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A STICKY-PRICE VIEW OF HOARDING

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ABSTRACT

Hoarding of staples has long worried policymakers due to concerns about shortages. We quantify how sticky store prices---delayed price adjustment to shocks by reputable retailers---exacerbate hoarding. When prices are sticky, households hoard not only for precautionary motives but also non-precautionary motives: they stockpile as they would during a standard retail promotion or for the purpose of retail arbitrage. Using US supermarket scanner data covering the 2008 Global Rice Crisis, an episode driven by an observable cost shock due an Indian ban on raw rice exports, we find that sticky prices account for a sizeable fraction of hoarding. Hoarding is mostly for own use and more prevalent among richer households. Our findings are consistent with media reports of distributional concerns associated with hoarding during the Covid-19 Pandemic.

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1 Introduction

Household hoarding of staples—the accumulation of inventories during disasters or supply disruptions—has long been a concern of governments.[1] Most recently, the COVID-19 pandemic has led to a widely-documented run on staple foods, hand sanitizers and masks, creating shortages in crucial items needed by public health workers. There are also a number of famous historical episodes: Amartya Sen's influential *Poverty and Famines* argued that hoarding played a key role in the 1943 Bengali Famine, while historians have emphasized the role of gas hoarding by consumers during the energy crises of the 1970s, which amplified prices at the pump and fed back into higher international oil prices.[2] Household hoarding is similarly thought to have aggravated the 2000s commodities boom and the 2008 global rice crisis.[3]

While discussions of hoarding naturally emphasize a precautionary motive, i.e. an outward shift in consumer demand due to a desire to hedge market uncertainty or because of some behavioral panic, we highlight and quantify how sticky store prices — delayed price adjustment to shocks by reputable retailers — exacerbate hoarding. After all, a large literature documents that retailers uniformly delay price adjustments after shocks (Bils & Klenow, 2004; Nakamura & Steinsson, 2008), including during disasters such as earthquakes, hurricanes or snowstorms that cause costs to rise (Cavallo *et al.* , 2014; Gagnon & Lopez-Salido, 2015). Even in quiet times, there are a number of reasons why stores may pursue sticky price strategies. These include menu costs, customer anger (e.g. Anderson & Simester, 2010; Anderson *et al.* , 2017; Rotemberg, 2005) and costly attention or information gathering (Mankiw & Reis, 2002; Woodford, 2009). During market disruptions, concerns about customer anger or the imposition of anti-price gouging laws may be amplified.[4] In other words, theory and evidence suggest that prices may be sticky in hoarding periods.

Sticky prices are likely to exacerbate hoarding for a number of reasons, regardless of the un-

[1]See (Gráda, 2009) for a review of the role of hoarding in famines going back as far as back Antioch as far back 362 A.D.

[2]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."

[3]See, e.g. "How Fear Turned A Surplus into Scarcity," *National Public Radio*, November 4, 2011.

[4]For instance, the first US state law directed at price gouging was enacted in New York in 1979, during a period of commodity market instability and concerns about shortages. Since then anti-gouging laws have proven popular—the majority of states have adopted some type of regulation (Davis *et al.* , 2008). These measures typically get adopted during or following commodity shortages (see, e.g., Zwolinski, 2008; Giberson, 2011).

derlying mechanism causing stickiness. Perhaps the simplest follows directly from basic supply and demand logic: for a given a shift in demand due to precaution, a lack of price response will result in greater quantity sold. However, Benabou (1989) shows that sticky prices create at least two additional incentives for anticipatory stockpiling following a cost shock to a storeable good, even holding precautionary demand fixed.[5] The first is an implicit promotional effect: sticky prices offer a temporary sale to consumers. Recognizing that prices will rise in the future when the sale ends, consumers are then driven to shift demand intertemporally and stockpile (Gönül & Srinivasan, 1996; Erdem *et al.* , 2003; Sun *et al.* , 2003; Sun, 2005). The second is retail arbitrage or resale. Households can hoard to take advantage of the strategies of or constraints on reputable retailers by buying and reselling at a later date through informal channels (i.e. online or through smaller retailers that are less bound by reputation norms).[6]

While the potential role of sticky prices is recognized by economists, quantifying its importance has been challenging because of the lack of sufficiently detailed micro-data.[7] To understand how sticky prices influence hoarding behavior, it is necessary to go beyond aggregates and observe both the *shelf* prices households face and the inventories that they hold. This poses a difficulty, as many large-scale hoarding episodes are historic or in developing countries where granular data is difficult to come by.

We exploit the availability of US supermarket scanner data during the 2008 Global Rice Crisis to systematically analyze the determinants of hoarding. This episode is, we believe, the first instance of large scale hoarding for which detailed retailer and consumer micro-data is available. No doubt the availability of scanner data in a few years covering the COVID-19 pandemic will permit detailed further research, but this rice hoarding episode provides a particularly clean setting in which to consider the role of sticky prices, as we explain further below. Further, a number of our

[5] It is possible for there to be simultaneously sticky prices and bounded speculative storage in a game between consumers and firms when there are menu costs. Benabou (1989) extends classic menu cost models (i.e. fixed costs of price adjustment following Barro, 1972; Sheshinski & Weiss, 1977), which feature firm's nominal costs rising due to inflation, to allow for storeable goods. The well-known sticky pricing strategy, or (S,s) rule, derived under non-storeability is shown to hold when there are only moderate amounts of speculative storage.

[6] Such retail arbitrage strategies are akin to speculative or resell motive discussed in commodity markets (Scheinkman & Schechtman, 1983; Deaton & Laroque, 1992) that apply even in flexible price settings.

[7] While there is now a large body of research on the role of institutional speculators in the 2000s commodity bubble (see, e.g. Kilian & Murphy, 2014; Hamilton, 2009; Tang & Xiong, 2010; Singleton, 2013; Acharya *et al.* , 2013), the role of households has remained unexplored. See also Gorton *et al.* (2013) and Fama & French (1987) on the more general on the relationship between inventory and commodity prices and Bessembinder (1992) for the relationship between hedging by institutional investors and futures prices.

findings foreshadow current news reports on hoarding during the pandemic.

We begin by documenting aggregate patterns in wholesale prices and quantities during the crisis. Market disruptions in the form of a ban on Indian rice exports in the fall of 2007 led to an increase in the international price of rice of more than 300 percent, peaking in April and May of 2008. In other words, the root cause of the episode was a relatively pure supply shock, with no corresponding shock to public health or safety that might trigger a simultaneous change in demand (as in a pandemic or natural disaster). This makes the episode a particularly clean one in which to study sticky prices. Rice futures markets similarly spiked in late April, predicting a roughly 20 percent increase in prices throughout the summer.

Household hoarding coincided with or slightly lagged the increase in wholesale prices: retail store sales were 40 percent higher than average in late May and early April 2008. Elevated Google search volumes (Choi & Varian, 2012; Da *et al.* , 2011) for the term "rice price" coincided with abnormal store sales, pointing to consumer awareness of the cost shock and the potential for higher prices in the future (Goel *et al.* , 2010). These searches were prompted by significant media coverage in mid-April 2008 of rising food prices and the cost shock to rice (Fang & Peress, 2009; Engelberg & Parsons, 2011).

We then turn to the micro-data and show evidence of ubiquitous stickiness in prices at the *retail* level. Shelf prices for rice at retailers in our sample remained near-uniformly flat even as wholesale price rose. Retail prices stayed effectively constant through the most hoarding periods, and subsequently only slowly increased to a permanently higher level (in line with the permanent long run increase in wholesale prices). The lack of retail price response in the face of a clear cost or *supply* shock highlights a key contribution of our study. Discussions of pricing during hoarding episodes typically focus on the dangers (or lack thereof) of gouging by retailers—with price-gouging usually referring to sharp increases in prices to match increased hoarding-driven *demand*.[8] Hesitancy to increase prices even to match cost changes observed in our data suggests that concerns over gouging (or, alternatively, concerns over the restrictiveness of anti-gouging regulations) may be misplaced, at least for the relatively reputable retailers observed in our data.

One advantage of our data relative to earlier studies on price stickiness during disasters is that

[8]See https://www.nytimes.com/2020/03/27/us/coronavirus-price-gouging-hand-sanitizer-masks-wipes.html, https://hbr.org/2013/07/the-problem-with-price-gouging-laws, or https://www.ftc.gov/public-statements/2006/02/moneyball-and-price-gouging

our panel allows us to estimate household inventories. We use a standard algorithm (see, e.g., Hendel & Nevo, 2006) and show that consumer hoarding actually preceded any increase in retail prices. Put differently, consumers purchased rice in bulk at relatively low cost before shelf prices rose, suggesting they may have benefited from sticky prices during the hoarding period.

In the third part of our paper we ask what fraction of hoarding during the 2008 rice crisis can be attributed to sticky prices. Answering this question requires credible estimates of consumer price elasticities. We recover these elasticities using an IV approach and our scanner data, adjusting to account for a dynamic stockpiling incentive following Hendel & Nevo (2006). Because we are interested in the total quantity responses of consumers when prices change, we conduct our analysis at the local market level (in our main analysis, we use zipcodes as a proxy for the local market, but we obtain similar results at higher levels of aggregation). Our primary approach is instrumental variables strategy (in the general style of Hausman, 1996) exploiting the fact that supermarket chains practice uniform pricing across stores, as documented in DellaVigna & Gentzkow (2017). For each chain×market×time period we construct a leave-market-out chain-level average price. In other words, the average price at stores in the same chain, but located in other markets. We then aggregate across stores to create a market level instrument. Not surprisingly, we find very elastic demand for rice. Our estimates imply that a temporary price discount of 10 percent would generate an increase in quantity purchased of roughly 9 percent.

To quantify stickiness, we consider the extent of the cost shock. Comparing the long run price of rice (i.e. in late 2008 and 2009) to the price during the hoarding period indicates that sticky prices generated an implicit promotion of at least 22 percent, that is, prices were 22 percent below the long run level. This long run price corresponds to an approximately 30 percent passthrough from global raw rice prices (which converged to a long run level over 85 percent higher than the pre-crisis level) to retailers. This is similar to what studies have found for other storeable goods such as coffee (Nakamura & Zerom, 2010). Combining a 22 percent implicit promotion with our estimated elasticity suggests that sticky prices can account for approximately half of the 40 percent increase in quantity purchased during the crisis.

While these estimates suggest that sticky prices contributed significantly to hoarding, we cannot in general differentiate the fraction of excess purchases due to precaution versus other channels. However, if we are willing to entertain additional assumptions, we can use the granularity of our consumer panel to infer whether hoarding purchases were for own use or resale. Our strategy is based upon identifying exceptionally large purchase precisely during the hoarding period, relative to each particular household's history of purchases. While we find a handful of consumers that appear to be purchasing for arbitrage purposes, the large majority of households increase their purchases by quantities small enough that meaningful resale would be difficult. Eliminating potential resellers from our sample does not substantially change aggregate hoarding, suggesting that individual consumption is largely responsible for the observed patterns.

