

A Sticky-Price View of Hoarding *

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Abstract

Governments worry that household hoarding of staple foods during times of high prices destabilizes commodity markets. The conventional view has hoarding—due to consumer precaution or panic—amplifying supply shocks and creating shortages. Using U.S. store-scanner data during the 2008 Global Rice Crisis, we reject this narrative. Areas with rice-eating populations had more hoarding but no difference in store price dynamics or stockouts. We find support instead for a reverse-causal channel, whereby sticky store prices lead to hoarding. Anticipating higher prices, rice-eating households bought rice from slow-to-adjust stores that implicitly offered promotions. Policy implications differ across these two views.

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1 Introduction

Household hoarding of staple foods—defined as the accumulation of inventories during times of high prices—has long been a concern of governments, particularly in developing countries. For instance, Roman Emperor Julian blamed hoarding for creating artificial shortages and famine in Antioch in 362 A.D. (Gráda, 2009). Hoarding is conventionally portrayed as a precautionary or panicked response by households to supply shocks, leading to price-inelastic consumers who amplify price shocks. This narrative has been of interest to economists dating back to Adam Smith¹ and has been invoked as a key factor in a number of catastrophic shortages. A prime example is the disastrous Bengal Famine of 1943, as discussed in Amartya Sen’s influential *Poverty and Famines*.

Under the conventional view, amplification from hoarding both destabilizes local markets and contributes to global commodity fluctuations. For instance, gas-hoarding by consumers during the energy crises of the 1970s is commonly accepted to have amplified prices at the pump, which then fed back into higher oil prices globally. Historian Priest (2012) writes: "Motorists, whose consumption of gasoline rose from 243 gallons per capita in 1950 to 463 gallons per capita in 1979, compounded supply problems by hoarding fuel, idling their engines in gas lines, and frantically topping off their tanks with frequent trips to the local filling station." Put simply, this view has consumer hoarding on the right-hand side leading to higher prices or scarcities on the left hand side. Accordingly, governments typically respond to hoarding episodes as they did during the energy crisis: by imposing anti-price-gouging laws or other measures aimed at protecting fearful consumers and forcing producers to maintain supply.

The focus of our paper, the 2008 Global Rice Crisis, is widely thought to illustrate exactly this channel: causality running from household precaution to prices. Governments and the media blamed panic for exacerbating the price response following an otherwise ordinary supply shock, which occurred when India banned exports of rice in late 2007 (see, e.g., Dawe & Slayton, 2010; Slayton, 2009). International commodity prices for rice surged between January and June 2008 before crashing by nearly 50% in July 2008 following news of untapped supply from Japan. Retrospectives on this episode emphasize a fear narrative ("How Fear Turned A Surplus into Scarcity," *National Public Radio*, November 4, 2011). In developing countries such as the Philippines—which faced riots due to rising rice prices—governments pushed anti-price-gouging or anti-profiteering policies aimed at producers or merchants. Hoarding eventually even reached the U.S. ("A Run on Rice in Asian Communities," *New York Times* May 1, 2008). Google searches for "rice" spiked in the month of April 2008.

However, despite the popularity of this narrative, and a large body of research on the role of institu-

¹See, e.g. Book 1 (Chapter 7) of *The Wealth of Nations*

tional speculators in the commodity bubble that preceded the financial crisis (see, e.g. [Kilian & Murphy, 2014](#); [Hamilton, 2009](#); [Tang & Xiong, 2010](#); [Singleton, 2013](#)), there is little work we know of that systematically assesses the impact of *household* hoarding on the price of staples. In other words, does hoarding actually lead to higher store prices which then feedback to higher commodity prices? While recent commodity price research emphasizes the role of institutions and financialization,² the role of households has remained unexplored. As Kenneth Arrow wrote in his review of Sen's book "when situations of scarcity arise, hoarding is always blamed. But the evidence for the degree and effects of hoarding is usually difficult to come by. . ." ([Arrow, 1982](#)).

We are able to directly study hoarding and test the household precaution narrative in the context of the 2008 Rice crisis in large part because of the availability of detailed micro-data from Nielsen. Data on shelf prices allow us to see exactly what consumers face, rather than relying on commodity or wholesale prices. Further, panel data on quantities—household purchases and store sales—allow us to directly measure hoarding behavior, as opposed to using indirect aggregate proxies that might conflate purchases by retailers, wholesalers, and households. Such quantity data also allow us to measure potential stockouts of rice due to hoarding, and to compare patterns in other placebo goods. Finally, and perhaps most critically, the granular nature of both price and quantity data allow us to analyze *cross-sectional* differences across locations—for example, comparing price dynamics in counties with different levels of hoarding.

As a baseline, we find substantial evidence of household hoarding across the US: there were abnormally large quantities of rice sold by stores and purchased by households in April and May of 2008, coinciding with the peak of global rice prices. These hoarding patterns are heterogenous across locations, with substantial sales concentrated in counties with high rice consumption (proxied either by ex-ante per-capita purchases or on the basis of demographics). However, areas with the most severe hoarding intensity *did not* experience larger price adjustments, as would be predicted by a narrative in which precautionary hoarding amplifies prices. If anything, these areas experienced smaller price increases on average.

One worry is that a lack of price adjustment may simply be an artifact of stale prices due to stockouts, i.e. that many consumers were simply unable to buy during hoarding periods ([Weitzman \(1991\)](#)). Household panel data suggests that this is not the case. Households were more likely to purchase rice during April and May of 2008 as compared to other months, and were also more likely to purchase large quantities of rice. Furthermore, there is no evidence that areas with more significant hoarding experienced differential stockouts. Given this, and our evidence on prices, the standard causal channel in which precautionary hoarding amplifies a supply shock seems inaccurate.

²See also [Gorton et al. \(2013\)](#) and [Fama & French \(1987\)](#) on the more general on the relationship between inventory and commodity prices.

As an alternative, we propose a narrative in which sticky prices on the right-hand side lead to hoarding on the left-hand side. We find that both global and U.S. wholesale prices led retail shelf prices by a number of weeks, consistent with the large macroeconomic literature on sticky store prices (see, e.g., [Bils & Klenow, 2004](#); [Nakamura & Steinsson, 2008, 2013](#)). Wholesale prices spiked following the Indian export ban, and remained permanently above pre-ban prices in the wake of news from Japan. Store level prices saw no immediate spike, and only slowly rose to match the increase in international prices. Furthermore, this rise was asynchronous across stores, resulting in price dispersion from the perspective of households.

Given the slow response of shelf prices, and the substantial media attention devoted to rice supply disruptions in this period, we hypothesize that hoarding is simply anticipatory stockpiling. Consumers—foreseeing coming increases implied by wholesale prices and news stories—shift their demand dynamically and purchase from slow-to-update stores.³ Seen through this lens, consumers view sticky shelf prices as implicit promotions by retailers, and respond as they would to any temporary retail sale.

Consistent with this sticky-price hypothesis, we find that consumer hoarding in April and May of 2008 coincided with the peak of wholesale rice prices but *preceded* any increase in retail rice prices. Furthermore, we find that household demand was actually *more* price elastic during this hoarding episode: stores that were relatively slow to adjust saw the greatest sales. In addition, counties with stores that updated relatively quickly on average did not see a difference in sales overall. These findings stand in contrast to models of panic or precautionary hoarding—particularly those involving a feedback loop between prices and hoarding—which imply consumers becoming *less* elastic during hoarding episodes. That is, absent sticky prices, i.e. if prices were higher, these elasticities suggest that there would be much less or no hoarding.

The traditional precautionary narrative has consumers bearing the costs of hoarding episodes, with benefits either accruing to retailers through high prices, or dissipating as a result of the misallocation of goods to early actors. Alternatively, in our sticky-price view, the failure of retailers to update prices actually benefits consumers, who are able to buy and store rice at low prices instead of paying the high prices suggested by the wholesale level. This beneficial strategy comes at the cost of stores. We provide back-of-the-envelope calculations that suggest that a typical store lost on the order of \$50 per week by failing to adjust prices in the face of anticipatory stockpiling at the peak of the hoarding period. Given the approximately 40,000 stores that sell rice in the US, we estimate that retailers lost roughly 8 million dollars on aggregate during the most intense 4-week period. Our analysis suggests that government policies aimed at restricting sellers would only make prices stickier and encourage more hoarding.

As a final empirical exercise, we use an event study to further distinguish the traditional narrative from

³There is related evidence that changes in state sales tax, when enough media attention is given, results in consumers responding to and optimizing over these taxes ([Baker et al., 2017](#)).

our sticky price view and to pin down the source of sticky prices. Our household panel data records the type of store in which rice purchases are made, including an indicator for warehouse outlets such as Sam's Club or Costco. On Wednesday April 23, 2008, Sam's Club announced that they were limiting members to four supersized bags. In the precautionary view, hoarding should precede either rationing due to scarcity and higher prices. Our event study finds the opposite. The Sam's Club announcement on a Wednesday was followed by a spike in household purchases the following weekend.

Our event study also helps us to distinguish between potential explanations for why prices were sticky. There are at least three widely-used models of sticky store prices: menu costs (e.g. [Barro, 1972](#); [Sheshinski & Weiss, 1977](#)), costly attention or information gathering (e.g. [Mankiw & Reis, 2002](#); [Woodford, 2009](#)), and customer anger (e.g. [Rotemberg, 2005](#); [Nakamura & Steinsson, 2011](#)). Given the magnitude of the international and wholesale price change, it is difficult to rationalize the observed price dynamics in a menu cost model. We also find inattention difficult to square with the data for two reasons. First, futures markets reflected information about the persistence of the supply shock: the prices and volatility of July and September rice futures contracts peaked around April 23rd. These futures markets serve as a relatively cheap venue for gathering information. Furthermore, the revealed choices of Sam's club and other retailers to announce quantity restrictions indicates that they were aware of the supply disruption before any consumer hoarding took place. As such, our results suggest that concerns regarding customer anger may be the most likely explanation for sticky prices during this period.

One way of framing the precautionary narrative is that households act as hedgers in commodity markets: that is, that households overbuy at relatively high prices as a form of insurance, and thereby lose money in expectation. Our evidence instead points to households as more akin to competitive arbitrageurs ([Scheinkman & Schechtman, 1983](#); [Deaton & Laroque, 1992](#)) who take advantage of mispricing at the retail level—rather than in commodities markets—for personal profit. In other words, we do not observe households who hoard losing money, but rather gaining money on average. Our analysis also highlights the dangers of equating store prices and raw global prices: we find that the prices consumers faced had little direct relationship with aggregate prices, and that household hoarding had little feedback into those prices. Instead, hoarding is simply the consequence of sticky prices in the presence of cost shocks.

Our paper proceeds as follows. In Section 2, we briefly relate our paper to several literatures beyond hoarding. In Section 3, we provide background on the 2008 Global Rice Crisis. In Section 4, we describe the data. In Section 5, we test the panic narrative for hoarding. In Section 6, we provide evidence for the sticky-price view. We conclude in Section 7.

2 Related Literature

Our paper is related to and contributes to several literatures outside of the study of hoarding and commodity markets. The mechanism causing consumers to hoard is reminiscent of the recent literature on the importance of anticipatory stockpiling when stores run promotions (see, e.g., [Hendel & Nevo, 2006](#)). This work finds that temporary promotions for storable goods like rice generate larger increases in sales than would be implied by static consumption elasticities. This is because consumers dynamically adjust, shifting their purchases forward in time. Furthermore, as in the hoarding period we study, consumers tend to be more price elastic during promotions. That is, the degree of stockpiling is particularly sensitive to the size of the discount. A key challenge in this literature comes in separately identifying the static elasticity and the stockpiling effect, which are typically conflated in observed consumer responses to a price decline. However, in our context, a stockpiling incentive is generated by stores' delayed reaction to a price *increase*, meaning that we expect no static consumption response, and any permanent income effects will bias us against finding a stockpiling effect. In this sense, our setting allows for relatively clean identification of dynamic demand effects.

