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RESEARCH ARTICLE

The Short- and Long-Term Costs of a Severe Drought on Retail Peanut Butter Prices and Consumers

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Abstract

This article investigates the short- and long-term costs of an extreme weather event on retail food prices and consumer expenditures. We utilize the 2011 severe peanut drought as a quasi-natural experiment and find that retail peanut butter prices increased 21.3% as a result of the drought-driven shock in farm peanut production and prices. Moreover, we identify long-term costs due to positive asymmetric price transmission as retail peanut butter prices returned to pre-shock levels much more slowly and remained on average 6.2% higher for 4 years after farm peanut prices returned to pre-shock levels. For consumers, the drought increased peanut butter costs, and the persistence of higher prices in peanut butter led to long-term consumer costs. Peanut butter expenditure on average increased by 4.8% post-shock, with lower-income households increasing expenditures even more. A simple calculation estimates that higher peanut butter prices inflicted a cost of $1.08 billion during the shock, and sticky post-shock peanut butter prices imposed a cost of $628 million to U.S. consumers.

Keywords: Drought; Extreme weather cost; Food price; Peanut butter

JEL Codes: D40; L66; L81; Q18; Q54

1. Introduction

Climate change and rising global temperatures have increased the frequency of extreme weather disasters (e.g., heat waves, floods, and droughts) and will continue to do so in the future (IPCC, 2014). Extreme weather disaster events have been estimated to cost on average $44.3 billion per event in the U.S. between 1980 and 2019 (NOAA NCDC, 2020). Starting in the summer months of 2011, a severe drought linked to climate change (Mann et al., 2017) hit the major peanut-growing areas of the U.S. (Scott, 2012). As seen in Figure 1, large swaths of peanut-growing areas in Texas and Oklahoma were under the most severe category of drought (exceptional) and the remaining peanut-growing areas in the Southeast, especially Georgia, were under the second most severe category of drought (extreme).[1]

Coupled with below-average planted acres, both the extreme severity and extensive reach of the drought reduced domestic peanut supplies.[2] These factors drastically fueled an increase in farm price of peanuts as reported by the Economic Research Service in the U.S. Department of

[1]Areas of exceptional drought, the most severe, experience widespread crop and pasture losses, imminent fire risk, and water shortages that result in water emergencies. Areas of extreme drought, the second most severe, experience major crop and pasture losses, extreme fire risk, and water shortages that require restrictions. Degree of drought is classified by National Oceanic and Atmospheric Administration.

[2]Furthermore, excessive heat from drought conditions led to increased aflatoxin contamination caused by soil fungi, rendering parts of the peanut supply useless or requiring costly processing (Scott 2012).

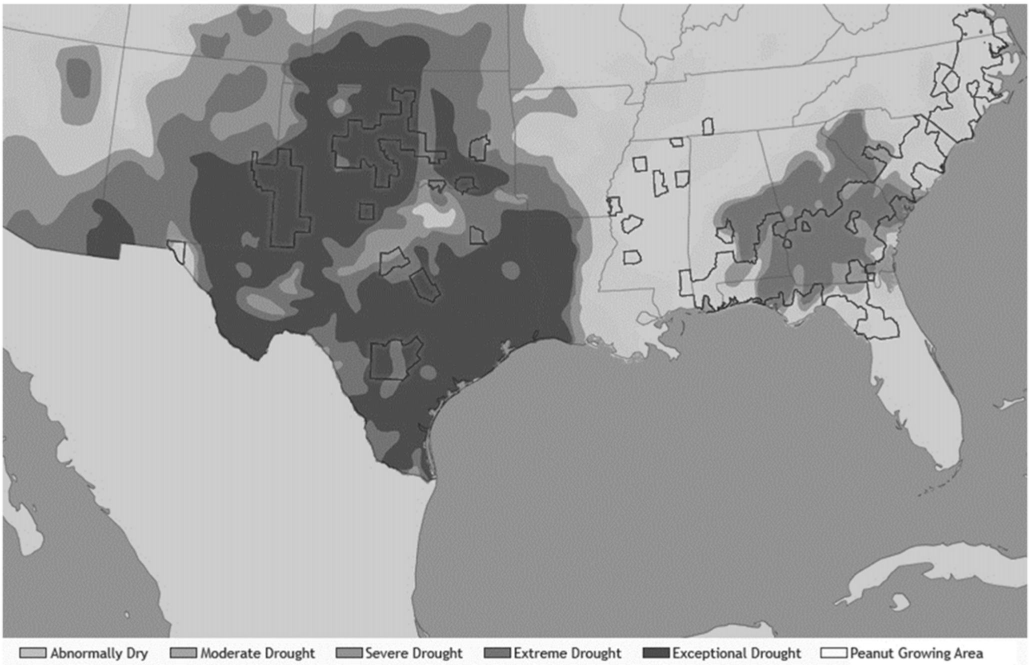

Figure 1. Peanut drought. Source: Scott, 2012.

Agriculture (USDA ERS, 2011). Figure 2 plots the monthly average peanut price received at the farm collected by USDA's National Agricultural Statistics Service (NASS) surveys, which shows that prices jumped over 40% within a month in October, 2011.[3] Peanut prices remained at a heightened level for over a year and eventually returned to pre-shock levels during 2013.

In the U.S., 45% of the peanut crop is used to produce peanut butter (Schnepf, 2016), prompting the question of the drought's impact on retail peanut butter prices. Peanut butter is a key staple in many US households with approximately 3.9 pounds of peanut butter produced and available for each person per year (USDA ERS, 2016).[4] A very affordable source of calories and protein, peanut butter is included in the WIC program food package to supplement nutritionally at-risk expecting mothers and children. With the popularity of peanut butter, any price increase will have consequences for vast numbers of U.S. consumers, especially for lower income households.[5]

Retail peanut butter in the U.S. is required by law to be at least 90% peanuts, and the most common type of peanuts used in the manufacture of peanut butter—runner peanuts—account for 80% of the U.S. peanut crop.[6] Figure 3 shows the national posted price of runner peanuts which exhibited an even more drastic price spike compared to overall peanut prices seen in Figure 2.[7] Figure 4 plots the average price of retail peanut butter along with the average retail

[3]The majority of the contracts established between peanut shellers and farmers are set 6–9 months before harvest but allow the farmer to retain ownership to participate in the marketing loan program, similar to an option contract.

[4]As a reference, average annual ice cream consumption is 13 pounds per capita and average annual tuna consumption is 2.4 pounds per capita.

[5]About 94% of American homes have at least one jar of peanut butter in their pantry according to the National Peanut Board.

[6]According to the American Peanut Council.

[7]The national posted price is not necessarily the price of peanuts received at the farm, but is a price developed by the USDA Farm Service Agency based on current market conditions and indicators such as shelled prices and international bids. Its main purpose is to set the repayment rate for peanut loans, and it provides a general proxy for peanut prices.