Our granular data also allows us to characterize the propensity to hoard across demographic groups. Unsurprisingly, we find stronger hoarding in areas that tend to eat more rice. Perhaps more interestingly, we find that higher income households hoard significantly more than low-income households, consistent with reports on hoarding during the COVID-19 pandemic. This also matches past research on the relationship between income and coupon usage or other more standard promotions (see Kwon & Kwon, 2007). One explanation is liquidity concerns: low income households may simply be unable to take advantage of implicit promotions.

We conclude by briefly discussing external validity—namely that a number of our findings foreshadow media reports on hoarding during the Covid-19 Pandemic—and drawing out two potential policy implications of our analysis. The first is that concerns over price gouging at large scale retailers, like those featured in the scanner data, may be misplaced. The second concerns the distributional consequences of sticky prices and hoarding.

2 Data

Our primary sources of retailer and household data are the Nielsen datasets held at the Kilt's Center. Retail scanner data includes prices and quantities sold at the product level from thousands of 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—differing 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 price definitions, for example defining price as the average price for an 80-ounce bag or the price of the most popular UPC within each store. 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 $5.33 for 80 ounces. On average, median income in the counties in which the stores are located is just over $57,000.

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 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 monthly 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 in this restricted sample is just under $59,000, and the average household has just over 2.5 people.

3 Background: News Coverage, Consumer Attention and Hoarding

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. According to 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.[9] The black line in Figure 1 plots the global price of rice over this period, showing 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. Despite this correction, the global price converged to a level well above the pre-ban average.

This boom-bust price pattern is disconnected from fluctuations in energy 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 is highly subject to government interventions and manipulations. This is particularly a feature of rice relative to other food staples—for example, barley, corn, and wheat—which track the price of oil much more closely.

Given the lack of connection 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 due to a precaution narrative.[10] There were numerous media reports of hoarding and related events between India's October 2007 ban and Japan's 2008 agreement:

- March 2008: Media reports of hoarding in Egypt
- April 2008: Media reports of hoarding in the 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: Philippines government asks for an emergency meeting

  April 19-May 10: Coverage of hoarding in US stores

[9] The 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.

[10] Retrospectives on this episode emphasize a precaution or fear narrative ("How Fear Turned A Surplus into Scarcity," *National Public Radio*, November 4, 2011 and "A Run on Rice in Asian Communities," *New York Times* May 1, 2008).

- May 2008: potential for supply from Japan via agreement with United States. Crisis ends.

Given the extent of press coverage, producers and stores were likely aware of the cost shock emanating from the India ban, and they certainly could have aggregated this information from rice futures and wholesale prices. In Figure 2, we plot the prices of rice futures contracts for delivery in May, July and September of 2008. At the peak of the hoarding period in April 2008, consumers and stores both expected rising rice prices in the medium term. July futures prices for rice were above May and both prices were much above September futures prices. In other words, the market expected prices to rise until at least September 2008, and this information was publicly available. These futures indicated a 10 to 20 percent increase in raw rice prices.

The blue line in Figure 1 shows a search volume index on Google Trends for the term "Rice," specifically the weekly intensity of Google searches in the US between 2007-2009. 100 is normalized as the highest intensity over the period. The red vertical line denotes the week of April 20th, 2008. There is a notable spike in search volume interest in April consistent with wider interest among media and households over this same period. This elevated Google search points to consumer awareness of the cost shock and the potential for higher prices in the future. These searches were likely prompted by significant media coverage in mid April 2008 of rising food prices and the cost shock to rice. These search patterns suggest that consumers were particularly attentive to store prices for rice during this period.

4 Store Sales, Sticky Prices and Household Inventory

In this section we document severe consumer hoarding coinciding with or slightly lagging the shocks to global and wholesale rice prices shown in Section 3. We then show that, for effectively all retailers, rice prices on the shelf were sticky—largely unchanged—in the face of these shocks. In other words, while consumer hoarding followed a sharp increase in wholesale prices, it actually preceded any increase in shelf prices. Consumer inventory—computed using a standard algorithm—led retail prices. This is consistent with a sticky-price stockpiling view as a motive for consumer hoarding in this episode.

Without access to retail level data, one might naturally interpret these plots as evidence of a precautionary motive: consumers built up inventories when international prices were at their peak. That is, the precautionary or hedging narrative has consumers purchasing excess quantities in the face of high prices. Implicitly, this view depends on flexible retail-prices: with scarcity driving up prices, and consumers responding by increasing purchases.

However, the blue line, which displays retail prices, shows that—in line with store sales—inventories actually peaked *before* store level prices because store prices are sticky. This granular data suggests that consumers, aware of the rise in global prices from the media, futures prices, or other sources, might have seen that prices on the shelf were still low and chose to stock-up, even holding fixed their precautionary demand.

4.1 Behavior of Store Sales and Prices

We begin by showing the sharp jump in consumer purchases that occurred during the rice crisis. The red line in Figure 1 shows a significant spike in store-level purchases, peaking in late April and early May, 2008. Average purchases at the store level in this *hoarding period*—which we define as the last two weeks in April and first two week of May, 2008—were 11909 per week, 40 percent above the average of 8476 in all other weeks in our sample period. The most intense week of hoarding featured average purchases that were more than 65 percent above average. Notably, this increase in store sales roughly coincided with or slightly followed the peak of international prices. The same pattern is evident in Figure 3, where the red line once again captures store-level purchases and the black line captures a proxy for *US wholesale prices*, which largely track international rice prices.

Figure 3 also shows evidence of the key phenomenon considered in our study: sticky store prices. The light blue line displays the time series of the weekly average shelf price of rice at retailers in our sample. While wholesale prices began to rise before the peak of hoarding in late April and Early may, store-level prices do not rise at all with wholesale prices, staying flat or even declining slightly until after the peak of hoarding. In other words, hoarding anticipates delayed updating of shelf-prices.[11]

[11]One potential concern is that the observed delay in adjustment of our price index might be an artifact of consumer substitution across types or qualities of rice. For example, if retailers increased all rice prices, and consumers responded by substituting to the cheapest products, the two effects might cancel out in our aggregated price index. To address this, Appendix Figure A.II replicates Figure 3 but includes a measure of prices that holds product types fixed. In particular, this figure shows the average price across stores for the most popular UPC within each store, defined based upon 2007 revenue.

Crucially, this delayed updating is not simply an average effect: virtually all stores failed to update prices until after the hoarding period. To show this, Figure 4 displays the fraction of stores that *updated retail prices* in the wake of the shock to international prices. While there is no standard definition of price adjustment, we take what we believe to be a relatively conservative approach. We define a store to have updated its price if the price is greater that 125 percent of the 2007 average. The red portion denotes the hoarding period as defined above. Note that during this period, a very small fraction of stores updated prices, according to our metric, and even this limited fraction appears to be on trend with gradual and standard price increases relative to 2007. However, in the weeks following the hoarding period, stores update rapidly: within a few weeks more than half of stores updated prices and more than 75 percent updated within a few months.

These patterns are consistent with a large literature in macroeconomics: retail or supermarket prices, which consumers face, are sticky and lags the wholesale prices. 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.

4.2 Behavior of Household Inventory and Store Prices

Given that excess store sales actually preempted any change in store prices, we next turn to a new motive for consumer hoarding: an *implicit promotion* generated by sticky prices. The logic of this motive is simple: if there is a shock to wholesale prices, but retailers are slow to respond, consumers have an incentive to build up inventories before shelf-prices rise. The implicit discount (relative to a sustainable long run price) generated by sticky prices will cause consumers to shift demand dynamically and stock up.

To analyze the role of a sticky-price stockpiling motive, we require a view into consumer inventories. While we are unable to observe inventories directly, the dynamic purchase history in our household panel allows us to infer them following the method of Hendel & Nevo (2006). To do so, we estimate monthly consumption as the average household purchase $\bar{q}_i = \sum_{t=1}^{T} \frac{q_{it}}{T}$ over the entirety of our sample for each consumer i. Setting initial inventories in our sample to zero for all households, we then calculate inventories for household i at time τ as $\sum_{t=1}^{\tau}(q_{it} - \bar{q}_i)$. Put differently, inventories at any time τ are measured as the cumulative sum of deviations in purchases from the individual long long-run average purchase in our sample.

Figure 5 shows that household inventories follow a pattern consistent with a sticky-price stockpiling or implicit promotion motive. The black line again shows the time-series of international rice prices. The red line shows average consumer inventory in our household panel, constructed according to the process described above. In line with the store sales patterns shown in Figure 3, household inventories just slightly lag the rise in international prices. Consumers sharply built up inventories following the shock to global prices and gradually drew them down.

In Table 2 we show more formally that changes in household inventories predict changes in shelf prices, but that the opposite is not true. This holds at both the national aggregate level, and locally, at the county level. In the first two columns, we focus on time series regressions using national aggregates. In the first column, we regress monthly changes in shelf prices on lagged changes in monthly inventory. We see that the coefficient of interest is 0.055 and statistically significant at the 5% level. In the second column, we regress monthly changes in inventory on lagged changes in shelf prices. We find a coefficient of -0.851 but it is not statistically significant.

In columns 3 and 4, we use panel data at the county level to run analogous regressions, including both county and month fixed effects. In column 3, we find a highly statistically significant coefficient of 0.023 when regressing changes on shelf prices on lagged changes in inventories. This suggests that the counties in which households built up larger inventories later saw larger changes in shelf prices. This again aligns with the sticky-price driven implicit promotion motive.

Conversely, in column 4 we find no evidence that county level changes in shelf prices predict county level changes in inventories. Areas that saw larger than average jumps in shelf prices *did not* see corresponding jumps in household inventories. In general, the basic patterns displayed in Figure 5 and Table 2 are difficult to rationalize with precaution as the sole driver of this hoarding episode well, and align well with a implicit promotion view.

5 Estimating Elasticities and Calculating Counterfactuals

The relative timing of changes in global prices, store sales, and shelf prices suggest that sticky prices is likely to have played a major role in the 2008 rice hoarding episode. In this section, we gauge and quantify the importance of stick prices. Doing so naturally requires us to estimate the elasticity of demand for rice among consumers in our sample, which we estimate using an IV strategy described below. We then consider the responses implied by this elasticity in the context of the observed retail price patterns and cost shock in our sample to understand the importance of sticky prices in explaining observed hoarding patterns.

5.1 Sample and Zip-Level Approach

In principle, we could use either household panel data or store level data to calculate demand elasticities. While there are advantages to each, a major disadvantage of household-level data is that we are unable observe prices for households who do not purchase rice. As a result, using the household panel would require us aggregate or associate these households to a particular store price or zipcode-average price.

