

# Hoard Behavior During Commodity Bubbles\*

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First Draft: October 10, 2014

This Draft: December 22, 2015

## Abstract

Hoarding by households is often blamed for causing commodity market panics and bubbles. Using US supermarket scanner data on household purchases during the 2008 Rice Bubble, we provide an estimate of household hoarding when export bans led to a spike in prices worldwide in the first half of 2008. We distinguish hoarding from rational precautionary demand by comparing the timing of purchases with the expectations implied from futures markets for US rice. Even as futures traders expected in early May little risk of shortages, households nearly doubled their purchases from April to June. Much of this increase came from households with no previous purchases or taste for rice. We then estimate the effect of hoarding on prices by comparing mean reversion in prices in counties with different amounts of hoarding.

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\*We thank seminar participants at Peking University, Warwick University, Cambridge University, NBER Universities Conference on Commodities, HKUST, New York University, PUC-Rio, UDELAR and Yale University for helpful comments. We are also grateful to Manuel Arellano, Orazio Attanasio, Hank Bessembinder, Richard Blundell, Ing-Haw Cheng, Marcelo Fernandes, William Goetzmann, Bo Honoré, Guy Laroque, Valerie Lechene and Elie Tamer for useful conversations. de Paula gratefully acknowledges financial support from the European Research Council through Starting Grant 338187 and the Economic and Social Research Council through the ESRC Centre for Microdata Methods and Practice grant RES-589-28-0001.

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# 1. Introduction

Hoarding of commodities, defined as the accumulation of inventories during times of high prices, has long been blamed for creating artificial shortages, commodity market panics, and price bubbles. Hoarding’s role in exacerbating shocks has been recognized as early as 362-63 A.D., when the Roman emperor Julian accused merchants of speculative hoarding and creating artificial shortages and famine in Antioch, “where everything is plenty, everything is dear” (see [Gráda \(2009\)](#) also for review of literature on hoarding). During the recent episode of high global commodity prices from 2003-2009, preceding the Financial Crisis, there were also widespread fears of institutional investors hoarding oil and thereby destabilizing global markets.<sup>1</sup> A large literature has understandably focused on the role of producers or institutions. But the results have been inconclusive for two key reasons: (1) a lack of detailed commodity positions data and (2) how to differentiate hoarding from a rational storage benchmark.<sup>2</sup>

While hoarding driven by large institutions has received the bulk of the academic attention, a neglected but potentially important source of hoarding in the economy is by households. For instance, studies of famines, such as the Bengali Famine of 1943-1944—one of the worst in history when several million people died of starvation, was thought to have also been exacerbated by hoard behavior of households with erroneous expectations about supply (see [Sen \(1983\)](#)). During commodity boom of 2003-2009, there were also reports of widespread hoarding of various agricultural commodities, particularly in developing countries.

In this paper, we study one such episode, the 2008 Global Rice Crisis ([Dawe, Slayton, et al. \(2010\)](#)) that emanated in Asia. Rice, a staple for billions in developing countries, is

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<sup>1</sup>There is a large body of work on the extent to which speculators played a role in the commodity bubble (see, e.g., [Kilian and Murphy \(2014\)](#), [Hamilton \(2009\)](#), [Tang and Xiong \(2010\)](#), [Singleton \(2013\)](#)) and more generally on the relationship between inventory and commodity prices (see, e.g., [Gorton, Hayashi, and Rouwenhorst \(2012\)](#), [Fama and French \(1987\)](#)).

<sup>2</sup>In traditional storage models of commodity pricing (see, e.g., [Scheinkman and Schechtman \(1983\)](#), [Deaton and Laroque \(1992\)](#)), high prices are typically correlated with low inventories. Hence, the accumulation of inventories in the midst of rising prices, or hoarding, is only a necessary condition of a bubble. Rational expectations of rising prices can also justify accumulation of inventories.

government-controlled and typically uncorrelated with other commodity prices. But against the backdrop of high commodity prices, the Indian government, worried about its food security, banned rice exports in late 2007, thereby triggering quid pro quo bans by other exporting countries and subsequently astronomical prices for importing countries like the Philippines by the first quarter of 2008 (Slayton (2009)).

While the broader international events have been widely analyzed, our interest lies in examining the spillover of this supply shock to the US, which has not been studied. Just as in developing countries, there was media coverage during the months of April to June of 2008 of a run on rice in supermarkets across the United States. A number of the large stores such as Walmart, Costco and Sam's Club even instituted rationing over this period. Indeed, anecdotal evidence suggest that hoard behavior might have been behind the price increases even though though Federal officials said there was no rice shortage in the United States. For instance, 50-pound bags of long-grain rice were selling for \$32 to \$38 in New York City's Chinatown groceries in the week around May 1, 2008, which was an increase of about 35 percent over a month previous. "We don't even eat that much rice," one Asian-American woman who didn't want to be identified as a hoarder said. "But I read about it in the newspaper and decided to buy some." ("A Run on Rice in Asian Communities", New York Times, May 1, 2008).

