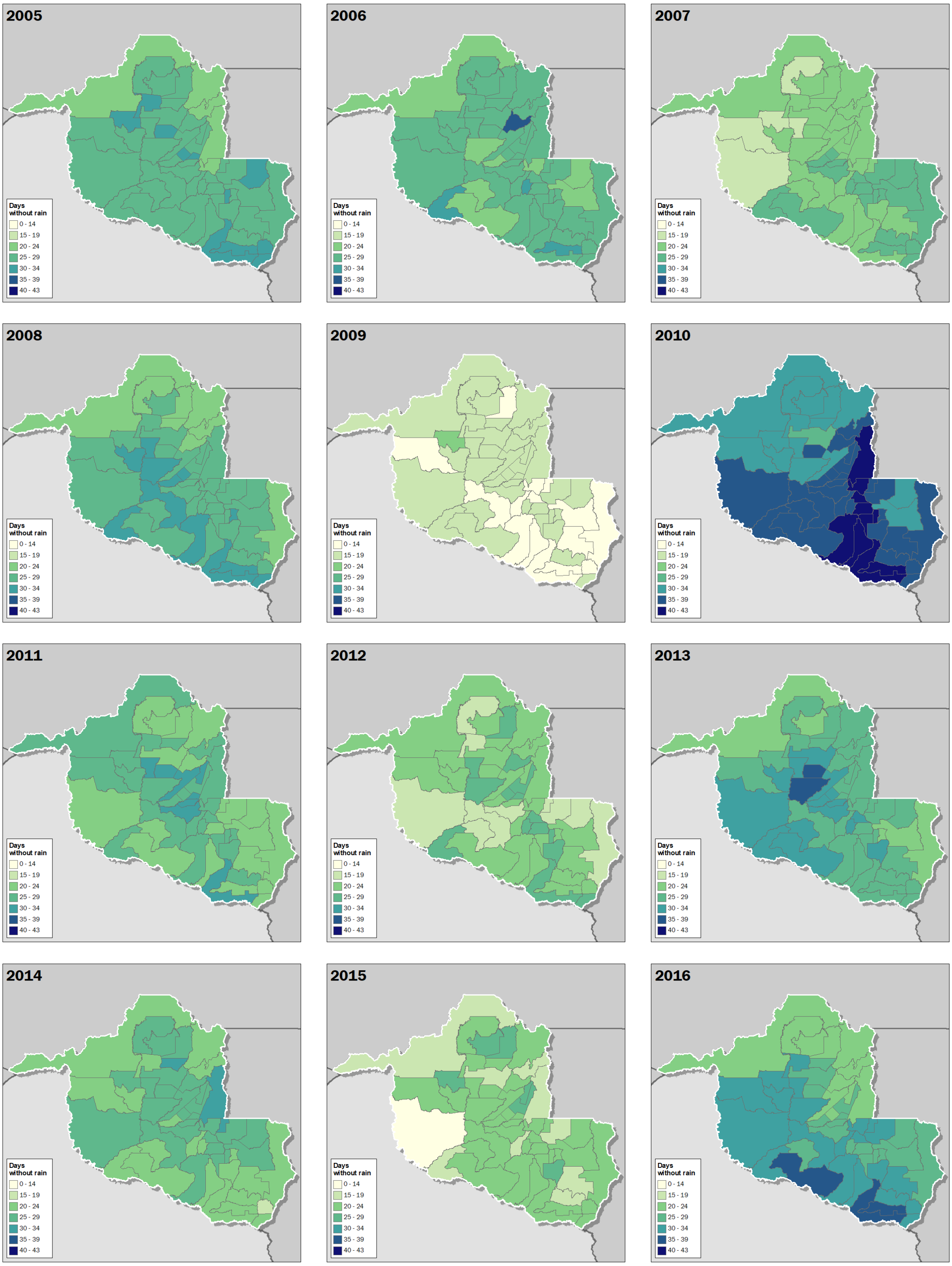


Figure 6: Variation