Our analysis is also relevant to two outstanding questions in the large literature on sticky prices: what are the causes of sticky prices and what are the costs? [Gorodnichenko & Weber \(2016\)](#) argue for the need to gather evidence on costs that are robust to particular macro-economic models. They use the reaction of stock prices to inflation announcements to quantify these costs. We are explicitly able to estimate a back-of-the-envelope cost for store losses. Furthermore, our event study on warehouse clubs provides even more direct evidence for customer anger as a cause of sticky prices, as opposed to menu costs or rational inattention.

Finally, our paper is related to recent work showing that store prices are sticky even in the aftermath of disasters, be it earthquakes, hurricanes or snowstorms (e.g. [Cavallo *et al.*, 2014](#); [Gagnon & Lopez-Salido, 2014](#)). Rightly, these papers use these disasters as a proxy for a demand shock. Households naturally might want to purchase staples ahead of time since restaurants may be closed and travel may be difficult. Stores, in turn, might not raise prices during times of peak demand to avoid customer anger or due to loss-leader pricing strategies (see, e.g., [Chevalier *et al.*, 2003](#)). However, because it is difficult to separate supply shocks caused by a disaster from these demand shocks, it is hard to isolate pure anticipatory motives for stockpiling in these episodes. An advantage of the 2008 rice crisis is that it allows us to focus on a pure supply shock and rule out conflicting demand channels.

3 Background

Rice is the main food staple for billions of people and global supply is subject to significant regulations from governments around the world. Consequently, international rice prices often exhibit distinct patterns relative to other commodities. As described in [Dawe & Slayton \(2010\)](#) and [Slayton \(2009\)](#), the 2008 Global Rice Crisis was triggered by India's politically motivated 2007 ban of rice exports, and continued until Japan agreed to release their rice reserves to global markets in mid 2008.⁴ Figure 1 plots the international price of rice over this period, and reflects these events: a sharp increase following the first vertical line, which represents the Indian ban on exports in October 2007, and a correction corresponding to the second vertical line, which represents the Late May 2008 news of an agreement by Japan.

Notice that this boom-bust price pattern is disconnected from fluctuations in energy or other commodity prices during this period. The price of oil began to rise in 2005, peaked in late 2008, crashed in 2009, and recovered in 2010. Conversely, the price of rice was relatively flat until the India Ban was announced, and crashed well before the price of oil. Moreover, even after the price of oil recovered it did not track the price of rice, which remained largely subject to government regulation. This is a fairly particular feature of rice when compared to other food staples—for example, barley, corn, and wheat—which track the price of oil much more closely. Despite this, coverage of the rice crisis got lost to some extent in the shadows of the generalized energy crisis.

Because of the disconnect between the boom-bust pattern in rice prices and more general commodity price fundamentals, prevailing narratives of the rice crisis suggest that hoarding generated artificial shortages and drove up prices. Evidence for this precaution narrative has been largely anecdotal, based primarily on hoarding episodes in different countries. Notably, there were numerous media reports of hoarding and related events between India's October 2007 ban and Japan's 2008 agreement:

- March 2008: Egypt
- April 2008: Phillipines, Haiti, Vietnam, Indonesia, Brazil, U.S.

April 4: Food riots in Haiti due to spiking rice price

April 12: UN peaceworker killed

April 15: Phillipines government asks for an emergency meeting

April 23: Warehouse clubs like Sam's Club and Costco limit purchases of large bags of rice⁵

⁴The supply of rice from Japan has traditionally been withheld from world markets through a trade agreement between the US and Japan that mandates that Japan buy US rice.

⁵CNN report "Skyrocketing rice prices has Sam's Club limiting sales" April 24, 2008.

By the end of April, hoarding had spread to the U.S. Rationing by warehouse clubs on April 23 is typically interpreted as a response to hoarding in April. Indeed, Figure 2 shows a search volume index on Google Trends for “Rice.” The black line displays weekly intensity of Google searches for “Rice” in the US between 2007-2009. 100 is normalized as the highest intensity over the period. The red line denotes the week of April 20th, 2008. There is a spike in search volume interest in April consistent with wider interest among media and households over this same period.

However, in the absence of detailed and timely data on household purchases and shelf prices, testing these prevailing narratives is challenging. Consumers face prices in retail stores that can differ significantly from aggregates. While global prices are determined in commodity markets, shelf prices are set by stores with a variety of strategic considerations. While standard narratives rely on a correspondence between global and retail prices, this connection need not hold in general. We now turn to describing micro-data that allow us to unpack this relationship.

4 Data

Our primary sources of store and household data are the Nielsen datasets held at the Kilt’s Center. Store scanner data includes prices and quantities sold at the product level from thousands of retail stores. We restrict our sample to the years of 2007-2009, and include weekly data on just under 9000 unique stores. While detail on a wide variety of rice products are available—which differ by brand, bag-size, and type—we aggregate these to create two primary variables of interest. The first is straightforward: the total volume of rice sold in ounces across all products. The second, price, is slightly more complicated. To aggregate across products to a single store level price index, we take a sales weighted average across all products, normalized to 80 ounces. Results are robust to alternative aggregates, for example the average price for an 80-ounce bag. We merge on demographic information at the county (FIPS Code) level. Panel A of Table 1 presents summary statistics on store level data. The average store sells approximately 8500 ounces of rice per week, with an average price of \$5.37 per 80 ounces. On average, median income in the counties in which the stores are located is just over \$57,000, and just under 5% of the county population is Asian.

The household panel has over 100,000 demographically balanced U.S. households who use hand-held scanners to record every bar-coded grocery item purchased. The broader dataset runs from 2004-2009 and records every purchase made at the Universal Product Code (UPC) level. There is also detailed demographic information. Appendix Figure A.I plots the distributions of the various demographics of the Nielsen Panel. There are on average 2.6 household members, and the average age is approximately 50 years. Median household income is around \$48,000 dollars, and most of the sample has some college education. Consumers in

the panel stay on for an average of three years, and there are approximately 18,000 households with five or more years of purchase histories.

We restrict our panel to households who appear at least once in each year from 2007-2009, and who buy rice at least once over this period. This leaves us with just over 1.1 million monthly observations on roughly 42,000 households. We construct quantity purchased by households by aggregating over all rice purchases at the household level. Panel B of Table 1 presents summary statistics on our restricted household sample. The average quantity purchased by a household in a given month is approximately 10 ounces, although households typically purchase about 80 ounces in months in which they actually buy rice. Average household income is just under \$59,000, and the average household has just over 2.5 people.

5 Tests of the Precautionary View of Hoarding

In this section we conduct a series of tests of the standard precautionary narrative. In other words, we ask whether consumer hoarding generates price increases and goods shortages. To do so, we exploit the richness of our data to test the most natural cross-sectional implications of this narrative: If the narrative is true, we should expect the locations that experience the most intense hoarding to see the most significant price increases and shortages. Our analysis proceeds in three steps. We first confirm that there was indeed a significant hoarding episode in late April and early May of 2008, and that the extent of hoarding differed across geographic locations. We then use disaggregated store level price and quantity data to show that there was no differential price increase in stores located in locations that experienced the highest degree of hoarding. Finally, we use our household panel to show that consumers were not more likely to face stockouts—i.e. to face quantity constraints—in areas that saw significant hoarding.

5.1 Behavior of Store Sales and Prices

We begin our analysis by confirming the existence and extent of the hoarding episode in U.S. retail stores. The first column of Panel A in Table 2 shows the results of a simple regression of weekly store level rice sales on a dummy variable equal to one for all stores during the hoarding period. In our weekly data, we define this to be the weeks of April 19th to May 10th. We further include store and week-of-year fixed effects (i.e. 52 week dummies, to control for seasonality). Our sample includes all store-weeks between 2007-2009, and we cluster standard errors at the county level. The coefficient suggests that, during the hoarding period, stores sold 3780 additional ounces of rice per week on average, which represents an approximately 45 percent increase over the mean. The estimate is highly significant.

The extent of hoarding is perhaps easier to see in the solid black and red lines presented in all three panels

of Figure 3. These present average store level sales in ounces, with the sample split into two geographic groups in each panel. Even without detail on the make-up of these groups, an aggregate pattern is clear. There was a spike in quantity sold across geographies in the last weeks of April and first weeks of May of 2008.

The differences between the red and black solid lines in each of these panels highlights our next result: there was significant geographical heterogeneity in the *intensity* of hoarding during this period. In all three panels, the sample of stores is split into two groups. Black lines show averages for those in “high demand” areas while red lines show averages for those in “low demand” areas. In Panel A, we define “high demand” on an ex-post basis: the 10 states which saw the largest proportional deviation in quantity sold during the hoarding period. These states include Connecticut, California, Florida, Louisiana, Massachusetts, Nevada, New Hampshire, New Jersey, New York and Utah. By construction, the spike in the black line is larger than that of the red line, but the difference in magnitude is noticeable. Even in proportional terms, the increase in quantity sold in these high hoarding states was more than double that of other states.

The solid black and red lines in Panels B and C repeat this exercise with ex-ante definitions of high demand areas based on pre-determined county characteristics. Panel B compares counties with large Asian populations—the top 5 percent of counties by fraction of population—to other counties. Because rice is a staple in the diet of many Asian American households, we expect these communities to have higher demand for rice, and to be more sensitive to fluctuations in rice markets. Panel C compares counties with above median per-capita rice purchases in 2007, the calendar year before the rice crisis. The solid lines in Panels B and C show the same pattern as in Panel A: even under these ex-ante definitions, “high demand” areas saw more hoarding than other areas.

The last three columns of Panel A in Table 2 show results from regression analogs of these plots. We display the coefficient β_1 from the following specification. For store i , in county j and week t we estimate:

$$\text{Volume}_{ijt} = \beta_0 + \beta_1(\mathbb{1}\{t \in \text{Hoarding Period}\} \times \mathbb{1}\{j \in \text{High Demand Area}\}) + \gamma_i + \delta_t + \epsilon_{ijt} \quad (1)$$

Our dependent variable of interest is again weekly store-level volume. Our primary regressor of interest is the interaction of an indicator for the hoarding period with a proxy for location j being a high demand area. Our three proxies are exactly those included in Figure 3: hoarding states, counties with a high proportion of Asian residents, and counties with above median rice purchases per capita in 2007. We include store fixed effects γ_i and week fixed effects δ_t . We cluster standard errors at the county level.

Across all three specifications, we see that our proxies for high demand areas indeed translate to larger and statistically significant increases in quantity sold during the hoarding period. The coefficient in the

second column suggests that high hoarding states saw a differential rise of just over 5000 ounces per week when compared to other states. The comparative increase in counties with high Asian populations is also large, at just over 4000 ounces. Similarly, stores in high rice consuming counties sold just over 3000 additional ounces per week during the hoarding period, on average, when compared to other counties.

We next show that these high demand areas—which experienced more hoarding—did not see differential increases in prices. The similar patterns in the red and black dashed lines in all panels of Figure 3 show the basic intuition behind this result. Again, black and red denote high and low demand areas, respectively, across our three definitions. While quantities purchased are sharply different during the hoarding periods across high and low demand areas, the price patterns follow roughly the same trajectories. In all panels, both lines follow a shallow upward trajectory—with the same slope—from early 2007 until the hoarding period. Subsequently, both rise for a short period following the hoarding episode, before converging to a new, higher level. The slopes are similar throughout, and the net increases appear the same. From the plots, the only noticeable difference is that overall price-level is lower in high demand areas.

In Panel B of Table 2 we show the same result in a regression format. To do so, we run the following cross-sectional specification:

$$\text{Price Increase}_{ij} = \beta_0 + \beta_1 \mathbb{1}\{j \in \text{High Demand Area}\} + \epsilon_{ij} \quad (2)$$

Here, $\text{Price Increase}_{ij}$ is defined as the difference between the maximum and minimum price from March to June, 2008. We consider three regressions using the same proxies for high demand areas described above. In all three, we find that high demand areas saw significantly *smaller* price increases between March and June, 2008 when compared to other areas. To give a sense of size of the difference, these high rice demand areas saw increases that were between \$0.17 and \$0.43 per 80oz bag of rice lower. All estimates are highly significant. In short, there is little compelling store price evidence to indicate that hoarding amplified the price effects of the supply shock.⁶

5.2 Evidence on Stockouts

While the previous subsection shows that there is no differential impact of hoarding on prices across locations, an alternative interpretation of the standard narrative has precaution initially impacting the market through quantity restrictions. In other words, higher hoarding in particular locations might destabilize the local market by exhausting retailer’s inventories, even without a price response.