With this in mind, we focus our analysis on our store level data, which poses challenges of its own. Consumers may respond to an increase in rice prices at a given store by both decreasing purchases and substituting across stores. Consequently, naively calculated price elasticities combine a consumption response and cross-store substitution. Because our counterfactual focuses on the response of *aggregate* quantities purchased to market wide changes in price, we aggregate individual stores and conduct our analysis at the market level. In our main specifications, we take a zipcode as a market, and hence aggregate our data to the zipcode level.[12] In other words, our object of interest is the sensitivity of average store level quantity sold in zipcode j ($\bar{Q}_{jt}$) to changes in the *average* price of rice in j : ($\bar{P}_{jt}$).

5.2 First-Stage Regressions

We propose an instrumental variables strategy for $\bar{P}_{jt}$ that exploits the tendency toward national uniformity of prices across retail chains, as documented in DellaVigna & Gentzkow (2017).[13] To begin constructing our zipcode level instrument, our first step is to develop a proxy for store level prices ($P_{i,k,j,t}$ for store i belonging to store chain k in zip-code j in week t) using a retail chain level leave-out mean. That is, for store i which belongs to chain k in zipcode j we construct the average

[12] Our results are robust to using more general definitions of a market (e.g. states).

[13] Chain-level policies explain a significant portion—but not all—of individual prices. For example, a regression of zip-level prices on the chain level instrument we describe below has an R^2 of 0.7. This rises to 0.89 in our specification with full fixed effects.

weekly price at retail chain k excluding all stores in zipcode j: $\bar{P}_{k,xj,t}$. Here, the xj subscript denotes the exclusion of zipcode j in the mean.

The purpose of this instrument is to exclude variation in prices that is driven by or correlated with store level variation in demand. We rely on the fact that prices at individual stores that are members of national chains are, at least in part, driven by chain level decisions. The key assumption for identification is that individual store level demand is orthogonal to national pricing policies.

There are two natural potential issues with our instrument, which follows generally in the tradition of those proposed by Hausman (1996) and Nevo (2001) (although distinct due to an explicit focus on *chain* versus product specific pricing).[14] The first is the presence of time varying chain specific demand shocks—for whatever reason, consumers across the country want to buy rice from a given chain in a given week—with a corresponding chain level price response. While such a shock could be generated by chain level advertising policies, we otherwise hope that such shocks will be absorbed by state × week fixed effects. The second is the possibility that certain stores, or spatially clustered groups of stores, are so dominant in a given chain that they effectively determine the national pricing policy. This latter issue we can address using our data on the geographic distribution of stores (which we do in our specifications that exclude *high concentration* zipcodes below). In general, although our strategy requires strong assumptions, we believe it provides a valuable first pass to understanding consumer elasticities in this market.

Before conducting our zipcode level instrumental variables strategy, we first confirm that our chain level leave out mean is correlated with store level prices. To do so we regress weekly log prices at the store×week level ($log(P_{i,k,j,t})$) on the leave-out mean ($log(\bar{P}_{k,xj,t})$):

$$log(P_{i,k,j,t}) = \gamma_0 + \gamma_1 log(\bar{P}_{k,xj,t}) + \theta_i + \eta_{s(j)} \times \tau_t + \varepsilon_{i,k,j,t} \tag{1}$$

Here θ_i is a store fixed effect and $\eta_{s(j)} \times \tau_t$ is a state×week fixed effect. We cluster standard errors at the zipcode level.

The first column of Table 3 shows that chain level pricing is indeed predictive of individual

[14] Specifically our approach is distinct because our instrument considers the average price for rice averaged across different UPCs, and only includes prices at the same retailer (and not the price at other retailers in different markets). Furthermore, we ultimately generate a weighted average across retailers and include state × time fixed effects.

store level pricing. Our specification, which includes the full set of fixed effects shown in Equation 1 gives a coefficient of roughly 0.9 which is highly statistically significant. This is consistent with DellaVigna & Gentzkow (2017). While the degree to which our instrument explains the first stage suggests our IV regressions will be quite similar to the OLS, we view this as a validation of our assumption that prices reflect chain level policies rather than idiosyncratic local variation in demand.

To aggregate our store price leave-out mean to the zipcode level we construct a within zipcode average of chain level leave-out means, weighted by the shares of each chain in the zipcode:

$$\bar{P}_{xj,t} = \sum_{k} \omega_{kj} \bar{P}_{k,xj,t}.$$

Here, ω_{kj} is the share of total stores in zipcode j that are members of chain k. In our main IV specifications, we instrument for $log(P_{j,t})$ with $log(\bar{P}_{xj,t})$ in our first stage:

$$log(P_{j,t}) = \gamma_0 + \gamma_1 log(\bar{P}_{xj,t}) + \theta_j + \eta_{s(j)} \times \tau_t + \varepsilon_{j,t}. \tag{2}$$

Here θ_j represents a zipcode fixed effect and $\eta_{s(j)} \times \tau_t$ is again a state×week fixed effect.

In the remaining columns of Table 3, we show our first stage results, which are consistent with those shown at the store level. Average store prices at the zipcode level are well predicted by the national pricing strategies of the stores operating within the zipcode. In columns 2-4, the unit of observation is the zipcode-week. In column 2 we use the full sample, and find a highly significant coefficient of .955. The third column—labeled *non-hoarding*—leaves out the weeks of the hoarding period, which we define as April 19th to May 10. The results are virtually identical to the full sample.

In the fourth column, which is labeled *low concentration*, we show that our approach is robust to excluding areas in which chains have particularly large presences (in case demand in those areas is driving pricing policies). To do so, we leave out stores in what we call *high concentration* areas for each chain. Specifically, for each chain k, we calculate the fraction of stores in each state. If that fraction exceeds 0.32 (the median), we omit all stores in chain k in that state. Our estimated coefficient is very similar to our earlier results at 0.976.

The final column shows that our first stage results are robust to defining a market at the state rather than zipcode level. We aggregate our date to the state level (with a leave out chain price excludes stores in the state in question). The coefficient is smaller at 0.812 but still strongly significant with an F-statistic of 118.1.

5.3 Second-stage Regressions

Our second-stage regressions for the average store sales in a zipcode×week level ($\bar{Q}_{jt}$) is given by

$$log(\bar{Q}_{jt}) = \beta_0 + \beta_1 log(\bar{P}_{jt}) + \theta_j + \eta_{s(j)} \times \tau_t + \varepsilon_{jt}. \tag{3}$$

Here $\bar{Q}_{jt}$ represents the average store level quantity sold within zipcode j, and $\bar{P}_{jt}$ represents the average zipcode level price. Again θ_j represents a zipcode fixed effect and $\eta_{s(j)} \times \tau_t$ a state week fixed effect. This specification hence focuses only on *cross-zipcode* variation in prices within a state×week. Under the assumption that households located in a zip code buy their rice from stores in that zip code, the coefficients identify price sensitivities that are based only on intertemporal substitution or true consumption elasticities.[15]

In the first column of Table 4, we present results from a simplified OLS version of Equation 3, which provides a baseline elasticity while also allowing us to validate the aggregate increase in sales during the hoarding period. Specifically, we regress log quantities on log prices while controlling for week of year fixed effects (to adjust for seasonality), zipcode fixed effects, and an indicator equal to one in all zipcodes during the hoarding period (April 19th to May 10). The coefficient on Hoarding Period is 0.321 and statistically significant. This implies that average store level volume in a zip-code rose by 37.85 percent (100*(exp(0.321)-1)=0.3785) during the hoarding period. As expected, this is very similar to the estimated 40 percent increase we found when considering simple means in Subsection 4.1.

The estimated elasticity with this minimal set of fixed effects is -0.719, suggesting that a 1 percent increase in average zipcode level prices decreases sales by just over 0.7 percent. We find similar results when using an OLS approach to estimate the full specification outlined in Equation 3, with a coefficient of -0.849.

[15] Our estimates based on state level aggregation display similar results.

In columns 3 through 5, we conduct a two stage least squares approach on various samples. All provide results consistent with the OLS. Throughout, in the first stage, we instrument for log prices according to the specification outlined in Equation 2. Column 3, which includes the full sample, gives an elasticity of -0.825. Column 4, which excludes the hoarding period, gives an elasticity of -0.874, and column 5, which excludes stores in *high concentration* zipcodes, gives an elasticity of -0.818. While defining a market at the state level considerably reduces our sample size, it has little effect on the magnitude or significance of the elasticity, which we estimate at -0.802. In what follows, we take the coefficient in column 4 as our preferred estimate, as it is not contaminated by the unusual dynamics occurring during the hoarding period. This estimate suggests that, in normal times, a one percent increase in rice prices generates a roughly 0.87 percent reduction in rice purchased.

5.4 Gauging the Importance of the Sticky-Price Motive

In this subsection, we use our estimated price elasticities to account for the excess quantity sold. Of course, doing so requires an estimate on the implicit price discount faced by consumers at the time. During the hoarding period the average price of an 80 ounce bag was $4.69. Ultimately, this price rose to $6.04 on average in the post-hoarding period of our sample. Note that this suggests an approximately 30 percent pass-through from from global raw rice prices to retail prices, which is similar to what studies typically find for other storeable goods such as coffee (Nakamura & Zerom, 2010).[16]

From an ex-post perspective, this represents an implicit 22 percent promotion on rice. In other words, households benefited from a more than 20 percent discount in prices during the hoarding period. Directly applying our demand elasticity estimates (-0.874) to this discount suggests that stickiness was responsible for half of the 40 percent increase in quantity purchased during the crisis.

However, using our estimates directly requires a strong assumption, which is that -0.874 captures the relevant demand elasticity for consumers facing a one-off (and large) deviation in prices. As Hendel & Nevo (2006) note, consumer responses during promotional periods may be higher relative to consumer responses to permanent price changes, exactly because consumers shift de-

[16] The IMF rice series indicates that global prices in the post-hoarding period were 86 percent above the 2007 price.

mand dynamically and stock up, as we have emphasized. While the variation in our instrument may include some short term promotions,[17] it is likely to also include some longer term price trends. Consequently, it is possible that the above may be an underestimate of the appropriate elasticity.

To account for this underestimation, we scale our estimated elasticity by 1.3 based on the findings in Hendel & Nevo (2006). With this scaled estimate, we find that a 23 percent discount during the hoarding period accounts for a 26 percent increase in sales (0.874*1.3*0.22), representing more than 65 percent of the total hoarding observed during this episode. These exercises are approximate, and represent a range of potential estimates based on a series of reasonable assumptions.

5.5 Consumption Versus Retail Arbitrage

We cannot in general distinguish between how much of the hoarding was due to precautionary, implicit promotion effect or retail arbitrage with this approach, only that stick prices contributed significantly to hoarding. However, we can potentially distinguish between own use and resell using our house panel data. Notably, households may purchase in bulk in order to resell at higher prices through alternative means, perhaps online or through non-traditional retailers.[18]

Specifically, we track within-household purchases over our full sample period, and define retail arbitrageurs as households that exhibit extraordinary purchases during the hoarding period (relative to their history). We define an extraordinary purchases as five or more standard 80 ounce bags of rice (400 ounces or more). We see this as a cautious definition, assuming that arbitrage on a scale of fewer than 5 bags is unlikely to be profitable. We then consider two definitions of retail arbitrageurs. We define *likely retail arbitrageurs* as households that never purchase more than one bag (80 ounces) of rice in a month outside of the hoarding period, but purchase 400 ounces or more in at least one month during the hoarding period (for households, defined as April and May, 2008). As a more conservative approach, we define *potential retail arbitrageurs* as households that never purchase more than five bag (80 ounces) of rice in a month outside of the hoarding period, but purchase 400 ounces or more in at least one month during the hoarding period.