in onset of the rainy season in each year

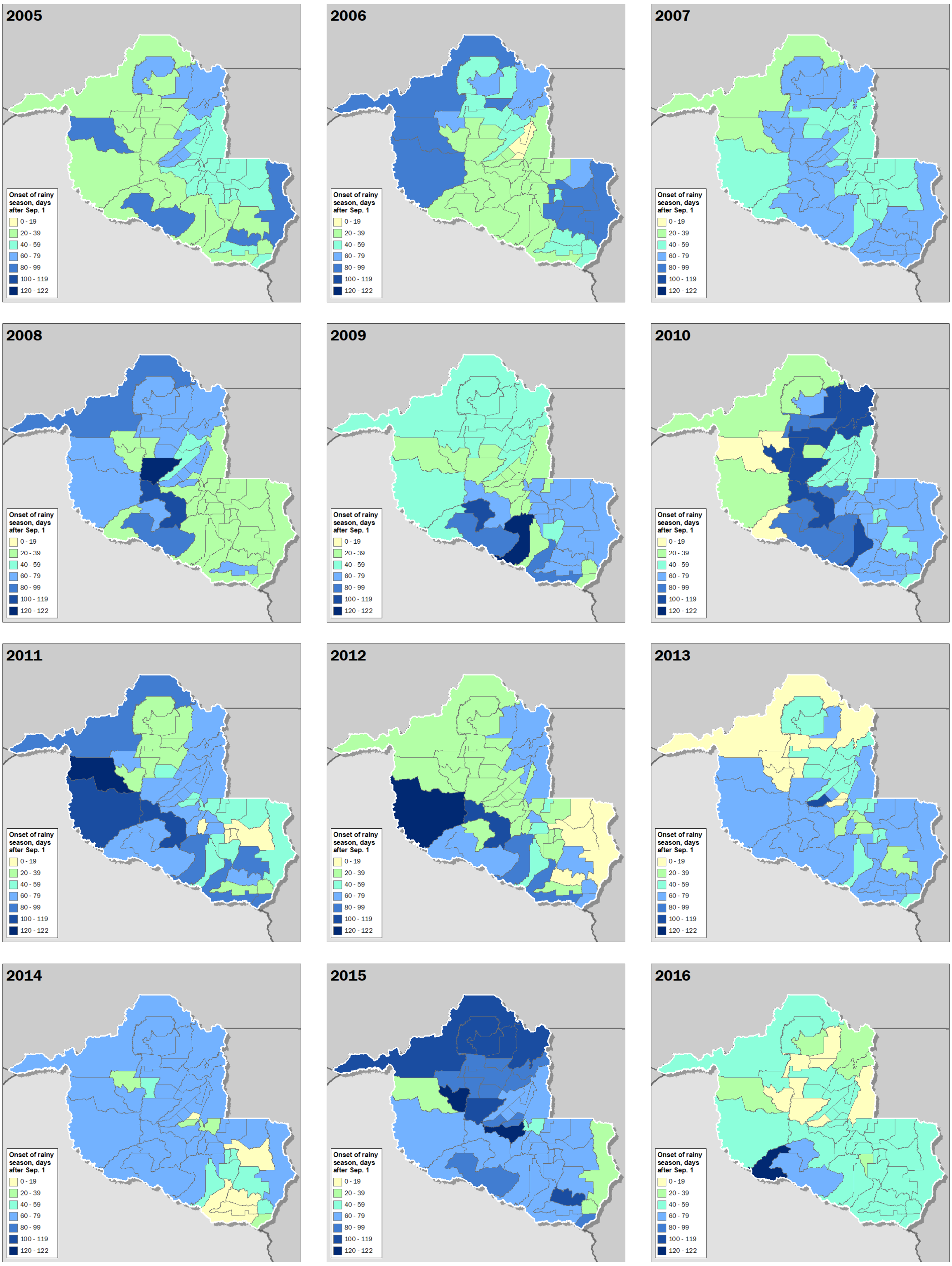