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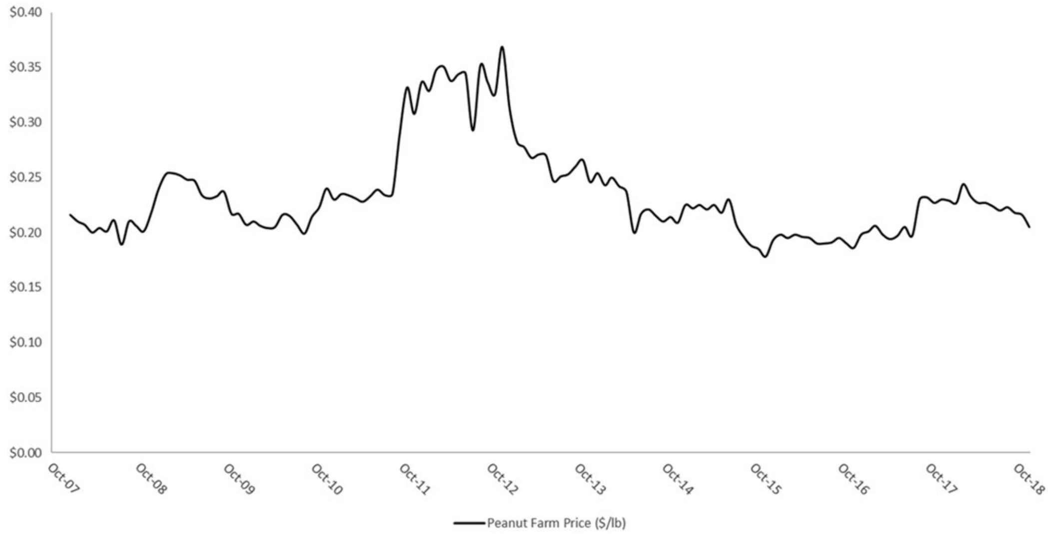

Figure 2. Farm price of peanuts ($/lb.). Source: US Department of Agriculture, National Agricultural Statistics Service.

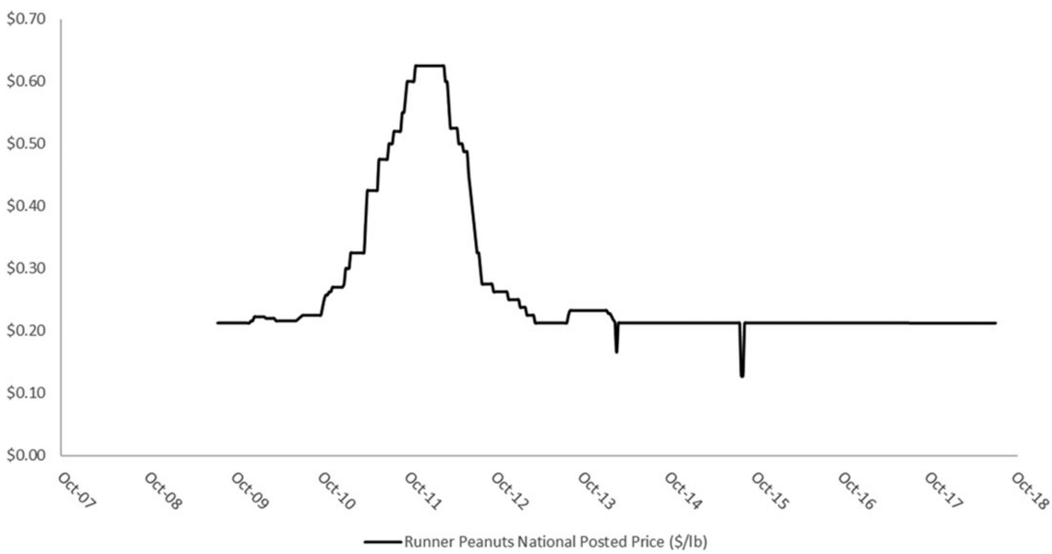

Figure 3. National posted price of runner peanuts ($/lb.). Source: US Department of Agriculture, Farm Service Agency.

price of two other processed staple foods: retail white bread and retail processed pasta as a comparison.[8] Unsurprisingly, retail peanut butter prices spiked in conjunction with the increase in farm peanut prices. However, the prices of retail peanut butter did not return to pre-shock levels within the same time frame that farm peanut prices did. This type of asymmetry in price pass through, characterized by a faster retail price response to an increase in input prices than

[8]Average price of retail peanut butter is the average retail price of creamy peanut butter per pound for U.S. cities. Average price of retail white bread is the average retail price of pre-packaged regular white bread per pound for U.S. cities. Average price of retail processed pasta is the average retail price of all long thin pasta (including macaroni and shells and excluding fettuccine and linguine) per pound for U.S. cities. Data are from the Bureau of Labor Statistics.

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Figure 4. Average retail price of peanut butter ($/lb.). Notes: Average price of retail peanut butter is the average retail price of creamy peanut butter per pound for U.S. cities. Average price of retail white bread is the average retail price of pre-packaged regular white bread per pound for U.S. cities. Average price of retail processed pasta is the average retail price of all long thin pasta (including macaroni and shells and excluding fettuccine and linguine) per pound for U.S. cities. Source: Bureau of Labor Statistics.

to a decrease, has been termed positive asymmetric price transmission or "rockets and feathers."

In this article, we answer two related questions: (1) What are the short- and long-term impacts of a severe peanut drought on the final retail prices of peanut butter? (2) What are the short- and long-term impacts on consumers' spending and does it vary across income groups? We use the drought-induced shock as a quasi-natural experiment to examine the impact of an extreme weather event on retail peanut butter prices utilizing an event study framework. Specifically, we use a national panel data set to examine the changes in retail price at the UPC (Universal Product Code) product level, thus reducing potential bias from substitution effects masked by the aggregation and averaging processes inherent in a retail price index. Furthermore, the panel data set allows us to examine heterogenous impacts on households with varying incomes.

This article provides several novel contributions to the literature that are useful to researchers and policy makers. First, we show the impact of a severe drought on retail food prices, and we estimate that retail peanut butter prices increased 21.3% in response to the 2011 drought. Second, we show the long-term costs of the drought where retail peanut butter prices lingered on average 6.2% higher for at least 4 years before returning to pre-drought levels. Third, we show that the impact of the peanut butter price increase was heterogenous across income groups with low-income groups experiencing the largest impact. Finally, we highlight the impact of a drought on consumers and estimate that U.S. consumers spent $1.08 billion extra on peanut butter during the drought and a total of $628 million extra in the 4 years after peanut prices had returned to pre-shock levels.

The remainder of the paper is structured as follows: Section 2 provides the literature review and our contribution to the literature. Section 3 describes the data. Section 4 provides the identification strategy and econometric model. Section 5 describes the results and the robustness checks we employ. Section 6 discusses policy implications and concludes the paper.

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2. Literature Review

Droughts, which account for 14% of extreme weather damages, are particularly damaging to agriculture and have led to large supply shocks in agricultural production (Dhoubhadel, Azzam, and Stockton, 2015; Kuwayama et al., 2019; Leister, Paarlberg, and Lee, 2015). NOAA NCDC (2020) estimate that in the U.S., each drought costs $9.4 billion on average, primarily due to wasted input for agricultural production and insurance payouts of failed crops. However, most of the analysis on drought cost has focused on damages to agricultural producers. Downstream costs, especially in developed countries with lengthy food production chains, have often been overlooked in drought damage estimation by researchers and policy makers.

The literature has shown that changes in commodity crop prices can lead to retail price changes of processed food products (Berck et al., 2009; Richards and Pofahl, 2009). The transmitted impact of the 2011 drought on retail peanut butter prices was highlighted by popular press due to the severity of the drought and the drastic increase in both peanut and peanut butter prices (Henry, 2011; O'Toole, 2011). Furthermore, positive asymmetric price transmission after exogenous shocks is commonly found in the empirical literature (Saghaian, Özertan, and Spaulding, 2008). Peltzman (2000) establishes positive asymmetric price transmission as the norm rather than the exception for most products. In a meta-analysis, Bakucs, Fałkowski, and Fertő (2014) find positive asymmetric price transmission to be more common in agricultural sectors with more governmental support, which is true of the U.S. peanut sector with governmental peanut marketing loans and income support programs (Schnepf, 2016).

