A Sticky-Price View of Hoarding *

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Abstract

Household hoarding of staple foods during periods of scarcity is conventionally portrayed as driven by precaution. By paying high prices for inventories to hedge price uncertainty, households are thought to destabilize commodity markets. However, retail prices are sticky, responding with delay to supply shocks. Hoarding hence conflates precaution with anticipatory stockpiling due to sticky prices. With U.S. scanner data covering a classic 2008 rice hoarding episode, we find that household inventories anticipated delayed retail-price adjustment. There would be significantly less hoarding absent sticky prices. Traditional policy measures invoked during commodity-market bubbles or shortages can be counterproductive under the sticky-price view.

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1 Introduction

Household hoarding of staple foods—the accumulation of inventories during times of scarcity—has long been a concern of governments in both the developing and developed world. For instance, Roman Emperor Julian blamed hoarding for artificial shortages and famine in Antioch as far back 362 A.D. (Gráda, 2009). Under the conventional view, such hoarding is motivated by *precaution*: households face abnormally high store prices, but are driven to purchase excess quantities as insurance against future price uncertainty. This in turn pushes prices even higher.

The precautionary narrative has been of interest to economists since Adam Smith[1] and has been invoked as a key factor in a number of famous shortages. For instance, gas hoarding by consumers during the energy crises of the 1970s is commonly accepted to have amplified prices at the pump, feeding back into higher oil prices globally.[2] Household hoarding is also thought to have exacerbated the 2000s commodities boom.[3] Since hoarding can destabilize local markets and potentially contribute to broader market fluctuations, governments typically respond to hoarding episodes by imposing anti-price-gouging laws or other measures aimed at protecting fearful consumers and forcing producers to maintain supply.

Despite its popularity, there is little work we know of that systematically tests this conventional view. 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),[4] the role of households has remained unexplored. As Kenneth Arrow wrote in his review of Amartya Sen's influential

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

[2] 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."

[3] For instance, media reports pointed to hoarding of cotton and other food stuffs in various countries such as China during this period ("Chinese Take a Cotton to Hoarding", *Wall Street Journal*, January 29, 2011).

[4] 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.

Poverty and Famines—which examined the destabilizing role of precautionary hoarding in the Bengali Famine of 1943—"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).

In this paper, we consider the validity of the conventional narrative—precautionary demand as the key driver of hoarding—in the context of the 2008 Global Rice Crisis, which occurred alongside the 2000s commodities boom. Our key concern with this narrative is that it assumes highly flexible *retail* prices, which must rise before consumers hoard, and which those consumers must fear will be volatile in the future. Of course, this stands in contrast to the pervasive adjustment delays documented in a large macroeconomic literature on sticky prices (see, e.g., Bils & Klenow, 2004; Nakamura & Steinsson, 2008). Regardless of the mechanism generating sticky prices—menu costs, customer anger (e.g. Rotemberg, 2005) or costly attention or information gathering (e.g. Mankiw & Reis, 2002; Woodford, 2009)—Benabou (1989) shows that they create an incentive for anticipatory stockpiling when goods are storeable.[5]

Put another way, in the presence of sticky prices, precautionary motives will be conflated with a standard anticipatory stockpiling effect. If stores are slow to adjust prices in response to cost shocks, they offer an implicit and temporary "sale" to consumers. Precisely as in Hendel & Nevo (2006), consumers then shift demand intertemporally and stockpile, recognizing that prices will rise in the future when the sale ends. Such anticipation generates excess purchases—hoarding—even in the absence of any uncertainty or precautionary demand. While somewhat subtle, the distinction between the two mechanisms is crucial from a policy perspective: while price controls or other typical government interventions may neutralize precautionary motives, they also might exacerbate

[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.

stockpiling due to sticky prices.

A key challenge to testing the precautionary narrative, and in disentangling precaution from anticipatory stockpiling due to sticky prices, is the availability of sufficiently detailed micro-data. To understand household hoarding behavior, it is necessary to go beyond aggregates and observe both the local prices they are exposed to and the inventories that they hold. This poses a difficulty, as many large-scale hoarding episodes are historic or in developing countries where such data is difficult to come by.

Studying the 2008 Global Rice Crisis allows us to overcome these data limitations. This hoarding episode is widely thought to illustrate exactly the conventional narrative. 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 May 2008 before crashing in June 2008 following news of untapped supply from Japan. Retrospectives on this episode emphasize a precaution or 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), with Google searches in the U.S. for "rice" spiking in the month of April 2008. Given this US exposure, we are able to exploit Nielsen scanner data in our analysis. The fine grained nature of this data allows us to precisely measure local store price and household inventory dynamics.

We begin our paper by rejecting a key feature of the precautionary narrative: that hoarding consumers pay *abnormally high* prices due to a hedging motive. To do so, we proceed in three steps. First, we show the extent of hoarding using both store sales and a standard algorithm (see, e.g., Hendel & Nevo, 2006) to infer household rice inventories.

For example, we find that in April and May of 2008 store sales were 38% higher than average. This hoarding coincided with or slightly lagged wholesale and international rice prices, which spiked following the Indian export ban, and remained permanently above pre-ban prices in the wake of news from Japan. Second, we show evidence of ubiquitous stickiness in prices at the retail level: store prices saw no immediate spike, and only slowly rose to match the increase in international prices. Third, we show that, given this stickiness, consumer hoarding actually preceded any increase in retail prices. In other words, consumers purchased rice in bulk at relatively low prices.

If stickiness enables consumers to buy before store prices rise, then households actually benefit from hoarding episodes (with retailers bearing the costs). This also stands in contrast to the traditional precautionary narrative, in which consumers pay a premium and bear the costs of hoarding episodes, with benefits either accruing to retailers through high prices or dissipating as a result of misallocation. Of course, in practice, both motivations may be at play: even consumers who correctly anticipate price increases may want insurance against price uncertainty.

In the second part of our paper, we empirically disentangle anticipatory stockpiling from precautionary demand. Specifically, we estimate the fraction of excess purchases that can be attributed directly to sticky prices by asking how much of the observed hoarding during the 2008 rice crisis would have been avoided had retail prices adjusted immediately alongside wholesale prices. During the worst of the hoarding, the average price of an 80 ounce bag of rice remained close to the pre-crisis average at roughly $4.61 before rising to a post-crisis level of $5.97.

From the perspective of an informed consumer following global trends, this effectively represented an implicit 23 percent discount. By recovering consumer's demand elasticities for rice outside the hoarding period, and adjusting for the dynamic stockpiling incentive following Hendel & Nevo (2006) we can calculate our counterfactual: the total quantity purchased in a world with flexible prices. Any excess purchases not explained by sticky prices can then be attributed to precautionary demand. While our baseline approach implicitly assumes consumers have perfect foresight about how much retail prices would go up by, the qualitative features of the exercise holds for virtually any reasonable model of expectations formation.

In order to conduct this decomposition, we require credible estimates of consumer price elasticities. Because we are interested in the response of consumers when all 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 an instrumental variables strategy exploiting the fact that supermarket chains practice uniform pricing across stores, as documented in DellaVigna & Gentzkow (2017). For each chain$\times$market$\times$time period we construct a leave-market-out chain-level average price. In other words, the average price at stores belonging to the same chain, but located in other markets.