We show that this rice episode provides a setting to study household hoard behavior through which we can address the methodological issues in the literature. First, we have plentiful data on hundreds of thousands of household purchases, the dates of these purchases and prices from Kilt's Center Nielsen Supermarket Scanner and Store Price data. This allows us, in contrast to the literature, to study hoarding at a micro-level as opposed to simply just using aggregate inventory data.

Second, there is also an active futures market for rice delivered in the US, with which we can then extract the expectations of futures traders on how temporary or persistent the supply shock to rice would be in the US. By comparing the timing of the household purchases

with the evolution of futures markets' expectations, we can deduce whether the purchases were rational or precautionary demand in nature or irrational (extrapolative) hoarding in nature.

Third, the household data includes demographic information and importantly past rice purchases, which allow us to identify households that are heavy rice eaters versus those without any previous taste for rice. We can then also identify hoarders as households who buy rice for the first and last time during the crisis. The idea is that those households without any previous taste for rice and who start buying rice for the first and last time during the crisis cannot be driven by precautionary demand. So their demand is driven purely by speculative expectations (or some irrational form of herding), which we can again compare to the extracted expectations from the futures market for US rice. The latter two points stand in contrast to the existing literature which has been unable to cleanly identify hoarding by commodity merchants or institutions.

We begin by establishing key facts to support our use of the 2008 Global Rice Crisis as an exogenous shock to available supply and expectations and thereby study the spillover effects on US markets and households. First, using the Nielsen Store Pricing data, we establish that these higher global prices during this period were also passed through to higher store prices in the United States starting at around April 2008, which then precipitated the run in the months of April, May and June.

We then infer the expectations from future contracts prices regarding whether the supply shock was temporary or persistent using an approach originally proposed by [Samuelson \(1965\)](#).<sup>3</sup> The key idea is to compare both the price and the price volatility of a nearby futures contract (which in our case is for delivery in July) to the price and price volatility of the next closest contract (in our case, for delivery in September) in the months of April, May and June. The nearby contract is essentially the spot price of rice, which determined

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<sup>3</sup>[Samuelson \(1965\)](#), who examined commodity futures pricing with demand and supply shocks that are slowly mean-reverting, also pointed out that high spot prices with low inventory indicate a stock out and low subsequent prices as supply and demand adjusts in the longer term.

by current supply and demand conditions. On the other hand, the futures price of rice in the September contract provides us an assessment by professionals of whether supply issues will persist beyond the nearby contract deadline. If market participants think that the current shock to supply is temporary, only the nearby contract prices move with the shock while the distant contract price is insensitive to this shock since prices would have already mean-reverted by the time the distant contract expires.

The futures price data suggests that futures market participants realized by April 17th of 2008 that the Asian supply shock would affect US rice markets as both the price and price volatility of both futures contracts climbs dramatically. In fact, the price volatility of the September contract climbs above that of the July contract, pointing to substantial worries of a prolonged crisis. But by May 1st, the volatility patterns had reverted back to normal with the price volatility of the September contract trading well below that of the July contract. By May 19th, on news that additional potential supply from Japan was found via an agreement with the United States, the market panic effectively ended as the volatility of the September contract dropped to the level before the crisis as does the price of the September future contract.

The typical household in our sample buys rice from the supermarket twice a year and conditional on a purchase, buys 78 ounces of rice. The unconditional mean of household rice purchase is 10 ounces. So for the typical household, there is no reason for them to abnormally increase their purchases (i.e. buy more than they usually do) by mid-May or June since futures prices by September would have already fallen back to normal both in terms of level and volatility.

Our main dependent variables of interest are the quantities bought by households each month and the number of rice transactions or scans each month. We relate these dependent variables of interest to our key independent variables of interest, which are dummy variables for April, May and June of 2008, along with control variables including month dummies (to control for seasonality), the current price of rice faced by different households, household

fixed effects, and our lagged dependent variables. This allows us to measure whether or not households bought abnormal quantities of rice during these months, adjusting for a variety of household characteristics as well as the price of rice that households face. The dummy variables for April, May and June 2008 are picking up abnormal demand common across households during this crisis episode. One advantage of our setup in studying the purchase decisions of atomistic households compared to the literature which models aggregate inventory is that we can rule out reverse causality in our regression specifications since households are small (Deaton and Muellbauer (1988) and Nevo (2010)).