Some of the main theoretical explanations behind positive asymmetric price transmission have been market power (Borenstein, Cameron, and Gilbert, 1997; Meyer and von Cramon-Taubadel, 2004) and menu cost (Ball and Mankiw, 1994; Loy, Weiss, and Glauben, 2016; Meyer and von Cramon-Taubadel, 2004). Unlike most food commodities, peanuts operate in a "thin market" with no public futures markets and prices are often set by private contracts between grower and buyers. Thin markets can lead to less competitive and more opaque markets with significant market power throughout the production chain. At the farm level, 80% of peanuts are purchased by two peanut shellers from growers (Schnepf, 2016), potentially exerting considerable market power for the first stage of peanut butter production. Finally, U.S. food retailers are highly concentrated and exert considerable market and pricing power (Hovhannisyan, Cho, and Bozic, 2019). The considerable market power throughout the peanut processing chain and other potential factors such menu costs and uncertainty likely lead to positive asymmetric price transmission under which a shock in input costs can lead to persistently heightened final retail prices.[9]

This article provides evidence of positive asymmetric price transmission in retail food products after drastic weather-induced supply shocks, an understudied area of the current literature. From a policy perspective, the results further highlight how both the magnitude and duration of retail price changes from the drought can result in significant economic implications for consumers beyond the end of the drought itself.

3. Data

The data set for this article comes from the Information Resources, Inc. (IRI) Consumer Network longitudinal panel data.[10] The IRI company provides households with a handheld in-home scanning device and other incentives to record all UPC-based consumer product purchases and tracks the prices and quantity of each item purchased along with household demographics. The purchase information includes quantities, prices, discounts, and coupons used, and household information includes demographic information such as household size, household income, age of household

[9]Due to data limitations, we are unable to explore how market concentration of retailers impacts the price increase.

[10]See Muth et al. (2016) for a detailed description of the methodology, characteristics, and statistical properties of the data set.

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Table 1. Average retail peanut butter prices and share of expenditures by retail channel

Channel	Average Price ($/lb.)	Share
Grocery	$2.56	60.2%
Drug Store	$2.43	1.6%
Mass Merchandiser	$2.42	3.4%
Supercenter	$2.36	16.1%
Convenience Store	$2.83	0.1%
Dollar Store	$2.38	0.7%
Club Store	$1.96	14.4%
Other	$2.55	3.4%

head, ethnicity, race, and presence of children. The households are a representative sample of the whole U.S. and provide comprehensive coverage of U.S. retail prices among different retail channels where consumers shop.[11] The consumer panel data provide comprehensive prices of retail peanut butter at a wide array of outlets and also contain data on coupons, discounts, and the actual out-of-pocket price paid by consumers.[12] The unit of observation in the data set is the product purchased by a specific household at a specific date in a specific store chain in a specific geographic market.

Table 1 shows the average price of peanut butter per pound for the eight different possible retail channels. Retail peanut butter items are cheapest in club stores followed by supercenters and are most expensive in convenience stores. In terms of expenditures, 60% of peanut butter items are purchased at grocery stores followed by 16% of supercenters. At the other end, convenience stores are only responsible for 0.1% of peanut butter products sold.

For the first component of the empirical analysis examining retail peanut butter prices, we aggregate the data set to the average price of a specific retail peanut butter item in a specific store chain in a specific geographic market during a specific month (e.g., the average price of a 16 ounce private label's creamy peanut butter sold at a particular grocery store in the Pittsburgh, PA market during January 2012). The data set contains prices for 2,209 UPC-level peanut butter products at 518 different chains nationwide in 61 markets spanning 11 years for a total of 982,974 observations. For the second part of the empirical analysis examining the impact on consumers, we aggregate the data to total peanut butter expenditure for each household in a specific month.

Table 2 presents the average total expenditure and volume purchased of peanut butter for each household each month broken down by income brackets and shows the average household spends $5.18 per month on peanut butter with higher-income households spending slightly more.

[11]One potential limitation is that the composition of the Consumer Network Panel may be weighted toward households that choose to scan their data after years of shopping history, and thus more likely to be price sensitive and have particular habits toward certain food items. Furthermore, the Panel potentially oversamples older white households with relatively high incomes and educational attainment (see Einav, Leibtag, and Nevo, 2008). As a result, estimated differences in impacts by income levels may be underestimated and downward biased.

[12]The consumer network panel categorizes stores into 8 channels: grocery stores, drug stores, mass merchandisers, supercenters, convenience stores, dollar stores, club stores, and others. Grocery stores include common chains that mainly sell food products. Mass merchandisers sell both food and non-food products. Convenience stores include food stores attached to gas stations. Club stores include wholesale stores. Other includes all other channels of retail such as online retailers and hardware stores.

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Table 2. Average monthly household peanut butter expenditure and volume by income

Annual Income Brackets	Expenditure ($)	Volume (oz)
0 to $9,999	$4.90	37.56
$10,000 to $11,999	$4.74	36.68
$12,000 to $14,999	$4.62	36.65
$15,000 to $19,999	$4.62	36.50
$20,000 to $24,999	$4.75	37.68
$25,000 to $34,999	$4.87	38.46
$35,000 to $44,999	$4.91	38.67
$45,000 to $49,999	$5.15	40.46
$50,000 to $59,999	$5.18	40.46
$60,000 to $69,999	$5.24	40.77
$70,000 to $99,999	$5.41	41.66
>$100,000	$5.69	42.44
Average	$5.18	40.14

4. Methodology

The exogenous and drastic nature of the severe drought presents a quasi-natural experiment framework to causally identify and estimate the short-term (during) and long-term (after) effects of the drought-induced commodity price spike.[13] Specifically, we model the 2011 drought as a discrete treatment and examine the change in retail peanut butter prices during and after the price spike to identify the effect of the drought on retail peanut butter prices. Both Figures 2 and 3 show that farm peanut prices were relatively stable except for the tremendous spike starting in 2011, evidence in support of modeling the drought as a discrete change.

First, we provide further visual evidence on the changes in both farm peanut prices and retail peanut butter prices corresponding to the occurrence of the drought. In Figure 5, we plot the residuals of the log of farm peanut prices after controlling for month fixed effects and the residuals of the log of peanut butter prices after controlling for fixed effects associated with months, store chain, market, and product. Farm peanut prices were generally stable, spiked after October 2011, and stayed high for over a year. Farm peanut prices started to fall in October 2012 but remained higher than pre-shock prices. Around October 2013, 2 years after the start of the price hike, prices dropped back to pre-shock prices and relatively stabilized, with a minor dip, until the end of data set. Farm peanut prices correspond with the drought conditions in 2011, which was drastically higher until a full harvest in 2012, which allowed farm peanut prices to drop back to normal.

Based on these trends, we separate the data into three periods: pre-shock (January 2008 to September 2011), shock (October 2011 to September 2013), and post-shock (October 2013 to December 2018). We select two full year cycles of peanut production for the shock period as the typical harvest season for peanuts begins in October.[14] Examining the prices of peanut butter in Figure 5, we can see that peanut butter prices correspondingly increased with the increase in farm peanut prices. However, the fall in peanut butter prices is much more gradual and does not return to pre-shock levels significantly after peanut prices returned to pre-shock levels. Table 3 separates the average retail peanut butter prices and farm peanut prices into the three periods and

[13]We define short term as during the drought-induced farm peanut price shock and long term as after the drought-induced farm peanut price shock.

