The Effect of Drought on Entry, Exit, and Firm Performance in Rural Kenya

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Abstract

In the absence of insurance and credit markets, the effect of adverse environmental shocks on rural firms is ambiguous because they shift both demand and supply curves. Demand for food staples may increase if households have low agricultural production, yet supply may also be constrained if the shock disrupts supply chains. I use spatial and temporal variation in the 2016-2017 drought in Kenya to characterize the effect of drought-induced food insecurity on local firm outcomes. Firms in areas directly affected by drought have lower sales, profits, and hire fewer workers than firms in non-drought areas. Economic theory predicts that poor economic performance should lead to higher rates of firm exit. Yet, results show that the number of firms increases in drought areas compared to non-drought areas. The higher number of firms is a result of both new entry and retention - households are more likely form new businesses as a coping strategy following shocks and existing firms are more likely to hold onto their businesses as the opportunity cost of labor decreases. Subsector analysis reveals substantial heterogeneity. Firms selling higher-value food products (meat/fish and fruits/vegetables) experience greater declines than staple grain sellers in markets directly affected by drought. This is consistent with consumers in drought regions decreasing consumption of non-necessity food items.

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1 Introduction

Droughts are detrimental to rural households because they lower crop yields and endanger livestock, generating shortages of essential food resources that would count toward household consumption budgets. Droughts also affect total household consumption by lowering potential revenue earned through sale of crops in output markets (Dercon, 2002). In the absence of insurance and credit markets, households have few avenues for consumption smoothing and may sell household assets or engage in temporary coping strategies to generate income (Hoddinott, 2006; Carter and Lybbert, 2012; Janzen and Carter, 2018). While these impacts and responses at the household or intra-household level are popular research topics, much less is known about how local firms fare in the wake of shocks. Moreover, ex ante, predicting the effect of this type of adverse environmental shock on rural firms is difficult because supply and demand shocks occur simultaneously and affect local and national markets.

To learn about how environmental shocks affect rural markets, I use data from 6,000 firms in 157 markets spread across four counties in Kenya collected annually from 2013-2017 (McKenzie and Puerto, 2017). During the last period, one quarter of markets covered by the data experienced a drought that lowered production of staple crops. The precipitating event was rain failure in the 2016 and early 2017 cropping cycles that mainly affected northwestern and southeastern Kenya, including one county covered by the data. Using spatial and temporal variation in the drought intensity in a differences-in-differences specification, I study the effect of drought-induced food insecurity on retail outcomes, including revenue, profit, hiring, entry, and exit. The data feature full market censuses from all locations and a panel of women-owned firms that were surveyed six times over four years. These data allow comparing firms engaged in staple food retail (rice, maize, beans, etc.) with service firms and other non-food retailers as well as estimating the number of competitors in each sector.

In theory, firms located in areas directly and indirectly affected by drought both face demand and a supply shocks. During the 2016 drought, maize prices increased across Kenya, providing evidence that national maize production losses were large enough to induce a supply shock in all markets, even if production losses were localized to drought areas. In a typical year, agricultural households rely on a mix of foods from own-production and foods purchased from local rural markets. Without complete insurance and credit markets or government transfers, agricultural households facing a production shock have fewer resources to meet consumption needs at the same time that they plausibly have higher demand for food staples purchased from local firms to substitute for a lack of own-production.

In drought areas, firms have customers who experience production and consumption shocks which, in turn, cause a demand shock for all rural firms and a supply shock for firms in the agricultural value chain (e.g. sellers of drought-affected staple grains and crops). In non-drought areas, firms' customers are also farming households but do not experience a severe production shock and are less likely to engage in coping strategies to recover losses. If production in non-drought areas remains stable, farming household welfare could increase via higher maize prices from selling crops to the market, for which there is mixed evidence in prior studies (Dorosh and Barrett, 1996; Magrinia et al., 2017). Therefore, firms indirectly affected by drought could see an increase in aggregate demand if farming households in their local economy benefited by selling crops to the rest of Kenya at higher prices.

Empirical results show that in areas directly hit by drought, firm performance declines compared to non-drought areas. According to the market census, firms decrease hiring by 0.13-0.27 workers, a 50% decrease depending on the model specification. Sales decrease by 12-23% relative to the non-drought mean and profits decrease by 13-27%. Yet, the number of competitors increases by 23%. By contrast, in non-drought areas, the number of competitors decreases and firm performance improves - sales increase by 18%, profits by 32%, and hiring increases two-fold while the number of competitors declines by 18%. At first glance, the decline in sales, revenues, and workers suggests that aggregate demand in drought-affected markets decreases, likely related to how rural retailers customer base comprises smallholder farming households who experience crop failures and decreases in income. But, evidence that firm entry increases following drought suggests that local aggregate demand is distributed across more firms that enter after the shock occurs.

A few factors could contribute to increasing firm entry after drought. First, increasing output prices could induce new firms to enter. Output price data for maize shows a marked increase during the drought period across all markets in Kenya. Therefore, it would not explain differential entry in drought and non-drought areas because output price increases are common across markets. Furthermore, increases in maize output prices are related to a decline in production and increasing cost of acquiring maize to sell in markets, which would not induce competitive entry. Another explanation is that as farming households are made worse-off by lower crop yields, they engage in coping strategies such as starting small businesses to generate income (Di Falco and Giorgi, 2019). This explanation matches the patterns observed in the data - there are more firms with fewer workers and lower sales and profits. Evidence that firms in non-drought areas increase sales, profits, and hiring with increased firm exit affirms the hypothesis that non-drought markets gain after drought occurs in other locations. Instead of starting new businesses, local workers are hired into existing businesses as they expand.

Data from the panel of women-owned firms show similar patterns in drought and non-drought markets. Women-owned firms in drought areas have lower sales, revenues, workers, and more competitors compared to non-drought areas. The panel allows comparing the same firms over time (unlike the full sample of market census firms which is treated as a repeat cross-section) and reveals a surprising result: firms in drought areas are more likely to remain open during drought and firms in non-drought areas are more likely to exit. Firms remaining open is consistent with local economic circumstances where the opportunity cost of labor decreases so that firm operators are willing to accept worse performance to generate modest returns that enable them to endure the drought. In non-drought areas, if market conditions improve it may induce firms to exit as better opportunities become available. Seasonal or year-to-year exit and entry is a common feature of rural markets in developing countries (McKenzie and Paffhausen, 2017). Among firms in the panel, 72% of firms who started in 2013 were operating in the last survey round (corresponding to the period of drought). Only 55% of firms were active during all 6 survey rounds, showing that firms entered and exited year to year. It is possible that firm exits in non-drought areas were temporary and firm owners would come back once the economic cycle ends.

Examining response to drought by subsectors reveals important heterogeneity. First, retail and service firms (representing tradeables and non-tradeables) are likely to respond differently to drought if customers propensity to purchase goods or services changes. About 75% of retail firms in both samples sell food goods. Retail firms that sell food staples are more likely to experience supply chain shocks associated with lower crop production. Since customers in drought areas have lower incomes, they are more likely to reduce consumption of non-necessity goods and services, which would lead to lower performance among service firms compared to retail firms. Yet, results show that the service sector fares better in drought areas compared to retail firms. This is a surprising result because we would expect retail sales to be higher as households substitute from own-production to purchased food.

To understand heterogeneity within the retail sector, I disaggregate the retail sector into different categories based on types of goods sold - staple grains, vegetables/fruit, and meat/fish, and non-food retail. I observe that sales, profits, and hiring decreases for firms in drought regions in all categories. But, firms that sell higher value food products (vegetables/fruit and meat/fish) fare worse than staple grain sellers. This is consistent with households meeting their basic food needs by purchasing staple foods and lacking additional resources after the drought to purchase non-necessities. The opposite occurs in non-drought areas. Meat/fish sellers sales and profits increase substantially more than the other food and non-food retail categories. This increase for meat/fish retailers suggests that households in non-drought areas benefited from higher staple grain prices and increased purchases of luxury foods. Notably, there are no increases in competition in any of the retail categories in non-drought areas. This is consistent with the previous finding that local consumer demand likely increased and firms hired more workers but did not face increases in competition.

Rural markets are an important part of the rural economy and an essential source of food staples for agricultural households around the world. Understanding how rural markets function has important implications for food security - including stability in supply chains, availability of goods and services, and understanding small and medium firms as indicators for broader patterns of economic growth. Tschirley et al. (2015) find that share of consumption from own-production varies from 33% in the bottom quintile of income to 59% in the top quintile for rural households in East and Southern Africa. Poorer, rural households rely most heavily on own-production but the share of household food budgets spent in markets is substantial across all income quintiles, suggesting that the rural firms that sell goods and services are a sizable part of the rural economy.

The public policy response to droughts includes a mix of direct cash transfers and in-kind distribution of foodstuffs. When food markets experience a shock and prices spike, in-kind food distribution could provide a more secure food sources for recipients (Gadenne et al., 2017). On the other hand, direct cash transfers allow people to make purchases and invest in income-generating activities (Blattman et al., 2013) but may incentivize price increases (Cunha et al., 2019). Neither policy instrument has been tested in the presence of an aggregate shock, such as drought. This research informs those discussions by clarifying how rural markets cope with sourcing food and other goods to areas that are experiencing temporary environmental shocks.