⁶Our store price index is weighted by store sales. One might worry that the sticky prices could be driven by households substituting toward larger bags which have lower unit prices than smaller bags. This could then create the appearance of sticky prices even if prices were flexible. This is not the case, however, as results are similar using specific UPC product prices that are unweighted by sales.

In this subsection we exploit our household panel data to show that this sort of quantity response—which we refer to as a stockout—did not occur more frequently during the hoarding period, and did not occur differentially in the areas that experienced the most significant hoarding. We start in Panel A of Figure 4, where we plot the fraction of households in buying rice in each month. We see that the months of April and May 2018 had the highest proportion of households buying rice in our sample period. In other words, more households, not fewer, were able to purchase rice during the hoarding period.

In Panel B of Figure 4, we show that households also do not appear to have faced a constraint on the intensive margin. In this plot, we show the fraction of households purchasing rice at all quantities, from small bags to big bags, conditional on any purchase. This plot shows that, in addition to households being less likely to forgo purchasing rice, they were also less likely to purchase small quantities of rice. During the months of April and May, a smaller fraction of those purchasing rice chose small bags (below 80 ounces), a larger fraction chose to purchase effectively all larger quantities.

In Table 3 we display regression results to further support the findings in Figure 4, as well as a series of specifications to test whether there were differentially more stockouts in high demand areas. In both, we use our monthly household panel from 2007-2009. To show that stockouts were not more common during the hoarding period generally, we run the following specification for household i in county j and month t :

$$\text{Purchase}_{ijt} = \beta_0 + \beta_1 \mathbb{1}\{t \in \text{Hoarding Period}\} + \gamma_i + \delta_{m(t)} + \epsilon_{ijt} \quad (3)$$

In Panel A, we define Purchase_{ijt} to be a binary indicator for any purchase of rice. In Panel B, we define it to a binary indicator for the purchase of 80 or more ounces of rice. As the panel is monthly, we define the hoarding period to be the months of April and May 2008. We include household fixed effects γ_i to consider within-household variation and include month-of-year (e.g. January) fixed effects $\delta_{m(t)}$ to adjust for any seasonality.

The first columns of both panels show the results of this specification, indicating that a given household was more likely to purchase rice—and more likely to purchase a large bag of rice—during this period on average. In Panel A, our estimated coefficient suggests that the monthly probability of a household purchasing rice was 3 percentage points higher during the hoarding period. In Panel B, our estimated coefficient suggests that households were 1.8 percentage points more likely to buy more than 80 ounces of rice. Both results are highly significant.

To see whether there were differentially more stockouts in high demand areas, we run the following

specifications, again for household i in county j and month t :

$$\text{Purchase}_{ijt} = \beta_0 + \beta_1(\mathbb{1}\{t \in \text{Hoarding Period}\} \times \mathbb{1}\{j \in \text{High Demand Area}\}) + \gamma_i + \delta_t + \epsilon_{ijt} \quad (4)$$

Purchase_{ijt} is defined in panels A and B as described above, the hoarding period is defined as April and May of 2008. Here we include household (γ_i) and month (δ_t : e.g. January 2007) fixed effects. We once again use our three proxies for high demand area: hoarding states, counties with a large fraction of Asian residents, and counties with high per-capita rice consumption in 2007 in the second, third, and fourth columns, respectively, of both panels.

Across all three definitions—and both panels—we see no evidence of differential stockouts in high demand areas. While a negative coefficient would suggest that a lower fraction of residents were able to buy rice (using the definition of Purchase_{ijt} in Panel A) or able to buy a large quantity of rice (using the definition of Purchase_{ijt} in Panel B), we find tightly estimated 0 coefficients across all specifications. To summarize, the results in this table suggest that households were more likely to make purchases—and larger purchases—of rice during the hoarding period, and that this pattern does not differ in high demand areas. While we are unable to observe latent demand, and hence unable to directly observe whether or not any consumers were prevented from purchasing rice, the fact that household purchases increased on both the intensive and extensive margins provides evidence against such constraints. Given these findings—and our previous results on prices—we reject the cross-sectional implications of the precautionary narrative.

6 Tests of the Sticky-Price View of Hoarding

If hoarding does not cause price movements—as our cross-sectional evidence suggests—how should we interpret the relationship between prices and hoarding during the 2008 rice crisis and related episodes? We propose an alternative sticky-price narrative of hoarding, whereby sticky store prices on the right-hand side lead to hoarding on the left-hand side. A large literature in macroeconomics finds that store prices are slow to adjust to cost or supply shocks. This stickiness is present across countries for many goods and, as we demonstrate below, is also observable in rice prices. We posit that such sticky prices cause hoarding in the presence of persistent cost shocks for storeable goods. If retailers do not immediately respond to a cost shock, but consumers understand that it will be incorporated in prices eventually, then those consumers have incentive to stockpile. In this view sticky prices act, implicitly, as a temporary price-reduction or promotion. Consumers respond accordingly by shifting their demand forward in time and stocking up before prices rise.

In this section we offer two pieces of evidence supporting this view. We first show time series evidence that consumer hoarding in the US coincided with the peak of international commodities and wholesale rice prices, but significantly preceded the peak of US shelf prices. While straightforward, this analysis is only possible because we are able to distinguish store level prices and quantities from wholesale transactions. We then show that consumers actually appear to have been more price-elastic during this period, as they might in response to a retail sale, rather than less elastic, as a precautionary or panic narrative would suggest.

6.1 Time Series Evidence that Hoarding Anticipates Sticky Prices

Our first piece of evidence shows that volumes sold in stores significantly led retail prices, but coincided with spikes in wholesale prices. This pattern suggests that households were (i) cognizant of the broader rice supply shock, (ii) understood that, given sticky store prices, it was profitable to stockpile in anticipation of coming price increases. In other words, consumers front-ran retail prices for their own future consumption. We show this pattern in Figure 5. The red line displays a proxy for the wholesale price,⁷ which is quite similar to the international price pattern shown in Figure 1. The blue line displays the weekly average shelf price based on our store level rice price index. The black line displays average weekly sales at the store level, based on the scanner data. All variables are normalized by the average over the period shown: 2007-2009.

Notice that the retail or supermarket price, which is what consumers face, is sticky and lags the wholesale price of rice. This sticky price finding is unsurprising in light of the large body of work in macroeconomics documenting exactly these patterns. In particular, we note the similarity of our finding to work of [Nakamura & Zerom \(2010\)](#) on the gradual passthrough of wholesale coffee prices to retail coffee prices. The finding that shelf prices are sticky is true for stores around the world (see [Nakamura & Steinsson, 2013](#)). As such, we expect that similar patterns were evident in other countries. However, the critical finding in Figure 5 is that store sales volume leads sticky shelf prices. In other words, hoarding anticipates the gradual updating of shelf-prices.

In Figure 6, we display the fraction of stores that *updated prices* in the wake of the shock to international prices. A store is defined to have updated its price if the price is greater than 125 percent of the 2007 average. The red portion highlights the hoarding period: again the weeks from the 19th of April through the 10 of May 2008. Only a small fraction of stores updated their prices during this period of time. It took several months before a majority of stores updated their prices. This staggered price adjustment is also consistent with various models of store price setting. Note that an implication of this figure is that households faced dispersion in store prices of rice.

⁷The proxy is based on average f.o.b. price for long grain rice at selected milling centers in Southwest Louisiana. The data is provided by USDA, based on data from Agricultural Marketing Service's *National Weekly Rice Summary*.

6.2 Demand Elasticity Test

We next turn to the distinct implications of the precautionary and sticky price narratives for consumers demand elasticities. The precautionary narrative has clear predictions: consumers should become more price-inelastic during the hoarding period. Alternatively, under the sticky price narrative, consumers should not become more inelastic, and if anything may become more elastic, as in [Hendel & Nevo \(2006\)](#).

Consistent with this sticky-price view, household demand was more price elastic during the hoarding episode. In Figure 7, we show that there was excess hoarding at stores holding “sales” during the hoarding period—which we define as a price that is less than or equal to 90 percent of the store level January-February 2008 average. The solid black line displays the average store level quantity of rice sold in ounces for stores *holding promotions* during the middle and peak of the hoarding period: the week of the 3rd of May, 2008. The dashed black line displays the average store level price for these stores based on our store level rice price index. The dashed red line displays the average store level price in all other stores, while the dashed red line displays the average store level price for all other stores based on our store level rice price index. As the figure shows, average sales for stores holding sales at the peak of the hoarding period were roughly 30 percent higher.

In Figure 8, we show how relationships between price and quantity vary across months *within counties* over our sample period: 2007-2009. To do so, we display coefficients from the following regressions for store i in county j and month t :

$$\text{Quantity}_{ijt} = \alpha + \sum_{m=1}^T \left[\beta^m (P_{jt} \times \gamma_m) \right] + \gamma_t + \eta_i + \gamma_t \times \theta_j + \varepsilon_{ijt} \quad (5)$$

For these plots, both price and quantities are in levels (ounces for quantities, our index, normalized to an 80 ounce bag, for price). γ_t is a month fixed effect, η_i is a store fixed effect, and θ_j is a county fixed effect. Effectively, we use $\gamma_t \times \theta_j$ to account for any county month specific effect, and consider only variation in price across stores within a county and month. The coefficients we plot are β^m , the monthly relationship between price and quantity.

The plots show that in the months of the hoarding period, April and May 2008, there was a stronger negative relationship between price and quantity when compared to all other months (We highlight in red the months of the hoarding period: April, and May of 2008). Unsurprisingly, all months are negative, suggesting that *within a given county and month*, stores with higher prices sell lower quantities. The plots show, however, that this relationship was particularly strong during the hoarding period. This suggests that consumers may have actually been more elastic during the hoarding periods.

We next conduct a set of regressions to investigate this relationship more detail. To do so, we estimate

a slightly different version of the specification above. For store i in county j and week t , our most general specification is:

$$\text{Log}(\text{Quantity}_{ijt}) = \alpha + \beta \text{Log}(P_{jt}) \times \mathbb{1}\{t \in \text{Hoarding Period}\} + \gamma_t + \eta_i + \gamma_t \times \theta_j + \varepsilon_{ijt} \quad (6)$$

Effectively, we switch to weekly data to take advantage of the richness of the data, convert to logs to estimate coefficients that can be compared to traditional elasticities, and include a single interaction with the hoarding period (the weeks of April 19th-May 10th), rather than a full set of β coefficients for all months. Given that we have moved to weekly data, γ_t here represents a week fixed effect. In all specifications we cluster standard errors at the county level.

We show results from this specifications in Table 4. Across the first four columns, we gradually saturate with the fixed effects above to focus on variation coming from different sources. In the first column, we include no fixed effects to include all variation in prices, but do add a dummy variable equal to one during the hoarding period. Unsurprisingly, both price and the interaction of price in this regression are negative and large. In the second column, we further include store and week-of-year fixed effects, which causes both the coefficients to shrink substantially. The third column adds fixed effects for all weeks.

This third column emphasizes the increased magnitude of the price quantity relationship during the hoarding period. The coefficient on $\log(\text{Price})$ suggests that, on average, across the period, stores with one percent lower prices saw 0.92 percent higher purchases. However, the coefficient on $\text{Log}(\text{Price}) \times \text{Hoarding Period}$ suggest that a one percent lower price was associated with even higher purchases during the hoarding period: 1.05 percent. The difference between the two is highly significant. Give the fixed effects, this specification exploits cross-sectional variation in prices coming both within-counties, and across counties. While we do not explicitly isolate supply shifters, this approach suggests that consumers were overall more elastic during the hoarding episode.