[14]https://www.nationalpeanutboard.org/news/5-things-you-dont-know-about-harvesting-peanuts.htm

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Table 3. Average retail peanut butter and farm peanut prices by period

Price	Pre-Shock	Shock	Post-Shock
Peanut Butter	$2.09	$2.72	$2.67
Farm Peanut	$0.22	$0.32	$0.21

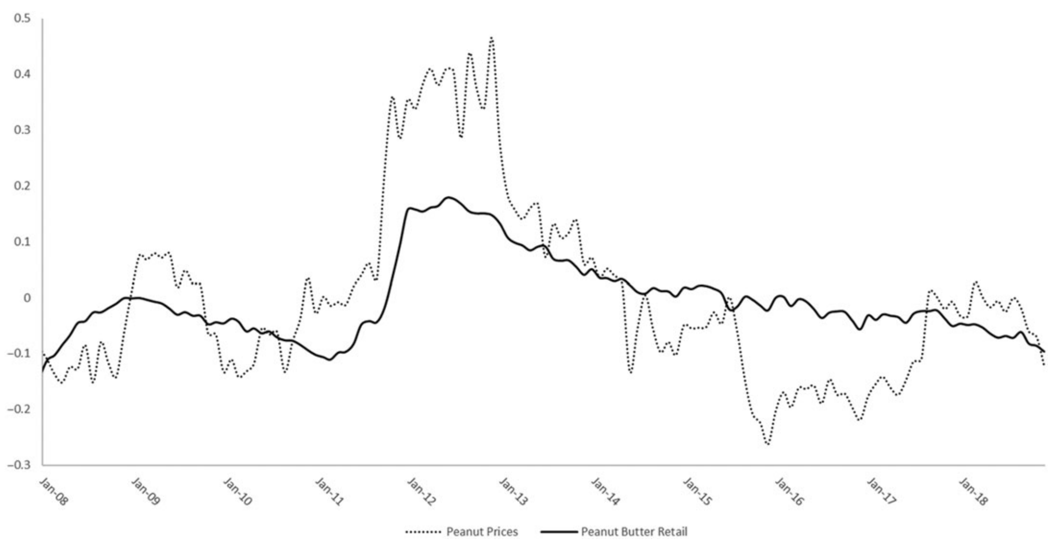

Figure 5. Residual plot for farm peanut prices and retail peanut butter prices.

presents additional preliminary evidence of the long-term effects of the shock. Farm peanut prices between the pre-shock and post-shock periods are relatively similar, with post-shock period prices even slightly lower. However, post-stock peanut butter prices are higher on average than pre-shock.

With the preliminary indicators for these periods, we provide further evidence for the period designations by regressing the log of farm peanut prices on indicators of the period designations using equation (1).

$$\log(PeanutFarmPrice_t) = \beta_0 + \beta_1 shockY1_t + \beta_1 shockY2_t + \beta_3 postshock_t + t + \varepsilon_t \quad (1)$$

We separate the entire time period into: pre-shock, shock, and post-shock, and we further divide the shock period into the first year of the shock, $shockY1_t$ and second year of the shock, $shockY2_t$ for a total of 4 time periods: pre-shock, shock year 1, shock year 2, and post-shock.[15] $shockY1_t$ is a dummy variable where $shockY1_t$ is equal to 1 during the first year of the shock, and equal to 0 otherwise. Similarly, $shockY2_t$ is a dummy variable where $shockY2_t$ is equal to 1 during the second year of the shock, and equal to 0 otherwise. We use $postshock_t$ as the indicator for the post-shock period, where $postshock_t$ is equal to 1 during the after the shock, and equal to 0 otherwise. Finally, we include a linear time trend to control for any general price increase over time such as inflation. For equation (1), the dependent variable is the national average farm peanut prices at the month level from USDA NASS in Figure 2 with 132 observations. In Table 4, results from the model specified in equation (1) indicate a significant increase in farm peanut prices during both years of the shock period. During the post-shock period, farm peanut prices returned to

[15]Shock year 1 is between October 2011 and September 2012, and shock year 2 is between October 2012 and September 2013. Post shock is between October 2012 until the end of the data set.

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Table 4. Price change in farm peanuts due to 2011 drought

Uses Equation:	Equation (1)
Panel A. Dep. Var. is log price of peanuts at the farm	
Shock Year 1	0.413***
	(0.0269)
Shock Year 2	0.278***
	(0.0436)
Post-Shock	0.00388
	(0.0479)
Linear Time Trend	−0.0005
	(0.0006)
Constant	−1.498***
	(0.0185)
Observations	132
R^2	0.713
Panel B corrects the estimates of interest to percentage change	
Shock Year 1	51.1%***
Shock Year 2	32.0%***
Post-Shock	Not Sig

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.
Notes: Robust standard errors in parentheses. Panel A is the raw estimates of equation (1) examining the percentage difference in prices of farm peanut prices between the pre-shock, shock year 1, shock year 2, and post-shock periods. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$ and reports the percentage change.

pre-shock levels given that the coefficient on $postshock_t$ is not significantly different than zero. As we cannot directly interpret the regression coefficient on a dummy variable in a semilogarithmic regression as percentage change (Halvorsen and Palmquist, 1980), we use the percentage estimator, $\Delta\% = \exp(\beta) - 1$, from Halvorsen and Palmquist (1980) to convert the raw estimate results to percentage change. Table 4 shows that compared to the pre-shock period, farm peanut prices were 51% higher during the first year of the shock period and 32% higher during the second year of the shock period. After 2 years, there is no significant difference between pre-shock and post-shock peanut prices. The results of Table 4 provide further evidence that the spike in drought-induced farm peanut prices ended after 2 years.

For our main specification analyzing the impact of the price spike on retail peanut butter prices, we use the average price at the UPC level for each retail peanut butter item at each store chain at a specific month. We use equation (2) where p indexes UPC-level individual products,[16] s indexes store chain, m indexes geographic markets (similar to Metropolitan Statistical Area), and t indexes month.

$$\log(PBPrice_{psmt}) = \beta_0 + \beta_1 shock_t + \beta_2 postshock_t + Seasonal_t + UPC_p + Chain_s + Market_m + \varepsilon_{psmt} \quad (2)$$

[16]We drop one UPC fixed effect in the regression.

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The dependent variable $\log(PBPrice_{psmt})$ is the log of the deflated retail peanut butter price of product p in store chain s in market m during month t.[17] As discussed in the previous section, we divide the time span into three separate periods of pre-shock, shock, and post-shock with the period shock ranging between October 2011 and September 2013 and post-shock period ranging from October 2013 until the end of the data set. We use $shock_t$ as the indicator for the shock period and $postshock_t$ as the indicator for the post-shock period.

We control for individual UPC product fixed effects, store chain fixed effects, geographical market fixed effects, and seasonal fixed effects at the month of year level. Seasonal fixed effects control for seasonal variation constant across all stores, such as seasonal changes in consumer preferences for peanut butter and seasonal differences in input cost of labor or other peanut butter ingredients. The geographic market fixed effects control for any time constant, market-specific attributes including spatial market powering, regional variation in consumer preferences for peanut butter, and other geographic cost differences. Store chain fixed effects control for any time constant store chain-specific attributes including store chain pricing decisions, or unique bargaining agreements with manufacturers or producers.