To illustrate the logic behind this instrument, consider a hypothetical chain with a single store in California and many stores in New York. We effectively instrument for the price in California using the average price of stores in New York. The key identifying assumption is the lack of *chain specific* demand shocks. After constructing this store level instrument, we aggregate—assigning weights according to the relative concentration of different chains within a zipcode—to construct a zipcode level instrument.

Our IV approach suggests that, in typical periods, a one percent drop in average rice prices generates an approximately 0.85 percent reduction in market level purchases. In our preferred specification, which adjusts this elasticity following Hendel & Nevo (2006), we estimate that, of the 38 percent increase in quantity purchased during the hoarding period, 26 percentage points are attributable to anticipatory stockpiling resulting from an implicit 23% price discount due to sticky prices. In other words, roughly 70 percent of hoarding was due to anticipation, while the remaining 30 percent was due to precautionary motives. This baseline counterfactual suggests that, had prices not been sticky, there would not have been much of a hoarding episode at all. We briefly consider alternative models of expectations formation, including extrapolative or those based on futures prices, with similar results.

In the third part of our paper we consider and rule out a number of alternative explanations. One worry is that a lack of store 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). Another worry is that stores might not raise prices during times of peak demand due to loss-leader pricing strategies (see, e.g., Chevalier *et al.* , 2003)— stores might lose on rice and gain sales when customers come in to buy rice but also noodles.

Finally, we use our findings to address a traditional policy response during commodity market bubbles or shortages. During commodity market bubbles, be it the 2000s commodities boom and bust or energy supply shocks of the 1970s, governments respond to market instability with anti-price-gouging measures meant to address the role of household hoarding. These measures might be sensible when households hoard for precautionary reasons, but can be counterproductive if household hoarding is driven by sticky retail prices. Indeed, as we discuss below, these measures might even contribute to commodity market instability. The role of policy uncertainty in generating commodity price volatility has been little analyzed.

Our paper proceeds as follows. In Section 2, we provide background on the 2008 Global Rice Crisis. In Section 3, we describe the data. In Section 4, we provide evidence of sticky prices during this hoarding episode. In Section 5, we disentangle precautionary demand from promotional stockpiling due to sticky prices. We consider alternative explanations in Section 6. In Section 7, we discuss the implications of our analysis for traditional policy responses to address commodity market bubbles or shortages. We conclude in Section 8.

2 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.[6] The red 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. Despite this, coverage of the rice crisis got lost to some extent in the shadow of the generalized energy crisis.

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. Evidence for this precaution narrative has been largely anecdotal, based primarily on hoarding episodes in different

[6]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.

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: 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
- July 2008: supply from Japan via agreement with United States. Crisis ends.

Producers and stores were likely aware of the cost shock emanating from the India ban or could have easily 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.

Furthermore, stories on rice price movements were widely covered in the media, meaning information was available even to agents not paying close attention to futures markets. There were increasing numbers of stories in US media regarding the rice crisis around the world leading up to the US episode. As a result, consumers were likely aware that there had been cost shocks to rice which might influence their purchases.

By the end of April, hoarding had spread to the U.S. Indeed, 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.

3 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—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 $5.37 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 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 is just under $59,000, and the average household has just over 2.5 people.

4 Sticky Prices, Store Sales and Household Inventory

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. This stands in contrast to the literature on sticky prices, which finds that store prices respond to cost shocks with a substantial delay. In this section, we show that, for effectively all retailers, rice prices on the shelf were sticky in the face of large shocks to the global and wholesale price. We then show that, 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 inconsistent with the view that precaution was the primary driver of consumer hoarding in this episode.

4.1 Behavior of Store Sales and Prices

We begin in Figure 3 by showing aggregate time series evidence on consumer purchases (as measured by store sales) and *retail* prices, alongside more standard price aggregates. Crucially, while the large jump in consumer purchases during this episode roughly coincided with spikes in wholesale prices, it significantly led any growth in retail prices, which were sticky. The red line in Figure 3 shows 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. Note that the black line (quantity purchased) and red line (wholesale price) move upwards sharply in April of 2008. In contrast, store prices only began to rise after the peak of store sales. In other words, hoarding anticipates the gradual updating of shelf-prices.[8]

In Figure 4, we demonstrate that this gradual-updating pattern is not simply an average effect: virtually all stores failed to adjust their prices during the hoarding period. To show this, we display 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 highlights the peak of the hoarding period: the weeks from the 19th of April through the 10 of May 2008. Note that during this period, a very small fraction of stores updated prices, according to our metric. However, in the weeks following the hoarding period,

[7]The 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*.

[8]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.

stores began to update rapidly. Within a few months more than 75 percent of stores had updated.

These patterns are consistent with a large literature in macroeconomics: the retail or supermarket price, which is what consumers face, is sticky and lags the wholesale price of rice. 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. As such, we expect that similar patterns were evident in other countries. In the section that follows, we discuss the implications of these patterns and conduct further tests on the role of sticky prices in the hoarding episode.

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 an alternative explanation of consumer hoarding: an anticipatory stockpiling motive. 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 an anticipatory 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 an anticipatory stockpiling motive. The black line shows the time-series of international rice prices, identical to that shown in Figure 1.[9] 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 rose, and gradually drew them down.

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. However, the blue line, which shows stores prices, shows that—in line with store sales—inventories actually peaked *before* store level prices rise. This is hard to rationalize with a purely precautionary motive, but aligns well with anticipatory stockpiling. Consumers, aware of the rise in global prices from the media, futures prices, or other sources, saw that prices on the shelf were still low and chose to stock-up.

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 in-

[9] Here, the price is normalized to its average over the sample period.

ventories later saw larger changes in shelf prices. This again aligns with the anticipatory stockpiling 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 primary driver of this hoarding episode well, and align well with an anticipatory stockpiling view.

5 Estimating Elasticities and Calculating Counterfactuals

The relative timing of changes in global prices, store sales, and shelf prices suggest that precautionary motives were likely not the primary driver of hoarding during this episode, and that anticipatory stockpiling is likely to have played a major role. Of course, the two explanations are not mutually exclusive. Consumers may have been driven by a stockpiling motive due to sticky prices, while simultaneously fearing future price volatility. The two were likely both drivers of the excess quantities of rice purchased during the hoarding episode.

In this section, we empirically disentangle the relative roles of these two motivations. The basis of our strategy is a simple thought experiment: how much of the observed hoarding would have disappeared if prices had adjusted immediately? During the peak of hoarding, average prices stayed relatively close to their pre-crisis average of $4.61 per 80-ounce bag. Subsequently, prices rose to a post-crisis average of $5.97. For forward looking consumers, this amounted to an effective 23 percent discount on rice. Our approach asks how much of observed hoarding can be explained by consumers reacting as they would to any significant sale—anticipatory stockpiling—and how much is left over. We attribute the remainder to precautionary motives.

The key input necessary to calculate our counterfactual—the quantity of rice purchased in a world without sticky prices—is the elasticity of demand for rice. In what follows, we describe an IV strategy for calculating this demand elasticity and then explicitly discuss the decomposition.

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. As a result, 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.[10] 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 national uniformity of prices across retail chains, as documented in DellaVigna & Gentzkow (2017). Specifically, we first develop an instrument for store level prices ($P_{i,k,j,t}$ for store i belonging to

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

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 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 assumption. 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. Note that this demand has to emanate from taste specific shock which we view as unlikely. 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.