The fourth column shows similar results when including $\gamma_t \times \theta_j$ fixed effects—in other words a fixed effect for each county \times week. This approach directly restricts to cross-sectional variation across stores *within* counties. Again, a 1 percent change in prices is associated with a change in quantities just below 1 percent on average, but the relationship is just under 0.20 percent more severe during the hoarding period. This suggests that within local areas, stores with relatively low prices sold significantly more during the hoarding period.

This greater price sensitivity is highly consistent with our sticky price narrative. For a given future price, consumers who see lower prices today face a large implicit promotion, and hence have greater incentive to stockpile today. Furthermore, to the extent there are fixed costs associated with traveling to or uncovering

the cheapest store within a county, consumers may be more likely to actively seek out cheaper stores during the hoarding episode.

At face value, this price sensitivity is also inconsistent with the precautionary narrative. However, one potential objection is that even if precautionary consumers are relatively inelastic—i.e. unwilling to change the overall quantity they purchase—they may be more willing to bear the search costs necessary to find a relatively cheap option locally. This might generate the large negative coefficient based on within-county variation shown in the fourth column of Table 4.

To address this possibility the fifth column displays a slightly different version of the above, focusing only on *across* country variation. To do so, we collapse our data to the county level and regress log total quantity at the county level on log average price at the county level, as well as average price interacted with the hoarding period. We include county and week fixed effects. Interestingly, while there is still a large negative elasticity on average across counties, there is no differential effect in the hoarding period. While this suggests that any increased elasticity during the hoarding period occurs across stores within counties, the crucial takeaway is that there is no differential *positive* difference during the hoarding period. In other words, there were not "panicking" counties, in which prices and quantities surged simultaneously. This result is difficult to reconcile with a story in which fearful or precautionary consumers are highly price-inelastic.

6.3 Estimates of Store Losses

A key feature of precautionary narratives is that consumers lose in hoarding episodes. Beyond the direct costs associated with a supply shock, hedging (or panic) cause households to overspend. However, in our sticky price narrative, stores bear additional incidence of the supply shock—and consumers actually benefit—during the hoarding period. Because stores maintain artificially low prices, consumers are able to stock-up at low prices rather than paying the post-supply-shock cost. Firms effectively subsidize this stock-up by failing to raise prices.

To estimate the cost of this subsidy, we roughly calculate the foregone profits store's lose out on not raising prices. To do so, we simply assume that excess purchases during the hoarding period would have also been made—perhaps more slowly—if stores had immediately raised prices to the ex-post level. After the episode, stores saw prices rise by approximately \$1.20 per 80 ounce bag. The excess hoarding during the period in question was 3780 ounces per week. Combining these, we find that the average store lost approximately \$50 per week due to anticipatory stockpiling. Giving the 9000 stores in our sample, this translates to roughly \$450,000 USD per week in-sample. Of course, we see only a subsample of stores, so

the aggregate impacts are much larger. Across the United States, there are around 40,000 stores that sell some rice. So the overall effects are much larger. Scaling up to account for these stores, we estimate aggregate losses of 8 million dollars during the intense 4-week hoarding period.

An important concern is whether these estimates and implications extrapolate to other settings outside the U.S., for example, in developing countries. We believe that our results are likely to be relevant in such contexts for at least two reasons. First, sticky prices are well documented in stores across both developed and developing markets. Second, there is nothing specific about U.S. consumers ability to anticipate future prices of staples. If anything, households in developing countries—where staples represent a larger fraction of household expenditures—may follow prices more closely.

6.4 Placebos

One question is the distinction between our paper and earlier work on sticky store prices in the aftermath of disasters, be it earthquakes, hurricanes or snowstorms (see, e.g., [Cavallo *et al.* \(2014\)](#), [Gagnon & Lopez-Salido \(2014\)](#)). A crucial difference is that those paper view such disasters as demand shocks, at least in part. Facing restricted access to roadways and potentially closed restaurants, many consumers stockpile staples during disasters. Evidence suggests that producers often do not raise prices during these times, and other periods of peak demand, perhaps due to loss-leader pricing strategies (see, e.g., [Chevalier *et al.*, 2003](#)). However, this demand shock interpretation makes it difficult to isolate a pure speculative or anticipatory motive for stockpiling.

To confirm that our findings were not driven by an aggregate demand shock for staples, and to test for potential substitution into other commodities during the rice crisis, we check to see whether a similar hoarding effect occurred in rice substitutes such as noodles, dumplings, and spaghetti. With a large enough run on rice, we might expect spillovers into rice substitutes.

Figure [A.II](#) indicates that there is no such spillover when we consider noodles and dumplings or spaghetti. In fact, aggregate sales of either category do not exhibit any abnormal increase around April and May 2008 when compared to similar periods in 2007 and 2009. Regressions similar to those we conduct in earlier subsections confirm this finding (if anything, we see slight decreases in purchases during these periods). In sum, our placebo tests using other staple foods like pasta or noodles do not find any discernible hoarding in this other staples.

7 Event Study: Why Sticky Prices

Our final exercise examines rationing at a small set of retailers: warehouse clubs, as a way of further distinguishing between hoarding narratives, and potentially providing insights into why prices may have been sticky. On Wednesday April 23rd, 2008, Sam's Club and Costco, the two dominant warehouse clubs, announced that they were instituting limits on the quantity of rice consumers could purchase. At Sam's Club, members were limited to four supersized bags of rice. This announcement came after international rice prices had risen, and was widely covered by media.

In the precautionary view, hoarding should precede scarcity, higher prices and rationing by these warehouse stores. In other words, stores like Sam's Club should ration because fearful customers hoarded and cut down their inventory. Alternatively, in a sticky-price world, rationing may be a countermeasure—taken by stores that are unwilling to increase prices—in order to avoid future inventory stockouts. In such a model stores recognize a supply shock and, worried about inventory but hesitant to raise prices, announce a rationing policy. Customers recognize that rationing portends coming price increases and engage in speculative stockpiling.

The key distinction between these two narratives is timing. In the first, rationing follows hoarding, in the second, rationing precedes hoarding. Fortunately, our household panel distinguishes between warehouses such as Sam's Club and other stores, allowing us to focus on this episode. Figure 9 shows that the warehouse clubs' announcement of rationing on a Wednesday came before a spike in household purchases over the weekend. This is consistent with our sticky-price view of hoarding.

This finding is also interesting from the perspective of the literature that considers the the nature of sticky prices. One strand suggests that customer anger is the likely explanation behind sticky prices (see, e.g., Rotemberg, 2005; Nakamura & Steinsson, 2011). as opposed to menu costs (see, e.g., Barro, 1972; Sheshinski & Weiss, 1977)) or costly attention or information gathering (see, e.g., Woodford, 2009; Afrouzi, 2017). Given that the cost shock led to price adjustments on the order of 50%, menu costs seem an unlikely explanation here (perhaps in contrast to standard inflationary settings). Moreover, the announcement of rationing by warehouse clubs indicates that retailers were aware of the rice supply shock, suggesting that costly attention stories are relatively unlikely. Furthermore, as we discuss below, the date of the rationing announcement was not random, but rather coincided with peak worries about supply in futures market. The fact that this futures market information was relatively cheap to acquire, and that retailers were evidently paying attention, provides further evidence against information gathering stories. As such, the customer anger explanation may be the most likely.

To confirm that the Sam's club announcement corresponded to peak worries in markets, we use prices

from US rice futures to infer the expectations of professional futures traders about the supply shock. The futures contracts for rice used in our analysis trade on the Chicago Board of Trade (CBOT) under the ticker symbol RR. The rice is typically for delivery in Arkansas. There are January, March, May, July, September, and November contracts. Our focus is on the months of April through June. Since the May contract—which is near delivery during the crisis—is less liquid than the July contract throughout the critical months in 2008, we take the July contract as our proxy for the nearby futures contract. The correlation between prices of the subsequent contracts (September and November) is quite high. Hence, we use the September contract as the “distant” contract and focus our analysis on the July and September contracts for expositional simplicity.

In Panel A of Figure 10, we plot the prices of these two futures contracts between March and July of 2008. Corresponding to the hoarding period, we see an increase in the price of both contracts. April 23, 2008 represents the peak of the futures prices, suggesting that the date of the Sam’s Club announcement is no accident. Stores likely recognized the information in futures markets when choosing rationing policies.

The volatility of futures prices also provides us an estimate of the risk of increasing rice prices. If the absolute level of volatility for the September futures prices is low, then it is a signal that the futures traders effectively think markets are back to normal. In Panel B of Figure 10, we plot out the term structure of futures price volatility. We use a 20-trading-day rolling window to calculate the standard deviation of continuously compounded daily returns for each contract. We find that the price volatility of the September futures actually crossed the price volatility of the July futures on April 7, 2008. This is an indication that futures market participants thought that the supply shock might be persistent. In other words, futures traders thought the supply shock might be serious in early April but then revised their expectations.

By mid-May, the volatility of the September futures was back to pre-crisis levels. The price volatility of the July futures eventually caught up to the September futures by the end of June. The pronounced drop in mid-May happened precisely on May 19, with news that an untapped supply had been found from Japan via an agreement with the United States. In other words, the futures market effectively did not think that there was much risk of price increases beyond this date. The relatively gradual rise in retail store prices after the drop in futures prices provides further evidence for sticky store prices.

8 Conclusion

In this paper we provide an alternative explanation for hoarding of food staples during supply shocks. In contrast to the traditional explanation—which emphasizes the role of precaution in leading to artificially high prices and shortages—we propose a reverse-causal channel, whereby sticky store prices lead to hoarding. Households, anticipating higher prices in the future, stockpiled rice from slow-adjusting stores. To

reject the traditional narrative, we exploit U.S. store scanner data during the 2008 rice-supply shock. The regions with the highest degree of hoarding saw no relative increase in store prices. We provide a variety of evidence that households were motivated to stockpile because they anticipated higher prices and were ex-ante and ex-post better off due to their timely purchases.

Policy implications differ across these two views. The conventional narrative places the blame on producers and stores and the cost on consumers. We show that, during this 2008 episode, stores actually lost revenues while consumers profited from speculative hoarding. Our analysis questions the automatic equivalence of store goods to wholesale or international prices. Consumers do not face wholesale prices, and hoarding at the store level did not cause the behavior of global prices. Instead, the difference between wholesale and shelf price patterns—coming as the result of sticky prices—provided customers with an incentive to purchase and store rice.

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TABLE 1: SUMMARY STATISTICS

	Panel A: Store Level Data			
	Mean	S.D.	Min.	Max
Volume (oz)	8461.9	19882.4	4	2815504
Price (80oz)	5.37	1.61	0.63	43.8
FIPS Population (1000s)	1173.4	2018.9	3.35	9840.0
Median Income (1000s)	57.2	15.5	22.4	120.1
Asian Fraction of Population	4.98	5.56	0	33.5
Total Stores	8870			
Weeks	156			
	Panel B: Household Panel Data			
	Mean	S.D.	Min.	Max
Quantity (oz)	10.1	57.0	0	10000
Quantity Cond. on Purchase (oz)	78.0	140.9	2	10000
Monthly Purchases	0.15	0.42	0	13
HH Income (1000s)	58.8	34.9	3	220
Household Size	2.58	1.33	1	9
Total Households	42172			
Months	36			

Summary statistics for store level and household panel data. Volume (oz) refers to volume sold at the store \times week level. Quantity refers to the total purchased by a household at the monthly level. Price is measured as the average unit price sold at the store \times week level, normalized to 80oz. Population, income, and race data are merged to stores at the county level.