Finally, individual UPC product fixed effects control for any product-specific attributes such as unique composition of different peanut butter products and unique pricing strategies for specific peanut butter items. The inclusion of individual product fixed effects also allows our specification to examine the change in the retail prices within a specific peanut butter item, eliminating potential endogeneity from sources such as the unobserved product quality of a peanut butter item, where higher quality peanut butter items are typically priced higher. The coefficients, β_1 and β_2, are estimates of interest that measure the changes in retail peanut butter prices during the shock and post-shock periods, respectively.

Furthermore, prices can differ substantially between chains and retail channels, which are typically located in different socioeconomic areas (Bitler and Haider, 2011). Different chains and retail channels cater to consumers of different demographics and can have different levels of bargaining power with wholesalers. The price transmission to final retail prices can be heterogenous across chains or retail channels with varying degrees of market power and facing different price elasticities. To estimate the heterogenous impact on different retail channels, we extend equation (2) by interacting $shock_t$ and $postshock_t$ with the different retail channels as seen in equation (3).

$$\log(PBPrice_{psmt}) = \beta_0 + \sum_{c=1}^{8} \beta_c channel_s * shock_t + \sum_{k=9}^{16} \beta_k channel_s * postshock_t + Seasonal_t + UPC_p + Chain_s + Market_m + \varepsilon_{psmt} \quad (3)$$

To estimate if there is a trend in retail prices after the shock and the rate at which prices fall back to pre-shock levels, in equation (4), we replace $shock_t$ and $postshock_t$ with indicators for each year (measured from October to September) during and after the shock, where $shockY1_t$ and $shockY2_t$ are the 2 years during the shock period, and $PostshockY1_t$, $PostshockY2_t$, $PostshockY3_t$ are year 1, year 2, year 3 after the end of the shock period, respectively.[18]

[17]We deflate prices using the U.S. Food Consumer Price Index from the Bureau of Labor Statistics.

[18]Year is defined as from October to September as discussed in the previous data section. That is, $shockY1_t$ spans October 2011 to September 2012, $shockY2_t$ spans October 2012 to September 2013, and $PostshockY1_t$ spans October 2013 to September 2014, etc....

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$$\log(PBPrice_{psmt}) = \beta_0 + \beta_1 shockY1_t + \beta_2 shockY2_t + \beta_3 PostshockY1_t + \beta_4 PostshockY2_t + \beta_5 PostshockY3_t + \beta_6 PostshockY4_t + \beta_7 Postshock5_t + Seasonal_t + UPC_p + Chain_s + Market_m + \varepsilon_{psmt} \quad (4)$$

Finally, for equation (5), we extend equation (4) by interacting each year indicator with retail channels to estimate the heterogenous retail price changes in each year.

$$\log(PBPrice_{psmt}) = \beta_0 + \sum_{c=1}^{8} \beta_c channel_s * shockY1_t + \sum_{c=9}^{16} \beta_c channel_s * shockY2_t + \sum_{k=17}^{24} \beta_k channel_s * postshockY1_t + \sum_{k=25}^{32} \beta_k channel_s * postshockY2_t \sum_{k=33}^{40} \beta_k channel_s * postshockY3_t + \sum_{k=41}^{48} \beta_k channel_s * postshockY4_t + \sum_{k=49}^{56} \beta_k channel_s * postshockY5_t + Seasonal_t + UPC_p + Chain_s + Market_m + \varepsilon_{psmt} \quad (5)$$

To estimate the impact on consumers, we use the data set aggregated to the peanut butter expenditure at the household level. We use equations (6) and (7) to examine the change during the shock and post-shock periods on the deflated total expenditure, $PBExp_{imt}$ and total purchased volume of peanut butter, $Totvol_{imt}$ where i indexes households. We control for individual household demographics, $household\ demo_i$, and seasonal and market fixed effects.[19] For equation (8), we extend equation (6) by interacting the variables $shock_t$ and $postshock_t$ with the variables $income_i$ to examine the heterogenous impact on households with varying income levels.

$$\log(PBExp_{imt}) = \beta_0 + \beta_1 shock_t + \beta_2 postshock_t + household\ demo_i + Seasonal_t + Market_m + \varepsilon_{imt} \quad (6)$$

$$\log(Totvol_{imt}) = \beta_0 + \beta_1 shock_t + \beta_2 postshock_t + household\ demo_i + Seasonal_t + Market_m + \varepsilon_{imt} \quad (7)$$

$$\log(PBExp_{imt}) = \beta_0 + \sum_{c=1}^{12} \beta_c income_i * shock_t + \sum_{c=13}^{24} \beta_c income_i * postshock_t + household\ demo_i + Seasonal_t + Market_m + \varepsilon_{imt} \quad (8)$$

5. Results

Table 5 presents the results of our main specification in equation (2), with raw estimates in Panel A and conversions to percentage change utilizing Halvorsen and Palmquist (1980) in Panel B. It is evident from Table 5 that retail prices for peanut butter increased on average 21.3% during the 2-year shock period in the immediate aftermath of the 2011 peanut drought. Furthermore, Table 5 shows that retail peanut butter prices stayed 6.2% higher in the 4-year post-shock period

[19]Household demographic controls include household size, income levels, race, Hispanic, age, marital status, and pet ownership.

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Table 5. Main specification: retail peanut butter price change due to 2011 drought

Dep Var.	Log(Retail Price)
Panel A	
Shock	0.193***
	(0.00280)
Post-Shock	0.0599***
	(0.00309)
UPC Fixed Effects	Yes
Store Fixed Effects	Yes
Market Fixed Effects	Yes
Seasonal Fixed Effects	Yes
Constant	0.988***
	(0.00167)
Observations	982,974
R^2	0.863
Panel B corrects the estimates of interest to percentage change	
Shock	21.3%***
Post-Shock	6.2%***

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.
Notes: Robust standard errors in parentheses, clustered at the market level. Panel A is the raw estimates of equation (2) examining the percentage difference in the retail price of peanut butter between pre-shock, shock, and post-shock periods after controlling for UPC fixed effects, store chain fixed effects, market fixed effects, and seasonal fixed effects. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$.

beginning in October 2013 when farm peanut prices returned to pre-shock levels. The sticky post-shock retail prices provide evidence of positive asymmetric price transmission in length and highlight the long-term impact of the drought on retail prices.

The first column of Table 6, with after-coupon price as the dependent variable, shows no meaningful difference with the results from Table 5 with shock period estimated changes of 22.8% compared to 21.3% and post-shock period estimated changes of 7.4% compared to 6.2%. To account for potential large changes in the cost of other peanut butter inputs beyond seasonal variation captured by seasonal fixed effects, the regression in the second column of Table 6 includes controls for the national average prices of palm oil, sugar, gasoline, electricity, plastic, and commercial paper interest rates. The results in column 2 show no substantial qualitative differences to our main results either with the shock period estimated change of 19.0% and the post-shock period estimated change of 6.6%. Due to the long timespan of the data, there is likely entry and exit of UPC products. As a robustness check for any composition effects, we drop all UPC products that survived less than 10 years in the data set in the third column of Table 6. Again, results are of similar magnitude with an estimated 29.8% increase in retail prices during the shock period and 5.7% increase in the post-shock period.

As a final robustness check, we aggregate to the average expenditure-weighted retail price at the brand-store-market level and average expenditure-weighted retail price at the store-market level in the first and second columns of Table 7. Like before, these results are qualitatively similar to the main specification with post-shock effects slightly larger in both columns of Table 7.