Before conducting our zipcode level instrumental variables strategy, we first confirm that our chain level leave out mean is highly predictive of 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 ($log(\bar{P}_{k,xj,t})$):

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

Here θ_i is a store fixed effect and $\eta_{s(j)} \times \tau_t$ is a state week fixed effect.

The first two columns of Table 3 show that chain level pricing is indeed highly predictive of individual store level pricing, consistent with DellaVigna & Gentzkow (2017). In column 1, which includes only store and week of year fixed effects (to adjust for seasonality), we see a strong relationship between the leave out chain price and store price, with a coefficient of almost exactly 1. In column 2, which includes the full set of fixed effects shown in Equation 1, we see a coefficient of roughly 0.9. Both are highly statistically significant.

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:

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

Here θ_j represents a zipcode fixed effect and $\eta_{s(j)} \times \tau_t$ remains 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 3-5, the unit of observation is the zipcode-week. In column 3 we use the full sample, and find a highly significant coefficient of 1.047. The fourth 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 fifth 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

1.028.

The final column 6 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

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

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.[11]

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 estimate 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. 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

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

using an OLS approach to estimate the full specification outlined in Equation 3, with a coefficient of -0.849.

In columns 3 through 5, we conduct a two stage least squares approach on various samples, and all provide results consistent with the OLS. 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 a one percent increase in rice prices generates a roughly 0.87 percent reduction in rice purchased.

5.4 Decomposing Hoarding Motives

In this subsection, we use our estimated price elasticities to decompose the excess quantity sold into two components: (i) a portion due to speculative storage on the part of households, and (ii) a portion due to precautionary motives. When constructing our counterfactuals we focus on our zipcode level estimates of consumer demand elasticities. To conduct our analysis we take the post-hoarding period as a baseline. In this period, prices were, on average, \$5.97 per 80 ounce bag. During the hoarding period , the average price was \$4.61 per bag. If we attribute the entirety of this difference to sticky prices (i.e. assume that the frictionless equilibrium price would truly have been \$5.97 during the hoarding period), then the \$1.36 difference in prices corresponds to a implicit 23 percent discount to a forward looking consumer ($1.36/5.97 \approx 0.23$).

To perform our decomposition, we ask how much of the observed hoarding can be explained by this discount. In other words, how much *less* hoarding would there have been if prices had been fixed at $5.97 during the hoarding period. To do so, we require price elasticities. As a conservative baseline, we take our estimated elasticity of -0.874 from the previous section. Taking this elasticity at face value, we estimate that consumers would respond to a 23 percent discount by increasing purchases by 20 percent. Recall that our estimates in the first column of Table 4 suggest that stores sold roughly 38 percent more than average during the hoarding period. This suggests that, conservatively, over 50 percent of the observed hoarding can be explained by consumer responses to sticky prices.

However, using our estimated demand elasticity directly requires a strong assumption, which is that our estimate 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, as consumers shift demand dynamically and stock up. While the variation in our instrument may include some short term promotions,[12] it is likely to also include some longer term price trends. Consequently, we expect that the above underestimates the fraction of hoarding due to sticky prices.

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 the 23 percent discount during the hoarding period accounts for a 26 percent increase in sales (0.874*1.3*0.23). This suggests that almost 70 percent of the total hoarding is attributable to speculative storage/sticky prices. We attribute the remaining 30 percent to precautionary motives.

Of course, the precise magnitudes of our decomposition depend on our model of expectations formation, and our baseline decomposition implicitly assumes that consumers have perfect foresight. However, the qualitative results of our exercise are similar for most

[12] 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 reallocations in response to short term promotions. In this case, using our estimated elasticity directly would be appropriate.

reasonable models of expectations formation. For example, suppose consumers had extrapolative expectations based on the path of wholesale prices, which moved by close to 100 percent in the months leading up to the hoarding episode. If these consumers similarly expected retail prices to double in the near term, then anticipatory stockpiling would easily explain the entirety of observed hoarding. Alternatively, suppose consumers price expectations followed the futures market, which showed rice futures 20 percent higher in May and June as compared with September. If consumers expectations for retail prices to follow this pattern—a medium term increase followed by a partial reversal—we would expect similar qualitative patterns to our baseline analysis, with anticipation accounting for a large portion of observed hoarding.

6 Alternative Explanations and Heterogeneity

6.1 Evidence on Stockouts

While the previous subsections emphasize sticky prices, one concern is the role of stockouts. Stockouts might present a complication to our analysis for a number of reasons. For example, it is possible that retailers responded to the international price shock by reducing their own purchasing (without adjusting prices) and that consumers correspondingly anticipated the potential that they would be entirely excluded from the market. Such a response might generate hoarding behavior even in the absence of any price dynamics. To address this, we show in this section that there does not appear to have been a quantity restriction during this period, and, whats more, there is no evidence of differential restrictions in areas that experienced the most significant hoarding.

To begin, we show, in Panel A of Figure 6, that there was not a restriction on households purchasing rice on the extensive margin. The month of April 2008 featured the highest fraction of households purchasing rice in our sample period, with the month of may also significantly higher than average. In other words, more households, not fewer, were able to purchase rice during the hoarding period. In Panel B of Figure 6, 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 5 we display regression results to further support the findings in Figure 6, 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:

$$\text{Purchase}_{ijt} = \beta_0 + \beta_1 \mathbb{1}\{t \in \text{Hoarding Period}\} + \gamma_i + \delta_{m(t)} + \epsilon_{ijt}, \tag{4}$$

where Purchase_{ijt} is defined to be a binary indicator for any purchase 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 column shows the results of this specification, indicating that a given household was more likely to purchase rice during this period on average. Our estimated coefficient suggests that the monthly probability of a household purchasing rice was 3 percentage points higher during the hoarding period.

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:

$$\text{Purchase}_{ijt} = \beta_0 + \beta_1(\mathbb{1}\{t \in \text{Hoarding Period}\} \times \mathbb{1}\{j \in \text{High Demand Area}\}) + \gamma_i + \delta_t + \epsilon_{ijt} \tag{5}$$

Purchase_{ijt} is described above and 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 include three definitions of "high demand". The first, shown in column 2, is 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. The second and third, shown in columns 3 and 4, respectively, are specified on the basis of pre-determined county characteristics.

Column 3 considers compares areas with large Asian populations—the top 5 percent of zipcodes 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. The final column considers zipcodes with above median per-capita rice purchases in 2007, the calendar year before the rice crisis.

Across all three definitions—and both panels—we see no evidence of differential stock-outs in high demand areas. While a negative coefficient would suggest that a lower fraction of residents were able to buy rice, 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 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 prevented from purchasing rice, the fact that household purchases increased on both the intensive and extensive margins provides evidence against such constraints.

6.2 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 these times, and other 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 were 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.

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.

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 pure speculative or anticipatory motive for stockpiling.