The bans that led to an increase in domestic rice prices in the US can be viewed as generating exogenous shocks to price and expectations, measured using the April, May and June 2008 month dummies on the right hand side of the regressions of interest. Consistent with there being a run on rice during these three months, we find that households dramatically increased their quantities purchased and frequency of their transactions during those three months of 2008. The effects are very robust and statistically significant. The typical household in our sample purchases around 10 ounces per month of rice. In April and May, they nevertheless purchase an additional 8 ounces and in June an additional 3 ounces and increase the frequency of their purchases by 33%. To address potential measurement issues on our price variable, we also implement a two-stage least squares (TSLS) version of our fixed effects ordinary least squares (FE) purchase regressions, instrumenting for the price of rice that a household faces with the International Monetary Fund (IMF) international rice price index. Our TSLS estimates are very similar to our FE estimates.

Given the expectations of the futures market and higher levels of futures price volatility in mid-April to mid-May, we cannot distinguish for all households whether the increased purchases in these dates are rational precautionary demand or unwarranted hoarding. From mid-May through June, when the futures price volatility is back to pre-crisis levels, we can nonetheless conclude that these purchases, which are 36% of the total increase in purchases, are likely driven by hoard behavior.

When we dig deeper into who bought rice in April, May and June, we find that many of these purchases are due to households who bought rice for the first (and indeed only time) during this period. The vast majority of our households enter the database in January 2007. We can then use a duration model to estimate the time until a household's first purchase of rice given that they have not purchased in the past. We find that households who had never bought rice before were significantly more likely to have their first and only purchase in April and May of 2008. We estimate that these first time rice buyers accounted for 17% of the households who purchased rice in April and 16% in May. Their purchases were significantly larger to other non-first time buyers.

Hence, we conservatively estimate that at least 15% of the total of rice purchases during April and May were also due to hoarding since these first time buyers, having displayed no previous taste for rice, could not be motivated by precautionary demand. These purchases were not rational from a speculative perspective either as futures markets prices indicated that participants already expected mean reversion in spot prices. Hence we label these additional 15% of the purchases in April and May as also (unwarranted) hoarding.

Finally, we provide an estimate of the effect of hoarding on prices. We have access to store-level Nielsen data that allows us to create a rice price index from local stores in different counties. We can use the fact that the aggregate world price shock generated cross-country dispersion in both household hoarding and also dispersion in price trends. We then try to estimate the impact of hoarding on prices by examining the extent to which there is more mean reversion of prices from May (the peak of hoarding) to July in counties with more hoarding. We find that localities with more hoarding in fact experienced much more mean reversion in prices.

We view our contribution as providing a strategy to distinguish hoard behavior from precautionary demand and providing an estimate of hoarding's effect on prices. Rice is easy to store, thus it is easy to understand why lower-income households for whom rice is a staple might panic and hoard if prices were rising as quickly as they did during early

2008. What is interesting in our context is that most of the households are fairly rich, which makes our findings regarding hoard behavior more surprising. Our findings will be relevant to developing countries' commodity markets, where (if anything), the hoarding effects we are measuring are likely to be much larger.

Our paper proceeds as follows. We describe our data in Section 2. We establish some key facts regarding the 2008 Global Rice Crisis that sets up our empirical design. We describe our rational benchmark using expectations from the US rice futures market in Section 4. We present our empirical strategies and findings in Section 5. We conclude in Section 6.

## 2. Data

Our data comes from the AC Nielsen's Homescan Consumer Panel. The panel has over 100,000 demographically balanced U.S. households, who use hand-held scanners to record every bar-coded grocery item purchased. The data runs for six years (2004-09) and records every purchase made at Universal Product Code (UPC) level. There is also detailed demographic information. Figure 1 plots the distributions of the various demographics of the Nielsen Panel. The mean age of the household is 50 years. Median household income is around \$48,000 dollars. There are on average 2.6 members in the household. 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 have geographic identifiers about our households. We then take only a panel in which households appear for all 3 years from 2007 to 2009 (though not necessarily in all months). Each household must have made at least one purchase in the rice category. There are 1,187,057 monthly observations for the roughly 44,000 households in our sample that had any consumption of rice between 2007 and 2009. Figure 2 reports the summary statistics of our panel. In each year, we have around 12,000 white households, 2,000 black households,



600 Asian households and 700 or so other ethnic groups. While Asians eat more rice as we describe below, they represent a very small part of our sample and hence the bulk of our results are not being driven by Asian households.

In addition to the Household Consumer Panel, we also have access to store level data on pricing of their products, which we use to create price level aggregates for rice, aggregated across all types and all size bags of rice. The average price is an aggregate weighed by the sales of all the products sold in each each week and county, averaged to produce a monthly average price-level per bag. So households in different locations and times are assumed to face the price averages calculated from the sales in that location and time. An alternative price-level variable could be obtained from the Household Consumer Panel as the unit value defined as the ratio between expenditures on rice and quantity purchased. The store data nevertheless allow us to impute prices even for those households that did not buy any rice in a given month. In addition, previous studies document that, whereas quantity information is usually accurately recorded in the Household Consumer Panel, prices paid are much less precise (see [Einav, Leibtag, and Nevo \(2010\)](#)). Our results are robust to the use of alternative price-level aggregates, such as the average price for a 32-ounce package or the average price for an 80-ounce package in the county.