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Table 6. Robustness checks: retail peanut butter price change

	Price After Coupons	Additional Controls	>10 years
Panel A			
Shock	0.205***	0.174***	0.261***
	(0.00331)	(0.0023)	(0.00716)
Post-Shock	0.0713***	0.0641***	0.0552***
	(0.00329)	(0.00288)	(0.0105)
UPC Fixed Effects	Yes	Yes	Yes
Store Fixed Effects	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes
Input Cost Controls	No	Yes	No
Constant	0.950***	0.0535	1.000***
	(0.00186)	(0.134)	(0.00535)
Observations	980,431	982,974	20,680
R^2	0.791	0.865	0.800
Panel B corrects the estimates of interest to percentage change			
Shock	22.8%***	19.0%***	29.8%***
Post-Shock	7.4%***	6.6%***	5.7%***

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

Notes: Robust standard errors in parentheses, clustered at the market level. All regressions in this table use variations of equation (2). The first column uses the log of the actual price paid after subtracting coupons as the dependent variable. The second column includes controls for national average prices of palm oil, sugar, gasoline, electricity, plastic, and commercial paper rates. Data on national average prices of palm oil, sugar, gasoline, electricity, plastic, and commercial paper rates come from Federal Reserve Economic Data maintained by the St. Louis Federal Reserve Bank. The third column drops all UPC products that lasted less than 10 years in the data set. Panel A is the raw estimates of examining the percentage difference in the retail price of peanut butter between pre-shock, shock, and post-shock periods after controlling for UPC fixed effects, store chain fixed effects, market fixed effects, and seasonal fixed effects. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$.

Table 8 shows the results of equation (3) converted to percentages for varying retail channels. During the shock period, retail peanut butter prices increased the most for club stores, supercenters, and mass merchandizers (26.8%, 25.4%, and 24.7%, respectively) and increased the least for dollar and convenience stores (14.9% and 9.7%, respectively). Post-shock, however, drug and convenience stores dropped prices the least compared to the shock period (18.6% increase during shock compared to pre-shock vs 13.5% increase during post-shock compared to pre-shock and 9.7% increase during shock compared to pre-shock vs 6.5% increase during post-shock compared to pre-shock, respectively). Drug stores and club stores retained the highest price increase post-shock (13.5% and 12.0%, respectively). Economic rationales discussed previously can potentially drive the differences in price responses across different retail channels. Differentiation in consumer demographics and market power across retail channels leads to variation in menu costs, consumer search costs, consumer price sensitivity and market power, all potentially resulting in different degrees of price transmission and asymmetry.

Panel A in Table 9 shows the results of equation (5), and the percentage changes from Panel B are also plotted in Figure 6 with 95% confidence intervals. The response in retail peanut butter prices to the farm peanuts rose was immediate with 22.5% and 20.1% increase in retail prices during the first and second year, respectively, after the start of the shock. However, the response in retail prices after the end of the spike was much more gradual. Retail prices stayed 11% higher

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Table 7. Price aggregation robustness checks: retail peanut butter price change

	Brand Level	Store Level
Panel A.		
Shock	0.180***	0.208***
	(0.00281)	(0.00338)
Post-Shock	0.0920***	0.135***
	(0.00422)	(0.00403)
Brand Fixed Effects	Yes	No
Store Fixed Effects	Yes	Yes
Market Fixed Effects	Yes	Yes
Seasonal Fixed Effects	Yes	Yes
Constant	1.029***	0.623***
	(0.00224)	(0.00217)
Observations	393,678	175,197
R^2	0.520	0.379
Panel B corrects the estimates of interest to percentage change		
Shock	19.7%***	23.1%***
Post-Shock	9.6%***	14.5%***

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.
Notes: Robust standard errors in parentheses, and clustered at the market level. All regressions in this table utilize modified versions of equation (2). The first column aggregates retail prices to the brand-store-market level. The second column aggregates retail prices to the store chain-market level. Panel A is the raw estimates of examining the percentage difference in the retail price of peanut butter between pre-shock, shock, and post-shock periods. The first column controls for brand fixed effects, store chain fixed effects, market fixed effects, and seasonal fixed effects, and the second column controls for store chain fixed effects, market fixed effects, and seasonal fixed effects. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$ and reports the percentage change.

Table 8. Retail peanut butter price change by retail channels

Time period	Groc	Drug	Mass	Super	Conv	Dollar	Club	Other
Shock	20.1%	18.6%	24.7%	25.4%	9.7%	14.9%	26.8%	15.8%
Post-Shock	4.4%	13.5%	8.6%	8.9%	6.5%	7.3%	12.0%	6.8%

Notes: This table reports the final percentage change after converting the raw results of equation (3) that estimates the change in retail peanut butter prices between pre-shock, shock, and post-shock periods by retail channels. All estimates are statistically significant at the 5% level.

the first year after farm peanut prices returned to pre-shock levels and gradually returned to pre-shock levels by the fifth-year post-shock.

The second column of Table 9 uses nominal price as the dependent variable to test if nominal prices also follow a similar decline, and results indicate the response is even slower with signs of prices staying permanently higher even after year 5 at 14.7%. The persistence of the nominal retail prices supports the possibility that menu costs contribute to positive asymmetric price transmission as retailers retain higher peanut butter prices post-shock and allow inflation to gradually reduce the prices to normal in real terms (Ball and Mankiw, 1994). Finally, Table 10 shows percent

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Table 9. Main specification: retail peanut butter price change by year

Dep Var.	Log(Real Price)	Log(Nominal Price)
Panel A		
Shock Y1	0.203***	0.250***
	(0.00304)	(0.00303)
Shock Y2	0.183***	0.246***
	(0.00282)	(0.00282)
Post-Shock Y1	0.105***	0.185***
	(0.00280)	(0.00280)
Post-Shock Y2	0.0772***	0.160***
	(0.00264)	(0.00267)
Post-Shock Y3	0.0481***	0.140***
	(0.00311)	(0.00312)
Post-Shock Y4	0.0217***	0.134***
	(0.00437)	(0.00439)
Post-Shock Y5	−0.00191	0.137***
	(0.00617)	(0.00620)
UPC Fixed Effects	Yes	Yes
Store Fixed Effects	Yes	Yes
Market Fixed Effects	Yes	Yes
Seasonal Fixed Effects	Yes	Yes
Constant	0.993***	1.024***
	(0.00177)	(0.00179)
Observations	982,974	982,974
R^2	0.865	0.867
Panel B		
Shock Y1	22.5%***	28.4%***
Shock Y2	20.1%***	27.9%***
Post-Shock Y1	11.1%***	20.3%***
Post-Shock Y2	8.0%***	17.3%***
Post-Shock Y3	4.9%***	15.0%***
Post-Shock Y4	2.2%***	14.3%***
Post-Shock Y5	Not Sig	14.7%***

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

Notes: Robust standard errors in parentheses, and clustered at the market level. Panel A is the raw estimates utilizing equation (4) of examining the yearly shock and post-shock percentage difference in final retail price of peanut butter items after controlling for UPC fixed effects, store chain fixed effects, market fixed effects, and seasonal fixed effects. The first column uses the log of the real retail price as the dependent variable. The second column uses the log of the nominal price as the dependent variable. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$.