Droughts in Sub-Saharan Africa are predicted to increase in frequency in severity as weather patterns shift as a result of climate change (Seneviratne et al., 2012). Researching the effect of climate shocks is imperative in order to understand how changing global climatic conditions are likely to reverberate into local economies. This research highlights how markets function to support or impair food security under adverse circumstances. Although agricultural households bear the brunt of the economic shock through a loss in agricultural output, it is possible that some of their consumption is smoothed through the presence of efficient markets where they can obtain foodstuffs to supplement consumption or sell assets for cash.

2 Supply and Demand Shocks in Rural Markets

The harvest season is a critical time for agricultural households' because they harvest crops that will be consumed throughout the year *and* make crop marketing decisions about whether and how much to sell to earn cash income. Environmental shocks threaten food security by decreasing agricultural yields and changing how agricultural households participate in rural markets. The net effect of an environmental shock on rural firms is ambiguous because they reconcile upward and downward pressure on aggregate demand with a negative crop supply shock. First, firms are affected through a demand channel. Aggregate demand for goods, especially food staples, could increase if agricultural households liquidate assets or seek wage work and increase their expenditure in local food markets to supplement household consumption. Yet, aggregate demand also faces downward pressure because households' agricultural income decreases as a consequence of lower crop production.

Second, firms are affected through a supply channel. One feature of agriculture-dependent economies is that local food supply chains face a negative supply shock if crop production declines because fewer households are selling crops to the market. In the Kenyan context, maize is the primary staple food commodity. In a study of maize traders, Bergquist and Dinerstein (2020) report that the poorest households in Kenya spends 14% of annual expenditure on maize and that maize traders purchase 50% of maize from small and medium scale farmers. A drought shock which affects the maize production of small farmers is likely to induce a negative supply shock for staple food retailers.

The theory of competitive markets predicts that if markets are sufficiently integrated, local firms in drought-affected regions can import foodstuffs from non-drought regions, and food prices will remain relatively stable (assuming that producers in drought-affected regions are price-takers). If prices are stable, and quantity sold rises, firm revenues will increase. However, if the supply shock increases prices, quantity demanded could decline enough to offset any uptick and the feedback effect will lower retail revenues as well as agricultural incomes. If the effect from a negative supply shock dominates, staple food prices would increase, possibly crowding out any gains from any expansion in aggregate demand, assuming retail margins are constant. These market dynamics imply that some sub-national markets are directly exposed to the supply shock, while others experience the indirect effect due to changes in input prices.

2.1 Direct and Indirect Effects of Drought

The firm-level microdata used for analysis come from four counties in Kenya - Kagamega and Kisii in southwest Kenya, and Embu and Kitui in southeast Kenya. Only markets in Kitui experienced severe drought that lasted two harvest cycles. However, drought also occurred in the northern regions, which are not included in the World Bank microdata. In examining the effects of drought, these counties cannot be treated as isolated or autarkic regions because crop failures in areas directly affected by drought spill over to non-drought areas through several mechanisms. First, the supply shock lowers the quantity of marketed crops circulating in the economy. In partial equilibrium, this supply shock raises prices. Second, if consumption levels remain stable, drought-affected farmers must rely more on local markets to purchase food, increasing aggregate demand, putting further upward pressure on prices.

The quantity produced and prices for maize are plotted in Figure 1. The figure on the right plots annual maize production (kg/ha) in drought and non-drought regions in the microdata (red and blue lines) and the rest of Kenya (dashed red and blue lines). It shows that there was a maize production decline in 2016-2017, consistent with a negative supply shock induced by crop failures among farmers in drought-affected areas. The drought began in October 2016 and lasted through September 2017. Average production decreased in 2016 compared to 2015 across all counties in Kenya. The directly-affected drought areas available in the micro-data had the sharpest decline and did not recover in 2017. The indirectly-affected, non-drought counties in the micro-data also experienced a relatively sharp decline from 2015-2016 but then exhibit a steep increase in 2017. Closer inspection revealed that only one of the three counties in the non-drought area (Kakamega) had higher than average annual production in 2017, suggesting that the bumper crop was isolated in one county, which is dropped in a robustness check.

The figure on the left plots monthly maize prizes for markets in drought and non-drought regions. The time series data come from the World Food Programme's Vulnerability Analysis and Monitoring (VAM) dashboard. The rest of Kenya - both drought and non-drought areas - also experienced clear maize price spikes during the drought period that peaked in June and July of 2017. This national trend in maize prices provides evidence that even firms in non-drought areas

Figure 1: Maize Prices and Production in Drought and Non-Drought regions, 2013-2017

were exposed to supply shocks, especially in maize markets.

The price increase reflects both the negative supply shock and the increase in demand for food staples in markets. It is not clear whether the demand shock or the supply shock contributed more to nation-wide price increases during drought because both put upward pressure on prices. It also appears that maize production declined markedly in drought areas compared to non-drought areas. As such, empirical results reflect the direct and indirect effects of drought. Firms operating in drought areas were directly affected by a local supply shock (crop failures), consumer demand shock, and price increases. Firms operating in non-drought areas experienced indirect consequences of drought caused by price increases and a supply shock in distant regions. Farmers in the non-drought area could have been made better off by the drought since they sold crops in favorable market conditions, as long as they are net-sellers of staple grains rather than net-consumers of staple grains. In that case, markets in non-drought areas could experience an uptick in demand.

In summary, there are three stylized facts about maize prices and production during the 2016-2017 drought that provide a basis to generate hypotheses about how firm performance would respond to this type of environmental shock. First, the crop production shock affected drought areas more than non-drought areas. Second, maize prices increased during the drought period and affected all markets in drought and non-drought areas. Third, consumers in drought areas are worse off following drought due to income effects (incomes are lower and staple prices are higher) and consumers in non-drought areas benefit as sellers of staple goods to the market (although they are not necessarily better off because they also have to pay higher staple prices).

3 Conceptual Framework

These stylized facts inform a conceptual framework drawn from microeconomic theory of market structure to guide interpreting changes in firm performance, changes in number of competitors due to entry and exit, and sectoral heterogeneity in drought and non-drought areas.

3.1 Firm Performance

Whether or not firm performance improves after a drought depends on how much customer demand for market goods changes after the drought shock. The resulting elasticity of demand for market goods is composed of income shocks and substitution effects. Crop losses generate an negative income shock, decreasing total household budgets and price increases in the key staple food decrease households purchasing power in markets. At the same time, households substitute between own-production and market goods. As own-production decreases, demand for market goods, in particular food staples, increases. Prior studies in East Africa have found that staple price shocks lower total household consumption and that demand elasticities for staple foods are less elastic than for other foods (Bai et al., 2020; Rudolf, 2019; Ecker and Qaim, 2011).

If consumer demand decreases after the drought, firms will experience lower revenues and profits relative to firms in non-drought areas. This occurs if the crop failure lowers farming income and subsequent consumer demand to a greater degree than other options that households exercise as coping strategies to increase incomes (by selling assets or seeking wage work). In that case, firm performance (sales, profits, workers) in markets directly affected by drought will be lower than those in non-drought areas.

In the non-drought, or indirect markets, there are two possible demand responses. First, if farmers produce the same quantity of crops, they will benefit as sellers of staple crops if higher prices pass through and they earn more farming income. But, as consumers of staple crops, households also face higher prices in markets, which could cause households to substitute market staples for own-production. Increases in sales, profits, and workers hired is indicative of greater consumer demand. While decreases in sales, profits, and workers hired would indicate that staple price increases lower consumers purchasing power, offsetting any gains from higher crops sales.

3.2 Firm Entry and Exit

Outcomes related to sector entry and exit provide evidence about whether the changes to market conditions caused by drought lead to differential competitive responses in drought and non-drought areas. Multiple responses are possible given changes to consumer and supply chain conditions. Lower local consumer demand could cause more firms to exit or temporarily close and fewer new firms to form in non-drought areas. Or the reverse could occur: higher consumer demand induces firm entry and fewer firm closures.

But, in settings with multiple market failures, especially missing credit and insurance markets that would otherwise facilitate consumption smoothing during shocks, these clean predictions from microeconomic theory likely will not hold. With reduced income from crop sales, households in drought-stricken areas may form new businesses to earn some cash income to sustain household consumption. As the opportunity cost of labor decreases, and if start-up costs are low enough, new firms could open despite worsening market conditions and old firms might remain operational that would have otherwise closed. In that case, despite decreases in consumer demand, competition may increase, further decreasing firm performance.

3.3 Differences by Sector

The consequences from drought for firms due to changes in the number of competitors and consumer demand depends on their sector. Household expenditure on market goods includes retail goods and services. Within the retail sector, some firms specialize in selling food staples with relatively inelastic demand while others sell non-necessity, luxury goods with less elastic demand - like vegetables, fruit, fish, and meat. About 70% of firms engage in the retail, or tradeable goods sector. The remaining 30% engage in services or non-tradeable sector. Among retailers, about 75% sell food-related goods - household staples such as maize, rice, sugar, beans, oil, and salt, or fresh market goods such as fruits, vegetables, meat, and fish.

Figure 2 provides intuition about how supply and demand shocks might look in a stylized, partial equilibrium graphs. The left figure plots demand and supply curves with expected demand shocks for retail and services firms. Households that experience crop failures may have a higher propensity to consume staple foods and withdraw spending from non-necessity goods and services. The service sector is about 30% restaurants and other food services, 30% tailors and sewing services, and 30% are barbers or salons, while the remaining 10% are split between transportation, bike repairs, welding, carpentry, and other repair services. Following a negative income shock, we could expect payment for services to decline as households defer expenditures on non-necessary services.