### **3. Spillover to US Rice Market**

As described expertly in [Dawe, Slayton, et al. \(2010\)](#) and [Slayton \(2009\)](#), the 2008 Global Rice Crisis was one of the most dramatic food events in the developing world. Rice is the main food staple for billions in Asia and is government controlled and typically uncorrelated with other commodity prices. But a politically motivated ban on rice exports by India in late 2007 led to high prices for importing countries like the Phillipines by the first quarter of 2008. The price of rice jumped several hundred percent in the middle of 2008. Specific details can be found in the references, but government ineptitude and corruption seemed to

have also played a role in the 2008 Rice Bubble.

For our study, we want to establish two facts. The first is that there was an idiosyncratic shock to rice emanating from Asia that was disconnected from global worries about energy prices at the same time. To see this, we plot in Figure 3 global rice prices from the IMF for a series of agricultural commodities: rice, barley, corn and wheat. The black line in each of the panels is the price of crude oil and the colored line is the agricultural commodity in question. First consider barley, corn and wheat. The prices of these three big commodities track the price of oil fairly well. The price of oil took off in 2005, peaked in late 2008, crashed in 2009 during the financial crisis and then rebounded with the recovery in 2010. It is easy to see even visually that the prices of these three commodities track this series of dramatic movements very well.

In contrast, notice that the price of rice does not track the price of oil. When the price of oil took off in 2005, the price of rice was actually very flat. It then spiked in late 2007 and in the first half of 2008 because of these aforementioned politically motivated export bans on rice and crashed before the price of oil when news of new supply from Japan led to a decline in late May 2008. 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. But the Japanese do not like US rice and keep it to feed animals. As such, there was a surplus of rice sitting in warehouses. The US had to make an exception to allow this rice to be sold on world markets and when news leaked that they would do so in mid May 2008, the price of rice immediately fell. Moreover, when the price of oil recovers after the financial crisis, the price of rice did not track it as again the price of rice was determined through government interventions. To some extent, coverage of the Rice Crisis got lost in the shadows of the generalized energy price crisis.

To see a bit more closely how the price of rice and the Global Rice Crisis is distinct from other higher food prices during this period, we show in Figure 4 a more detailed comparison between the price of rice versus a food price index, both of which come from the IMF. We

can see a similar scenario as in Figure 3 where the price of rice actually rose from \$400 US per metric ton at the end of 2007 to over \$ 1,000 US per metric ton at the beginning of May 2008. This 2.5-fold jump dwarfs the food price index increases, which track the price of crude oil. Notice that the price of rice already fell from \$ 1,000 US to \$ 800 US per metric ton when the price of food reached its peak at the end of 2008. Again, we can see that the price of rice has remained at around \$ 500 US to \$ 600 US per metric ton ever since, while the price of food has recovered after the financial crisis and reached even newer highs. US long-grain rice prices roughly also doubled during the same period before dropping 30% after the Japanese news leaked.

The second fact we wish to establish is that this shock emanating from Asia was passed through to the US. As the anecdotes from newspapers suggest, the 2.5-fold jump in the price of rice from the end of 2007 to the middle of 2008 was translated into the street price that people see in their supermarkets, though not by as high a factor since rice in supermarkets gets refined along the way. The anecdotal evidence from the New York Times reports indicate a jump of at least 35% in a short span of time. Figure 5 shows a search volume index on Google Trends for “Rice Prices.” There is a spike in search volume interest in April and May of 2008, consistent with wider interest among media and households over this same period.

We can use our store-level sales data to get a more precise measure of the store price of rice in the United States over this period. In Figure 6, we plot the price-level aggregate for the various size bags of rice. Notice that the price of rice was flat for most of 2007. Then from the end of 2007, we see the price of rice jumps just as in world markets, described above, with the biggest increases for bigger bags. For instance, the largest bags see a rise of nearly 75% over a short period of time. For the smallest bags, the price increase was around 30%. Prices, however, do uniformly flatten out after May of 2008, but they do not fall as they do in world markets. Most of the dramatic increases occurred from the end of 2007 to May 2008. The flattening out was no doubt related to the decline in global raw rice prices reported above.

In Figure 6, we also report sales volume in the US for the largest and smallest bags of rice. We see a jump in both around April and May 2008, but with a much bigger jump for the bigger bag. The fact that the biggest bag was subjected to the biggest price increase is a tell-tale symptom of hoarding in that the accumulation of inventory is best done with big bags as there are discounts with size.