**TABLE 2: CHANGES IN QUANTITY AND PRICE DURING HOARDING PERIOD
ACROSS HIGH VS. LOW HOARDING REGIONS**

Panel A: Changes in Volume During Hoarding Period				
Dependent Variable: Volume Sold at Store Level (Ounces)				
Hoarding Period: April 19th-May 10th	3780.121*** (234.026)			
Hoarding Period x Hoarding State		5058.750*** (536.972)		
Hoarding Period x Asian FIPS			4083.510** (1905.368)	
Hoarding Period x High Rice FIPS				3179.961*** (423.557)
Mean of Dep. Var.	8462.2	8462.2	8462.2	8462.2
N	2775809	2775809	2775809	2775809
Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	No	No	No
Week \times Year FE	No	Yes	Yes	Yes

Panel B: Changes in Price During Hoarding Period				
Dependent Variable: Store Level Price Change				
Hoarding State		-0.168 (0.129)		
Asian FIPS			-0.453*** (0.121)	
High Rice FIPS				-0.240*** (0.080)
Mean of Dep. Var.		1.33	1.33	1.33
N		8869	8869	8869

Panel A shows OLS regressions of weekly store level volume of rice sold in ounces on indicators for the hoarding period and the hoarding period interacted with 3 indicators for high demand locations. All weeks from 2007-2009 are used. The first column shows the coefficient on an indicator for the hoarding period—the weeks of April 19th-May 10th, 2008—and includes both store fixed effects and fixed effects for week of the year to control for seasonality. The remaining three columns include store and week \times year fixed effects, and show coefficients on the interaction between an indicator for the hoarding period and indicators that proxy for high demand locations. In the second column, our proxy is the set of states that experienced the largest proportional deviation in quantity sold during the hoarding period: Connecticut, California, Florida, Louisiana, Massachusetts, Nevada, New Hampshire, New Jersey, New York, and Utah. In the third column, our proxy is the set of counties with high Asian populations, defined as the top 5% of FIPS codes by proportion of population. In the fourth column, our proxy is the set of counties with above median 2007 rice consumption. Panel B shows cross-sectional OLS regressions of the maximum change in price during the hoarding period—defined as the difference between the maximum and minimum price between March and June, 2008—on the interactions included in the last three columns of Panel A. Standard errors are clustered at the FIPS county code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**TABLE 3: PROBABILITY OF STOCKOUTS DURING HOARDING PERIOD
ACROSS HIGH VS. LOW HOARDING REGIONS**

Panel A: Probability of Purchasing During Hoarding Period				
Dependent Variable: Household Purchases Any Rice				
Hoarding Period: April-May 2008	0.030*** (0.002)			
Hoarding Period x Hoarding State		0.000 (0.003)		
Hoarding Period x Asian FIPS			-0.005 (0.006)	
Hoarding Period x High Rice FIPS				-0.003 (0.002)
Mean of Dep. Var.	0.13	0.13	0.13	0.13
N	1182882	1182882	1182882	1182882
Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	No	No	No
Week x Year FE	No	Yes	Yes	Yes

Panel B: Probability of a Large Rice Purchase				
Dependent Variable: Purchase of 80oz or More				
Hoarding Period: April-May 2008	0.018*** (0.001)			
Hoarding Period x Hoarding State		0.002 (0.002)		
Hoarding Period x Asian FIPS			0.002 (0.006)	
Hoarding Period x High Rice FIPS				0.002 (0.002)
Mean of Dep. Var.	0.13	0.13	0.13	0.13
N	1182882	1182882	1182882	1182882
Household FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Month x Year FE	No	Yes	Yes	Yes

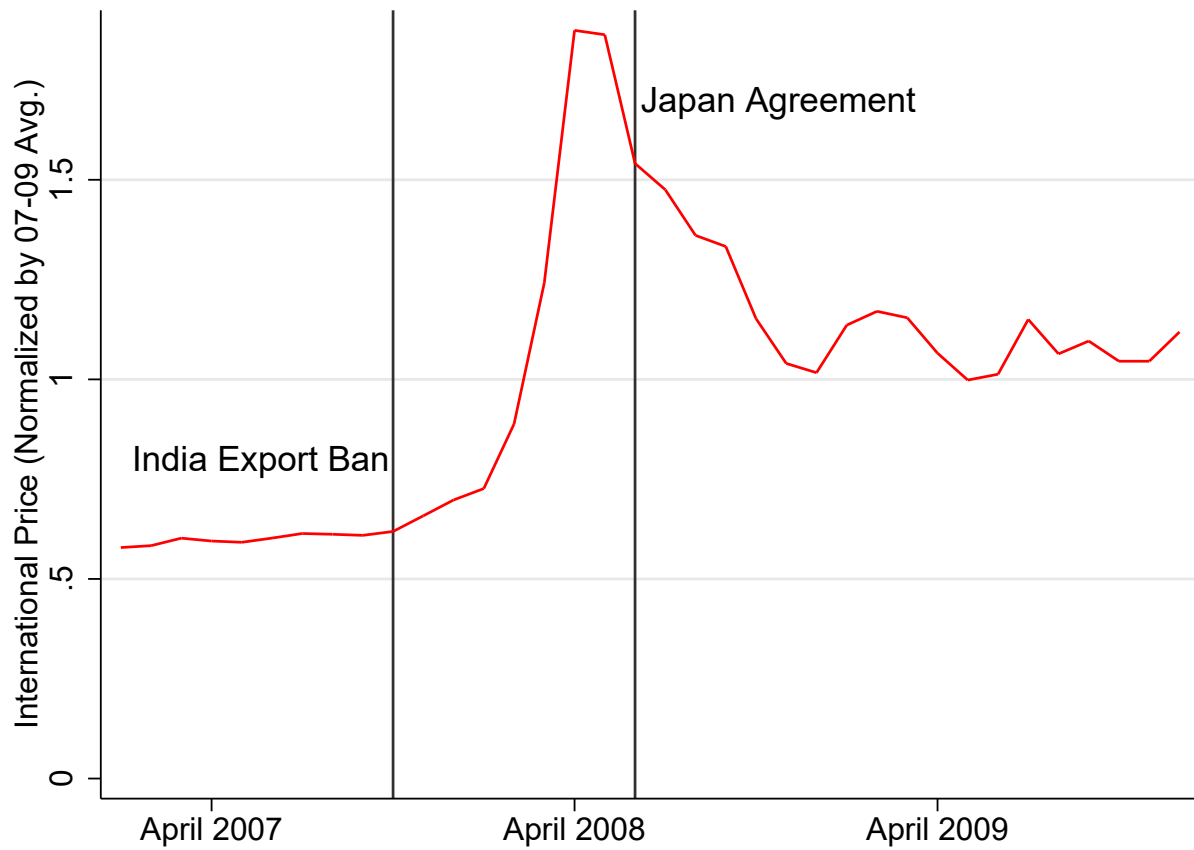
Panel A shows OLS regressions of an indicator for any purchase of rice at the household-month level on indicators for the hoarding period and the hoarding period interacted with 3 indicators for high demand locations. All months from 2007-2009 are used. The first column shows the coefficient on the hoarding period—the months of April and May, 2008—and includes both household fixed effects and fixed effects for month of year to control for seasonality. The remaining three columns include store and month x year fixed effects, and show coefficients on the interaction between an indicator for the hoarding period and indicators that proxy for high demand locations. In the second column our proxy is the set of states that experienced the largest proportional deviation in quantity sold during the hoarding period: Connecticut, California, Florida, Louisiana, Massachusetts, Nevada, New Hampshire, New Jersey, New York, and Utah. In the third column, our proxy is the set of counties with high Asian populations, defined as the top 5% of FIPS codes by proportion of population. In the fourth column, our proxy is the set of counties with above median 2007 rice consumption. Panel B repeats the exercise in Panel A, but with an indicator for a purchase of more than 80 ounces of rice at the household-month level as the dependent variable. Standard errors are clustered at the FIPS county code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: PRICE ELASTICITIES: HOARDING VS. OTHER PERIODS

	Dependent Variable: Log(Volume of Rice Purchases (Ounces))				
	Baseline		Within-County	Across-County	
Hoarding Period: April 19th-May 10th	−1.344*** (0.114)	−0.421*** (0.061)			
Log(Price)	−1.191*** (0.089)	−0.333*** (0.009)	−0.920*** (0.020)	−0.954*** (0.024)	−0.860*** (0.020)
Log(Price) × Hoarding Period	−0.527*** (0.037)	−0.260*** (0.021)	−0.125*** (0.017)	−0.186*** (0.015)	−0.015 (0.038)
Mean of Dep. Var.	8564.3	8564.3	8564.3	8882.4	52967.6
N	1383462	1383462	1383462	1298140	223691
Store FE	No	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	Yes	No
Week × Year FE	No	No	Yes	No	Yes
County × Week × Year FE	No	No	No	Yes	No
County FE	No	No	No	No	Yes

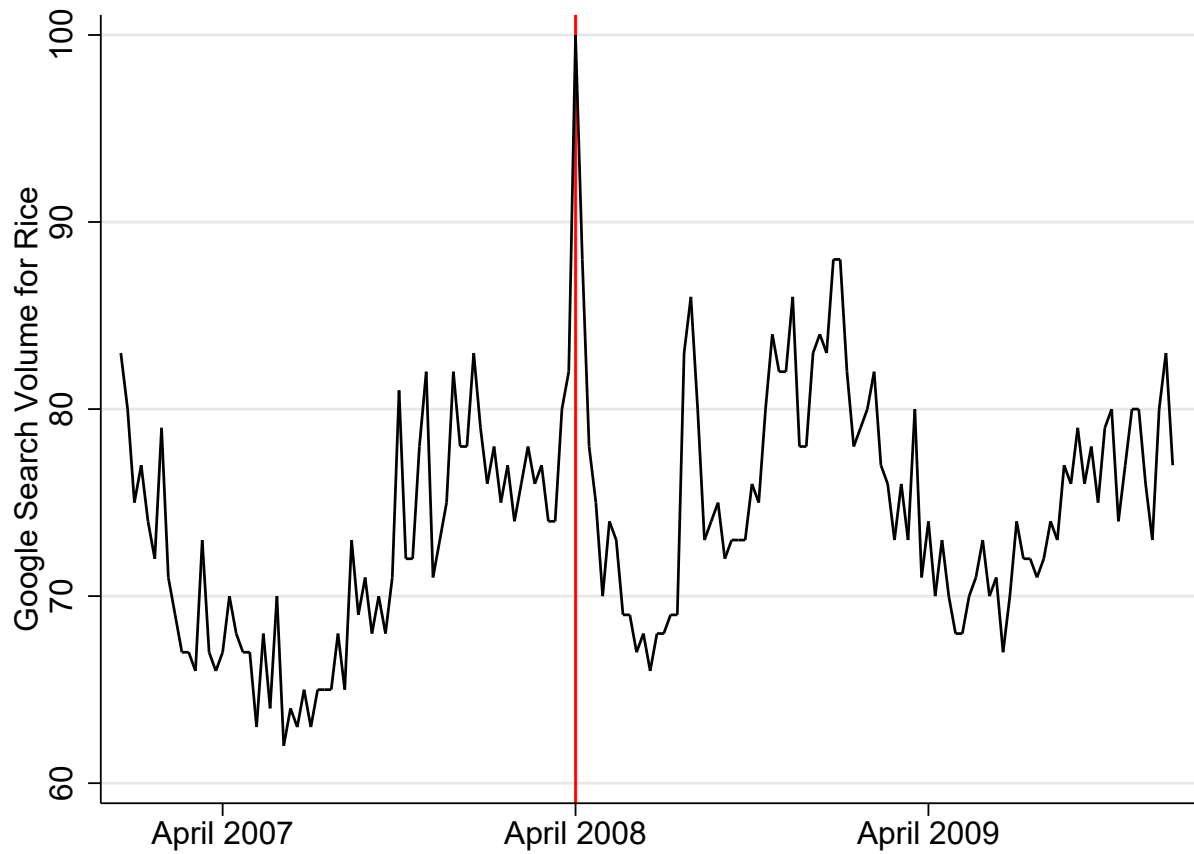
The first four columns show OLS regressions of the log volume of rice sales at the store-week level on the log price and the log price interacted with an indicator for the hoarding period: April 19th-May 10th, 2008. The first two columns include an indicator for the hoarding period itself, and the second column additionally includes store and week of the year fixed effects to control for seasonality. The third column includes store and week × year fixed effects. The fourth column includes store and county × week × year fixed effects. The fifth column collapses all data to the county fips code level, and shows a regression of the total volume sold at the county × week level on the log average price across stores in the county, and the log average price interacted with an indicator for the hoarding period.