6.3 Heterogeneity across Demographic Groups

To further confirm the existence and relevance of sticky prices in this context, our final exercises consider differences in hoarding and price dynamics across high versus low hoarding areas. We show that despite significant geographic variation in the degree of hoarding, price dynamics were similar throughout. We consider the same three definitions of high demand as used in the previous section: the states with the largest quantity of observed hoarding ex-post, zipcodes with large asian populations, and the zipcodes purchasing the largest quantities of rice ex-ante. The differences 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 all three 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 Table 6, we first 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 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 last three 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:

$$\text{Volume}_{ijt} = \beta_0 + \beta_1(\mathbb{1}\{t \in \text{Hoarding Period}\} \times \mathbb{1}\{j \in \text{High Demand Area}\}) + \gamma_i + \delta_t + \epsilon_{ijt} \tag{6}$$

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 7. 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 zipcodes with high Asian populations is also large, at just over 4000 ounces. 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 for two of the specifications., 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.

In Table 7, we then repeat out counterfactual analysis by estimating the demand elasticities within high demand zipcodes (we focus, as an example, on the definition based on 2007 rice consumption, the other definitions give similar results). In the first column, we see that for these high rice-eating areas, we estimate a coefficient of 0.246, suggesting that these high rice eating areas saw an increase that was roughly 25 percent higher than normal during this period. Furthermore both IV and OLS specifications provide estimates of demand elasticities of roughly -1.1. This suggests that, even without adjusting our estimates to account for dynamic shifts in demand, more than 70 percent of the hoarding episode may be explained by sticky prices.

6.4 External Validity

While these results show there was significant variation in the degree of hoarding across different regions, the general pattern: a spike in demand preceding an increase in prices, occurred even in low demand regions. Of course, 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 in terms of an ability to engage in intertemporal storage of staples. In other words, we would expect hoarding episodes in developing countries to similarly arise from *both* precautionary demand and anticipatory stockpiling due to sticky prices. Of course, food security is a larger concern in developing countries than in the US and hence precaution effects might loom larger quantitatively in these settings. It would be interesting to find detailed household purchase or store sales data in developing countries during the 2008 Global Rice Crisis and replicate our analysis there.

7 Policy Responses to Commodities Bubbles and Shortages

Household hoarding is often thought to destabilize commodity markets and has been used to explain events as varied as the energy crisis of the 1970s and the 2000s global commodities boom. The primary mechanism invoked by media or governments is precaution or panic: households who are willing to pay excessively high prices to hedge price uncertainty. This in turn leads to inelastic household demand, which may feedback into higher global commodity prices as can occur in commodity price models such as Deaton & Laroque (1992) or Routledge *et al.* (2000).

The traditional policy response during these periods of commodity market shortages has been to enact anti-price-gouging laws. For instance, the first US state law directed at price gouging was enacted in New York in 1979, during the period of commodity market instability and concerns about shortages. Since then anti-gouging laws have proven popular—nearly 30 states have adopted some type of regulation (Davis *et al.* , 2008). These measures typically get adopted during periods of commodity market shortages (see, e.g., Zwolinski, 2008; Giberson, 2011).

The logic of these measures is to reassure consumers by punishing producers that sharply increase prices, thereby presumably dampening the panic or precautionary motive and stabilizing commodity markets. However, our analysis suggests that a large fraction of hoarding may emanate from sticky retail prices and the consequent incentives for speculative stockpiling. Given this, typical anti-price-gauging measures are likely to be ineffective and may even be destabilizing. The enactment of anti-price-gouging measures during periods of tight commodity markets is likely to make retail prices stickier, creating a larger delay in the adjustment of retail prices to wholesale prices and generating even stronger incentives to hoard.

Consequently, government policies aimed at restricting price changes by sellers during times of cost shocks need to account for the possibility that such regulations might make prices even stickier. Indeed, Gorodnichenko & Weber (2016) present evidence that sticky retail prices have asset pricing implications. US firms in stickier retail price sectors suffer larger losses in stock prices with inflation announcements. It would be worthwhile to test whether the response of retail prices to cost shocks was stickier—or whether hoarding episodes were exacerbated—after the implementation of state anti-price-gouging laws.

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 points to precaution as the cause of high prices and shortages during hoarding episode—we show that hoarding conflates both precautionary demand and inter-temporal storage due to sticky prices. We estimate demand elasticities to disentangle these two sources of consumer purchases during times of high prices and find that if prices were not sticky, hoarding would have been significantly reduced during the 2008 rice crisis. Following the logic of our analysis, government anti-price-gouging measures often invoked during commodity market bubbles or shortages might actually contribute to instability. Policymakers should acknowledge the existence of sticky retail prices when considering regulatory interventions.

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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.

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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)	1.005^{***}	0.906^{***}	0.955^{***}	0.952^{***}	0.976^{***}	0.812^{***}
	(0.00400)	(0.0130)	(0.0175)	(0.0181)	(0.0215)	(0.0747)
F-Statistic	63158.5	4891.0	2972.5	2751.1	2058.5	118.1
N	1382371	1382371	223379	217652	178919	7644
Week FE	Yes	No	No	No	No	No
Week $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Store/Zipcode/State FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Week $\times$ Year FE	No	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^{***} (0.0152)	-0.849^{***} (0.0190)	-0.825^{***} (0.0456)	-0.874^{***} (0.0408)	-0.818^{***} (0.0592)	-0.802^{***} (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: PROBABILITY OF STOCKOUTS DURING HOARDING PERIOD ACROSS HIGH VS. LOW HOARDING REGIONS

	Probability of Purchasing During Hoarding Period			
	Dependent Variable: Household Purchases Any Rice			
Hoarding Period	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 $\times$ Year FE	No	Yes	Yes	Yes

Table 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 $\times$ 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 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 6: 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	3689.927^{***} (223.625)			
Hoarding Period x Hoarding State		4878.239^{***} (508.100)		
Hoarding Period x Asian FIPS			4013.055^{**} (1897.394)	
Hoarding Period x High Rice FIPS				3032.942^{***} (405.325)
Mean of Dep. Var.	8564.3	8564.3	8564.3	8564.3
N	1383462	1383462	1383462	1383462
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 Prices (80oz Bag)			
Hoarding Period	-0.542^{***} (0.012)			
Hoarding Period x Hoarding State		0.043^{*} (0.023)		
Hoarding Period x Asian FIPS			-0.055 (0.035)	
Hoarding Period x High Rice FIPS				0.043^{**} (0.020)
Mean of Dep. Var.	5.33	5.33	5.33	5.33
N	1383462	1383462	1383462	1383462
Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	No	No	No
Week $\times$ Year FE	No	Yes	Yes	Yes