[17] Given the relatively small aggregate change in consumption before versus after the hoarding period, despite a massive price change, it is possible that our estimated elasticity is largely driven by dynamic re-allocations in response to short term promotions. In this case, using our estimated elasticity directly would be appropriate.

[18] Online price gouging has received significant attention during the COVID-19 pandemic, e.g. https://www.nytimes.com/2020/03/14/technology/coronavirus-purell-wipes-amazon-sellers.html.

We put forth two broad takeaways from this exercise. The first is that there do appear to be retail arbitrageurs, including a small handful of households that never purchase outside of the hoarding period, and purchase more than 2000 ounces of rice in a single month within the period itself. In other words, there appear to be some households that purchase in patterns consistent with a resale motive.

The second is that these households do not appear to be responsible for a large fraction of the excess purchases we observe in our household sample. Figure 6 displays averages quantities purchased over time for (i) the full sample in black, (ii) the full sample excluding likely arbitrageurs in blue, and (iii) the full sample excluding potential arbitrageurs in red. While eliminating these households naturally reduces the peak of hoarding somewhat, the reduction is marginal, even for our conservative estimate. There is pronounced hoarding excluding these households. In other words, most hoarding is driven by households purchasing quantities that are larger than is typical for them, but not so large that they could profitably resell.

To quantify the patterns shown in Figure 6 , Table 5 shows regressions of monthly quantities purchased at the household level on dummies for hoarding months, as well as a constant. The coefficients on these dummies represent the quantity of excess purchases in the hoarding period. In the first column we include the full sample, while columns two and three exclude likely and potential arbitrageurs, respectively. The key result in these tables is that there was significant excess hoarding even in the populations excluding these arbitrageurs. For example, if we leave out the likely arbitrageurs, excess quantities purchased in April 2008 decline by only 10 percent relative to the full sample (while they decline by only 30 percent when leaving out all potential arbitrageurs).

5.6 Using Placebos to Address Peak Demand and Loss Leader Pricing

Another concern is that the patterns we observe might simply be an artifact of a focused period of peak demand for consumer staples more broadly, with stores keeping the price of rice low to draw in customers. Evidence suggests that producers often do not raise prices during periods of peak demand, perhaps due to loss-leader pricing strategies (see, e.g., Chevalier *et al.* , 2003). Perhaps rice, which is not typically considered a loss leader good, might serve a role during this particular hoarding period. To confirm that our findings are not driven by such loss leader pricing strategies, we check to see whether a similar hoarding effect occurred in rice substitutes such as noodles, dumplings, and spaghetti.

Appendix Figure A.III indicates that there is no such pattern when we consider noodles and dumplings or spaghetti. 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, i.e. stores do not appear to be practicing loss leader pricing.

The lack of excess demand for other goods displayed in these placebos also highlight a key difference 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, 2015). A crucial difference is that those papers view such disasters as demand shocks, at least in part. Facing restricted access to roadways and potentially closed restaurants, many consumers stockpile food during disasters due to the hassle of having to shop during or after the storm. However, this demand interpretation makes it difficult to isolate a sticky-price motive for stockpiling.

6 Heterogeneity by Geographic and Household Demographics

6.1 Heterogeneity Across High vs. Low Demand Areas

To further confirm the existence and relevance of sticky prices in this context, our final exercises consider differences in hoarding and price dynamics across demographic groups. We first consider price and quantity variation across areas with high vs. low demand for rice. We show that despite significant geographic variation in the degree of hoarding, price dynamics were similar throughout. We consider two definitions of high demand. The first, an ex-post measure, defines high demand areas as the ten states the experienced the largest proportional deviation in quantity sold during the hoarding period. The second, an ex-ante measure, is the set of zipcodes with above median rice purchases per capita in 2007. The differences in quantities between these areas and all other areas is perhaps shown most clearly in the solid black and red lines presented in all three panels of Figure 7.

In both panels, the sample of stores is split into two groups. Black lines show store sales averages for those in "high demand" areas while red lines show averages for those in "low demand" areas. The differences between the red and black solid lines in each of these panels shows that there was significant geographical heterogeneity in the *intensity* of hoarding during this period. We also plot average store prices across these two areas to see if there are any differences in the average gradual price adjustment pattern we documented earlier. Despite large differences in the magnitude of hoarding in these differences there is little difference in store price dynamics, i.e. the dotted store price lines, consistent with sticky prices.

In Panel A of Table 6, we estimate the differences in hoarding across these zip codes more formally. The first column of Panel A estimates the baseline or average hoarding across all areas using 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 zipcode level. The coefficient suggests that, during the hoarding period, stores sold 3780 additional ounces of rice per week on average, consistent with our earlier findings. The estimate is highly significant.

The last two columns of Panel A in Table 6 then split up this effect for high versus low demand areas using the definitions for areas as in the plots in Figure 7. We display the coefficient β_1 from the following specification. For store i, in zipcode j and week t we estimate:

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

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 proxies are exactly those included in Figure 7. We include store fixed effects γ_i and week fixed effects δ_t. We cluster standard errors at the county level.

Across both 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. Similarly, stores in high rice consuming zipcodes sold just over 3000 additional ounces per week during the hoarding period, on average, when compared to other zipcodes.

In Panel B, we repeat the specifications shown in Panel A, but include the price in store i, in zipcode j and week t as a dependent variable. The first column shows a significant negative coefficient on aggregate during the hoarding period. This simply reflects the fact that prices were much lower during these weeks compared with the average in the post-hoarding period. However, the remaining three columns show that there was little or no difference in prices across these regions, despite the massive difference in hoarding. While there are small positive coefficients, on the order of \$0.04, these are extremely small in comparison to the more than \$1 jump in prices seen after the hoarding episode concluded.

6.2 Heterogeneity by Wealth

We next consider heterogeneity in the quantity of rice purchased across the distribution of wealth in our household panel. Panel A of Figure 8 shows average quantities purchased inside (in red) and outside (in black) the hoarding period across all bins of household income available in our data.[19] The basic pattern is evident in this figure. At the very low end of the income distribution the difference in purchases is not substantial inside and outside of this period, while the degree of excess purchases in the hoarding period—the difference between the red and black lines—increases for higher income households. Panel B shows the degree of excess purchases more succinctly. Households with incomes below \$10000 exhibit the smallest excess purchases during the period, while the highest income individuals have the largest. Excluding a slight dip for those with income between \$100,000-200,000, the pattern is monotonic. Higher income households purchased more during the hoarding period.

Table 7 quantifies this basic pattern: low income households hoarded significantly less in this episode. This table shows regressions of monthly quantity purchased at the household level on month$\times$year fixed effects, a dummy for low-income households, and the interaction between the low-income dummy and the hoarding period (defined as April and May of 2008 in this monthly

[19] Our data does not report exact income levels, but rather income in relatively coarse bins. We plot each point at the midpoint of the relevant bin.

data). The coefficient on the low-income dummy represents the average difference in quantity purchased for low-income households, while the coefficient on the interaction shows the difference in excess purchases for low-income households during the hoarding period. A negative coefficient on the interaction suggests that low-income household hoard to a lesser degree. We consider four definitions of low income: the lowest bin in our sample (households within incomes below $5000), the lowest ventile, the lowest decile, and the lowest quartile.

Across all definitions we see negative and significant coefficients on the interaction, suggesting that low income households do not hoard to the same degree as middle and high income households. For the lowest household income bracket, the increase in rice purchased during the hoarding period was 4.8 ounces below the increase for other households. This is true despite the fact that the lowest income bracket purchases roughly 2.5 ounces more rice per month than wealthier households in normal times. For the lowest ventile, the increase in rice purchased during the hoarding period was 2.5 ounces below the increase for other households. Similarly, the lowest decile and quartile both saw increases that were roughly 1.5 ounces below the average the increase for higher income households.

Notably, this pattern holds both when considering the lowest income bracket, which is composed of households that actual purchase *more* rice on average in typical periods (compared with higher income households), and when considering the lowest quartile, households that purchase less rice on average compared with higher income households. While we cannot confirm the mechanism underlying these results, a natural explanation given the importance of sticky prices is the difference in liquidity across high and low income households. Even if both recognize the implicit promotion provided by sticky prices, low income households may be unable to take advantage of the promotion if they do not have sufficient cash on hand.

7 External Validity, Covid-19 Pandemic and Policy Implications

A number of empirical findings foreshadow reports on the nature and concerns of hoarding during the Covid-19 Pandemic—alleviating any concerns about external validity. First, reports point to some issues with retail arbitrage due to sticky prices, but the vast majority was for own use consistent with our findings. Second, much of the concerns were about hoarding by rich households creating distributional concerns for low income households, very much consistent with our findings.[20]

We see two potential policy implications that follow from our study. The first is that regulations and concern over price gouging for the types of reputable retailers observed in the Nielson data may be misplaced. The patterns we observe suggest that retailers are inherently slow at or unwilling to raise prices, even in the face of relatively straightforward cost shocks. Of course, this does not mean that price gouging does not exist, but rather that it may be concentrated in less formal establishments. Consistent with our sticky-price view of hoarding, media coverage of the Covid-19 hoarding episode points to price gouging among online resellers as being a far bigger issue than reputable retailers.[21] Quantity restrictions may be effective in preventing such price-gougers, to the extent that they operate by purchasing at formal establishments before prices rise (although our analysis suggests that this sort of retail arbitrage is not the primary driver of hoarding episodes).

Secondly, concerns over price gouging are often framed in terms distributional concerns: relatively low income or otherwise vulnerable groups may be unable to afford exorbitant prices. However, our results suggests that low income households hoard to lesser degrees even in the absence of any price increase. To the extent that this finding is driven by liquidity, this suggests that price controls may be insufficient to protect key groups in hoarding episodes. For example, low income households may not have sufficient cash on hand to stock up on staples before shortages occur. Policies that ensure protected groups retain access to staples—as, for example, some grocery stores have done for the elderly during the COVID-19 pandemic—should be considered within the regulatory toolkit.