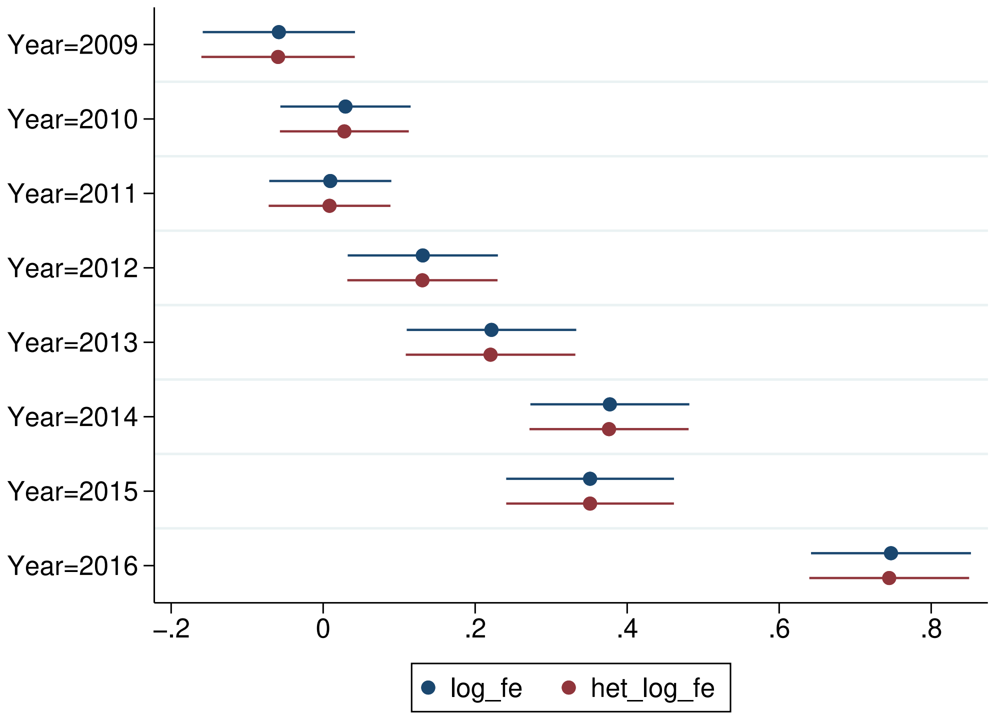