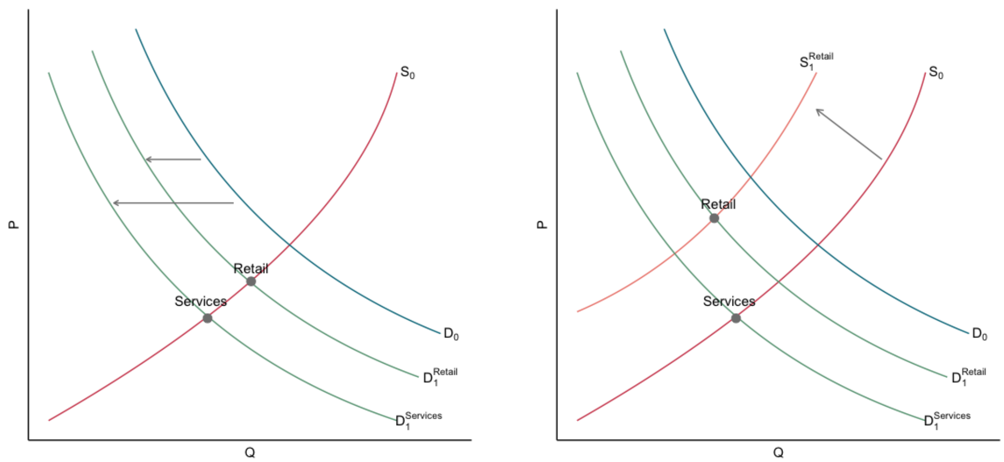

Figure 2: Stylized Demand and Supply Shocks in Partial Equilibrium in Drought Areas

Since retail firms will then sell more necessity food goods, a negative income shock among their customer base would cause the proportion of household budgets spent on food staples to increase, crowding out spending in other categories - causing demand for services to shift further inward than demand for retail goods. Yet, once a supply shock is incorporated as in the figure on the right, it is not clear whether retail firms would have better performance compared to service firms, even if aggregate demand for services declines more than for retail goods. And, even if aggregate consumer demand for staple goods increases, if the number of competitors also increases, there may not be any gains for firms as demand is spread over a larger number of firms.

The crop production shock only affects supply chains for firms directly related to the agricultural sector. For the retail sector, this means that they only experience a supply shock for food crops that were affected by drought. The most important food staple is maize, which I previously showed to have a price spike and production decline during the 2016-2017 drought. Detailed sub-national data on other food staples for this time period was not consistently available. But, Figures 4 plots monthly prices in Nairobi market from two different sources (World Food Programme and FEWSNET) for several other common food commodities in addition to maize - bread, vegetable oil, milk, beans, and sorghum as well as diesel and gasoline prices. Maize exhibits the sharpest increase, but sorghum, milk, beans, and vegetable oil prices also increase during the drought period, although they also tend to exhibit more price fluctuation over the entire time period. Gas and petrol prices, by contrast, are relatively stable during the drought period.

In a typical year, Kenya imposes import taxes on maize to support domestic production. Halfway through the drought in March 2017, the government of Kenya lifted import restriction to increase domestic supply of maize and lower prices (FAO.org, 2017). Kenya also typically engages in trade with neighboring countries, but Uganda and Tanzania both imposed export bans on maize during the drought period (FEWS NET, 2017), indicating that trade was constrained throughout the East African region.

4 Data

To study firm outcomes and competitive response to weather shocks, the ideal data set would include firm-level information on revenue and profits as well as market-level information about entry and exit and would have spatial variation in drought intensity. Micro-data collected through national household surveys or impact evaluations rarely include information about the competitive environment (number of competitors in the sector and entry and exit over time). To find appropriate data, I searched for primary data sources in the World Bank's Microdata Library. The data used for this study were originally collected as a part of an randomized impact evaluation of the GET Ahead Business Training program of the International Labor Organization. Details of the evaluation are provided in McKenzie and Puerto (2017). The data include surveys with over 6,000 firms in 157 markets spread across four counties in Kenya collected annually from 2013-2017. It includes medium and large rural markets with at least 15 firms. Market size ranged from 15 to 169 firms, with an average of 52 firms per market. A subset of firms were allocated among treatment arms related to training and mentorship. The researchers employed a clustered randomized design whereby markets were randomized into treatment and control and then firms within markets were randomized into treatment arms. This paper does not formally incorporate the randomized treatments into its analysis. Rather, for the purposes of this paper, I assume that those treatment assignments were uncorrelated to the occurrence of drought and are considered part of the error term.

The firm-level data from the World Bank surveys are organized as two samples, where the women-owned sample is nested within the census sample:

1. **Women-owned firms:** A panel of 3,558 women-owned firms in 157 markets. Respondents are matched across 6 surveys administered from 2013-2017. This was the group targeted to participate in the impact evaluation.

2. **Census firms:** A repeat cross-section of all firms located in each of the 157 markets. These firms cannot be matched across rounds but basic information was collected from each firm including sector, revenue, profits, and employment. There were 3 market census collected in 2014, 2016, and 2017, and the final census occurred during the drought, which affected about half of the 157 markets.

An important caveat in interpreting results is that only some women-owned businesses were eligible for the program. Specifically, they had to have a phone number, were younger than 55, had less than 3 employees, did not sell phone cards or Mpesa, were the owner of the firm (as opposed to employee), had profits less than 4000KSH, and had at least a year of education. The remaining women-owned firms were included in the census, but cannot be matched across rounds. Therefore, results using the the panel of women-owned businesses should be interpreted as representative of this sub-population and not of all women-owned businesses. For the first two rounds of the market census, gender of the firm owner was not collected. Therefore, gender-based comparisons using pre-drought data are not possible.

Table 1 shows descriptive statistics for firms included in this analysis. Column 1 are market census firms only, column 2 are women-owned firms, and column 3 are all firms. In the analysis, regressions are run on the full sample of market census firms (column 3) and the sub-sample of women's owned businesses (column 2). As expected, 99% of firms in the women's-owned firm are run by women, while 68% of all firms in the market were run by women in the 2017 census. Across both samples, firm owners' average age is between 38-40 years old, they have about 9 years of education, and their businesses have 8-10 years of tenure. Average sales are between 5,800-6,500 Kenyan shillings per week (about \$56-\$63 USD per week), and profits range from 1,600-1,800 Ksh per week (\$15-\$17 USD). Firms hired an average of .67 workers over the previous week and have between 9-10 competitors in their same sector.

About 70% of firms are in the retail sector, while 30% are in services. The analysis also uses retail sub-sectors to understand how different types of firms respond to drought conditions. About 28% of retail firms primary products are food staples and basic commodities, 42% sell fruits and vegetables, 5% sell meat and fish, and 25% engage in other retail (clothing, household goods, pharmacies, etc).

Table 1: Descriptive Statistics of Women-owned Firms and Census Firms

	(1) Market Census Firms		(2) Women-Owned Firms			(3) All Firms
Variable	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Owner Female	6425	0.56	2545	0.99	8970	0.68
		(0.50)		(0.08)		(0.47)
Age of Owner	6425	38.27	2544	40.62	8969	38.94
		(12.41)		(9.21)		(11.64)
Yrs Education	6425	9.57	2545	9.40	8970	9.52
		(3.62)		(3.09)		(3.48)
Age of Firm	6425	7.75	2545	10.43	8970	8.51
		(8.43)		(6.78)		(8.09)
Sales	6393	6548.38	2536	5865.73	8929	6354.50
		(8092.78)		(6897.77)		(7777.80)
Profits	6384	1814.23	2535	1662.27	8919	1771.04
		(2022.78)		(1808.72)		(1965.41)
Total Workers	6423	0.67	2544	0.66	8967	0.67
		(0.88)		(0.87)		(0.87)
Competitors	6245	8.96	2513	10.37	8758	9.37
		(10.30)		(10.41)		(10.35)
Retail Sector	6409	0.70	2543	0.72	8952	0.70
		(0.46)		(0.45)		(0.46)

Notes: The above table reports descriptive statistics (sample size, mean, and standard deviations) for the sub-sample of women-owned firms (column 2), census-only firms (column 1) and the combined census (column 3). The 2017 census was used because it is the only census that collected gender of the business owner. Not all women-owned firms present in each market during censuses are included in the repeat panel, since women-owned firms in the panel are about 28% of the total number of firms in the census, but women-owned firms represent 68% of all firms in the census. Differences-in-differences regressions use samples in Columns 2 and 3.

4.1 Defining Drought

The drought shock variable is defined following the ASAP warning system, which tracks 'anomaly hotspots for agricultural production' using satellite data (https://mars.jrc.ec.europa.eu/asap/). The ASAP warning system synthesizes rainfall and NDVI (greenness indices) information and issues warnings based on their anticipated impact on crop production (Rembold et al., 2019). The drought began in October of 2016, when the short rainy season failed in eastern and northern Kenya, and the long rains failed again for the April-May season in 2017 (Uhe et al., 2017).

Figure 3 plots the warning data for all counties in Kenya from the end of 2015 to 2017. The dark red and red bands indicate that the lack of rainfall and low NDVI index occurred during the cropping season, and were thus more consequential for food security outcomes. The figure is ordered based on drought severity by county. The four counties in the World Bank microdata are highlighted in blue boxes. Two out of the four counties (Kisii and Kakamega) did not experience any drought warning, one county (Embu) experienced partial warnings, and one county (Kitui) experienced extensive drought warnings. And, 17 other counties experience more severe drought than Kitui.