## 4. Rational Benchmark using Expectations from US Rice Futures Market

To separate hoarding from precautionary demand using the consumer panel data in the next section, we first use prices from the US rice futures market to infer the expectations of professional futures traders as to the persistence of the supply shock. The futures contracts for rice used in our analysis trade on the Chicago Board of Trade (CBOT) under the ticker symbol RR. The rice is typically for delivery in Arkansas. There are January, March, May, July, September and November contracts. Our focus is on the month of April through June. Since the May contract, which is near delivery during the crisis, is less liquid than the July contract throughout these critical months in 2008, we take the July contract as our proxy for the spot price. The correlation of prices for between prices of the subsequent contracts (September and November ) are quite high. Hence, we use the September contract as the “distant” contract and focus our analysis on the July and September contracts for expositional simplicity.

In Figure 7, we plot the prices of these two futures contracts starting in January 1 of 2008 and through November of 2008. We can see that there is an increase in the price of both contracts. The date of April 23, 2008 represents the peak of the futures prices. But there is a fairly pronounced drop in prices there after both in the nearby contract and the distant contract. The price of the September contract dips considerably below that of the July contract, which is evidence that futures traders think the price increases will not persist. We

can think of this downward sloping futures price curve as indicative that throughout these months of April, May and June, and certainly after April 23rd, futures traders expected at any given point in time for the prices to be falling.

If, on the contrary, the price of the September contract had risen above the July contract, that would have been evidence that the futures traders believed that the shock would persist and that the crisis might have gotten even worse. In other words, if we imagine the households' expectations of rice prices as being rational (and assuming they are risk neutral), there is no reason for them to buy or store rice for reasons of speculation.

Of course, precautionary household demand in the form of worrying about volatility is another driver of accumulation of inventory. Even if households thought that the price of rice might fall on average, they might be risk averse and worry about the volatility of prices which might lead them to store even if their expectations are for rice prices to be falling.

To address the issue of volatility, we can use an approach originally proposed by [Samuelson \(1965\)](#). He considered a continuous time commodity futures pricing model with demand and supply shocks that are slowly mean-reverting. The key idea from his model is to compare the volatility of the nearby futures contract (for delivery in July) to the volatility of the next closest contract (for delivery in September) in the months of April, May and June. If the market thinks that the current shock to supply is temporary then only the nearby contract prices moves with the shock while the distant contract price, that is the price in September, is insensitive to this shock since this shock would have already mean-reverted by the time the distant contract expires. On the contrary, to the extent that the volatility of the distant contract is at or even above the nearby contract below that of the nearby contract, the futures traders think that the shock is likely to persist or even get worst in the future.

The volatility of the futures prices also provides us an estimate of the risk of increasing rice prices. If the absolute level of the volatility of the September futures prices is low, then it is a signal that the market effectively thinks that markets are back to normal.

In Figure 8, we plot out the term structure of futures price volatility. We use the daily

price changes for each contract to calculate a 30-day rolling average of daily return volatility for each contract. We find that the price volatility of the September futures actually crossed the price volatility of the July futures on April 17th, 2008. This is an indication that futures market participants thought that the supply shock might be persistent. But it then quickly dropped significantly below by late April to early May. In other words, the futures traders thought in early April the supply shock might be serious but then revised their expectations.

By mid-May, the volatility of the November futures was back to the pre-crisis levels. The price volatility of the July futures eventually caught up to the September futures by the end of June. The pronounced drop in mid-May happens precisely on May 19th, on news that new supply was found from Japan via an agreement with the United States. In other words, the futures market effectively did not think that there was much risk of price increases beyond this date.

The higher level of July prices and volatility is driven by supply and demand conditions, including potentially hoarding effects which we demonstrate in the last part of the paper.

These dates then provide us a benchmark with which to judge whether abnormal purchases of rice by households were consistent with precautionary demand as opposed to hoarding driven by erroneous expectations.

## **5. Empirical Findings**

### **5.1. Abnormal Purchases of Rice During Rice Crisis**

#### **5.1.1. Fixed Effects Regressions**

We begin our empirical analysis by estimating how the purchases varied in the months of April, May and June of 2008. Our dependent variable of interest is household  $i$ 's purchases of rice in month  $t$ ,  $Y_{i,t}$ , where purchases are measured in two ways. The first is quantity, measured in ounces of rice using UPC codes 13 and 19 and including all rice bags. The

second is frequency of transactions in a month, which is how many times the rice UPCs were scanned.<sup>4</sup>

To get a sense of the magnitudes of this baseline sample, we report summary statistics for our panel in Table 1. We have roughly 1.2 million monthly observations. The typical household bought 10.18 ounces of rice per month and the standard deviation is 78 ounces.<sup>5</sup> The monthly frequency is the number of transactions per month, which is .15. The standard deviation is .42. The average price-level aggregate of rice bought in this sample is \$ 3.51 US. Household income is on average around \$ 59,590 US and there are 2.65 persons per household.

In short, the typical household in our sample buys rice from the supermarket twice a year and conditional on a purchase, buys 78 ounces of rice. Our null hypothesis is there is no reason for them to abnormally increase their purchases (i.e. buy more than they usually do) by mid-May or June due to precautionary demand since futures prices by then were pointing to pre-crisis levels of price volatility and low price levels in September. Indeed, it would have paid for them to delay their purchases until September by substituting to some other good.