Table 10. Retail peanut butter price changes by retail channel by year

Time period	Groc	Drug	Mass	Super	Conv	Dollar	Club	Other
Shock Y1	22.0%	16.1%	25.9%	26.0%	Not Sig	18.7%	25.6%	15.7%
Shock Y2	18.3%	20.9%	23.5%	24.9%	15.0%	11.4%	28.2%	15.9%
Post-Shock Y1	9.6%	15.4%	12.8%	14.0%	10.1%	8.6%	17.5%	9.1%
Post-Shock Y2	6.1%	13.1%	10.1%	11.8%	11.0%	6.7%	11.8%	7.9%
Post-Shock Y3	2.4%	9.9%	8.3%	10.2%	Not Sig	8.6%	10.0%	4.0%
Post-Shock Y4	Not Sig	6.2%	5.2%	5.6%	5.8%	4.7%	8.4%	2.5%
Post-Shock Y5	Not Sig	13.9%	Not Sig	Not Sig	Not Sig	3.4%	5.7%	4.4%

Notes: This table reports the corrected percentage change after converting the estimates of equation (5) that estimates the yearly change in the shock and post-shock periods in retail peanut butter prices by retail channels. All estimates are statistically significant at the 5% level unless noted as Not Sig.

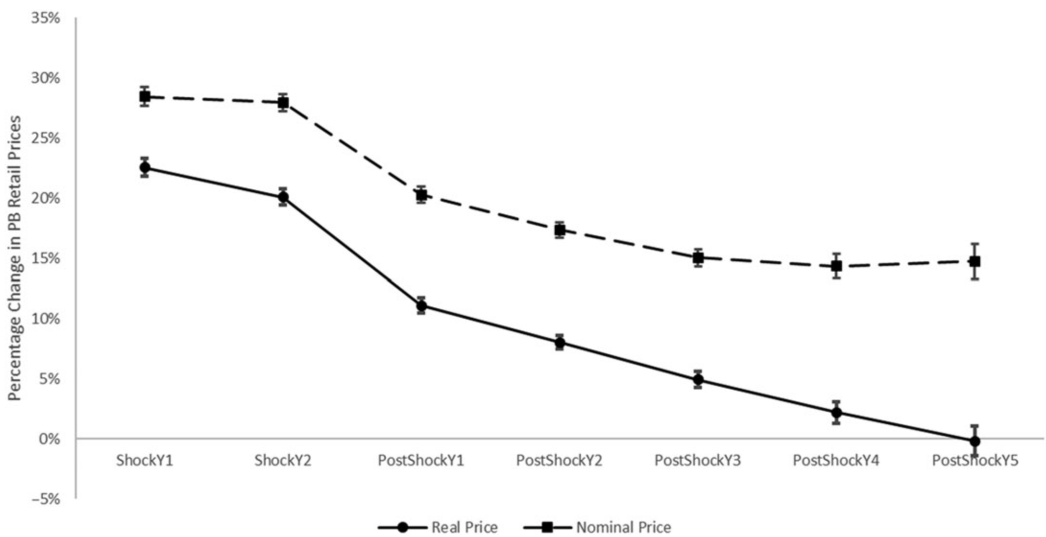

Figure 6. Yearly percentage change in retail peanut butter price with 95% confidence intervals.

change in retail peanut butter prices from pre-shock levels across retail channels. The trends in Figures 7 and 8 are consistent with our findings in Table 8 that convenience stores, drug, and dollars stores exhibited a smaller initial retail peanut butter price increase to the farm peanut price spike and a slower decline compared to other retail channels.

Having firmly established the long-term increase in retail peanut butter prices, we turn to its impact on consumers as specified by equations (6) and (7). In the first column of Table 11, households on average increased monthly expenditures on peanut butter by 21.9% during the shock period and by 4.8% during the post-shock period. The second column shows that households reduced total volume of peanut butter purchased by 1.1% and 0.8% during the shock and post-shock periods, respectively. The similar estimates on the increase in retail prices and increase in expenditure suggest that consumers are relatively price inelastic for peanut butter as commonly observed in the existing literature (Bakhtavoryan, Capps, and Salin, 2014) and did not substantially reduce the quantity of peanut butter purchases due to the price increase.

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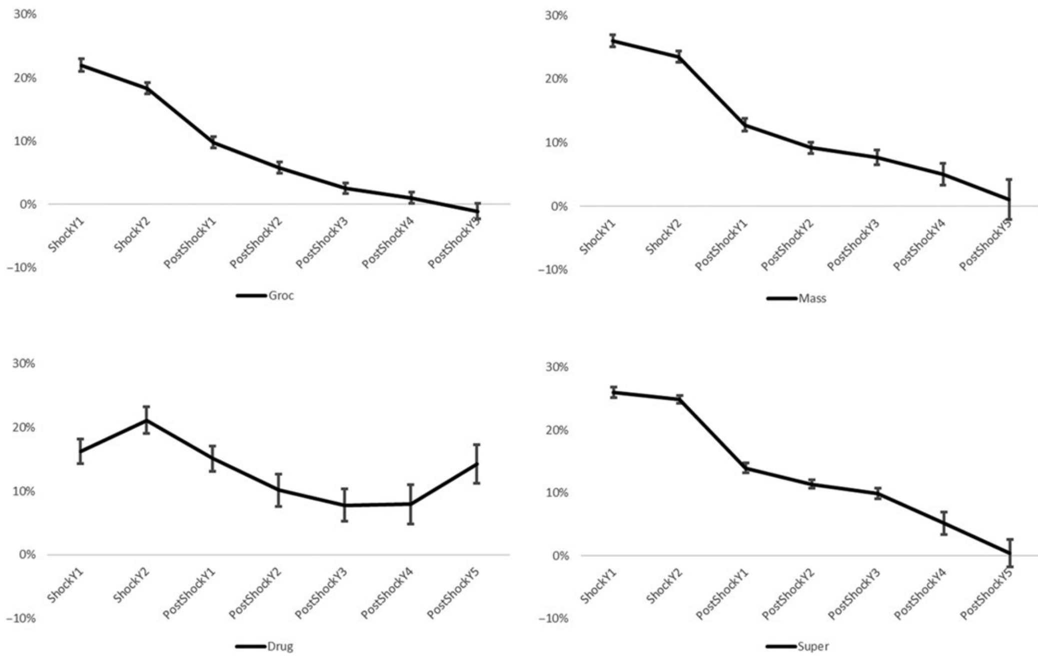

Figure 7. Retail peanut butter price change by year by retail channel.

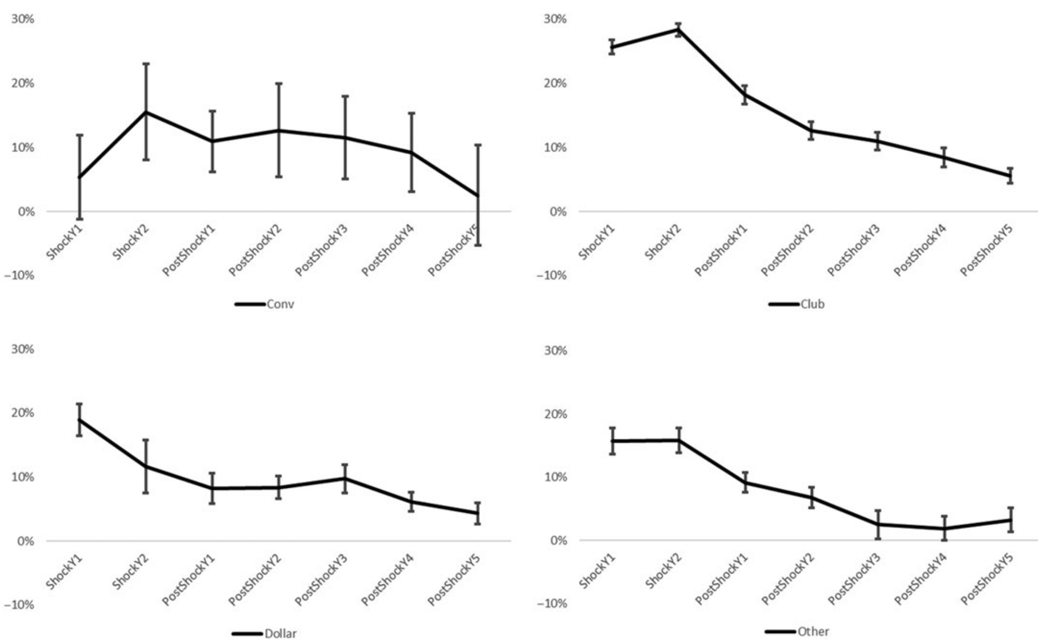

Figure 8. Retail peanut butter price change by year by retail channel.