Unlike negative rainfall shocks that are measured monthly, the climatic definition of drought is a prolonged period of low rainfall. Therefore, drought was defined by taking the 6-month mean of warning levels. All markets in Kitui county fell within this definition. Markets in Embu county were at the threshold of mild drought conditions. Embu county is dropped in a robustness check since farming households did not uniformly experience crop failures.

The last round of World Bank surveys collected from June to October 2017 for all counties captures the period of drought. But, effectively only one county experienced severe drought (Kitui), while the others were either mild and did not coincide with the cropping season or did not have drought conditions. Sixty out of 157 markets experienced the direct effect of drought - meaning that consumers in their local area likely experienced cropping failures. And the remaining 93 markets experienced the indirect effect of drought because consumers in their area likely did not experience crop failures, but cropping failures in other areas of Kenya put pressure on food supply chains. As described above, Figure 1 shows that the cropping failures throughout Kenya correspond to substantial price increases in maize markets, a primary staple food commodity that is important for ensuring food security.

5 Empirical Strategy

A differences-in-differences identification strategy is used to estimate the direct and indirect effects of drought. The drought variable is defined to begin at the same time for all markets, beginning in October 2016. For the census data, there are two pre-drought periods per market and one post-drought period. Markets are linked across years, but firms are not. For the women's-owned firms panel, there are five pre-drought periods, and one post-drought period, and firms are identified for each survey. With multiple pre-periods and one post period, I estimate two types of specifications. First, a classic difference-in-difference (Equation 1) permits estimating a 'between group' effect of drought in markets that were directly exposed to crop failures and markets where no crop failure occurred, but experienced indirect effects on supply chains. Second, a two-way fixed effects approach (Equation 2) provides a 'within group' estimate of the direct effect in drought areas compared to

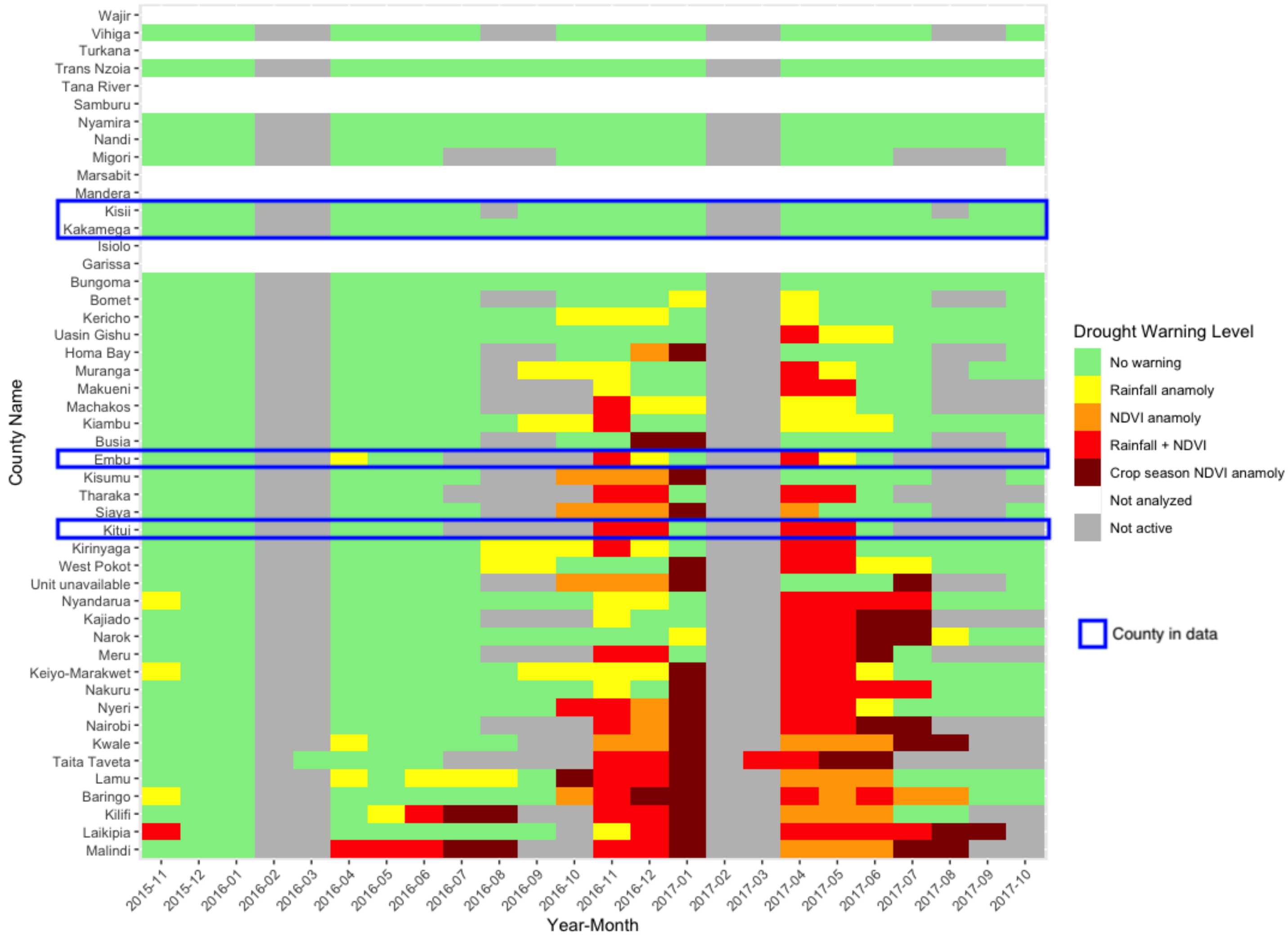

Figure 3: ASAP Drought Warnings for Kenyan Counties, 2015-2017

the pre-drought period.

5.1 Between-Group Effects: Differences-in-Differences

$$Y_{imt} = \alpha + \beta_1 Drought_m \times Post_t + \beta_2 Drought_m + \beta_3 Post_t + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \tag{1}$$

There are four primary outcomes, Y_{imt}, for firm i, in market m, in year t - total sales revenue over the prior week, profits over the prior week, number of paid workers over the prior week, and number of competitors in the same sector at the time of the survey. For the women-owned firms panel, an additional outcome 'firm open' is defined to equal one if the firm is operating during the survey. In this setting, it is common for small firms to open and close throughout the year or year-to-year. About 20% of the initial sample of women's firms are closed during each survey, although they are not necessarily permanently closed. About 45% of firms were closed for at least one survey, and 28% of the original sample were closed in the final round. This outcome provides evidence about whether firms that experience the direct effects of drought shock are more or less likely to remain open afterwards.

As is typical in a classic differences-in-differences specification, $Drought_m$ equals one for the group of markets which experienced the direct drought shock for all time periods. $Post_t$ equals one if the survey was completed after October 2016, the date that drought conditions started. The parameter β_1 on the interaction of $Drought_m$ and $Post_t$, identifies the effect of drought on areas that were directly affected. The parameter β_2 is the pre-period level difference between drought (direct) and non-drought (indirect) markets. In the preferred specification, market fixed effects are included such that $Drought_m$ drops out. The parameter β_3 represents the effect of post-period in non-drought markets and is interpreted as the indirect effect of drought in markets in the counties where there was no rain failure.

The term $\mathbf{X}_{mt}\Phi$ is a vector of controls. It includes market fixed effects and month-of-year fixed effects. Month-of-year fixed effects are included to capture regular variation that is common across markets due to seasonal changes in market conditions that occur year-to-year.

5.2 Within-Group Effects: Two-way Fixed Effects

$$Y_{imt} = \alpha + \beta_1 Drought \times Post_{mt} + \gamma_m + \tau_t + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \tag{2}$$

The main difference between Equations 1 and 2 is that market fixed effects γ_m and time fixed effects τ_t are included to flexibly control for pre-drought common time and market-level shocks. β_1 identifies the effect of drought in directly affected markets compared to their pre-period levels.

5.3 Differences by Sector: Triple Differences-in-Differences

$$\begin{aligned} &Y_{imt} = \alpha + \beta_1 Drought_m \times Post_t + \beta_2 Drought_m \times Post_t \times \mathbf{Sector}_i + \\ &\beta_3 Post_t + \beta_4 Post_t \times \mathbf{Sector}_i + \gamma \mathbf{Sector}_i + \lambda Drought_m \times \mathbf{Sector}_i + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \end{aligned} \tag{3}$$

To examine differential responses to drought by firm sector, a triple differences specification is used. The vector $\mathbf{Sector}_i$ is defined at the firm level. The first definition is $\mathbf{Sector}_i = \{Retail, Service\}$, where service is set as the reference category. Firm sectors were categorized as either retail or service according to how the firm owner reported their primary sector to the survey team. The second definition is $\textbf{Sector}_i = \{StapleGrains, Veg/Fruit, Meat/Fish, OtherRetail\}$ among retail firms only, where Staple Grain is the reference category. The objective is to understand how different types of firms respond to the drought shock in markets that were both directly and indirectly affected.