Our baseline regression specification then is

$$Y_{i,t} = a_0 + a_1Apr08 + a_2May08 + a_3Jun08 + \gamma\mathbf{X}_{i,t} + \epsilon_{i,t} \quad (1)$$

Our coefficients of interest are in front of *Apr08*, *May08* and *Jun08*, the dummy variables for April 2008, May 2008 and June 2008. As mentioned previously, these coefficients capture any variation in the expectations of future prices driving increases in the inventory behavior

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<sup>4</sup>We have also considered a third measure which is expenditures per month or price times quantity of purchases that month. The results are largely similar to our first measure, quantities, so we do not report these results but they are available from the authors.

<sup>5</sup>The monthly expenditure implied by this quantity is around 60 cents with a standard deviation of roughly 2 dollars. Since expenditures on rice make up a relatively low share of a household's total budget, one may be tempted to conclude that rice is a good of little importance to the household. Of course, rice is a staple in many cultures, possibly not easily substitutable, and expenditures on rice may not reflect its overall value for the household. (An extreme illustration of this point is the "paradox of value". Whereas water is vital for human beings, diamonds are not. Nevertheless, the cost of water is much lower than the cost of a diamond. Of course, early economists explain this discrepancy by pointing out that it is not the total "utility" of a good that matters, but the "utility" of a marginal unit of that good.)

of households around the Rice Crisis. The vector  $\mathbf{X}_{i,t}$  contains our rice price-level aggregate, household fixed effects and our lagged outcome variable  $Y_{i,t-1}$ . Any model of consumer demand would include the lagged dependent outcome since households that have recently bought a lot of the good and have it in storage would naturally demand less of the good. Crucially for us, including the lagged dependent outcome as we will show is important for gauging hoarding effects.

The results of our estimation are reported in Table 2. In column (1), we run the model with price and household fixed effects as controls. We leave out the lagged dependent variable to start so that we can present how it matters for our inference. The coefficients on April and May are 6.628 and 5.027, and statistically significant at the 1% level. The coefficient on June is 0.577 and not statistically significant. The coefficient on price is -.0221 as expected. The household fixed effects absorb unobserved heterogeneity (i.e. households who eat rice prefer expensive rice) and the negative coefficient in front of price reflects normal demand curve considerations. Notice that our sample period is 2007-2009. So most of the sample with which we are measuring this coefficient are normal non-crisis markets.

In column (2), we introduce the lagged outcome variable as an additional control and run an Arellano-Bond specification. We get stronger results than those in column (1). The coefficient on  $Y_{t-1}$  is -0.045 and statistically significant at the 1% level. That is, households who in the previous month bought rice buy less rice this month. This is consistent with many types of consumption and storage models. Importantly, we get larger coefficients on the April, May and June dummies as a result. The coefficient on April is now 8.175 as opposed to 6.628 in column (1). For May, the coefficient is 7.233 as opposed to 5.027. Importantly, the coefficient for June is 2.5 and statistically significant at the 1% level instead of .577. Moreover, the coefficient on price is -3.269 instead of -.221. In short, by controlling for previous the quantity of purchases the previous month, we get more sensible and accurate estimates for our variables of interest.

Note from our summary statistics Table 1 that a typical household purchases 10 ounces



of rice per month. From the AB specification in column (2), a household has abnormal quantities purchased of 8 ounces or 82% more in April, 7.2 ounces or 72% more in May and 2.5 ounces or 25% more in June. Hence, we find that the typical household over the three month period purchased 18 ounces extra rice in total. Using our analysis of the expectations from the futures market for US rice, which returned to pre-crisis levels by mid-May, we can argue conservatively that around 36% of these 18 ounces of May (3 ounces in the latter half of the month) and all of the rice purchases in June (2.5 ounces) are driven by hoarding as opposed to precautionary demand.

In columns (3)-(4) of Table 2, we have as the dependent variable the number of rice transactions in a month. In column (3), we find that the coefficients in front of April and May 2008 are both positive and statistically significant but the coefficient on June is close to zero. The coefficient on price is negative. In column (4), when we add the lagged dependent variable as a control, we get improved results as was the case for quantities purchased. Importantly, the coefficient on June 2008 is now .011 and statistically significant at the 1% level. The coefficient on price is also larger and more negative.

The mean monthly frequency of purchases is 0.15. So we find that the implied economic magnitudes are a 33% increase of the frequency of transactions in April 2008, 26% increase in May 2008, and a 7% increase in June of 2008. These findings are consistent with our quantities regressions. They suggest that there was significant hoard behavior into late May and early June.