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Table 11. Consumer impact of retail peanut butter price change

Dep Var.	Log(Expenditure)	Log(Quantity)
Panel A		
Shock	0.198***	−0.0106***
	(0.00455)	(0.00320)
Post-Shock	0.0466***	−0.00788*
	(0.00522)	(0.00442)
Demographic Controls	Yes	Yes
Market Fixed Effects	Yes	Yes
Seasonal Fixed Effects	Yes	Yes
Constant	1.268***	3.452***
	(0.00296)	(0.00258)
Observations	2,129,083	2,129,083
R^2	0.046	0.032
Panel B corrects the estimates of interest to percentage change		
Shock	21.9%***	−1.1%***
Post-Shock	4.8%***	−0.8%***

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.
Notes: Robust standard errors in parentheses, and clustered at the market level. Panel A is the raw estimates utilizing equations (6) and (7) of examining the percentage difference in consumer expenditure and total quantity of peanut butter between pre-shock, shock, and post-shock periods after controlling for household demographics, market fixed effects, and seasonal fixed effects. Demographic controls include household size, income levels, race, Hispanic, age, marital status, and pet ownership. Panel B converts the estimates to percentage change using $\Delta\% = \exp(\beta) - 1$.

Table 12 uses equation (8) to estimate the heterogenous impact across income groups and shows that post-shock expenditure changes are generally larger for households in lower-income brackets with the lowest income households increasing their spending by 9% post-shock. As peanut butter is among the cheapest sources of protein, lower-income households are more likely to be price inelastic for peanut butter. The literature has also shown that compared to higher-income households, lower-income households generally pay lower prices for the same goods because they often buy during sales and shop at cheaper stores (Broda, Leibtag, and Weinstein, 2009). However, when peanut butter prices increase, higher-income households have the option to buy more during sales and switch to cheaper stores when peanut butter prices increased to partially offset the price increase, while lower-income households are already exercising these options. Finally, lower-income households are more likely to purchase food items and peanut butter at dollar and convenience stores, more often the only option in low food access and rural areas and thereby able to exert more pricing power as spatial monopolies (Bitler and Haider, 2011).

Using these estimates, we perform a simple calculation to estimate the order of magnitude of the short-term and long-term impacts of the peanut drought on consumers. USDA ERS estimates 3.9 pounds of peanut butter produced per capita per year, which combined with an average pre-shock price of peanut butter of \$2.09 per pound corresponds to \$8.15 spent on peanut butter per capita per year. Multiplying per capita peanut butter expenditure by the U.S. Census Bureau's total U.S. population estimate of 310 million gives \$2.527 billion in total U.S. annual peanut butter expenditure. During the shock, peanut butter prices increased by 21.3%, which equates to \$538 million per year ($0.213 \times$ \$2.527 billion), and \$1.08 billion for the 2 years of drought.

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Table 12. Post-shock consumer impact of retail peanut butter price change by income

Annual Income Brackets	Post-Shock Expenditure
0 to \$9,999	9.0%
\$10,000 to \$11,999	8.4%
\$12,000 to \$14,999	7.9%
\$15,000 to \$19,999	4.5%
\$20,000 to \$24,999	5.5%
\$25,000 to \$34,999	4.8%
\$35,000 to \$44,999	5.6%
\$45,000 to \$49,999	5.6%
\$50,000 to \$59,999	3.9%
\$60,000 to \$69,999	3.8%
\$70,000 to \$99,999	4.3%
>\$100,000	4.0%

Notes: This table reports the corrected percentage change after converting the estimates of equation (8) that estimates the post-shock increase in consumer expenditure on peanut butter across varying income brackets. All estimates are statistically significant at the 5% level.

After the shock, the 6.2% average increase in the price of peanut butter equates to an increase of \$157 million in peanut butter expenditure (0.062 × \$2.527 billion). Retail prices lingered above pre-shock levels for at least 4 years after the shock ended costing consumers an additional \$628 million in the long-term.

6. Conclusion and Policy Implications

Droughts, floods, and drastic temperature changes can lead to significant impacts on agriculture and human welfare. Drought and poor agricultural management led to the U.S. Dust Bowl, resulting in drastic reductions in the value of agricultural land, production, and population decline (Hornbeck, 2012). In modern day Somalia, Maystadt and Ecker (2014) find evidence of conflicts stemming from extreme weather-driven livestock price shocks. The 2011 severe peanut drought serves as a quasi-natural experiment that allows us to examine how modern consumers in developed countries can be negatively impacted for years after a weather shock impacting agricultural production.

We find that the 2011 peanut drought increased retail peanut butter prices by 21.3% and that the subsequent restoration of retail peanut butter prices to pre-drought levels was much slower as retail peanut butter prices remained on average 6.2% higher 4 years after farm peanut prices returned to pre-drought levels. We also identify heterogeneity in consumer impact with lower-income consumers increasing peanut butter expenditures the most. A simple calculation estimates that consumers paid an additional \$1.08 billion for peanut butter during the drought and an additional \$628 million over the 4 years before prices returned to pre-drought levels.

As the frequency of extreme weather events, especially severe droughts, continues to increase (Peterson et al., 2013; Sheffield and Wood, 2008), so does the possibility of extreme weather shocks that pass through to retail prices. We show that the cost impact of a severe weather event can be more salient in both length and magnitude than traditionally assumed. In contrast to previous studies which have focused on the short-term impacts of weather, supply, and price shocks, this article establishes evidence of positive asymmetric price transmission in retail food persisting up to 4 years with substantial, long-term consequences for consumers. Although this article has focused on peanuts and peanut butter, previous research indicates that much of the U.S. food sector is highly concentrated with positive asymmetric price transmission likely to be the norm rather than the exception. Extreme weather shocks on other food retail prices may result in similar lingering impacts on consumers.

Policy makers may note that this article sheds light on an often-overlooked cost of extreme weather events. The direct economic costs of extreme weather events have been well studied in the literature with estimates ranging from $9.5 billion to $30 billion (Smith and Matthews, 2015) from crop insurance payouts and lost agricultural input cost. Our results indicate that the 2011 peanut drought imposed at least an additional $1.7 billion in cost to consumers due to increased peanut butter prices. Furthermore, the direct costs of extreme weather are often mitigated by insurance, emergency aid, and other government programs (Davlasheridze, Fisher-Vanden, and Klaiber, 2017; Deryugina, 2017; Deryugina, Kawano, and Levitt, 2018; Gallagher and Hartley, 2017). However, no existing programs currently attempt to mitigate the effects of food price increases from extreme weather to consumers.

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