5.4 Identifying Assumptions

In a classic differences-in-differences set-up, the identifying assumption is that trends are parallel before the event of interest and would continue to be parallel if the event had not occurred. The parallel trends assumption implies that counterfactual trends would have continued on the same path absent the drought shock and that the control group trend is a good counterfactual for the treatment group. The identification strategy described here deviates from the typical differences-in-differences in two important ways. First, I employ a difference-in-differences to understand the direct and indirect effects of the drought shock. Therefore, I do not assume that the non-drought area is a perfect control because firms in those markets also experience the drought shock via changes to their supply chains. Figure 1(b) showed that price changes in the main staple grain (maize) increased simultaneously in both regions after the drought. Yet, Figure 1(a) also showed that only one region experienced crop failures. Thus, effects are interpreted as direct effects of crop failure and the indirect effect of supply chain (price) shocks. Graphs of pre-trends in Figures 5 and 6 in the appendix affirm that trends are relatively parallel in the pre-drought period and both drought and non-drought markets change during the drought in 2017.

Second, differences-in-differences strategies are typically used to identify the effect of endogenous policy changes where the treatment variable is possibly correlated with the structural error term, such as when governments enact new policies. When sufficient pre-treatment periods are available, it is important to test whether pre-event trends are correlated with the treatment status. Table 7 in the appendix reports coefficients on regressions of primary outcomes - sales, profits, workers, competitors, and whether a firm is open - on indicator for drought, indicators for year, and their interactions and reports p-values from F-tests of joint significance on pre-trend interactions. The top panel is the census sample and fails to reject pre-trends for all four main outcomes. The bottom panel reports results for the women-owned firms panel and rejects that pre-trend interactions are zero for 2 out of 5 outcomes (number of workers, and whether the firm is open during the survey round), indicating that for the sample of women-owned firms, parallel trends is a more tenuous assumption than for the full census sample.

Often weather shocks can be considered 'random' since agents have no control over their climate conditions. The least conservative assumption would be to assume that drought is a perfectly random shock, uncorrelated with the error term. In that case, the identifying assumption would simply be that no time-varying unobservable confounders led to the drought and that drought is not a proxy for some other unobserved shock that is actually inducing the differences estimated by these regressions. The drought was declared a national emergency in February 2017 and garnered attention and resources from the Kenyan government put toward implementing policies to alleviate strain caused by low production (Government of Kenya, 2017; Uhe et al., 2017). In theory, it is possible that another shock or policy happened simultaneously, but the drought was a high profile event that affected the entire county.

Coefficients from the three primary econometric specifications are interpreted as the causal effect of drought on firms in drought and non-drought regions. Outcomes related to firm performance and market competition provide information about industrial organization of the rural markets respond to an aggregate environmental shock where one region experiences its direct consequences, while the other experiences the indirect consequences from changes in staple food prices and quantity produced. β_1 from equation 1 identifies the direct effect of drought on firms in drought areas relative to firms in non-drought areas (the difference-in-difference). The coefficient β_3 from Equation 1 is the average difference of firms in non-drought areas during the drought period (when post=1) and is interpreted as the effect of drought in markets that did not directly experience drought conditions. β_1 in equation 2 identifies the effect of drought on firms in drought areas compared to prior performance after controlling for year and market fixed effects (a two-way fixed effects within estimator).

6 Results

Results are first presented for differences-in-differences (DD) and two-way fixed effects (TWFE) specifications for market census firms in Table 2 and then for the women's-owned businesses panel in Table 3. The heterogeneous effects by sector using triple differences are presented for both samples for retail and service firms are in Tables 4 and 5. Finally, the last result in Table 6 examines heterogeneous effects among census firms for retail sub-sectors - staple foods, vegetables and fruit, meat and fish, and other retailers.

6.1 Effect of Drought on Market Census Firms and Women-Owned Firms

Table 2 shows results for the full sample of census firms and 3 shows results for the panel of women-owned firms. For the DD specifications of market census firms, sales, profits, and the total number of workers decrease in drought areas (β_1) and increase in non-drought areas (β_3). The TWFE of market census firms also show decreases of sales, profits, and workers in drought areas. Market census firms decrease hiring by 0.13-0.27 workers, a 50% decrease in both specifications. Sales decrease by 12-23% relative to the non-drought mean and profits decrease by 13-27% in the DD and TWFE specifications. Further, the number of competitors increases in drought areas and decreases in non-drought areas.

This pattern of increasing competition alongside decreasing firm performance (sales, profits, and number of workers) in drought-affected areas provides evidence that firms are worse off after the drought. It is difficult to distinguish which happened first - whether lower local consumer demand decreased sales, profits, and hiring, or losses in cropping income induced households to start businesses, increased competition and decreased the sales potential of existing firms. To examine which effect is more influential (demand versus competition), a t-test comparing β_1 and β_3 is useful. The coefficient on $Post \times Drought$ is the difference for firms in drought areas compared to firms in non-drought areas whose average change after drought is represented by the coefficient on $Post$. For the full census sample, the coefficients on sales, profits, and hiring in non-drought areas are all larger in magnitude than those for drought areas. A t-test of $\beta_1 + \beta_3 = 0$ for each outcome indicates whether drought firms also experienced an overall increase that is statistically different from zero - suggesting whether firm performance improved after the drought, but to a lesser degree than firms in non-drought areas.

Table 2 reports the p-values for the t-test of $\beta_1 + \beta_3 = 0$. The test fails to reject that sales and number of competitors were different than zero, but rejects that profits and workers hired are equal to zero in the post-period in the drought-affected markets. This provides mixed, but inconclusive evidence that firm performance also increased overall compared to the pre-drought period, but was nonetheless worse than firm performance in non-drought markets. There is a substantial difference in changes in competition between drought and non-drought areas - drought areas increase by 2.3 competitors over a mean of 9.8 competitors per sector, compared to a decrease of 1.8 competitors in non-drought areas, suggesting that increased firm entry played a role in spreading local demand across a larger number of firms. It is possible that an in increase in consumer demand in non-drought areas was high enough so that all firms benefited if consumers in non-drought areas are wealthier and spend more in markets if they earned higher income from crop sales. While in drought areas, mild increases in consumer demand were off-set by increased entry.

Table 2: Results: Market Census Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
β_1: Post×Drought	-642.577**	-195.043**	-0.125***	2.258***
	(314.490)	(87.378)	(0.032)	(0.727)
β_3: Post	998.661***	446.320***	0.534***	-1.769**
	(254.123)	(60.445)	(0.027)	(0.757)
T-test: $\beta_1 + \beta_3 = 0$	0.1329	0.0004	0.0000	0.3793
Market FE	Y	Y	Y	Y
Year FE	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5534.35	1404.96	0.25	9.81
Obs	20,623	20,542	20,960	20764
Adj R-Squared	0.03	0.05	0.11	0.31

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
β_1: Post×Drought	-1359.46***	-421.49***	-0.27***	5.22***
	(449.82)	(126.34)	(0.04)	(1.01)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5946.60	1520.83	0.43	10.25
Obs	20,623	20,542	20,960	20764
Adj R-Squared	0.04	0.05	0.11	0.32

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For the women-owned businesses panel in Table 3, sales decrease by 12% in both specifications, profits decrease by 8-10% and workers hired decreases by 14-34%, although the TWFE estimate is not different from zero. The number of competitors increases in both drought and non-drought areas, but estimates are noisier compared to the full census sample. Column 5 in Table 3 shows that firms in drought areas are 5 percentage points more likely to remain open compared to those in non-drought areas, although the two-way fixed effect specification estimates a precise null. By contrast, in non-drought areas, competition decreases and firm performance improves - sales increase by 18%, profits by 32%, and hiring increases 2-fold while the number of competitors declines by 18%.

It is surprising that increases in revenues and profits do not lead to increases in firm entry in non-drought areas since they create competitive pressure to bid away profits. Yet, column 3 in Tables 2 and 3 shows that firms increase hiring by about 0.5 workers in the market census sample and by 0.4 workers among women's owned firms. This suggests that instead of starting new businesses, workers are instead hired into existing businesses as they expand. while firms in drought areas are more likely to remain open compared to firms in non-drought areas, they are overall more likely to exit compared to the pre-period (-0.178 + 0.051 ¿ 0, p-value = 0.0000)) and the number of competitors increases (0.540 + 0.893 ¿ 0, p-value = 0.0215).

Table 3: Results: Women-Owned Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
β_1: Post$\times$Drought	-612.075***	-129.211**	-0.079**	0.540	0.051***
	(194.556)	(53.877)	(0.036)	(0.701)	(0.017)
β_3: Post	466.154***	267.342***	0.378***	0.893	-0.178***
	(165.582)	(39.609)	(0.026)	(0.600)	(0.012)
T-test: $\beta_1 + \beta_3 = 0$	0.2839	0.0008	0.0000	0.0215	0.0000
Market FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5184.64	1250.85	0.23	8.99	0.85
Obs	18982	18953	15679	8141	21239
Adj R-Squared	0.05	0.05	0.08	0.36	0.05

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
β_1: Post$\times$Drought	-636.49***	-101.53**	0.04	1.04	-0.00
	(161.65)	(44.97)	(0.03)	(1.62)	(0.02)
Market FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5304.70	1253.24	0.29	10.17	0.82
Obs	18982	18953	15679	8141	21239
Adj R-Squared	0.05	0.05	0.08	0.36	0.09

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales and profit sample sizes are conditional on whether the firm is operating during the survey round. Total workers sample size is smaller because one survey round did not include the question. Sample size for competitors is only available during market census rounds.