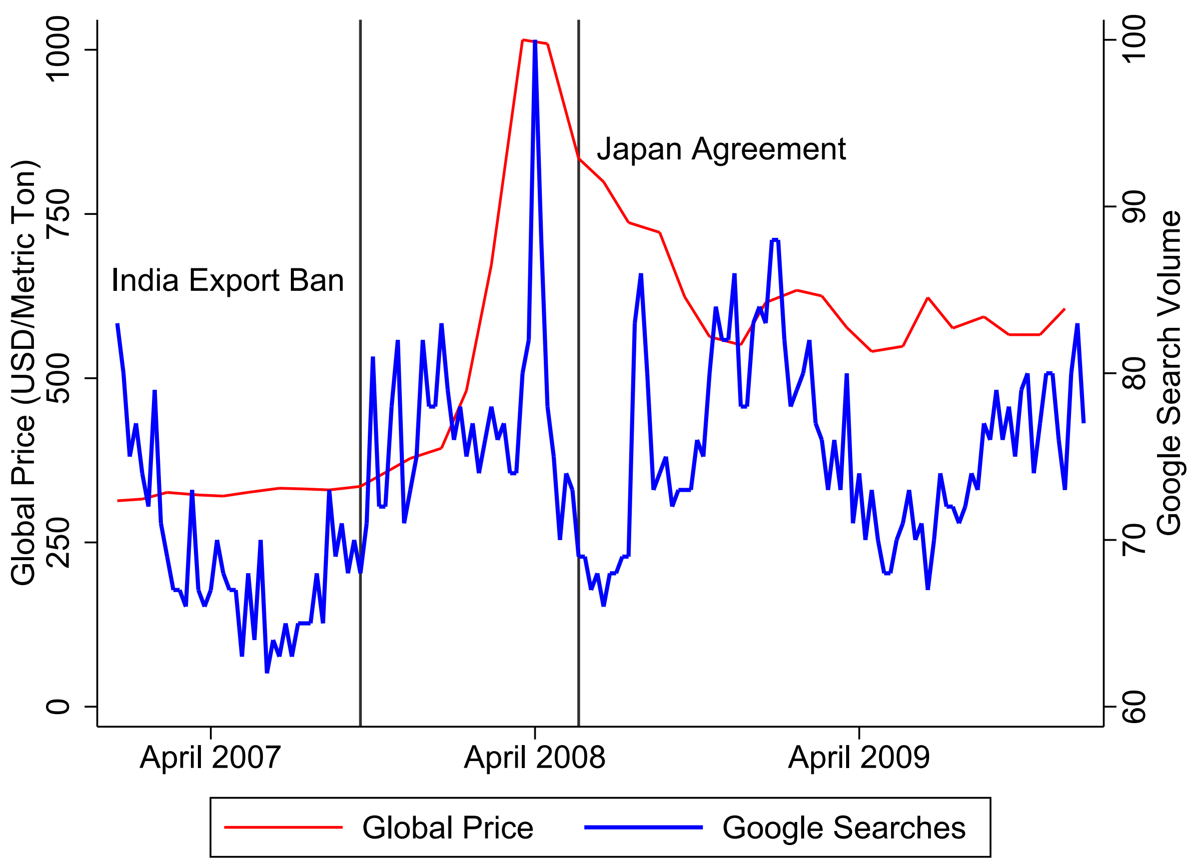
Panel A shows OLS regressions of weekly store level volume of rice sold in ounces on indicators for the hoarding period and the hoarding period interacted with 3 indicators for high demand locations. All weeks from 2007-2009 are used. The first column shows the coefficient on an indicator for the hoarding 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 repeats the exercise, but with store level prices, constructed as the average unit price paid with in 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: SECOND STAGE–DEMAND ELASTICITIES IN HIGH DEMAND ZIPCODES

	OLS		IV: Full Sample	IV: Non-Hoarding
Hoarding Period	0.246^{***}			
	(0.00839)			
Log(Price of 80oz Bag)	-0.697^{***}	-1.049^{***}	-1.153^{***}	-1.119^{***}
	(0.0349)	(0.0447)	(0.0754)	(0.0757)
Mean of Dep. Var.	9.056	9.062	9.062	9.054
N	47424	46644	46644	45448
Week FE	Yes	No	No	No
Week $\times$ Year FE	No	Yes	Yes	Yes
Zipcode/State FE	Yes	Yes	Yes	Yes

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. Only high rice consumption per capita zipcodes are included. Throughout, the unit of observation is the zipcode-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. All specifications show standard errors clustered at the zipcode level (or state level, in column 6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

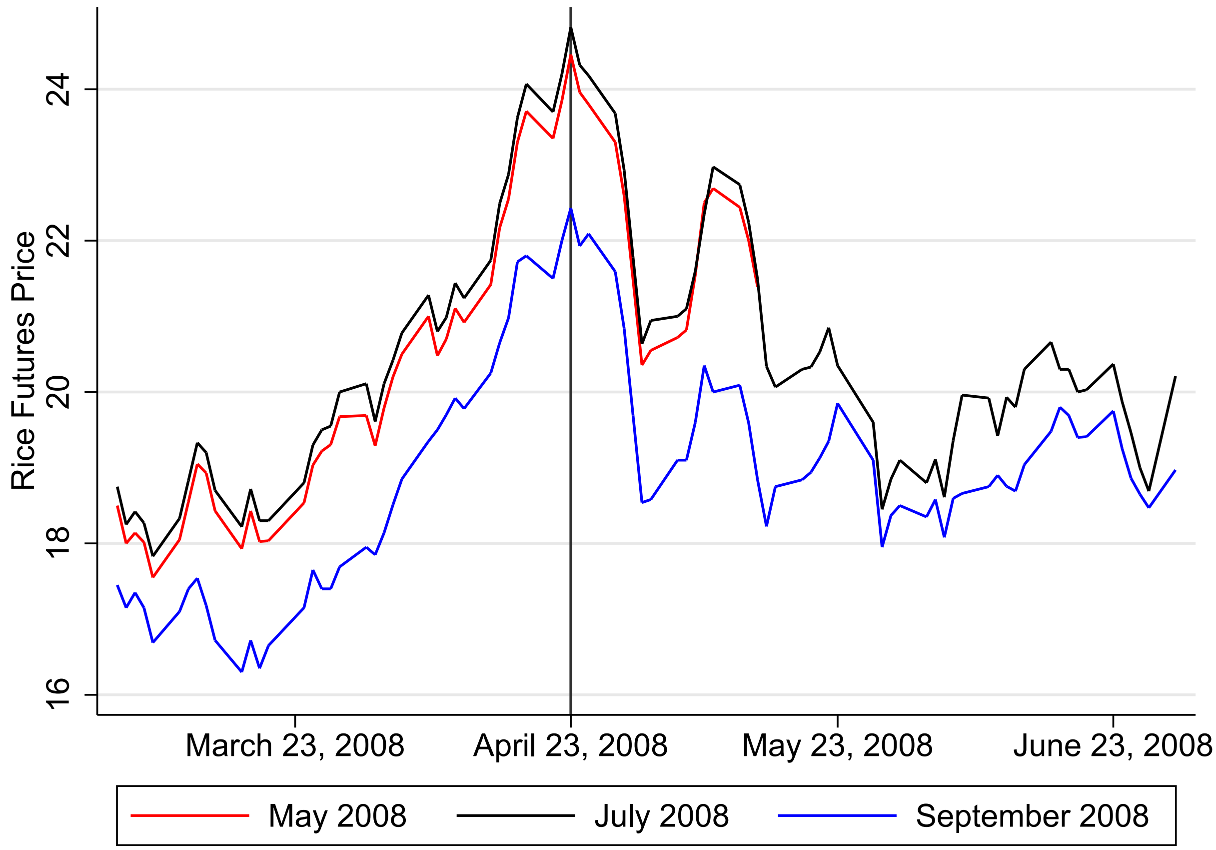
Figure 1: Global Rice Commodity Prices Rise Following India Export Ban



Notes: The red line displays monthly international rice prices in USD per Metric ton provided by IMF. 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. The blue line denotes Google search volume, normalized to a peak of 100 over our sample period.