8 Conclusion

Using US supermarket scanner data during the 2008 Global Rice Crisis, we point to the neglected role of sticky store prices in generating an additional motive for intertemporal storage. Following US news coverage of global supply disruptions, Google searches and household inventories

[20]For a contemporary report on this phenomenon, see a *Washington Post* article at https://www.washingtonpost.com/business/2020/03/20/if-coronavirus-doesnt-get-us-starvation-will-growing-number-americans-say-they-cant-afford

[21]See *Forbes* article coverage of this issue at https://www.forbes.com/sites/joanverdon/2020/03/04/coronavirus-related-price-gouging-is-a-risky-business-for-retailers/

spiked, anticipating delayed retail-price adjustment. Holding fixed precautionary demand, sticky shelf prices generate an incentive for households to hoard. Recognizing that prices are temporarily low, households shift demand intertemporally and stockpile as if they were facing a retail promotion or to engage in retail arbitrage. We estimate that this sticky-price effect can generate stockpiling responsible for a non-trivial portion of observed hoarding—with the vast majority of hoarding we attribute to own use. Interestingly, we find that hoarding is concentrated in richer households, consistent with distributional concerns reported in media during the Covid-19 Pandemic hoarding episode. We draw out new policy implications.

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TABLE 1: SUMMARY STATISTICS

	Panel A: Store Level Data			
	Mean	S.D.	Min.	Max
Volume (oz)	8564.1	19788.0	4	1648736
Price (80oz)	5.33	1.56	0.63	43.8
Local Population (1000s)	1173.4	2018.8	3.35	9840.0
Median Income (1000s)	57.2	15.5	22.4	120.1
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 and income are merged to stores at the zip level.

TABLE 2: HOUSEHOLD INVENTORIES PREDICT SHELF PRICES

	National Aggregates		County Level	
	Δ Shelf Price	Δ Inventory	Δ Shelf Price	Δ Inventory
Lagged Δ Inventory	0.055^{**}		0.023^{***}	
	(0.021)		(0.006)	
Lagged Δ Shelf Price		-0.851		0.035
		(1.409)		(0.037)
Mean of Dep. Var.	0.052	-0.041	0.061	-0.045
R^2	0.19	0.011	0.036	0.069
N	34	34	5425	5431
County FE	No	No	Yes	Yes
Month FE	No	No	Yes	Yes

Regressions of monthly changes in shelf prices on lagged monthly changes in consumer inventory, and vice versa. Shelf prices are measured as the average unit price paid by consumers in our household panel, averaged across all consumers. Inventories are calculated following the procedure in Hendel & Nevo (2006). For each household, we estimate monthly consumption based on average purchases throughout our sample period. We then construct inventories in each month as the cumulative difference between purchases and consumption up to that month. Columns 1 and 2 show results aggregated at the national level, while columns 3 and 4 show results aggregated at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 3: FIRST STAGE – STORE PRICES ARE DRIVEN BY NATIONAL CHAIN PRICING POLICIES

	Store Level	Full Sample	Non-Hoarding	Low Concentration	State Level
Log(Leave-Out Chain Price)	0.906^{***}	0.955^{***}	0.952^{***}	0.976^{***}	0.812^{***}
	(0.0130)	(0.0175)	(0.0181)	(0.0215)	(0.0747)
F-Statistic	4891.0	2972.5	2751.1	2058.5	118.1
N	1382371	223379	217652	178919	7644
Week FE	No	No	No	No	No
Week × Year FE	Yes	Yes	Yes	Yes	Yes
Store/Zipcode/State FE	Yes	Yes	Yes	Yes	Yes
State × Week × Year FE	Yes	Yes	Yes	Yes	No

First stage regressions of log rice prices on leave out chain level rice prices. In the first two columns, the unit of observation is the store-week prices are constructed as the average unit price sold within each store. To construct the leave out chain price for store i belonging to chain k in zipcode j and week t, we take the average week t price for all stores in chain k in excluding those in zipcode j. In columns 3-5, the unit of observation is the zipcode-week. Prices, in these columns, refer to the equal weighted average of the prices used in the first two columns across stores in zipcode j. The leave out chain price is similarly the equal weighted average of this measure across all stores in zipcode j. The final column shows a similar aggregation, but at the state level (and the leave out chain price excludes stores in the state in question). The column labeled non-hoarding leaves out the weeks of the hoarding period. The column labeled low concentration restricts the sample by leaving out stores in high concentration areas for each chain. Specifically, for each chain k, we calculate the fraction of stores in each state. If that fraction exceeds 0.32 (the median), we omit all stores in chain k in that state. The column labeled state level repeats the full sample specification, but averages prices and quantities at the state level. All specifications show standard errors clustered at the zipcode level (or state level, in column 6) in parentheses. Store/Zipcode/State FE refers to store fixed effects in columns 1 and 2, zipcode in 3 through 5, and state in 6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: SECOND STAGE–DEMAND ELASTICITIES

	OLS		IV: Full Sample	IV: Non-Hoarding	IV: Low Concentration	IV: State Level
Hoarding Period	0.321^{***}					
	(0.00505)					
Log(Price of 80oz Bag)	-0.719^{***}	-0.849^{***}	-0.825^{***}	-0.874^{***}	-0.818^{***}	-0.802^{***}
	(0.0152)	(0.0190)	(0.0456)	(0.0408)	(0.0592)	(0.157)
Mean of Dep. Var.	8.014	8.013	8.014	8.005	8.004	8.564
N	223691	223535	223379	217652	178919	7644
Week FE	Yes	No	No	No	No	No
Week $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Zipcode/State FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Week $\times$ Year FE	No	Yes	Yes	Yes	Yes	No

Regressions of log average store level volume sold on the log price of a 80oz bag, and, in column 1, a dummy for the hoarding period. The hoarding period is defined as the weeks of April 19th-May 10th, 2008. In columns 1-5, the unit of observation is the zipcode-week. In column 6, the unit of observation is the state-week. Prices are constructed as the average unit price sold within each store, and then averaged across stores. In all IV specifications, Log(Price of 80oz Bag) is instrumented with the Log(Leave-Out Chain Price). For each zipcode, this instrument is constructed using the following procedure: For store i belonging to chain k in zipcode j and week t, we take the average week t price for all stores in chain k in excluding those in zipcode j. We then take the equal weighted average of this measure across all stores in zipcode j. The column labeled non-hoarding leaves out the weeks of the hoarding period. The column labeled low concentration restricts the sample by leaving out stores in high concentration areas for each chain. Specifically, for each chain k, we calculate the fraction of stores in each state. If that fraction exceeds 0.32 (the median), we omit all stores in chain k in that state. The column labeled state level repeats the full sample specification, but averages prices and quantities at the state level (and constructs the leave out mean by excluding any store in the state in question). All specifications show standard errors clustered at the zipcode level (or state level, in column 6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5: OWN CONSUMPTION VERSUS RETAIL ARBITRAGE

	Full Sample	Without Likely Retail Arbitrageurs	Without Potential Retail Arbitrageus
April 2008	6.752^{***}	6.193^{***}	4.781^{***}
	(0.455)	(0.437)	(0.368)
May 2008	4.523^{***}	3.677^{***}	2.722^{***}
	(0.394)	(0.347)	(0.315)
N	1187057	1187057	1187057

Regressions of monthly household rice purchases in ounces for our household panel on dummies for April and May of 2008. Non-hoarding periods refers to all other months between 2007 and 2009, and represents the constant in the regression. *Full sample* refers to our full household panel. *Without likely retail arbitrageurs* excludes any households that (i) have a maximum purchase of 80 or fewer ounces of rice in any month outside of the hoarding period and (ii) purchase more than 400 ounces of rice in either April or May of 2008. *Without potential retail arbitrageurs* excludes any households that (i) have a maximum purchase of 400 or fewer ounces of rice in any month outside of the hoarding period, and (ii) purchase more than 400 ounces of rice in either April or May of 2008. Standard errors are clustered at the household level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6: CHANGES IN QUANTITY AND PRICE DURING HOARDING PERIOD ACROSS HIGH VS. LOW HOARDING REGIONS

	Volume Sold at Store Level (Ounces)			Price for 80 Ounce Bag		
Hoarding Period	3689.927^{***} (223.625)			-0.542^{***} (0.012)		
Hoarding Period x Hoarding State		4878.239^{***} (508.100)			0.043^{*} (0.023)	
Hoarding Period x High Rice FIPS			3032.942^{***} (405.325)			0.043^{**} (0.020)
Mean of Dep. Var.	8564.3	8564.3	8564.3	5.33	5.33	5.33
N	1383462	1383462	1383462	1383462	1383462	1383462
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	No	No	Yes	No	No
Week $\times$ Year FE	No	Yes	Yes	No	Yes	Yes

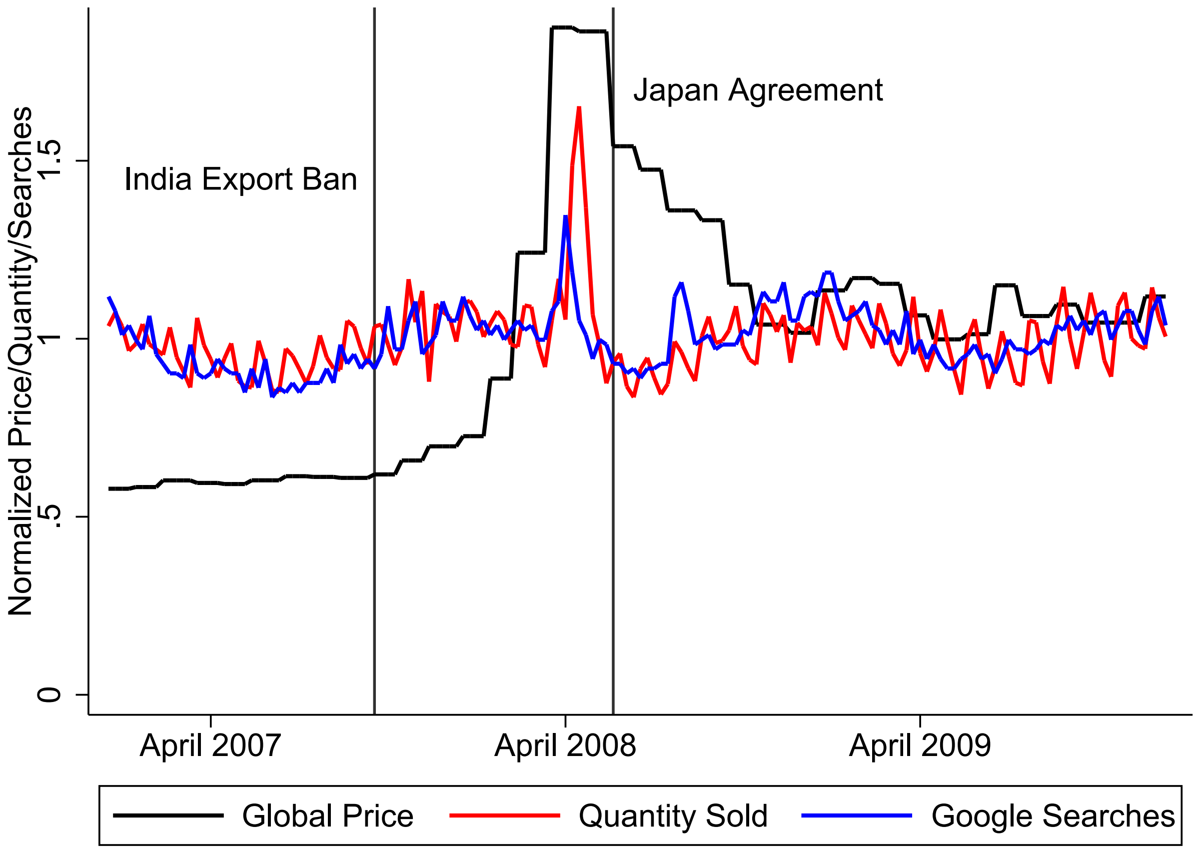
The first three columns show OLS regressions of weekly store level volume of rice sold in ounces on indicators for the hoarding period and the hoarding period interacted with indicators for high demand locations. All weeks from 2007-2009 are used. The first column shows the coefficient on an indicator 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 following two 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 above median 2007 rice consumption. The last three columns repeat the exercise, but with store level prices, constructed as the average unit price paid within store, normalized to 80 ounces. Standard errors are clustered at the FIPS county code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: HOARDING CONCENTRATED IN HIGHER INCOME HOUSEHOLDS