6.2 Effect of Drought on Competition and Performance by Sector

To explore how household demand for services, retail goods, and food and non-food goods change after the drought shock, I first compare whether retail firms perform better or worse than service firms. Second, I compare whether performance varies by different type of retail - staples foods, vegetable/fruit sellers, fish/meat sellers, and other non-food retailers.

6.2.1 Retail compared to Service Firms

Table 4 shows heterogeneous effects for retail and service firms for the market census firms using DD and TWFE specifications. The first two rows are the direct effect of drought on service firms (β_1) and retail firms (β_2), followed by a t-test for the the total effect on retail firms in drought areas ($\beta_1 + \beta_2 = 0$). The third and fourth rows report the indirect effect of drought on service (β_3) and retail (β_4) firms, and a t-test for the total effect on retail firms in non-drought areas ($\beta_3 + \beta_4 = 0$).

Performance of service and retail firms in drought areas are negative in terms of sales, profits, and workers, but differences are not significant. However, the total effect for retail firms is negative and significant for sales, profits, and workers. Both service firms and retail firms face increases in competition - service firms' number of competitors increase by 1.25 firms, while retail firms' number of competitors increase by an additional 0.61 firms, or 1.86 firms total. The TWFE specifications disagree with the DD specification - retail firms appear to have relatively better performance compared to service firms, although the net effect is still negative.

The opposite occurs for firms in non-drought areas. Service firms sales, profits, and workers increase, and retail firms performance increases even further compared to service firms. Retail firms competition decreases by 1.12 firms, while service firms point estimate on number of competitors decreases with a larger standard error. Alongside the DD estimates, it suggests that firm performance in the service sector is relatively more stable compared to retail firms. Service firm performance declines in drought conditions to a lesser extent than retail firms. Similarly service firm performance improves in non-drought conditions to a lesser extent that the improvement for retail firms.

A similar pattern holds for the women-owned firms panel in Table 5, although estimates tend to be noisier. In drought areas, retail firms fare worse in terms of sales and profits and there is no difference in hiring, number of competitors, or likelihood of remaining open. In non-drought areas, service firms' performance tends in improve, but the evidence is mixed relative to retail firms - who have worse sales, better profits, and hire more workers. And competition increases for service firms, although there is no significant difference with retail firms. Overall, it confirms a similar pattern that service firms fare slightly better than retail firms in drought areas and fare slightly worse than retail firms in non-drought areas with increases in number of competitors.

Table 4: Results: Retail Compared to Service Firms - Market Census Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Effect on Service Firms in Drought Areas:				
β_1: Drought × Post	-562.64	-148.58	-0.06	1.25**
	(371.91)	(105.38)	(0.05)	(0.53)
Effect on Retail Firms in Drought Areas:				
β_2: Drought × Post × Retail	-270.26	-63.65	-0.05	0.61
	(402.33)	(106.92)	(0.06)	(0.98)
T-test: $\beta_1 + \beta_2 = 0$	0.0247	0.0296	0.0032	0.0452
Effect on Service Firms in Non-Drought Areas:				
β_3: Post	238.97	228.25***	0.36***	-0.45
	(287.61)	(73.39)	(0.04)	(0.62)
Effect on Retail Firms in Non-Drought Areas:				
β_4: Post × Retail	1234.93***	310.67***	0.21***	-1.12**
	(255.51)	(62.52)	(0.04)	(0.56)
T-test: $\beta_3 + \beta_4 = 0$	0.0000	0.0000	0.0000	0.0450
Retail	1271.65***	-44.43	-0.44***	7.51***
	(168.80)	(40.85)	(0.02)	(0.66)
Drought × Retail	460.23	120.86	0.16***	-2.36**
	(313.97)	(76.27)	(0.03)	(1.11)
Market FE	Y	Y	Y	Y
Year FE	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5534.35	1404.96	0.25	9.81
Obs	20600	20520	20938	20741
Adj R-Squared	0.05	0.05	0.14	0.39

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Effect on Service Firms in Drought Areas:				
β_1: Post×Drought	-2290.35***	-610.33***	-0.38***	5.82***
	(460.08)	(126.53)	(0.05)	(1.05)
Effect on Retail Firms in Drought Areas:				
β_2: Post×Drought×Retail	942.96***	246.47***	0.22***	-2.08***
	(280.22)	(80.12)	(0.04)	(0.71)
T-test: $\beta_1 + \beta_2 = 0$	0.0060	0.0065	0.0001	0.0002
Retail	1816.54***	94.41***	-0.33***	6.54***
	(142.53)	(34.42)	(0.02)	(0.51)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5946.60	1520.83	0.43	10.25
Obs	20600	20520	20938	20741
Adj R-Squared	0.05	0.05	0.14	0.39

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts.

Table 5: Results: Retail and Service - Women-Owned Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Effect on Service Firms in Drought Areas:					
β_1: Drought × Post	-155.10	50.77	-0.04	-0.10	-0.01**
	(361.23)	(107.81)	(0.06)	(0.53)	(0.00)
Effect on Retail Firms in Drought Areas:					
β_2: Drought × Post × Retail	-547.67	-211.92*	-0.02	1.12	0.00
	(440.26)	(120.74)	(0.07)	(1.01)	(0.00)
T-test: $\beta_1 + \beta_2 = 0$	0.0044	0.0105	0.1864	0.2720	0.2151
Effect on Service Firms in Non-Drought Areas:					
β_3: Post	263.14	48.48	0.27***	1.00**	0.01***
	(255.80)	(73.69)	(0.04)	(0.48)	(0.00)
Effect on Retail Firms in Non-Drought Areas:					
β_4: Post × Retail	-283.02	165.42**	0.14***	-0.25	-0.00
	(274.77)	(79.18)	(0.04)	(0.74)	(0.00)
T-test: $\beta_3 + \beta_4 = 0$	0.9095	0.0000	0.0000	0.2947	0.0028
Retail	1688.66***	-18.88	-0.44***	7.00***	0.00
	(220.95)	(43.42)	(0.03)	(0.74)	(0.00)
Drought × Retail	472.58	108.59	0.16***	-2.04	-0.00
	(369.83)	(73.82)	(0.04)	(1.29)	(0.00)
Market FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5184.64	1250.85	0.23	8.99	0.85
Obs	17401	17373	14464	8134	17552
Adj R-Squared	0.07	0.05	0.14	0.44	0.02

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Effect on Service Firms in Drought Areas:					
β_1: Post×Drought	-276.98	-99.60	-0.08*	1.57	-0.01
	(324.06)	(87.24)	(0.05)	(1.49)	(0.00)
Effect on Retail Firms in Drought Areas:					
β_2: Post×Drought× Retail	-534.03	0.40	0.20***	-0.41	0.00
	(385.48)	(97.19)	(0.06)	(0.82)	(0.01)
T-test: $\beta_1 + \beta_2 = 0$	0.0001	0.0985	0.0016	0.4932	0.2682
Retail	1841.19***	36.81	-0.36***	6.28***	0.00
	(176.05)	(35.17)	(0.02)	(0.62)	(0.00)
Market FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5304.70	1253.24	0.29	10.17	0.82
Obs	17401	17373	14464	8134	17552
Adj R-Squared	0.07	0.06	0.14	0.43	0.02

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts.

6.2.2 Retail Sub-Sectors

Since drought conditions directly affect the food supply chain, it is reasonable to expect food retailers to have a different responses than non-food retailers. To examine these differences, Table 6 has results from a triple differences regression for market census firms where the retail sector category is disaggregated into subsectors - staple grain retailers, fruit/vegetable retailers, meat/fish retailers, and all other non-food retailers. Service firms were dropped from the analysis. Staple retailers are the reference category such that β_1 is interpreted as the effect of drought on staple retail firms and $\beta_2, \beta_3, and \beta_4$ are the differential effect for the various retail sectors. Because the net effect is also of interest, t-tests of total effect on retail categories are also included.

By examining the effect on subsectors of retail firms in drought areas, a few patterns emerge. First, firm performance decreases for all subsectors, but it decreases substantially more for meat/fish retailers compared to other types of retailers. Second, vegetable/fruit retailers, meat/fish retailers, and other retailers have fewer competitors compared to staple retail firms, but the total effect for those subsectors are not significantly different from zero. Staple retail firms experience a large uptick in competition - nearly 4.2 entrants compared to a mean of 10.5 firms per sector, a 40% increase. It is possible that barriers to entry into the staple food market are lower compared to the other types of firms. And potential entrants likely perceive that household demand for staple food will increase after crop failures. The result that vegetable/fruit retailers and especially meat/fish retailers decline substantially suggests that local consumers decreased consumption of these specialty foods compared to staples. This is consistent with households having to first meet their basic food needs by purchasing staple foods and not having additional resources after the drought to purchase non-necessities.

Coefficients for β_5 to β_8 repeat the same pattern for non-drought areas. The opposite occurs in non-drought areas. Staple food retailers sales, profits, and hiring increases (β_5). Vegetable/fruit sellers and other retailers are not different from staple sellers but increase overall in number (as seen in the t-tests for $\beta_5 + \beta_6 = 0$ and $\beta_5 + \beta_8 = 0$). Meat/fish sellers increase substantially more than the other retail categories, which suggests that consumers in the local area benefited from higher staple grain prices and increased purchases of luxury foods. Notably, there are no increases in competition in any of the retail categories. This is consistent with the previous finding that local consumer demand likely increased and firms hired more workers but firms did not enter.