### **5.1.2. Instrumental Variables Regressions**

To address potential endogeneity concerns for our price variable, we also estimate instrumental variable regression versions of our main specifications instrumenting our rice price variable. Possible sources of endogeneity for our price variable are omitted variables (e.g., prices of substitute or complementary goods which we do not include in our specification) and potential measurement error in our price-level aggregate as a measure of prices faced by

the consumers in our sample. In Table 3, we re-estimate FE specification of Table 2 using Fixed Effects Instrumental Variables (FE IV) regressions where we instrument for the price that each household faces with the international price of rice (Int Rice Pr). The international price series comes from the IMF and is in hundreds of USD per ton.

We first report the first-stage regression of the price each household faces on the other covariates from the OLS and Int Rice Pr. The coefficient in front of Int Rice Pr is 0.291, which is significant at the 1% level. The pairwise correlation of the price of rice with international rice prices is 0.1865. The F-statistic in the first stage is 110,315 and the Minimum Eigenvalue Statistic is 96,225, well above the usual critical values for the hypothesis of weak instruments. The model is exactly identified, so no over-identification tests were performed.

We then show the FE IV estimates. Notice that the coefficients from the FE IV estimates are similar to the FE counterparts in Table 2 for the most part. One difference is that the coefficient on April is now smaller, at 5.771 ounces as opposed to 8.175 ounces previously. The May coefficient is largely unchanged at around 7 ounces. The same is true for the June coefficient at 2.3 ounces. As a result, our estimate of the fraction of abnormal quantities purchases in these months that is driven by hoarding rises slightly to 39%. We obtain similar results for the FE IV specification with monthly frequency as the dependent variable of interest.

### **5.1.3. Rice Placebos: Noodles, Dumplings and Spaghetti**

We finish off our baseline analysis by checking to see if there was a similar hoarding effect in rice substitutes such as noodles, dumplings and spaghetti.<sup>6</sup> It is not clear that these are necessarily great substitutes for rice. To the extent that there is a big enough substitution and a big enough run on rice, perhaps there might be spillovers into rice substitutes. But Figure 9 indicates that there is no such spill-over when we consider noodles and dumplings or spaghetti. In fact, aggregate sales of either category do not exhibit any abnormal increase

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<sup>6</sup>Noodles and dumplings are a single category in our dataset.

around April and May 2008 when compared to similar periods in 2007 and 2009. We have also run analogous regressions for noodles and dumplings and for spaghetti as for rice and find no consistent evidence of hoarding coefficients for April and May 2008 (if anything, those coefficients tend to be negative).

## 5.2. Buyers without Taste for Rice

We have provided an estimate of the amount of hoarding by the typical household by comparing the timing of these purchases with expectations from the futures market. We conservatively estimated that 36% of the abnormal purchases during the three month period of April to June 2008 were driven by hoarding due to erroneous expectations—that is, the quantities purchased from mid-May to June after futures markets already realized that there would not be any prolonged supply issues.

However, we are not able to infer about motives behind the quantities purchased in April to mid-May using our previous approach. For instance, even in April the futures market expected mean reversion in prices as evidenced that the downward-sloping curve for futures prices. So a risk-neutral household ought to never have a rational motive to buy rice even in April. However, the typical household who purchases rice is likely to have some precautionary demand, particularly to the extent the household has a taste for rice. For instance, it is not irrational for Asian households who eat a lot of rice to hold more rice to the extent that they sense greater future price volatility associated with the good.

We show in this section, however, that many households with no previous purchases of rice in 2007 suddenly bought rice for the first and last time during this crisis period. We conclude that these households are hoarding since they ought to not have a precautionary demand motive since they did not even eat any rice to begin with.

To capture the likelihood that someone first buys rice during the period of interest, we estimate a simple discrete time duration model using only households who have entered the data starting in January 2007. That is, we estimate a duration model using our household

panel data to measure the time until a household's first purchase of rice given that they have not purchased in the past. If  $T_i$  is the (random) variable representing the period when household  $i$  first purchases rice, the probability that someone purchases rice in month  $t$  given that she has not yet bought any rice is then given by:

$$Pr(T_i = t; X_{it}) = h_{it}(X_{it}) \prod_{k=1}^{t-1} (1 - h_{ik})(X_{ik}) \quad (2)$$

where  $h_{it}(X_{it}) = Pr(T_i = t | T_i \geq t; X_{it})$  is the hazard rate for buying rice for the first time and  $X_{it}$  are (possibly) individual- and period-specific covariates.  $h_{it}$  is modeled as a linear probability model (LPM) and as a logit. Here we focus on results using monthly controls and (monthly) dummies for the period around the crisis:

$$h_{it} = h \left( \sum_{k=\text{Jan}, \dots, \text{Dec}} \alpha_k \mathbf{1}(t = k) + \sum_{l=\text{Mar 2008}, \dots, \text{Aug 2008}} \beta_l \mathbf{1}(t = l) \right)$$

where  $h(x) = x$  for the LPM and  $h(x) = \exp(x)/(1 + \exp(x))$  for the Logit.