	Dependent Variable: Quantity Purchased (Monthly)			
Lowest HH Income Bracket (<5000 USD)	2.492^{*}			
	(1.371)			
Lowest Bracket × Hoarding Period	-4.822^{**}			
	(2.092)			
Lowest Ventile HH Income		-0.608		
		(0.387)		
Lowest Ventile × Hoarding Period		-2.484^{**}		
		(1.014)		
Lowest Decile HH Income			-1.384^{***}	
			(0.307)	
Lowest Decile × Hoarding Period			-1.460^{*}	
			(0.828)	
Lowest Quartile HH Income				-1.344^{***}
				(0.320)
Lowest Quartile × Hoarding Period				-1.446^{**}
				(0.618)
Mean of Dep. Var.	10.2	10.2	10.2	10.2
N	1187057	1187057	1187057	1187057
Month FE	Yes	Yes	Yes	Yes

Regressions of monthly household rice purchases in ounces for our household panel on month fixed effects, indicators for the household's position in the wealth distribution, and those indicators interacted with a dummy for the hoarding period (April and May of 2008). In column 1, the indicator is equal to 1 if the household is in the lowest income bracket in our data (less than 5000 USD). In column 2, the indicator is equal to 1 if the household is in the lowest ventile of the income distribution. In column 3, the indicator is equal to 1 if the household is in the lowest decile of the income distribution. In column 4, the indicator is equal to 1 if the household is in the lowest quartile of the income distribution. Standard errors are clustered at the FIPS county code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

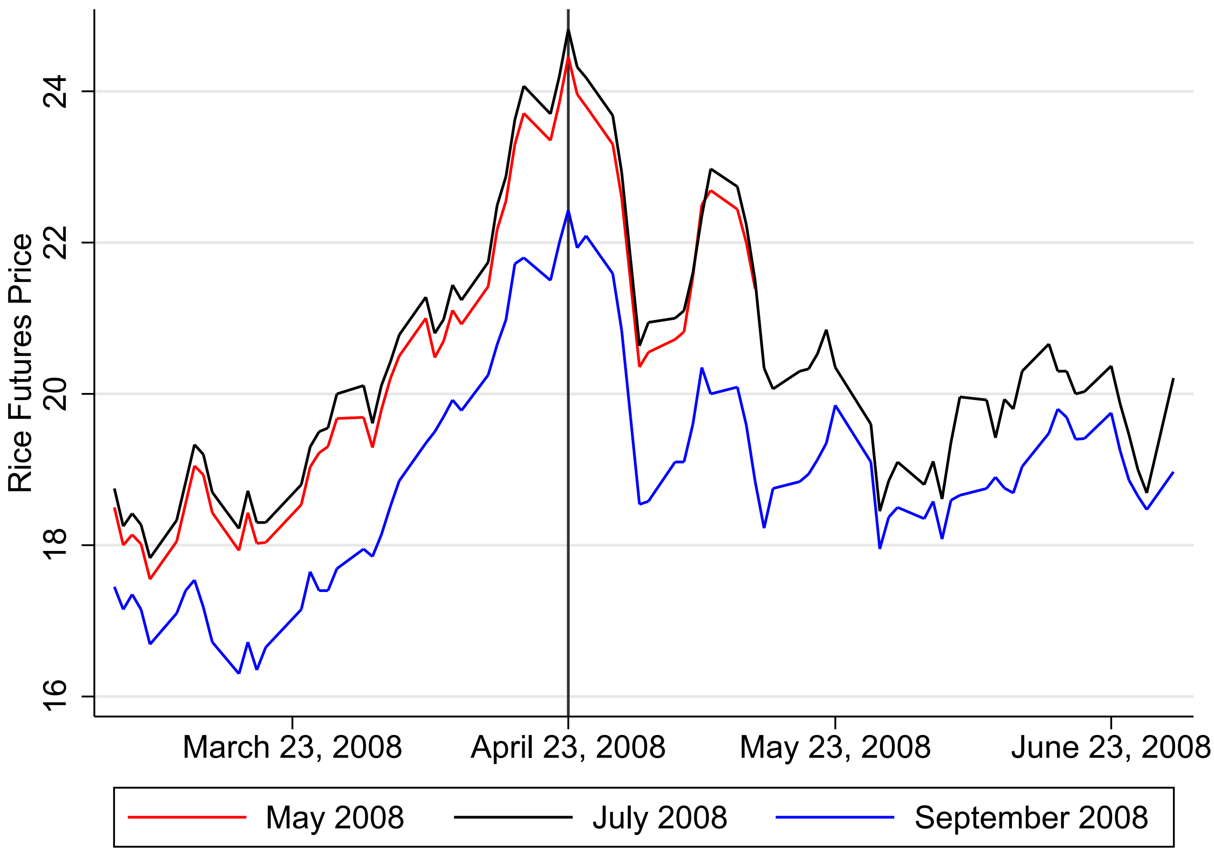
FIGURE 1: GLOBAL RICE COMMODITY PRICES RISE FOLLOWING INDIA EXPORT BAN



Notes: The black line displays monthly international rice prices provided by the IMF, the red line shows weekly total quantity sold for stores in our sample, and the blue line shows weekly Google search volume. All variables are normalized by the mean over the sample period. 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.

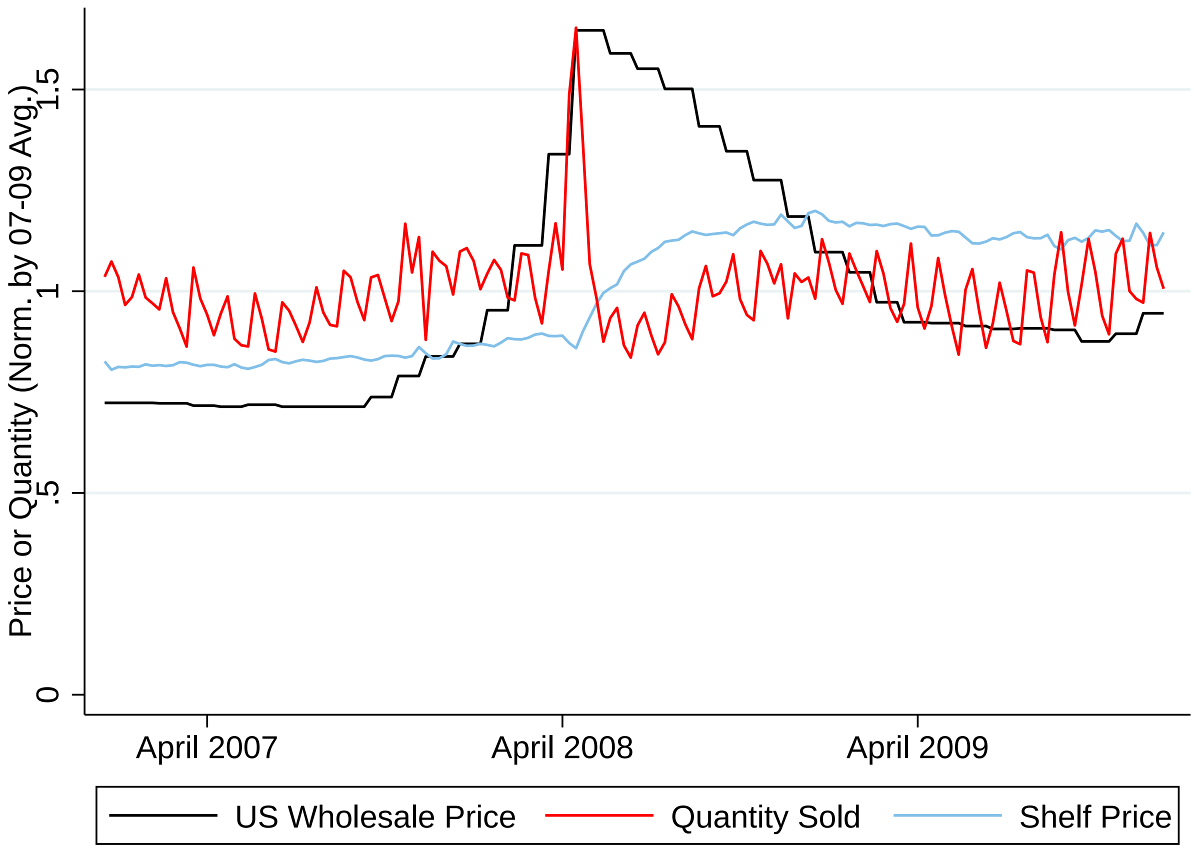
FIGURE 2: RICE FUTURES

FUTURES PRICES



Notes: Figure plots the prices for futures contracts for rice with expiration in May 2008, July 2008 and September 2008. 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.