Figure 7: Coefficients of year fixed effects in heads transported for fattening in April - June in response to an additional day without rain in March and April



Note: Coefficients are represented by the point, and the 95% confidence interval for the coefficient is represented by the bar.

B Robustness checks

Table 5: Non-parametric test by property volume of heterogeneous effects of rainfall on (IHS transformed) heads transported for fattening in April - June in response to an additional day without rain in March and April

	(1) All transactions	(2) Adult animals	(3) Calves
Days without rain	0.0006	0.0008	-0.0004
	(0.0009)	(0.0008)	(0.0006)
Onset t - 1	-0.0007**	-0.0006**	-0.0003
	(0.0003)	(0.0003)	(0.0003)
Onset t - 2	-0.0002	-0.0002	-0.0001
	(0.0004)	(0.0004)	(0.0002)
Onset t - 3	-0.0004	-0.0004	0.0000
	(0.0004)	(0.0004)	(0.0002)
Onset t - 1 * decile 2	-0.0002	-0.0003	0.0000
	(0.0004)	(0.0002)	(0.0004)
Onset t - 1 * decile 3	0.0007*	0.0005*	0.0002
	(0.0003)	(0.0003)	(0.0003)
Onset t - 1 * decile 4	0.0005	0.0003	0.0002
	(0.0005)	(0.0004)	(0.0004)
Onset t - 1 * decile 5	-0.0001	-0.0001	-0.0001
	(0.0007)	(0.0006)	(0.0005)
Onset t - 1 * decile 6	0.0005	0.0004	-0.0001
	(0.0007)	(0.0006)	(0.0005)
Onset t - 1 * decile 7	0.0004	0.0001	0.0005
	(0.0007)	(0.0005)	(0.0005)
Onset t - 1 * decile 8	0.0015**	0.0012**	0.0007
	(0.0007)	(0.0006)	(0.0005)
Onset t - 1 * decile 9	0.0016*	0.0010	0.0009
	(0.0008)	(0.0007)	(0.0006)
Onset t - 1 * decile 10	0.0020**	0.0014*	0.0012*
	(0.0008)	(0.0007)	(0.0006)
Onset t - 2 * decile 2	-0.0001	0.0000	-0.0000
	(0.0004)	(0.0003)	(0.0003)
Onset t - 2 * decile 3	0.0001	0.0001	-0.0000
	(0.0004)	(0.0004)	(0.0003)
Onset t - 2 * decile 4	0.0002	0.0005	-0.0001
	(0.0005)	(0.0005)	(0.0004)
Onset t - 2 * decile 5	0.0002	0.0003	-0.0001
	(0.0006)	(0.0005)	(0.0004)
Onset t - 2 * decile 6	0.0011	0.0012**	0.0003
	(0.0007)	(0.0006)	(0.0005)
Onset t - 2 * decile 7	0.0015*	0.0013**	0.0007
	(0.0008)	(0.0006)	(0.0006)
Onset t - 2 * decile 8	0.0022***	0.0020***	0.0011**
	(0.0007)	(0.0006)	(0.0005)
Onset t - 2 * decile 9	0.0020**	0.0016*	0.0011*
	(0.0010)	(0.0008)	(0.0006)
Onset t - 2 * decile 10	0.0026**	0.0021**	0.0021***
	(0.0010)	(0.0009)	(0.0007)
Onset t - 3 * decile 2	0.0004	0.0003	0.0002
	(0.0004)	(0.0003)	(0.0004)
Onset t - 3 * decile 3	0.0001	0.0003	-0.0002
	(0.0003)	(0.0003)	(0.0003)
Onset t - 3 * decile 4	0.0006	0.0008	-0.0002
	(0.0005)	(0.0005)	(0.0003)
Onset t - 3 * decile 5	0.0001	0.0003	-0.0003
	(0.0005)	(0.0004)	(0.0003)
Onset t - 3 * decile 6	0.0005	0.0008	-0.0004
	(0.0006)	(0.0006)	(0.0005)
Onset t - 3 * decile 7	0.0014**	0.0012*	0.0007
	(0.0006)	(0.0006)	(0.0004)
Onset t - 3 * decile 8	0.0014*	0.0012*	0.0008
	(0.0007)	(0.0006)	(0.0005)
Onset t - 3 * decile 9	0.0020***	0.0015**	0.0010*
	(0.0007)	(0.0006)	(0.0005)
Onset t - 3 * decile 10	0.0017*	0.0015*	0.0006
	(0.0009)	(0.0008)	(0.0006)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of observation is the property-year. All models include property-level fixed effects. Robust standard errors are in parentheses and are clustered at the municipality level (N = 52).

Table 6: Nonlinear effects on (IHS transformed) heads transported for fattening in April - June in response to an additional day without rain in March and April