FIGURE 1: INTERNATIONAL PRICES SPIKE FOLLOWING INDIA EXPORT BAN



Notes: The red line displays monthly international rice prices, normalized by the average over the period shown: 2007-2009. The first vertical line denotes India's ban on rice exports in October 2007, while the second vertical line denotes June 2008, to approximate the timing of Japan's agreement to release rice reserves in late May.

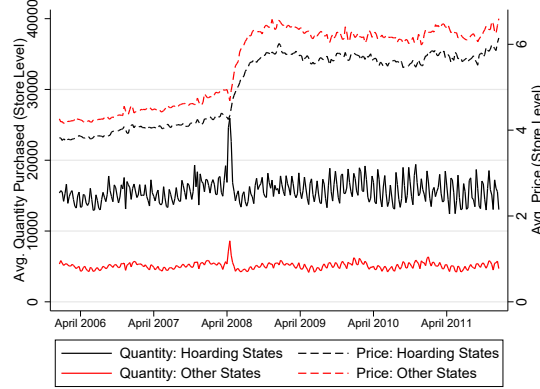
FIGURE 2: GOOGLE SEARCHES FOR RICE PEAK IN LATE APRIL 2008



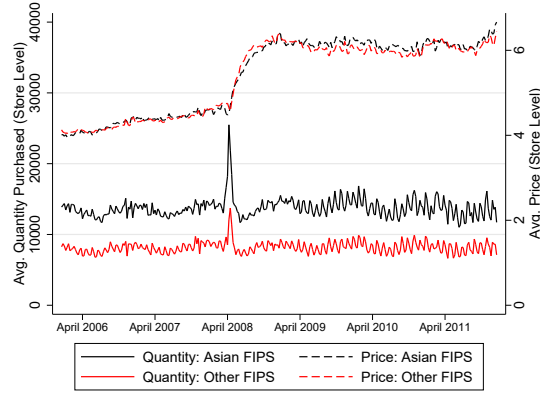
Notes: The black line displays weekly intensity of google image searches for “Rice” in the US between 2007-2009. 100 is normalized as the highest intensity over the period. The red line denotes the week of April 20th, 2008.

FIGURE 3: CROSS-SECTIONAL STRENGTH OF HOARDING DOES NOT PREDICT PRICE MOVEMENTS

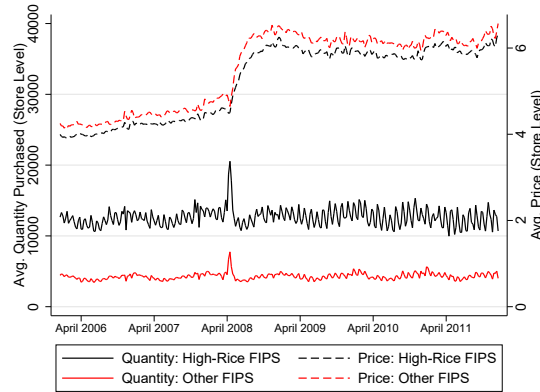
PANEL A: HOARDING VS. NON-HOARDING STATES



PANEL B: COUNTIES WITH LARGE ASIAN POPULATIONS VS. OTHERS



PANEL C: ABOVE VS. BELOW MEDIAN PER-CAPITA RICE CONSUMPTION



Notes: Plots show average store level prices and average store level quantity sold in ounces. In each, the sample of stores is split into two groups, with black lines showing averages for those in high demand areas and red lines showing those in low demand areas. Solid lines show quantities, while dashed lines show prices. We show three definitions of high demand areas. In Panel A, the black lines denote the 10 states which saw the largest proportional deviation in quantity sold during the hoarding period: Connecticut, California, Florida, Louisiana, Massachusetts, Nevada, New Hampshire, New Jersey, New York and Utah. In Panel B, the black lines represent the counties (FIPS codes) in the top quintile in terms of proportion of Asian Residents. In Panel C, the black lines represent counties (FIPS codes) who had above median rice purchases per capita in our sample of stores in 2007.

FIGURE 4: NO EVIDENCE OF STOCKOUTS DURING HOARDING PERIOD

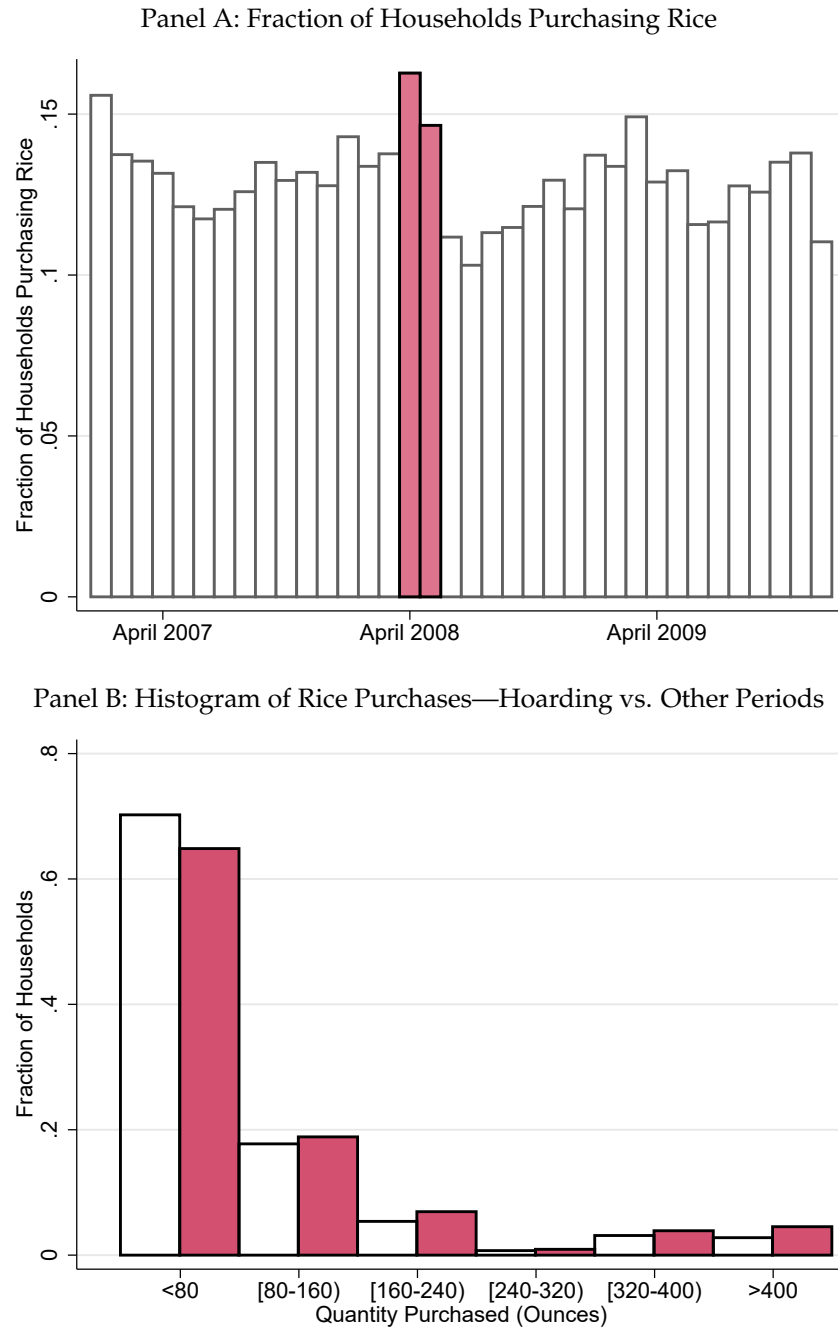
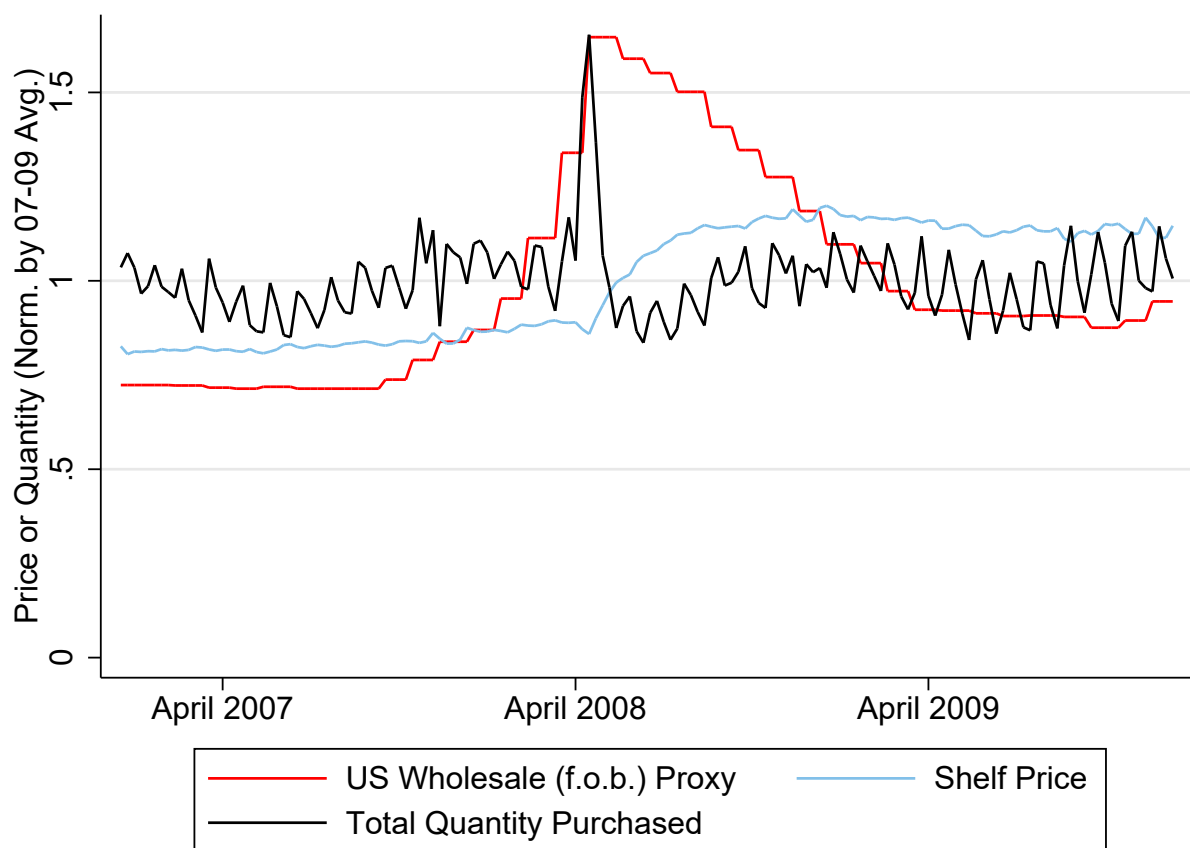
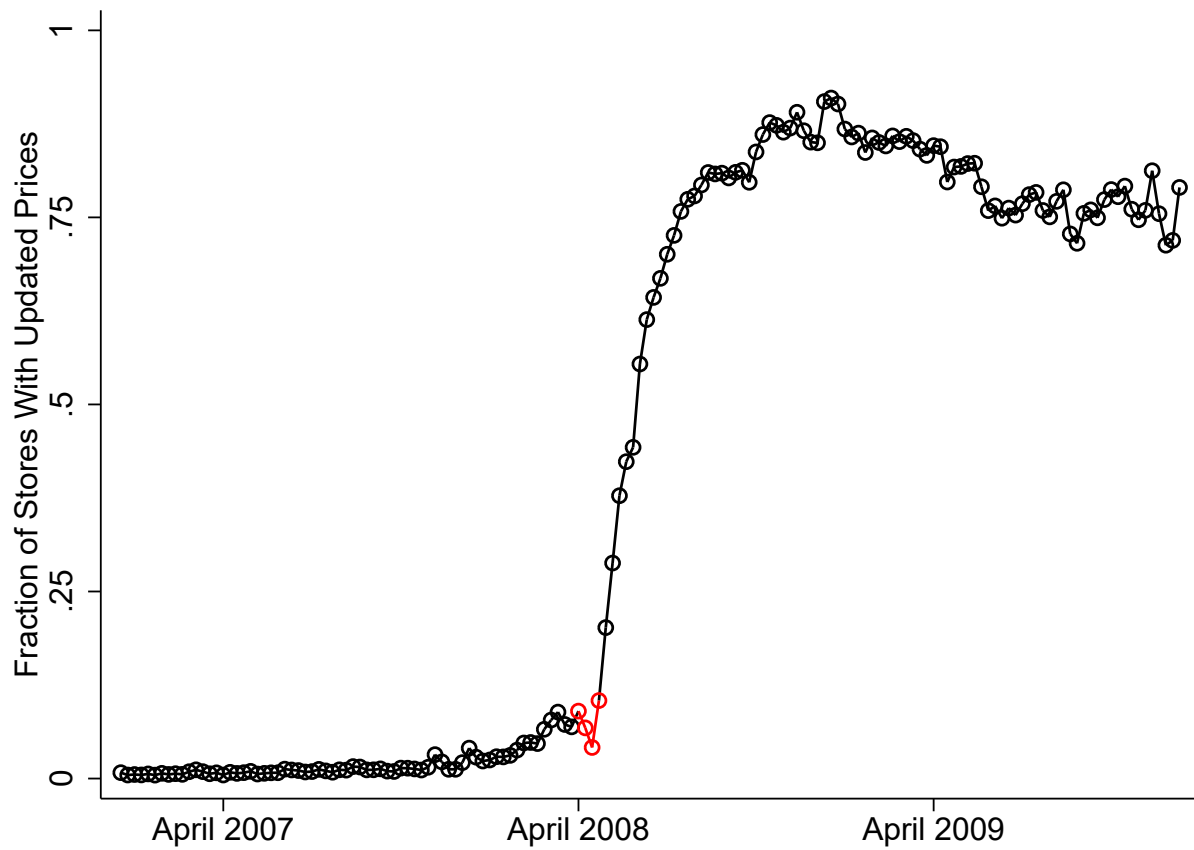