Table 6: Results: Retail Sub-Sectors - Census Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Effect on Staple Retail Firms in Drought Areas:				
β_1: Drought×Post	-430.34	-244.19	-0.10*	4.19***
	(599.45)	(158.92)	(0.06)	(0.97)
Effect on Retail Sub-Sectors in Drought Areas:				
β_2: Drought×Post×Veg/Fruit Retail	-510.94	0.16	-0.01	-5.25***
	(663.51)	(153.03)	(0.07)	(1.94)
T-test: $\beta_1 + \beta_2 = 0$	0.0311	0.0410	0.0548	0.4957
β_3: Drought×Post×Meat/Fish Retail	-7396.06***	-1016.53*	-0.71***	-4.02**
	(2122.82)	(550.12)	(0.19)	(1.59)
T-test: $\beta_1 + \beta_3 = 0$	0.0002	0.0156	0.0000	0.9004
β_4: Drought×Post×Other Retail	-178.57	150.79	0.01	-2.64
	(812.24)	(203.97)	(0.08)	(1.71)
T-test: $\beta_1 + \beta_4 = 0$	0.3541	0.5822	0.1846	0.2629
Effect on Staple Retail Firms in Non-Drought Areas:				
β_5: Post	851.71**	463.45***	0.54***	0.22
	(405.00)	(89.99)	(0.03)	(0.71)
Effect on Retail Sub-Sectors in Non-Drought Areas:				
β_6: Post×Veg/Fruit Retail	-89.21	-122.09	-0.02	1.53
	(388.54)	(87.12)	(0.03)	(1.26)
T-test: $\beta_5 + \beta_6 = 0$	0.0053	0.0000	0.0000	0.1440
β_7: Post×Meat/Fish Retail	5038.91***	765.20***	0.26***	-0.88
	(825.76)	(180.13)	(0.07)	(1.12)
T-test: $\beta_5 + \beta_7 = 0$	0.0000	0.0000	0.0000	0.5876
β_8: Post×Other retail	55.24	-4.46	0.08*	-0.35
	(489.77)	(113.12)	(0.05)	(0.82)
T-test: $\beta_5 + \beta_8 = 0$	0.0548	0.0001	0.0000	0.8806
Veg/Fruit Retail	-3751.66***	-402.57***	-0.04**	11.37***
	(280.87)	(53.84)	(0.02)	(1.32)
Meat/Fish Retail	-1196.44**	104.65	0.02	-3.88***
	(518.75)	(117.79)	(0.03)	(1.19)
Other Retail	-1544.55***	96.48	0.04*	-3.84***
	(325.34)	(65.13)	(0.02)	(0.72)
Drought×Veg/Fruit Retail	-266.81	-182.21	-0.09***	-3.75*
	(539.66)	(119.04)	(0.03)	(2.18)
Drought×Meat/Fish Retail	4873.76***	775.70**	0.64***	-0.61
	(1656.44)	(378.70)	(0.15)	(1.54)
Drought×Other retail	89.74	-201.25	-0.09***	0.35
	(587.21)	(124.15)	(0.03)	(1.05)
Non-Drought Mean	5561.76	1356.98	0.26	10.53
Obs	14700	14629	14926	14862
Adj R-Squared	0.12	0.09	0.16	0.67

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts. Regressions include month-of-year and market fixed effects.

6.3 Robustness Checks

Figure 7 in the appendix plots point estimates for the main treatment indicator $Post \times Drought$ across a range of specifications for main outcomes from the market census sample. The specifications checked include dropping Embu county, dropping Kakamega county, dropping market and month-of-year fixed effects for each TWFE and DD specifications. Embu county was dropped as a control county because it was marginally affected by drought according to the ASAP indicators and thus could cause downward bias in point estimates. Kakamega county was dropped as a check because that county reported high production of maize in 2017, indicating that local farmers had a bumper crop, which could could generate upward bias in estimates of the effect of drought because it was more prosperous making differences with drought-affected areas larger than they would have been in a normal year.

Across all four main outcomes, TWFE models result in larger point estimates compared to DD specifications. TWFE that drop Embu county are largest in magnitude, followed by TWFE with the full sample, and then TWFE that drop Kakamega, except when the outcome is profits. For DD specifications, dropping Embu county produces larger magnitude point estimates for sales, profits, workers compared to the main DD specification. Dropping Kakamega produces smaller magnitude point estimates than the main DD specification for sales and workers. Estimates for number of competitors are similar for all three. This pattern affirms the predicted direction from excluding each county - retaining Embu county shrinks point estimates to zero and retaining Kakamega pushes estimates away from zero.

7 Conclusion

Examining firm performance following an environmental shock that lowers crop production can help clarify how rural markets respond to supply chain shocks and shifts in local demand. Grabrucker and Grimm (2020) found that small firms can benefiting after weather shocks, but were not able to measure changes in competition. Micro-data used in this study featured two types of markets: 1.) markets directly affected by drought whose local consumer base experienced a crop production shock, and 2.) markets indirectly affected by drought via nation-wide increases in maize prices, but whose consumer base did not experience a production shock. Studying outcomes on firm performance alone is not sufficient to characterize rural market dynamics because firm entry and exit are important components. I use micro-data collected by researchers at the World Bank for an impact evaluation that fortuitously collected full market census which permitted assessing firm entry and exit. Differences-in-differences regressions showed that on average across all firm sectors, market census and women-owned firms in drought areas had worse performance (sales, profits, and hiring), but that firm entry increased, suggesting that part of firm performance is related to a larger number of firms competing for smaller local aggregate demand. Furthermore, firm performance improved (sales and profits), hiring increased, and more firms exited in non-drought areas - which is consistent with productive firms hiring while less productive firms exit the market.

In addition to describing entry and exit, evaluating performance heterogeneity by firm sectors reveals that firms in the retail sector have lower sales, profits, and hiring, and slightly more competitors than firms in the services sector. In theory, we would expect the drought shock to be most relevant for firms operating in the food sector, in particular in the staple food sector. Consumers in drought areas had a negative income shock. Prior work on consumer elasticities has shown that household spending on food staples is more inelastic than spending on non-staple foods. Triple difference regressions showed even though staple food retailers had worse performance in drought areas, they had fared better compared to vegetable/fruit sellers, meat/fish sellers, and other retailers. This pattern suggests that consumers demand for food staples was relatively inelastic compared to more luxury food items, especially livestock and fish. Firm entry also increased in the staples sector. Since the opportunity cost of labor decreases after a large-scale production shock, new and existing firm owners may be willing to bear worse market conditions and accept lower revenues.

Small firms are an important part of the rural economy throughout developing regions because they sell food staples and other goods to agricultural households even though they are not very profitable. A long literature in development economics has demonstrated that multiple market failures in credit and insurance prevent agricultural households from optimally investing in farming and non-farming activities (de Janvry et al., 1991). Other work has shown that weather shocks cause households to engage in coping strategies, such as selling household assets or starting businesses. This paper contributes to this literature by demonstrating that new firms enter drought-affected areas despite worse local aggregate demand. It also shows that firm owners in non-drought could benefit from staple price increases if farming households sell staple crops at higher prices. However, more data on consumer behavior in both settings is needed to understand the effect of maize price increases on agricultural households.

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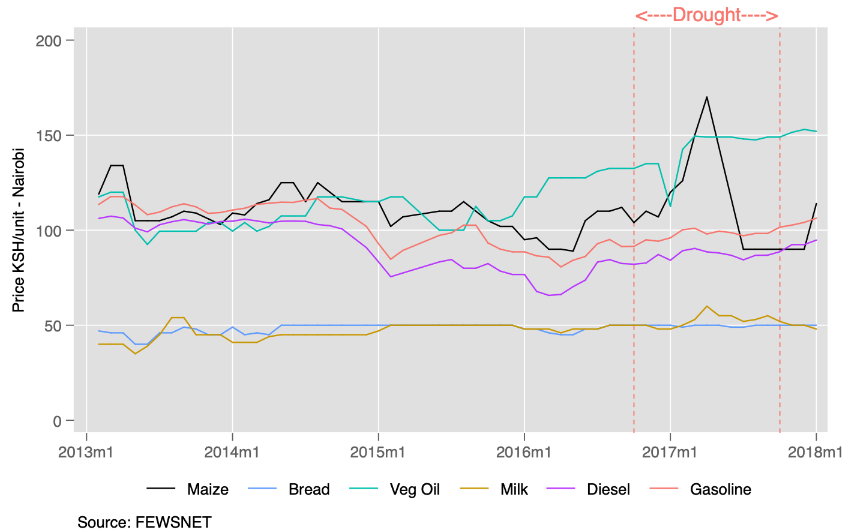
Appendix

A National Market Price Series from 2013-2017



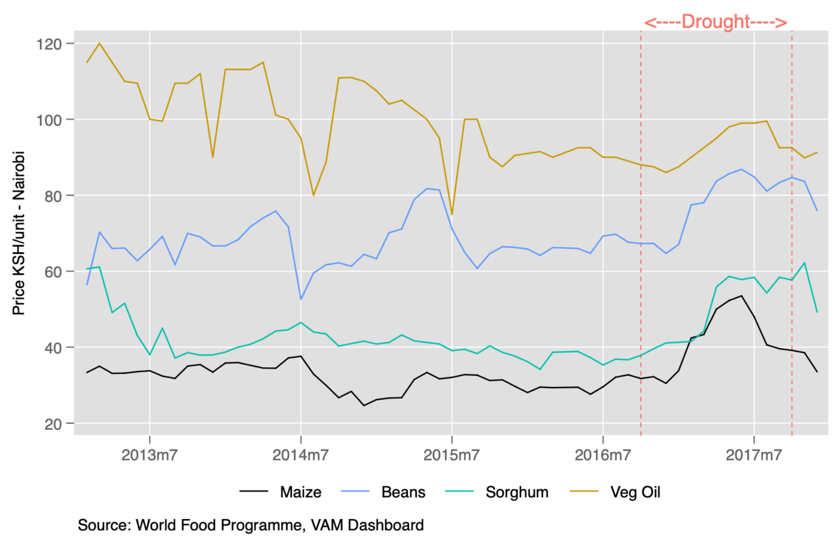


Figure 4:
FEWS NET and WFP Prices for Food Staples and Gas/Petrol in Primary National Market (Nairobi)