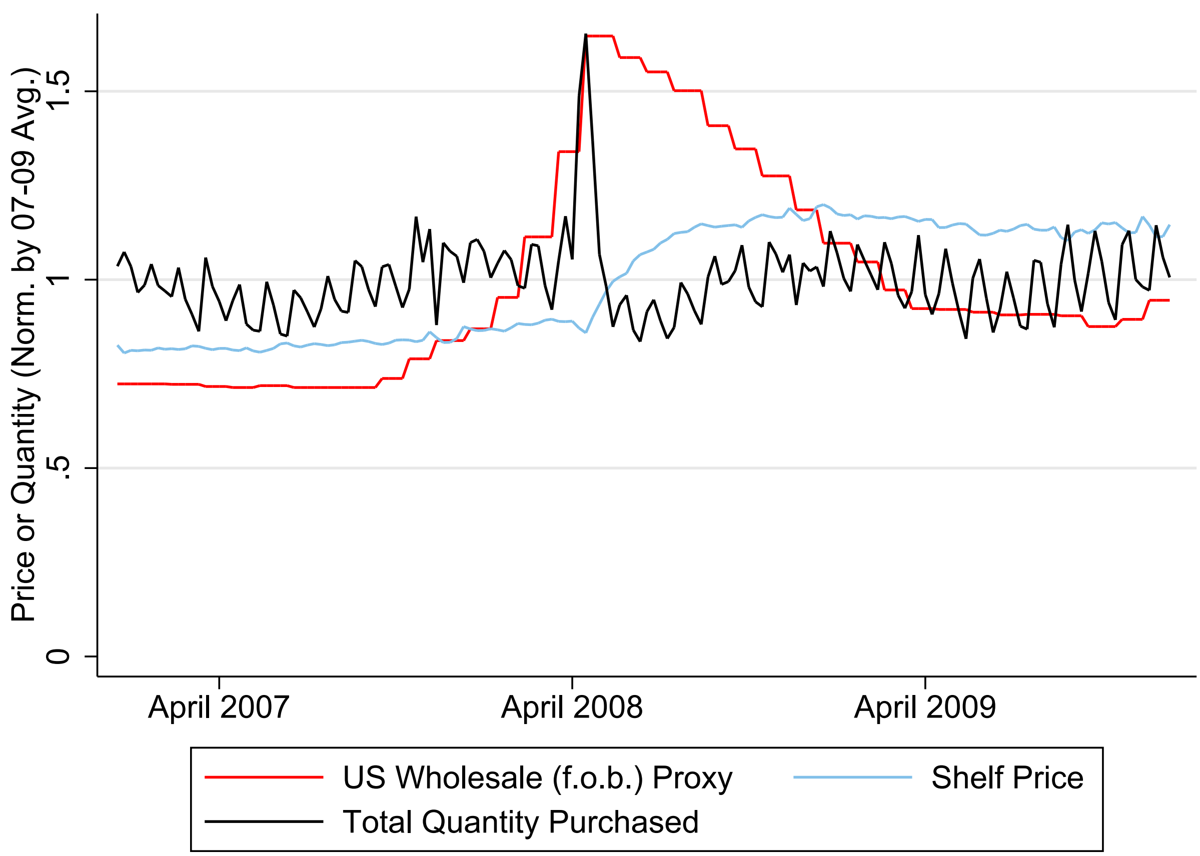
FIGURE 2: RICE FUTURES

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

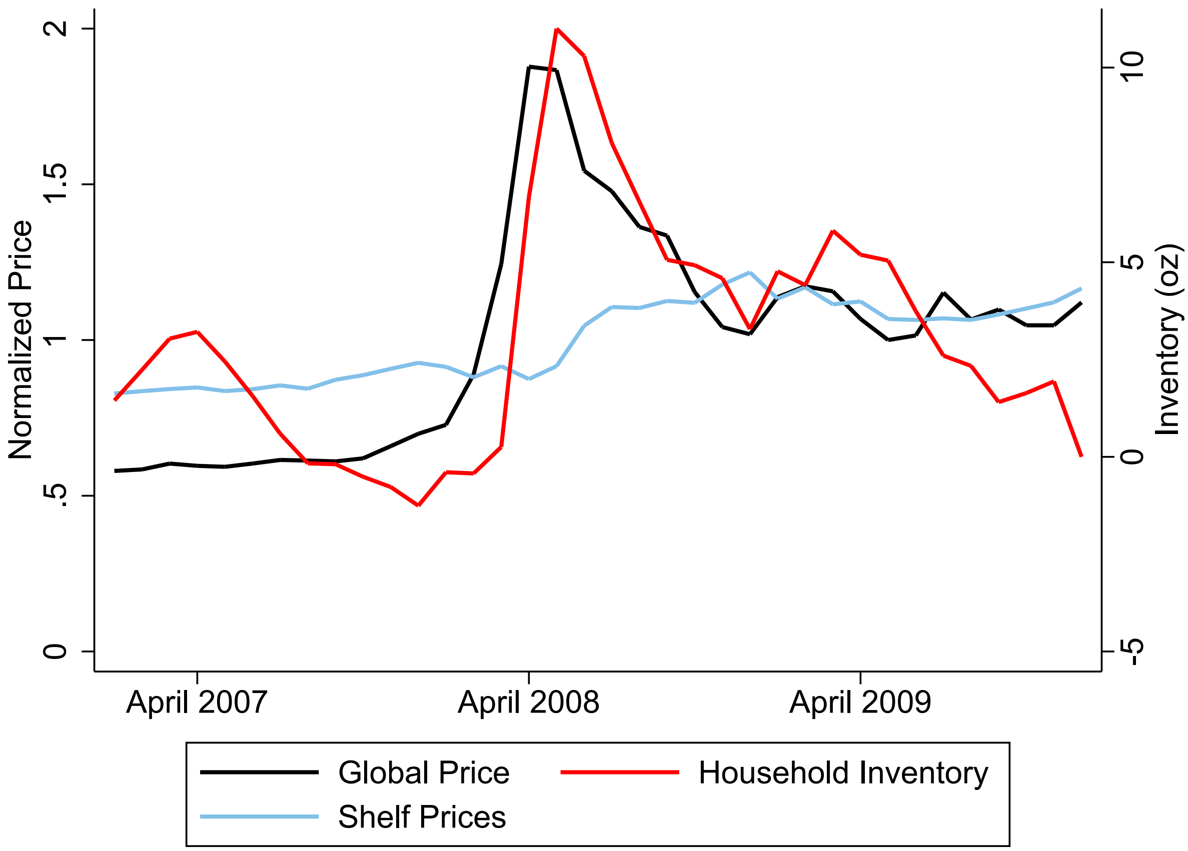


Notes: The red line displays a proxy for the US wholesale rice price at the monthly level. The proxy is based on average f.o.b. price for long grain rice at selected milling centers in Southwest Louisiana. Data provided by USDA, based on data from Agricultural Marketing Service, *National Weekly Rice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