FIGURE 5: HOARDING ANTICIPATES SHELF PRICE SHOCK



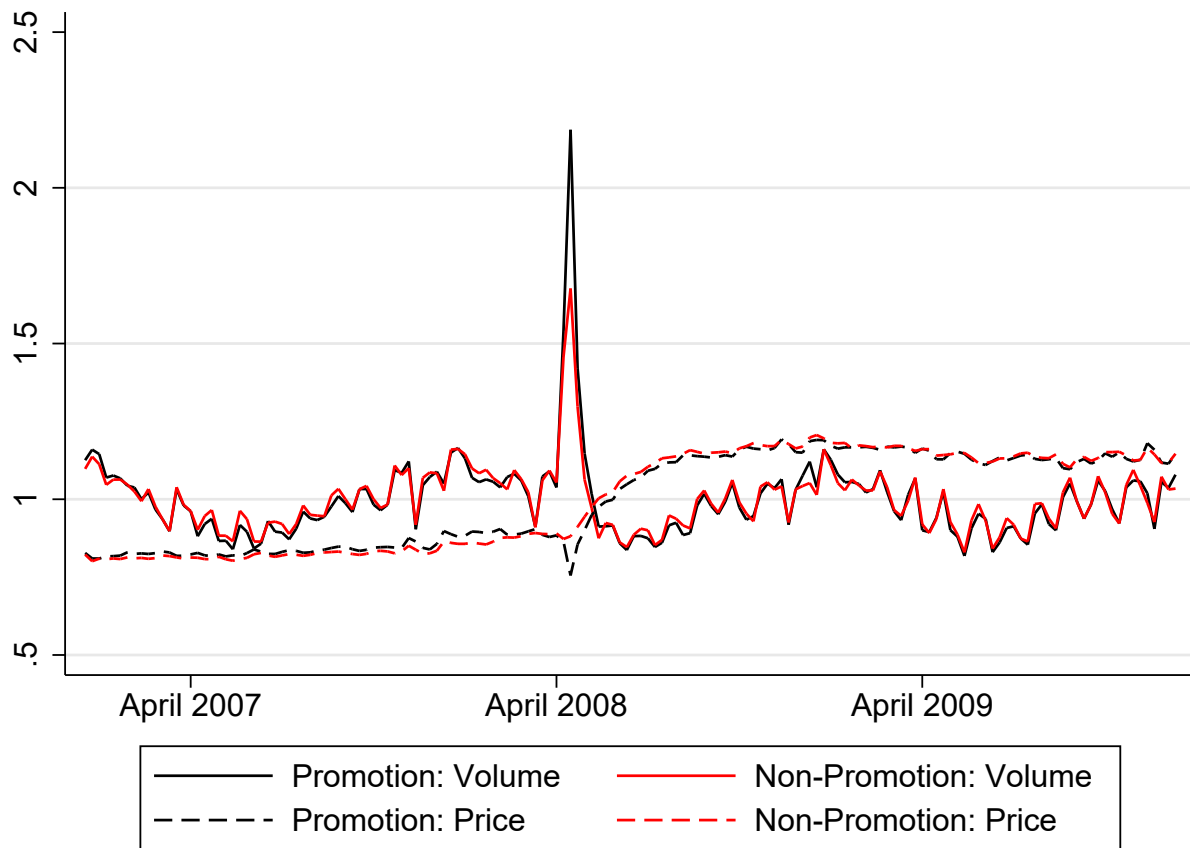
Notes: The red line displays a proxy for the US wholesale rice price at the monthly level. The proxy is based on average f.o.b. price for long grain rice at selected milling centers in Southwest Louisiana. Data provided by USDA, based on data from Agricultural Marketing Service, *National Weekly Rice Summary*. The black line displays average weekly sales at the store level, based on scanner data. The blue line displays the weekly average shelf price based on our store level rice price index. All variables are normalized by the average over the period shown: 2007-2009.

FIGURE 6: STORES UPDATE GRADUALLY TO HIGHER PRICE



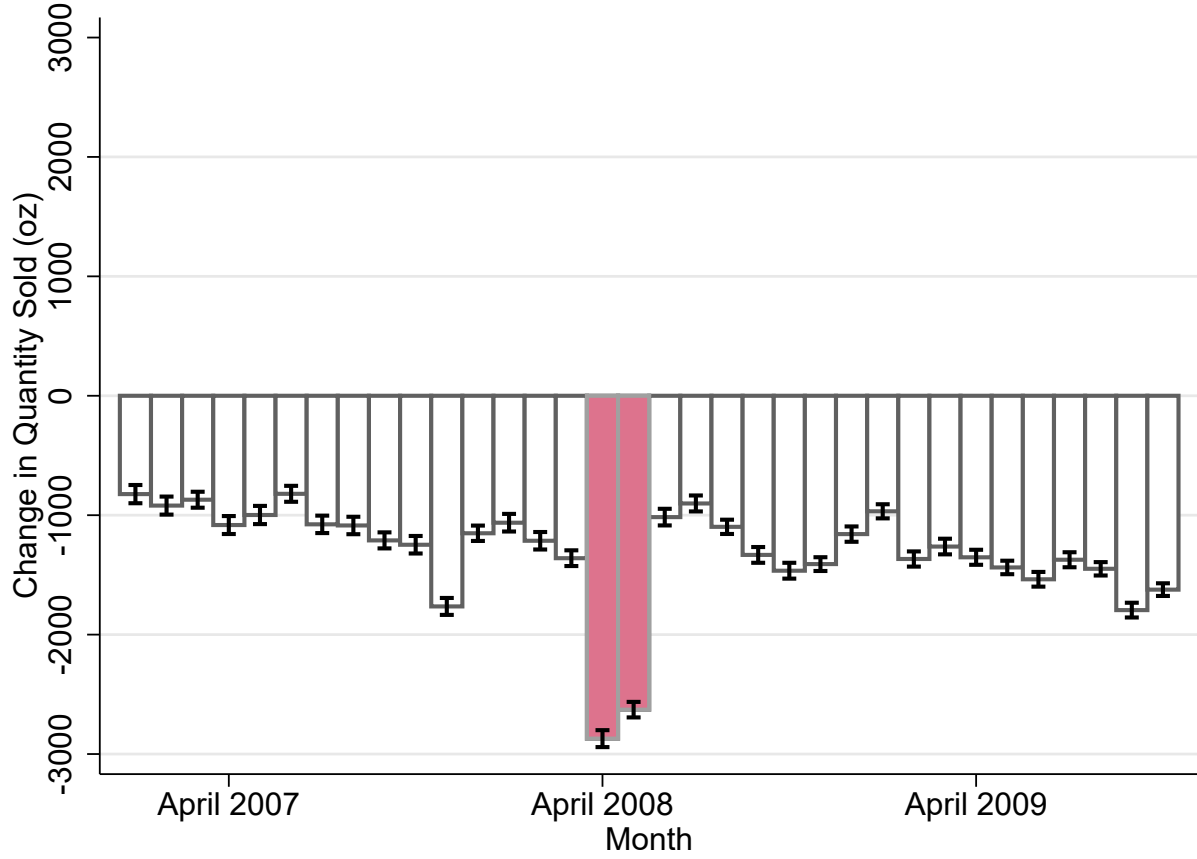
Notes: Plot displays the fraction of stores that have *updated prices* in the wake of the shock to international prices. A store is determined to have updated its price if the price is greater than 125 percent of the 2007 average. The red portion highlights the weeks starting on the 19th of April through the 10 of May 2008.

FIGURE 7: EXCESS HOARDING AT STORES HOLDING PROMOTIONS



Notes: The solid black line displays the average store level quantity of rice sold in ounces for stores *holding promotions* during the peak of the hoarding period: the week of the 3rd of May, 2008. The dashed black line displays the average store level price for these stores based on our store level rice price index. We define a promotion during this period as a price that is less than or equal to 90 percent of the January-February 2008 average. The solid red lines displays the average store level quantity of rice sold in ounces for all other stores. The dashed red line displays the average store level price for all other stores based on our store level rice price index.