B Parallel Trends

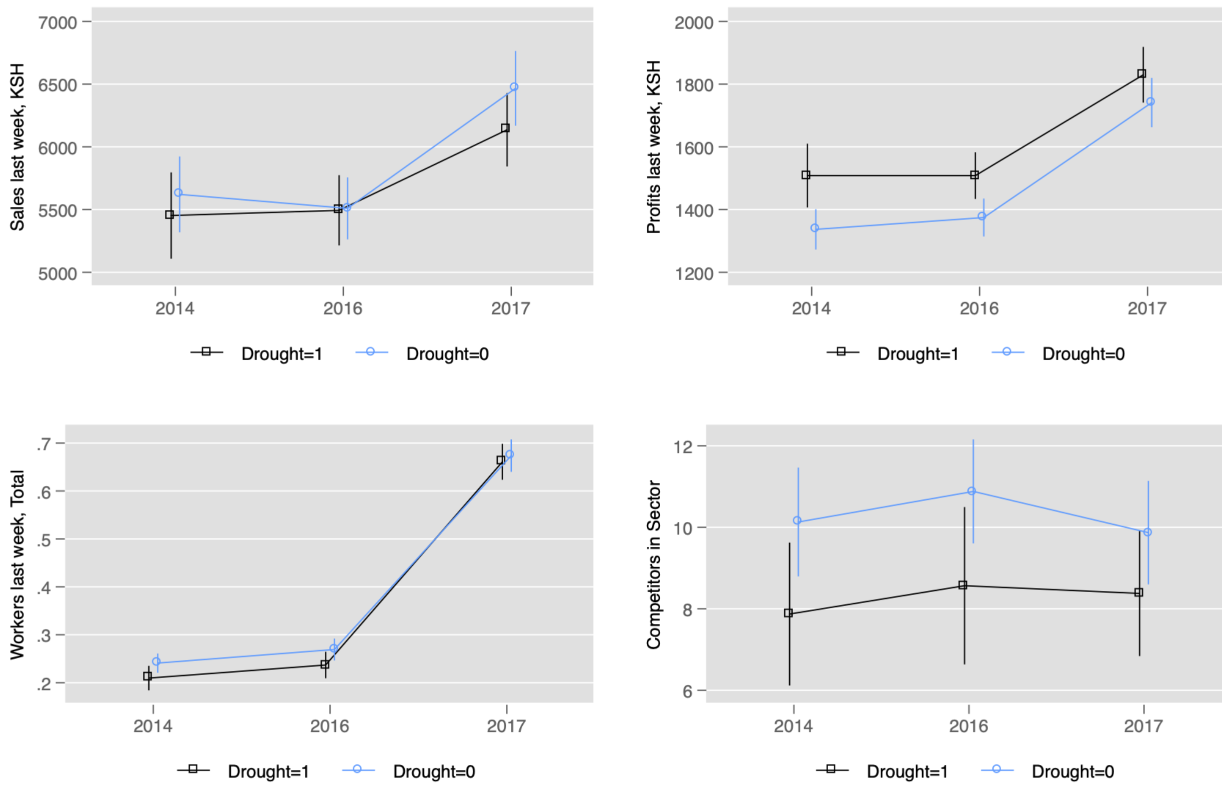


Figure 5: Trends for Market Census Firms

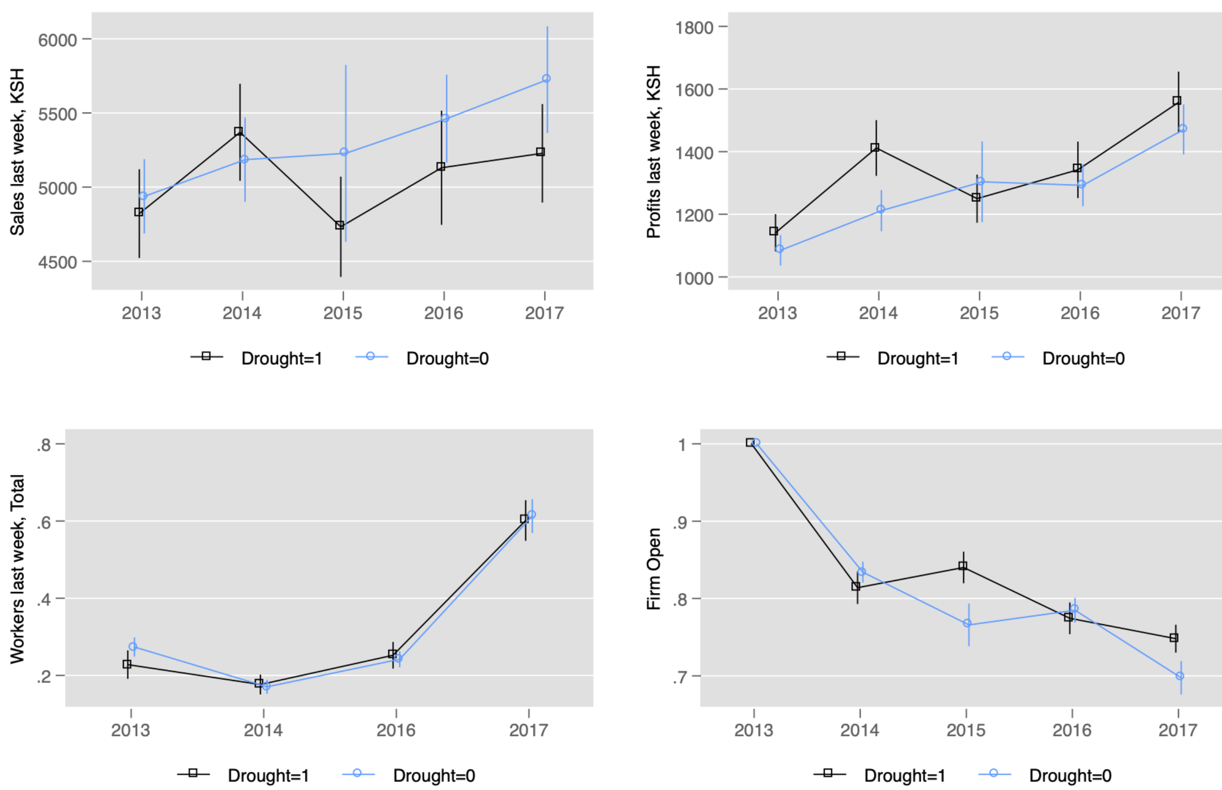


Figure 6: Trends for Women-Owned Firms

C Evaluating Pre-Trends

Table 7: F-test for Joint Significance of Pre-Trends

F-Test on Pre-Trends: Census Firms

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Drought=1 × Year=2014	161.546	82.736	-0.018	-0.767
	(310.939)	(83.504)	(0.032)	(0.987)
Drought=1 × Year=2016	314.580	44.976	-0.020	-0.823
	(248.300)	(69.139)	(0.032)	(0.846)
F-test	0.4337	0.6129	0.8225	0.5816
Obs	20623	20542	20960	20764
Adj R-Squared	0.00	0.01	0.08	0.01

F-Test on Pre-Trends: Women-owned Firms Panel

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Drought=1 × Round=1	371.072	-30.625	-0.034		-0.005
	(233.009)	(64.977)	(0.041)		(0.016)
Drought=1 × Round=2	347.757	87.850	0.023	-0.865	-0.025
	(249.974)	(70.842)	(0.041)	(0.734)	(0.017)
Drought=1 × Round=3	430.660*	4.709			-0.010
	(239.496)	(70.455)			(0.017)
Drought=1 × Round=4	278.387	65.685	-0.005	-0.242	-0.024
	(230.702)	(66.407)	(0.042)	(0.650)	(0.015)
Drought=1 × Round=5	227.100	-51.474	0.063		0.024
	(245.961)	(59.998)	(0.047)		(0.018)
F-test	0.5781	0.2688	0.0761	0.4764	0.0014
Obs	17369	17341	14442	8141	19457
Adj R-Squared	0.01	0.02	0.05	0.01	0.03

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports coefficients on regressions of primary outcomes - sales, profits, workers, competitors, and whether a firm is open - on indicator for drought, indicators for year (or survey round), and their interactions and reports p-values from F-tests of joint significance on pre-trend interactions. The top panel is the census sample and fails to reject pre-trends for all four main outcomes. The bottom panel reports results for the women-owned firms panel and rejects that pre-trend interactions are zero for 3 out of 5 outcomes. Survey rounds were used because there were two surveys in 2016.

D Robustness Checks

(a) Sales

(b) Profits

(c) Workers

(d) Competitors

Figure 7: Robustness Checks for Main Outcomes, Market Census Firms