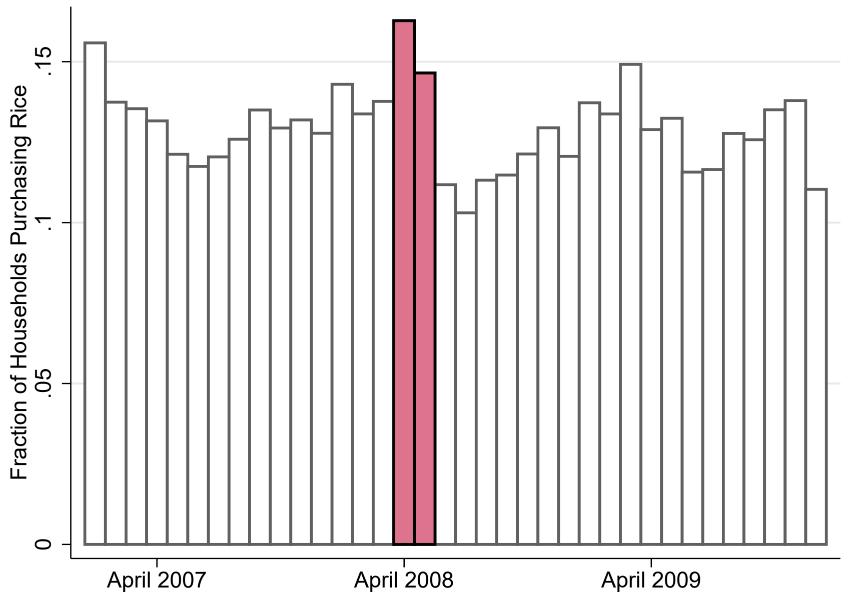
FIGURE 5: HOUSEHOLD INVENTORIES LEAD RETAIL PRICES



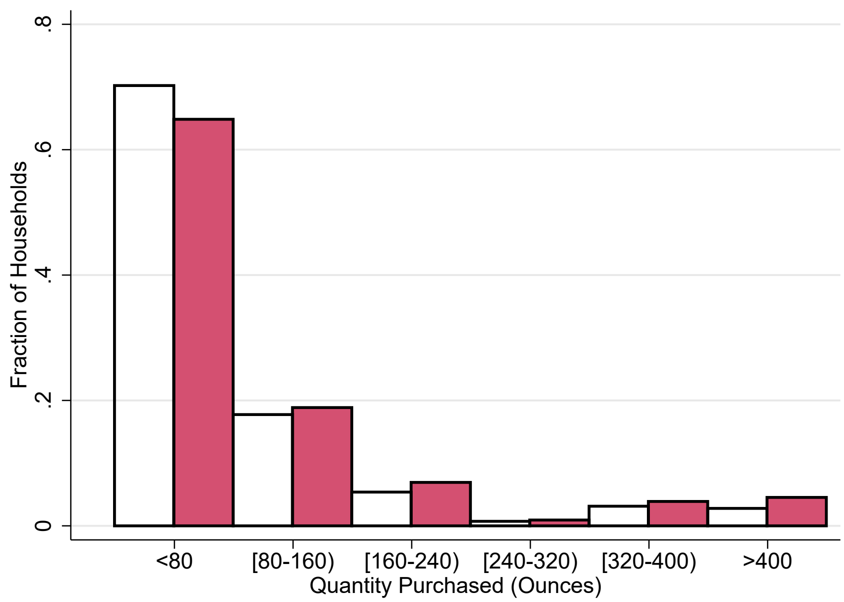
Notes: Black line shows global rice prices normalized to the mean over our sample period. The blue line shows shelf prices, calculated as the average unit price paid by households in our panel. The red line shows household inventories. Inventories are calculated following the procedure in Hendel & Nevo (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: NO EVIDENCE OF STOCKOUTS DURING HOARDING PERIOD

Panel A: Fraction of Households Purchasing Rice



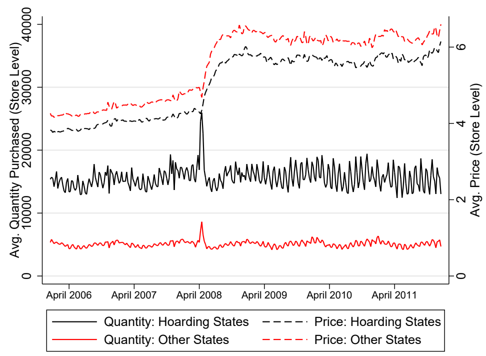
Panel B: Histogram of Rice Purchases—Hoarding vs. Other Periods



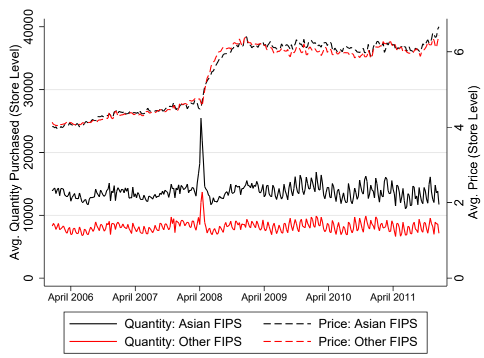
Notes: Panel A displays the fraction of households in our sample purchasing rice in each month from 2007-2009. Sample is drawn from the household panel, and includes only those who purchase rice at some point during the period. Panel B displays a histogram of rice purchases among those who purchase in a given month. In both, the red bars denote April and May of 2008.

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

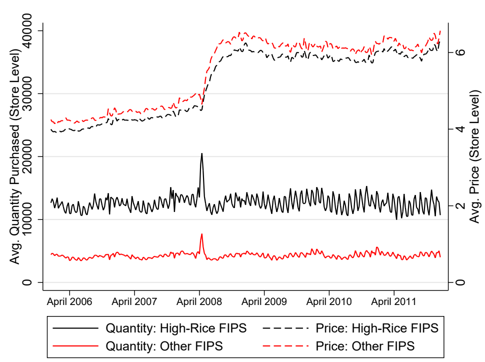
PANEL A: HOARDING VS. NON-HOARDING STATES



PANEL B: COUNTIES WITH LARGE ASIAN POPULATIONS VS. OTHERS



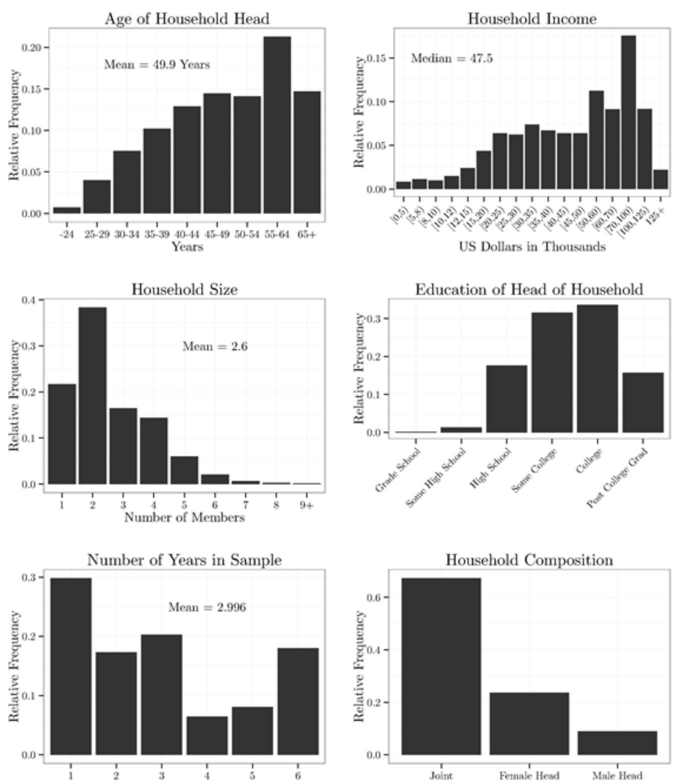
PANEL C: ABOVE VS. BELOW MEDIAN PER-CAPITA RICE CONSUMPTION



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 vigintile 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.