	(1) All transactions	(2) Adult animals	(3) Calves
DWR == 15.0000	-0.0594	-0.0588	-0.0216
	(0.0536)	(0.0470)	(0.0363)
DWR== 20.0000	-0.0443	-0.0407	-0.0223
	(0.0485)	(0.0464)	(0.0296)
DWR == 25.0000	-0.0077	-0.0056	0.0005
	(0.0474)	(0.0431)	(0.0322)
DWR == 30.0000	0.0368	0.0210	0.0367
	(0.0550)	(0.0486)	(0.0358)
DWR == 35.0000	-0.0981*	-0.0916*	-0.0374
	(0.0542)	(0.0469)	(0.0364)
DWR == 40.0000	-0.0081	-0.0308	0.0484
	(0.1130)	(0.0826)	(0.0775)
Onset t - 1 == 30.0000	-0.0070	-0.0231	-0.0033
	(0.0525)	(0.0449)	(0.0326)
Onset t - 1 == 40.0000	-0.0110	-0.0247	0.0066
	(0.0538)	(0.0446)	(0.0317)
Onset t - 1 == 50.0000	-0.0054	-0.0171	0.0117
	(0.0718)	(0.0635)	(0.0394)
Onset t - 1 == 60.0000	0.0526	0.0197	0.0402
	(0.0480)	(0.0390)	(0.0303)
Onset t - 1 == 70.0000	-0.0366	-0.0399	-0.0260
	(0.0620)	(0.0485)	(0.0373)
Onset t - 1 == 80.0000	0.0042	-0.0104	0.0024
	(0.0478)	(0.0370)	(0.0301)
Onset t - 2 == 30.0000	-0.0077	-0.0291	0.0077
	(0.0436)	(0.0380)	(0.0261)
Onset t - 2 == 40.0000	0.0512	0.0271	0.0382
	(0.0504)	(0.0402)	(0.0314)
Onset t - 2 == 50.0000	0.1150**	0.0963**	0.0656**
	(0.0500)	(0.0439)	(0.0272)
Onset t - 2 == 60.0000	0.0986**	0.0672*	0.0649**
	(0.0451)	(0.0375)	(0.0278)
Onset t - 2 == 70.0000	0.0532	0.0460	0.0176
	(0.0433)	(0.0344)	(0.0292)
Onset t - 2 == 80.0000	0.0432	0.0259	0.0324
	(0.0462)	(0.0404)	(0.0267)
Onset t - 3 == 30.0000	-0.0401	-0.0487	-0.0013
	(0.0570)	(0.0435)	(0.0351)
Onset t - 3 == 40.0000	0.0925***	0.0748***	0.0504**
	(0.0304)	(0.0242)	(0.0205)
Onset t - 3 == 50.0000	0.0923	0.0704	0.0594*
	(0.0591)	(0.0485)	(0.0332)
Onset t - 3 == 60.0000	0.0970***	0.0773***	0.0546**
	(0.0331)	(0.0249)	(0.0227)
Onset t - 3 == 70.0000	0.0733	0.0584	0.0358
	(0.0441)	(0.0367)	(0.0259)
Onset t - 3 == 80.0000	-0.0084	-0.0157	0.0050
	(0.0327)	(0.0296)	(0.0196)
year	0.0816***	0.0741***	0.0414***
	(0.0079)	(0.0068)	(0.0049)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unit of observation is the property-year. All models include property-level fixed effects. Robust standard errors are in parentheses and are clustered at the municipality level (N = 52).