FIGURE 3: HOARDING ANTICIPATES SHELF PRICE SHOCK

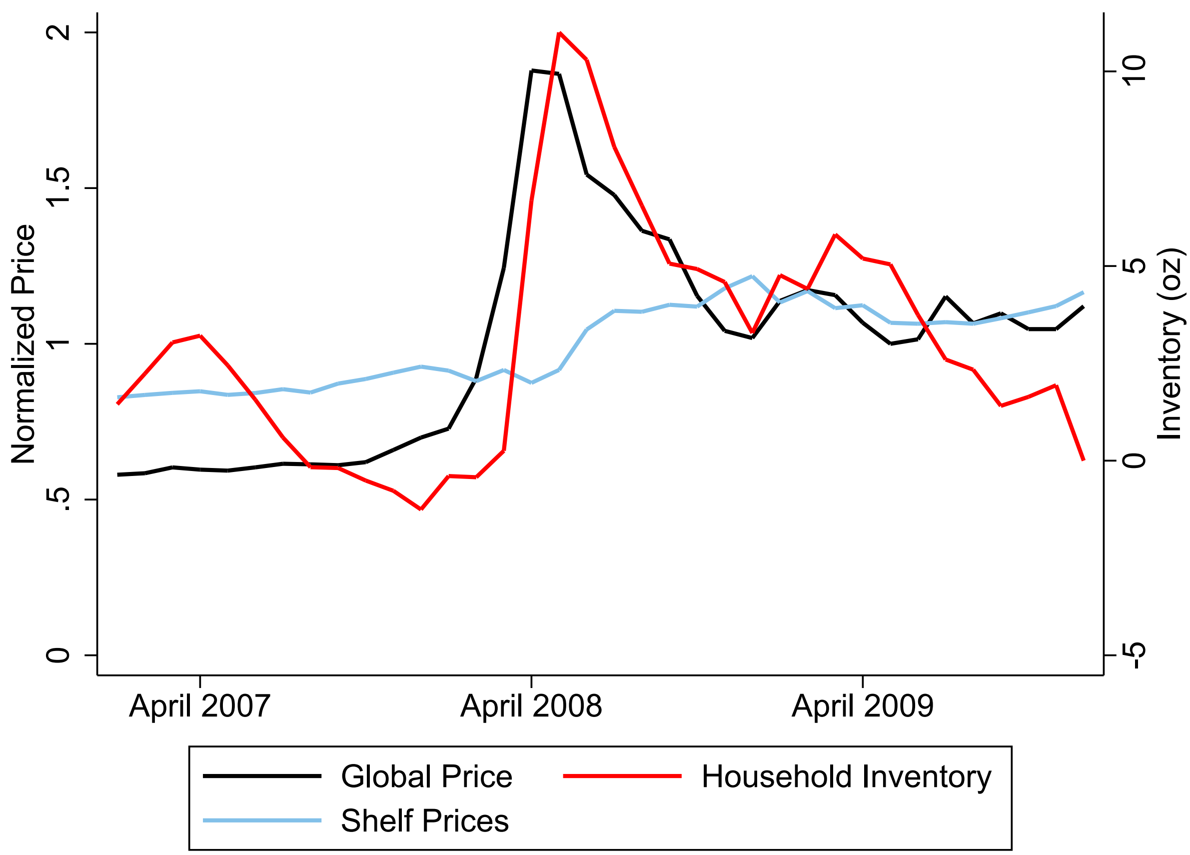


Notes: The black line displays a proxy for the US wholesale rice price at the monthly level. The proxy is based on average f.o.b. price for long grain rice at selected milling centers in Southwest Louisiana. Data provided by USDA, based on data from Agricultural Marketing Service, *National Weekly Rice Summary*. The red 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 4: STORES UPDATE GRADUALLY TO HIGHER PRICE

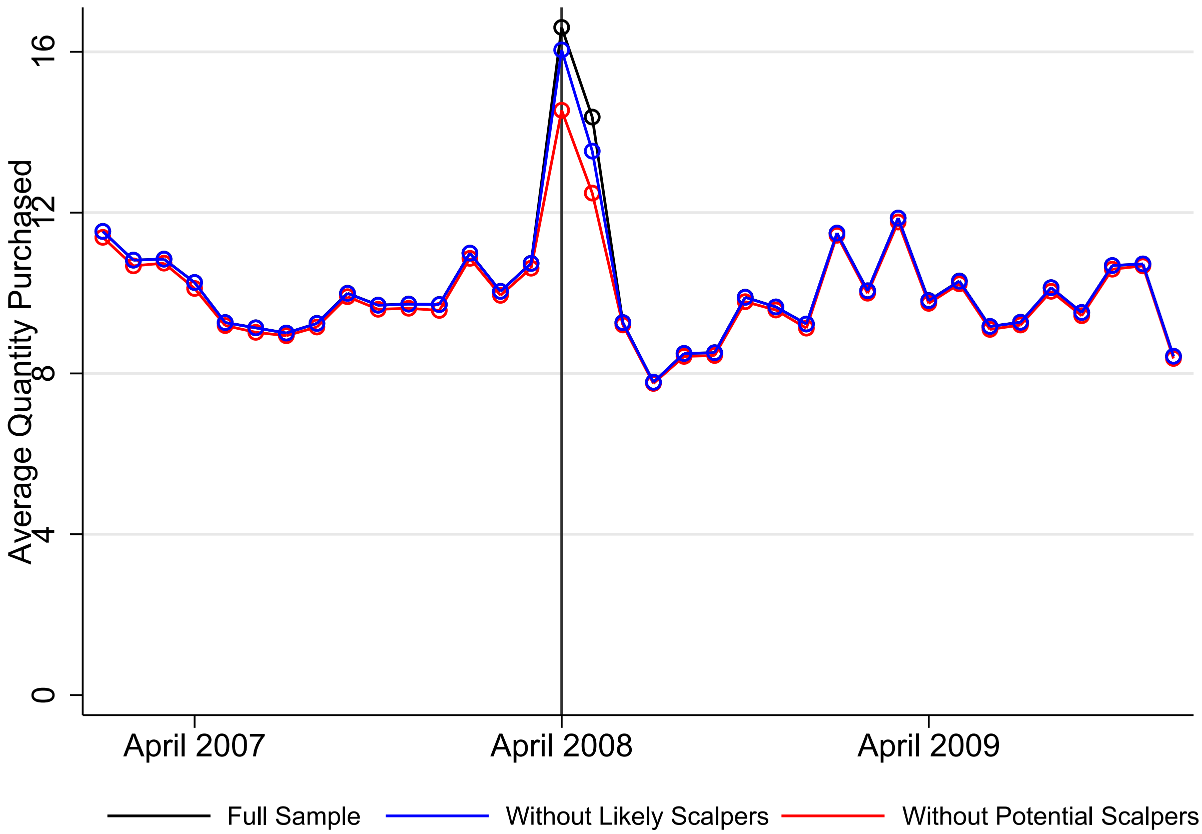
Notes: Plot displays the fraction of stores that have *updated prices* in the wake of the shock to international prices. A store is determined to have updated its price if the price is greater that 125 percent of the 2007 average. The red portion highlights the weeks starting on the 19th of April through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

FIGURE 5: HOUSEHOLD INVENTORIES LEAD RETAIL PRICES



Notes: Black line shows global rice prices normalized to the mean over our sample period. The blue line shows shelf prices, calculated as the average unit price paid by households in our panel. The red line shows household inventories. Inventories are calculated following the procedure in Hendel & Nevo (2006). For each household, we estimate monthly consumption based on average purchases throughout our sample period. We then construct inventories in each month as the cumulative difference between purchases and consumption up to that month.

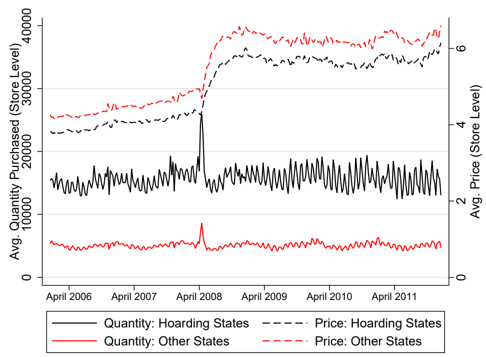
FIGURE 6: HOARDING PRIMARILY DRIVEN BY OWN CONSUMPTION



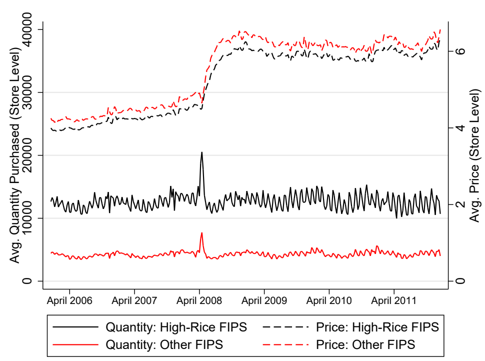
Notes: Plots of average monthly household rice purchases in ounces for our household panel. The vertical line represents April, 2008. *Full sample* refers to our full household panel. *Without likely scalpers* excludes any households that (i) have a maximum purchase of 80 or fewer ounces of rice in any month outside of the hoarding period and (ii) purchase more than 400 ounces of rice in either April or May of 2008. *Without potential scalpers* excludes any households that (i) have a maximum purchase of 400 or fewer ounces of rice in any month outside of the hoarding period, and (ii) purchase more than 400 ounces of rice in either April or May of 2008.

FIGURE 7: CROSS-SECTIONAL STRENGTH OF HOARDING DOES NOT PREDICT PRICE MOVEMENTS

PANEL A: HOARDING VS. NON-HOARDING STATES



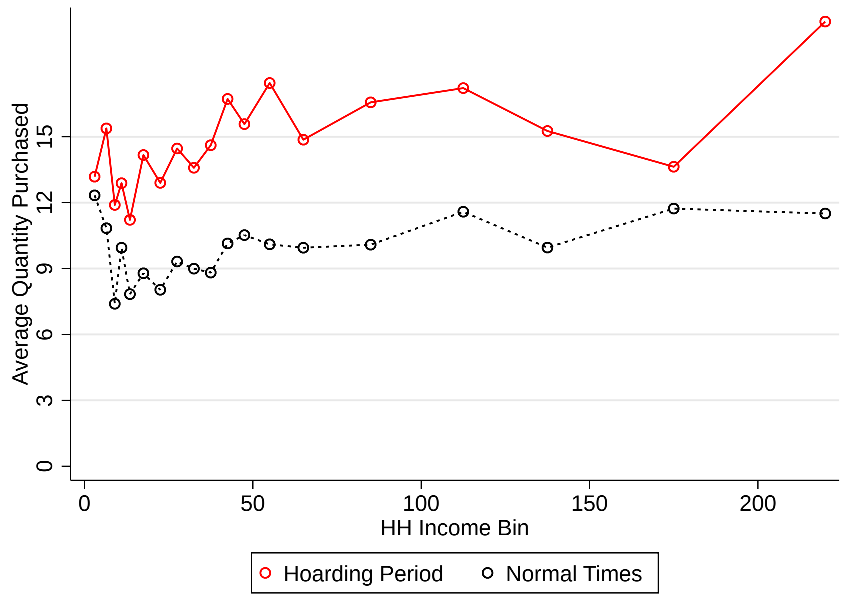
PANEL B: ABOVE VS. BELOW MEDIAN PER-CAPITA RICE CONSUMPTION



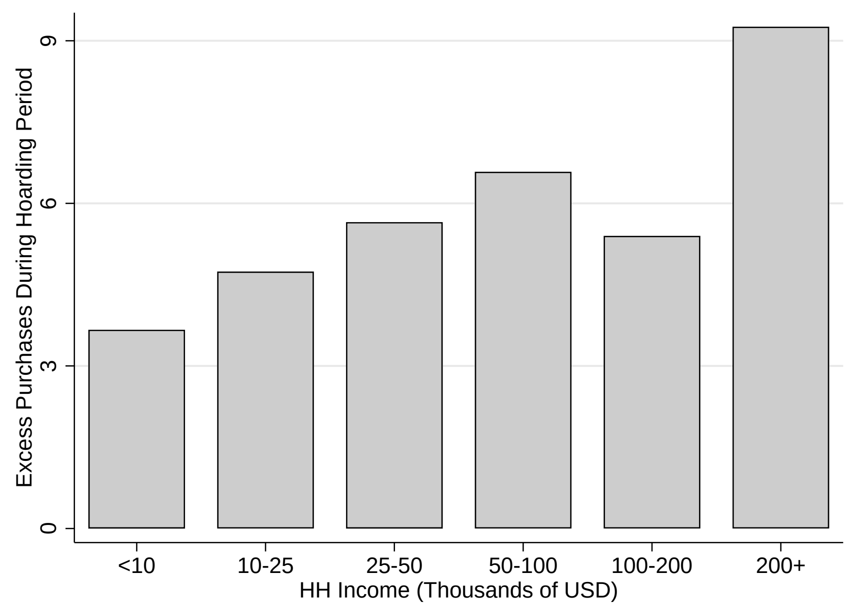
Notes: Plots show average store level prices and average store level quantity sold in ounces. In each, the sample of stores is split into two groups, with black lines showing averages for those in high demand areas and red lines showing those in low demand areas. Solid lines show quantities, while dashed 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 counties (FIPS codes) who had above median rice purchases per capita in our sample of stores in 2007.