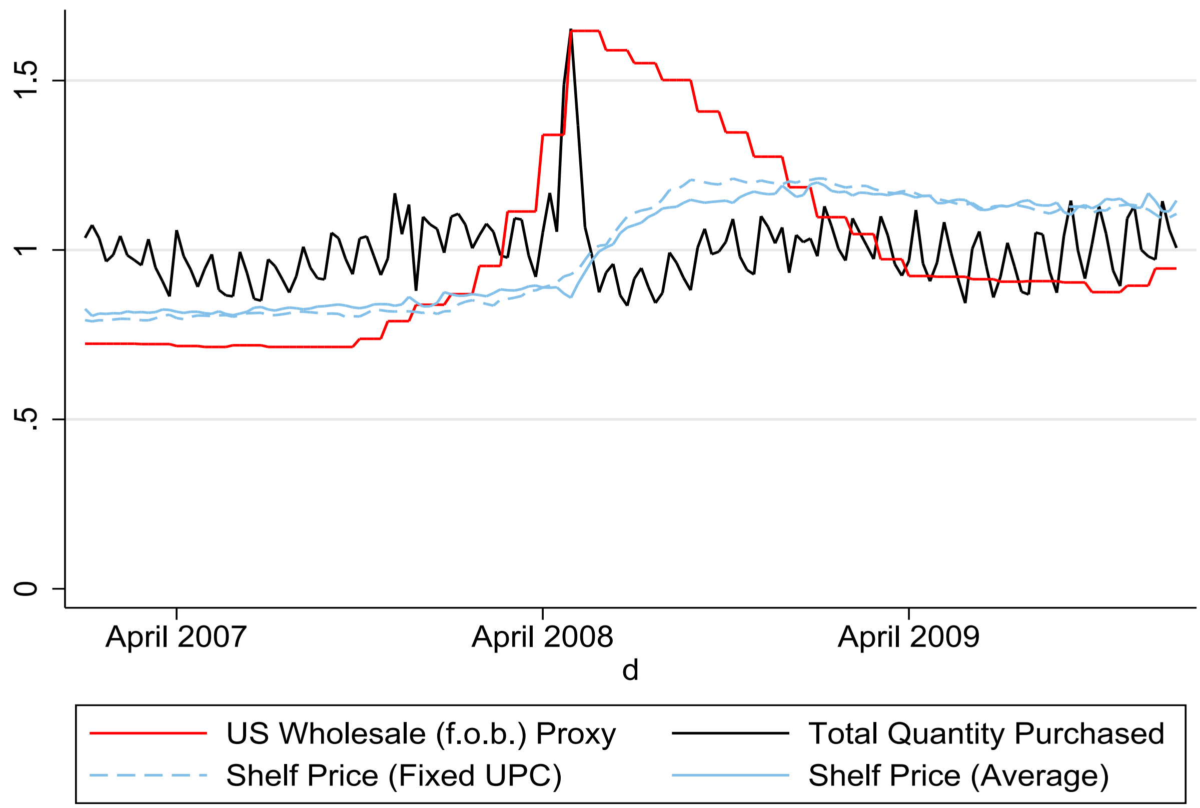
Internet Appendix: For Online Publication

FIGURE A.I: NIELSEN PANEL DEMOGRAPHICS



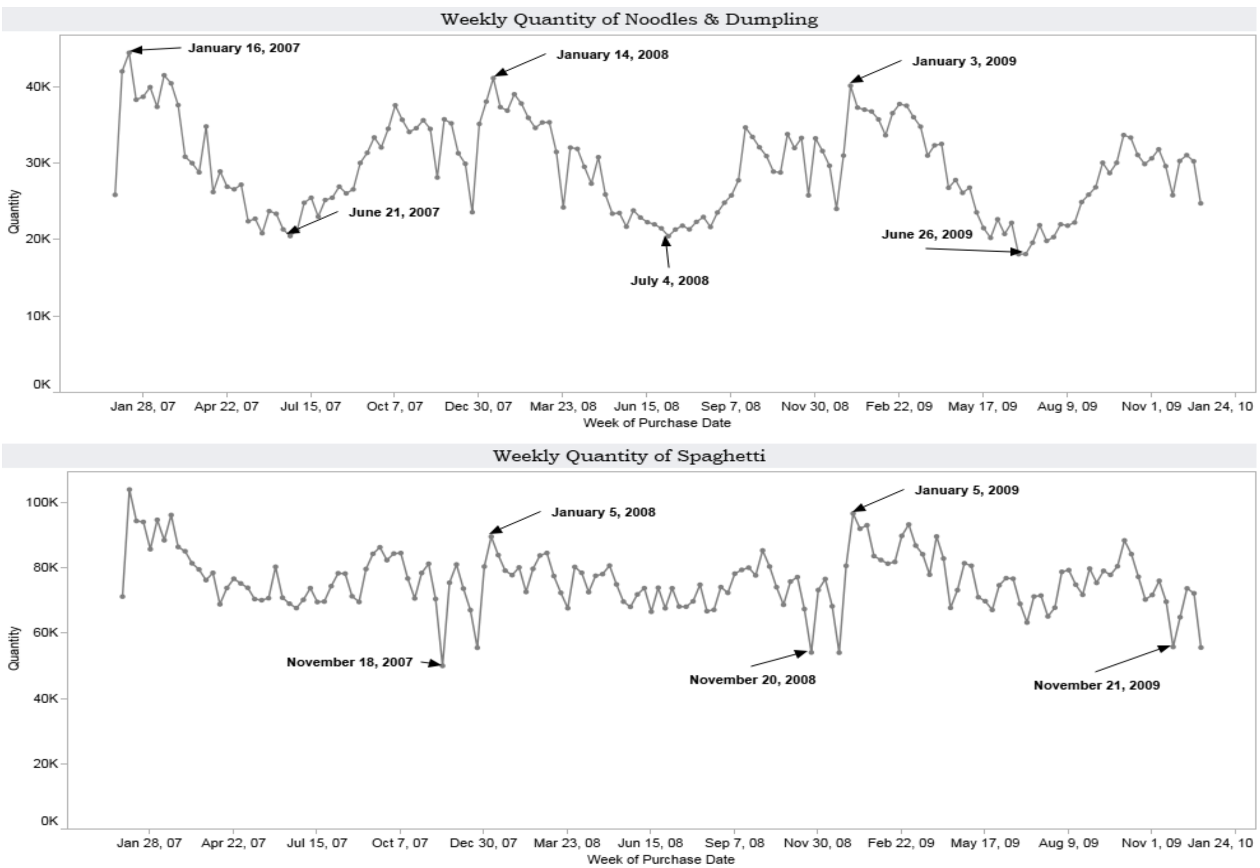
Notes: This figure plots the distribution of demographics of the overall Nielsen Panel.

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.