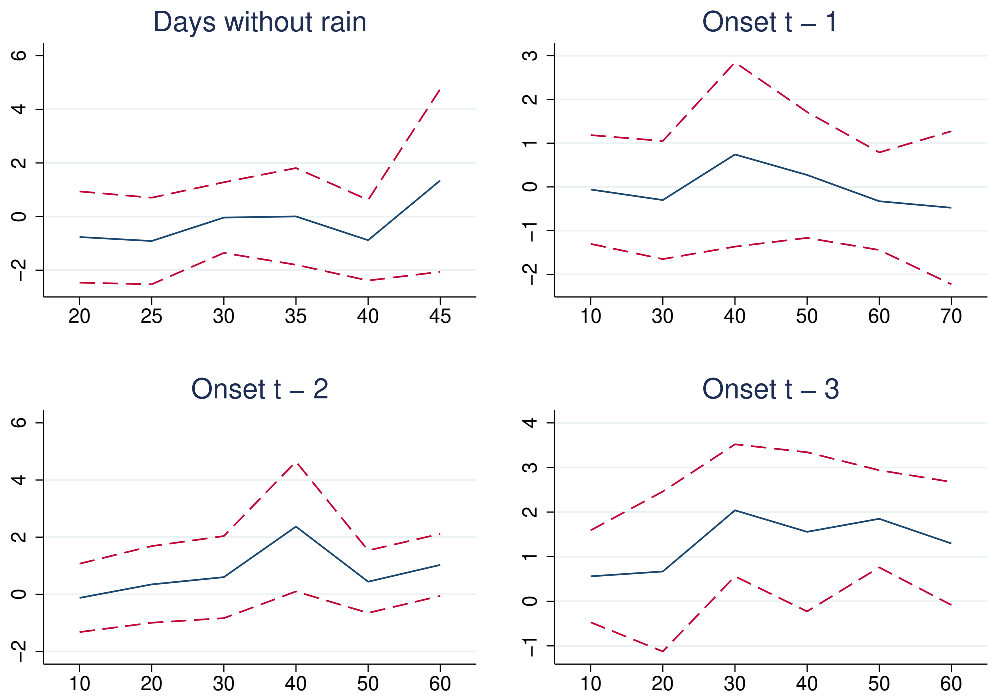


Figure 8: Nonlinear effects of rain on fattening early (adult only)

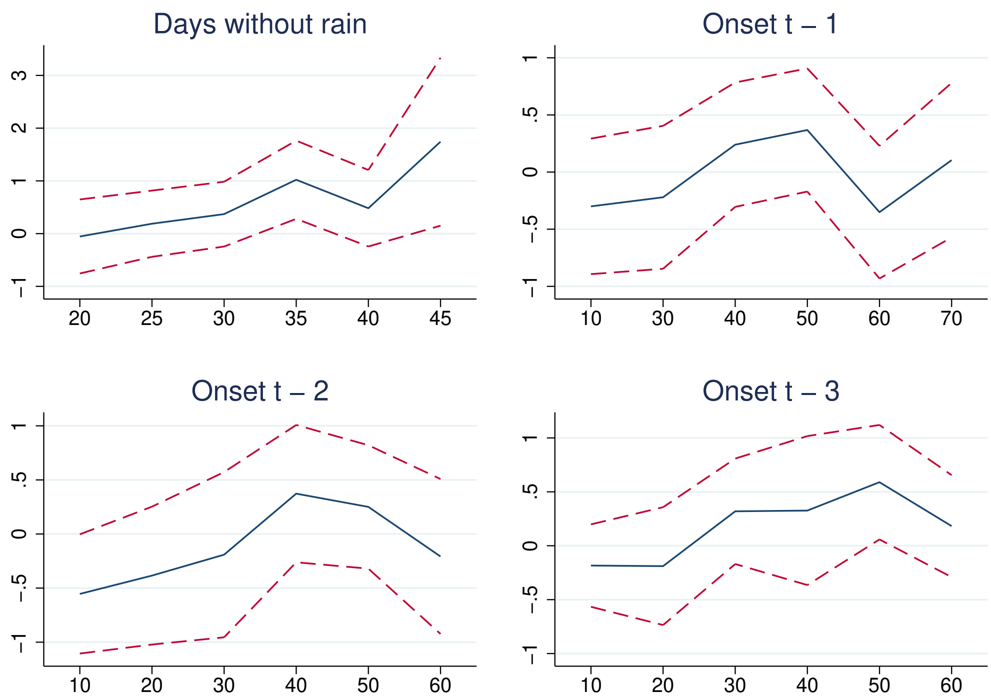


Figure 9: Nonlinear effects of rain on fattening early (calf only)