FIGURE 8: HOARDING CONCENTRATED IN HIGHER INCOME HOUSEHOLDS

Panel A: Average Purchases Within and Outside Hoarding Period by HH Income



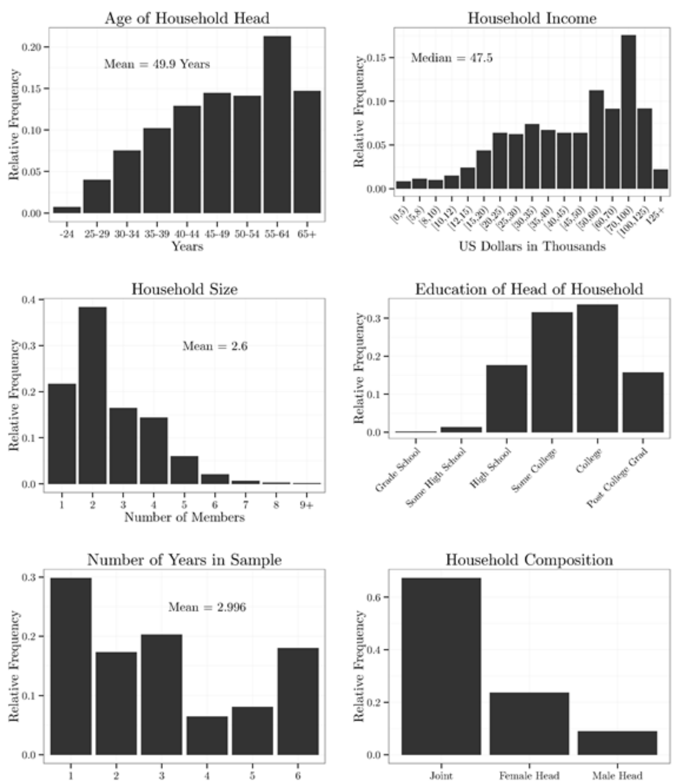
Panel B: Difference in Average Purchases Within and Outside Hoarding Period by HH Income



Notes: Top panel shows average rice purchase in ounces at the household-month level for each household income category available in our data. Red lines show average purchases during the hoarding period (April and May of 2008) while the black line shows average purchases between 2007-2009 outside of the hoarding period. Dots are located at the midpoint of the associated category. Bottom panel shows the difference in average purchases between the hoarding period and all other times for a collapsed set of income categories.

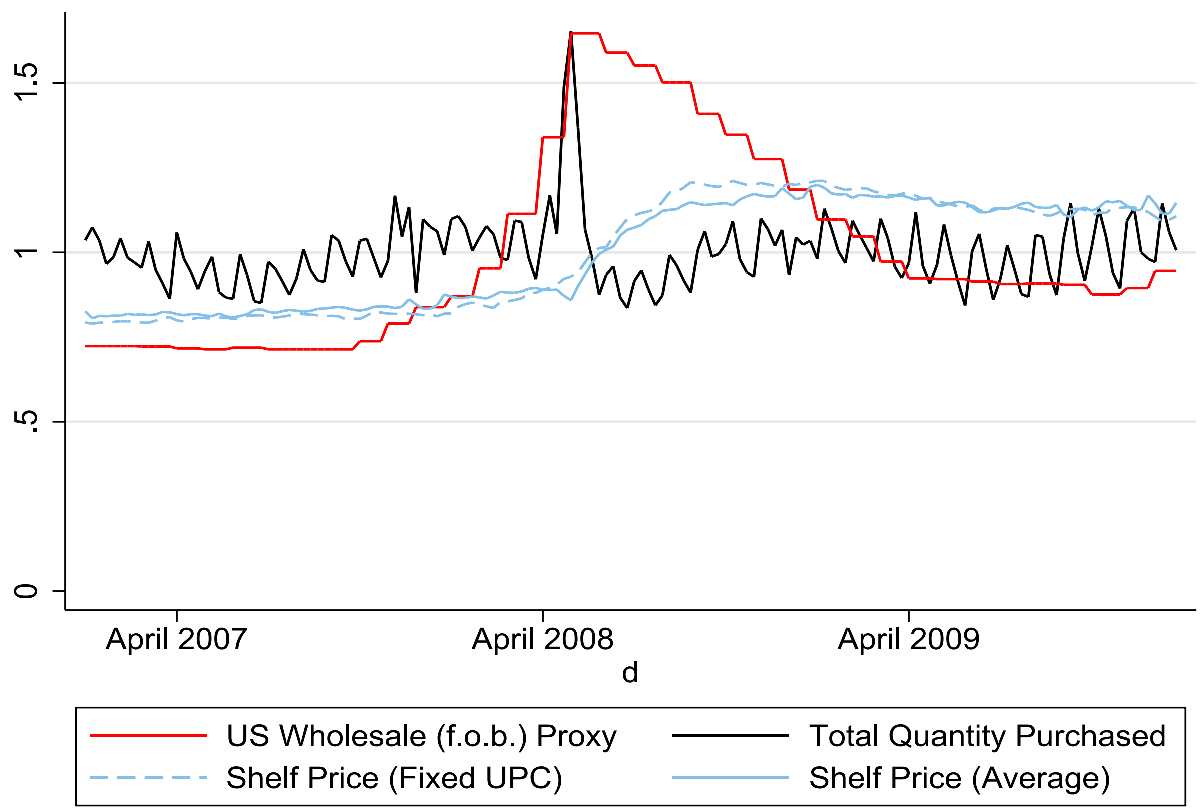
Internet Appendix: For Online Publication

FIGURE A.I: NIELSEN PANEL DEMOGRAPHICS



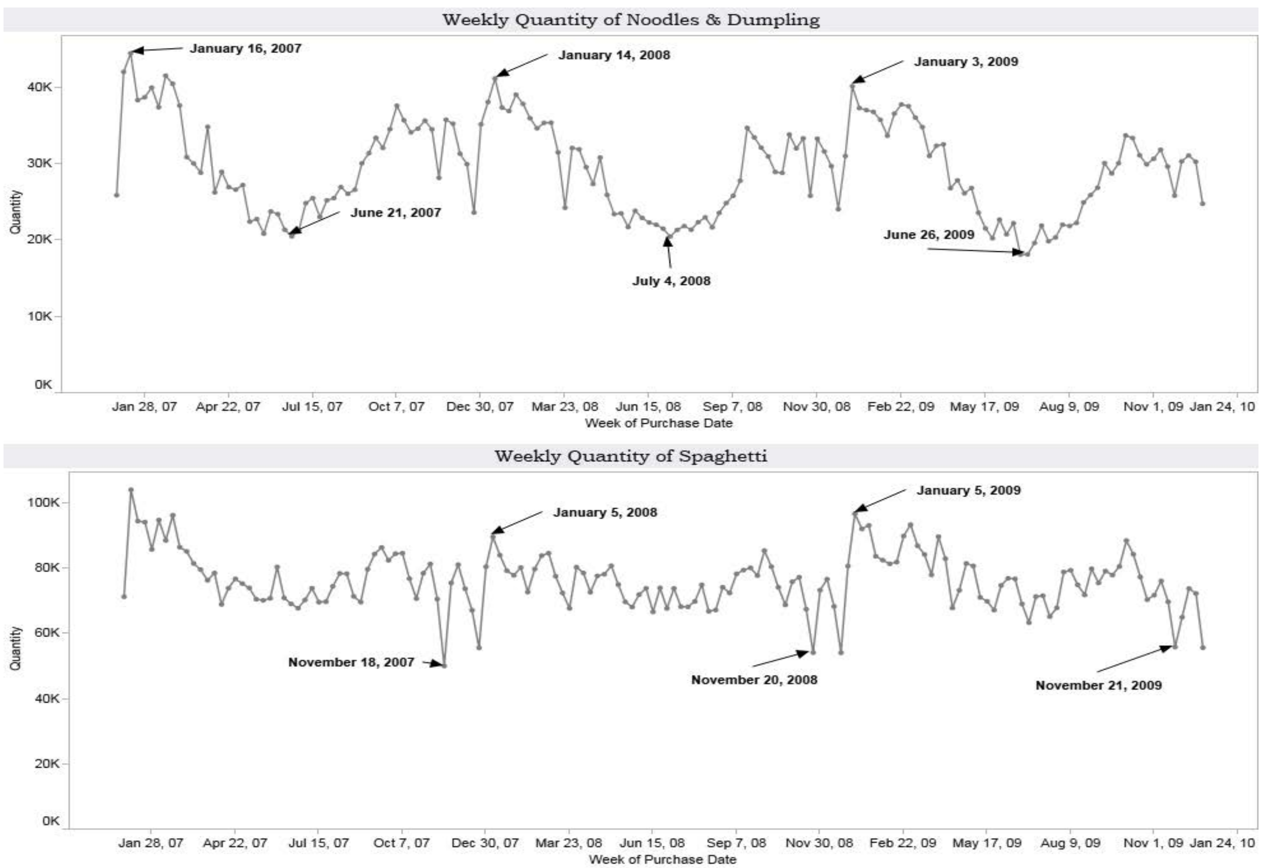
Notes: This figure plots the distribution of demographics of the overall Nielsen Panel.

FIGURE A.II: ALTERNATIVE PRICE MEASURES: FIXING PRODUCT CHARACTERISTICS WITHIN STORES (UPC)



Notes: This figure recreates Figure 3 but includes an alternative price metric. The solid blue line shows the average shelf price across products and stores, weighted by units purchased as in Figure 3, in other words, total expenditures on rice over total units sold. The dotted line shows the price for the most popular UPC code within each store (based on 2007 revenue) averaged across stores.

FIGURE A.III: 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.