FIGURE 8: INCREASED CROSS-SECTIONAL ELASTICITY IN HOARDING PERIOD

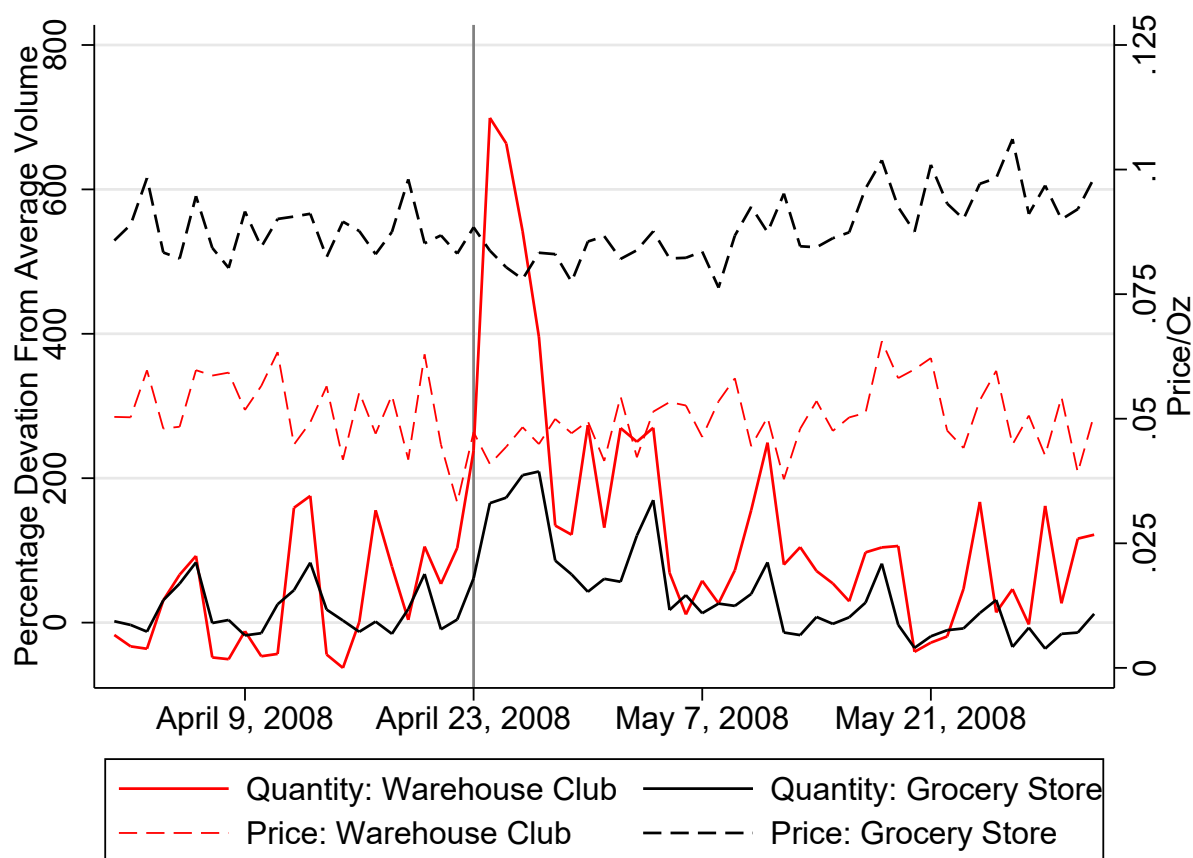


Notes: Bars show the month specific sensitivity of quantity to within location-variation in prices. In particular, we report coefficients β_i^m from the following regressions;

$$Quantity_{ijm} = \alpha + \sum_{m=1}^{36} \left[\beta_i^m (P_{jm} \times \gamma_m) \right] + \gamma_m + \theta_i + \gamma_m \times \eta_{c(i)} + \varepsilon_{ijm}$$

Here P_{jm} is the price index in store j and γ_m are *year* specific dummies. θ_i is an individual fixed effect, and $\eta_{c(i)}$ are dummies for the county in which individual/store i is located.

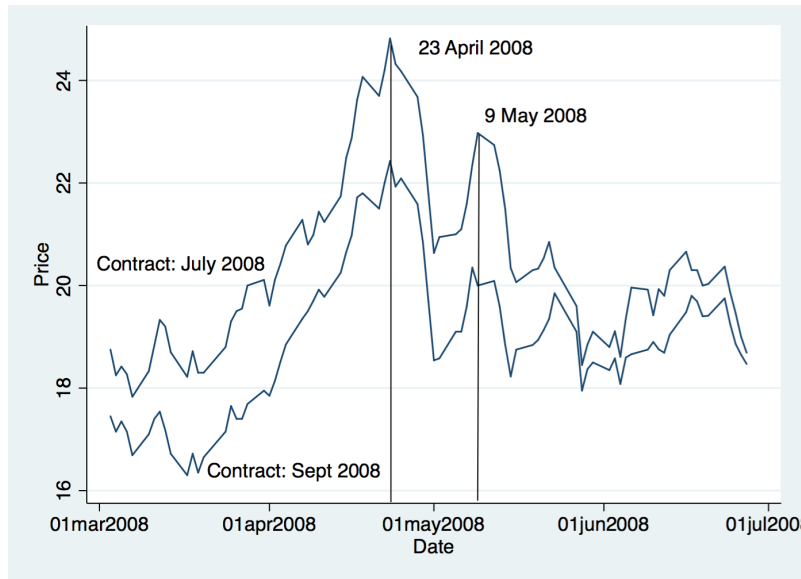
FIGURE 9: HOARDING IN WAREHOUSE CLUBS AFTER RATIONING ANNOUNCEMENT



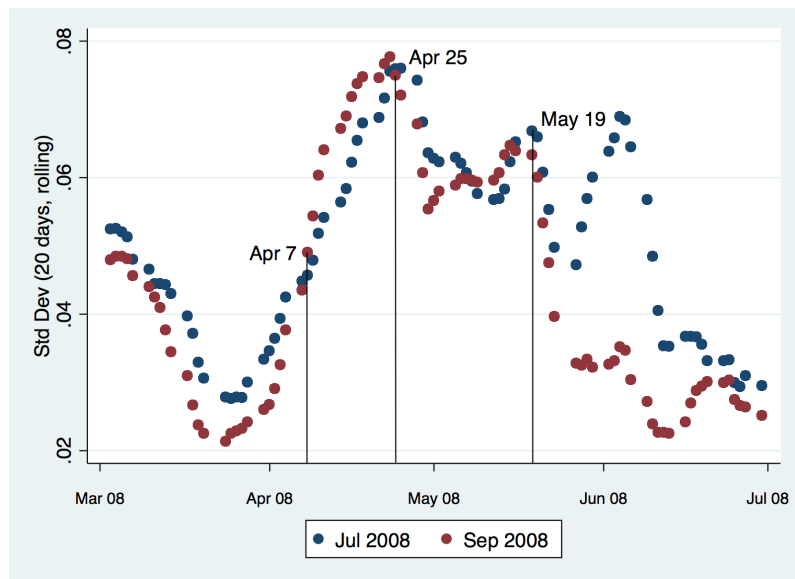
Notes: Red lines for quantities sold and price at warehouse club. Black lines for quantities sold and price at grocery stores. The vertical line is April 23rd, the date when Sam's Club announced rationing policy.

FIGURE 10: RICE FUTURES

PANEL A: FUTURES PRICES



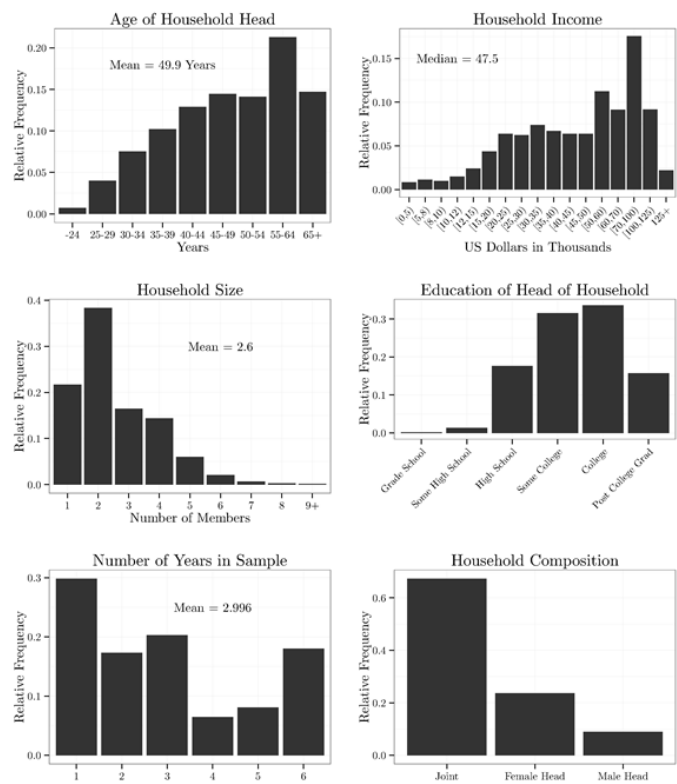
PANEL B: VOLATILITY FOR FUTURES PRICES



Notes:Panel A plots the prices for futures contracts for rice with expiration in July 2008 and September 2008. Panel B plots the volatility of the daily returns to futures contracts for rice with expiration in July 2008 and September 2008. The volatility measure is the standard deviation of continuously compounded daily returns using a rolling past-20-trading-days window. The futures contract is for 2,000 cwt (hundred weight), which corresponds to about 200,000 pounds or circa 91 metric tons, of rough rice, no. 2 or better.

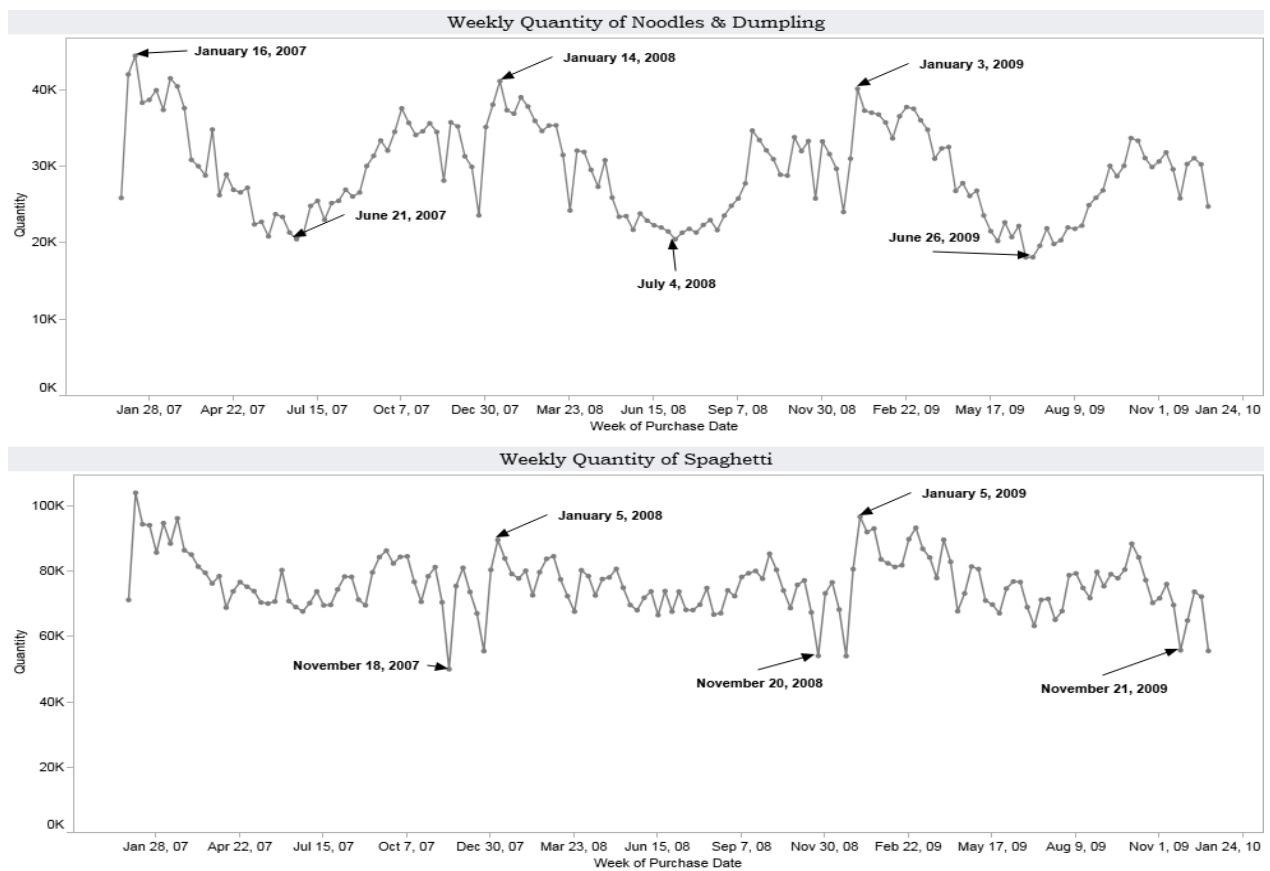
Internet Appendix: For Online Publication

FIGURE A.I: NIELSEN PANEL DEMOGRAPHICS



Notes: This figure plots the distribution of demographics of the overall Nielsen Panel.

FIGURE A.II: RICE SUBSTITUTES: WEEKLY QUANTITIES OF NOODLES AND DUMPLINGS AND SPAGHETTI



Notes: This figure plots the quantities purchased of noodles and dumplings and spaghetti over the 2007-2009 period.