C Roles of small, medium, large volume properties

Small, medium, and large volume properties demonstrate different production systems and roles in the supply chain. For discussion, I divide properties into quartiles by volume. Small volume properties (the first quartile) are primarily calf producers. Only 8% of their heads are sold for slaughter, and 33% of the heads they transact are less than 12 months, while 29% are more than 36 months. This importance of calves and older animals would be found on a calving ranch that sells young animals after weaning and discard breeding cows after their productive years. Large volume properties, in comparison, sell 39% of their heads for slaughter. Only 21% of their animals are sold at less than 12 months. Instead, 28 and 33% of their animals are sold between 25 - 36 and 36 months or more, respectively. This would be expected on a full cycle property that produces animals from birth to slaughter or a property that is responsible for intermediate fattening (*recria*), or the final fattening before slaughter (*engorda*). Medium volume properties appear to fill a wider number of roles in the supply chain, as they sell animals relatively evenly across age ranges compared to small and medium volume properties.

D Farm exits from the market

An alternative response to a worsening dry seasons is to leave the industry altogether. Because properties only appear in the dataset in years they were active, exiting properties would not be included in any regressions after a dry season. Therefore, my analysis could underestimate the overall response to an extreme dry season. Figure 10 shows that more than half of all properties operate until 2016. Attrition is relatively constant between 4 and 7% of the sample leaving the industry per year between 2008 and 2015.

The overall results mask great heterogeneity across volumes. Less than 40% of properties in the smallest quartile continue selling until 2016, compared to nearly 75% of the properties in the largest quartile. This captures a larger phenomenon, which is that the smallest volume properties are far more sporadic in their sales activity.

Figure 10: Histogram of final sale year in the GTA

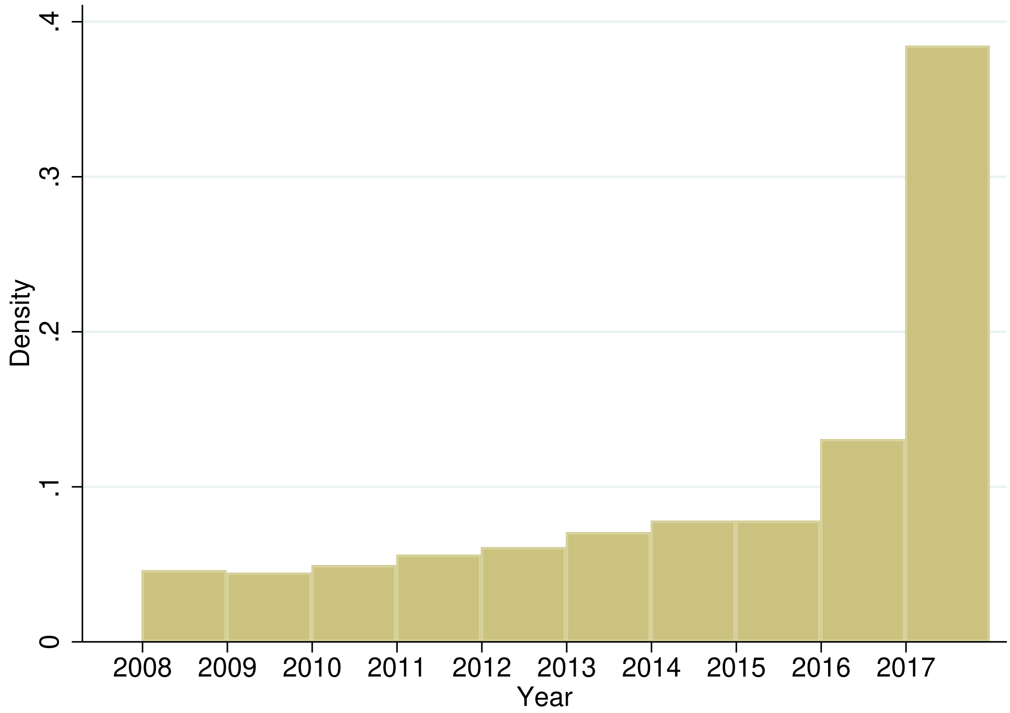


Figure 11: Histogram of final sale year in the GTA by volume quartile