Following [Jenkins \(1995\)](#), the analysis is easily implemented as a binary outcome model (LPM or Logit) where each observation corresponds to a given household and month, failures (= 1) mark whether a household first buys rice on that month and non-failures (= 0) record periods when no rice is (yet) purchased by that person. The results are reported in Table 4. In the first column, using LPM, we find that households who had never bought rice before were significantly more like to have their first purchase in April or May of 2008. In the second column, using the logit, we find similar results.

Recall that our sample gathers individuals who bought rice at some point between 2007 and 2009. Of those, there are 14,507 individuals who purchase rice only after March 2008. According to the hazard specification, we can calculate the probability that those people first purchase rice on April or May of 2008 as the probability of buying rice in April 2008 given that no rice had been yet purchased plus the probability of no purchase in April 2008, again given that until then no rice had been bought, times the probability of buying in May

2008, conditional on not having yet bought any rice. More precisely, we obtain:

$$\mathbb{P}(\text{first rice purchase on April or May, 2008}) = h_{i,\text{April, 2008}} + (1 - h_{i,\text{April, 2008}}) \times h_{i,\text{May, 2008}}.$$

The probability that those who had not yet bought rice would have their first purchase rice on April or May 2008 (according to the simple, linear model) is then computed to be 23.4% = 3390 people. On the other hand, the model projects 20.2% for the analogous probability of a first purchase in April or May not in 2008. This corresponds to 2,933 people out of those 14,507 individuals and about an additional (3390-2933=) 457 people are projected to buy rice during these two months of the crisis in contrast to comparable months in non-crisis years. This represents an increase of about 15.6%. (Essentially the same figures are obtained if we incorporate demographic covariates into the duration model.)

To investigate whether households were also more likely to *stop* buying rice during the crisis months, we also run a similar duration model for the month of last purchase in our panel. In the next four columns of the table, the dependent variable is the time until the last purchase by a given household. What stands out is that April and May 2008 attract positive coefficients for last purchase. Interestingly, many of those who purchased rice for the last time in April and May 2008 actually did buy rice for the first time between March and May 2008. In fact, once we remove those who first bought rice between March and May 2008 and last purchased rice in May or earlier, the positive spike in April and May for the hazard of a last purchase disappears. This is visually illustrated in Figure 10, which plots the coefficients for the LPM basic specification of our duration models “with” and “without” those who bought for the first time in April 2008 or later and for the last time in June 2008 or earlier. This indicates that the increase in the hazard of a first purchase during April and May 2008 is mostly due to individuals who didn’t buy rice after June 2008 again.<sup>7</sup>

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<sup>7</sup>We further investigate the purchasing behavior of those who purchase rice only on the crisis months. Whereas on average those households purchase larger amounts of rice than those who also bought in other periods, the quantity distribution is fairly similar across the two groups up to very high percentiles (i.e., up to the 95th percentile). The proportion of Asians is also slightly lower among those buying only during the crisis, but not appreciably so (2.9% versus 3.4% among those buying also in non-crisis months). The average

We then estimate the amount of rice purchased by these first and last time buyers of rice in Table 5 using a FE regression. We find that they purchase around 35 ounces in April and May of 2008, which is approximately three times as much as how many extra ounces the typical household bought. Combining our analysis from the duration model and this table, we conservatively estimate that at least another 15% of the total quantities bought in April and May are actually also driven by hoard behavior. So conservatively, when we combine our all our estimates, we find that around 45% of abnormal rice purchases from April to June (i.e. the 36% of the total abnormal increase from mid-May to June, and then the 15% of the abnormal increases from April to mid-May) is driven by hoard behavior.

### 5.3. Effect of Hoarding on Prices

As a result, we expect that there are significant price effects associated with this hoarding. To measure how large such effects are, we associate hoarding levels across counties with future price changes in these counties. The results are presented in Table 6. The regressions have Percentage Change in Price from May (the peak of the bubble) until July 2008 in a given county as the dependent variable. We chose July 2008 as a reasonable horizon over which mean reversion might occur.

Household hoarding in a county is then measured in two ways. First, it is the Total Quantity Purchased from April until May. The second is via a decomposition of this is total quantity into a predicted part and a residual using FE IV estimates from a regression of quantity on prices and monthly seasonal dummies using international prices as instrument for prices. The estimated coefficients are used to predict the quantity purchased by a household in a given month and the residual is classified as “Excess Hoarding”. The regressors are accumulated values of those variables over April and May of 2008.

To extent that household expectations are rational, we expect a positive coefficient in front of our two independent variables of interest, i.e. more household hoarding ought to

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income and household size are also comparable across the two groups (\$ 57,400 US versus \$ 59,700 US and 2.5 versus 2.7 household member in crisis-only buyers versus non-crisis-also buyers, respectively).

experience higher future price growth. In other words, household hoarding ought to be a signal of rising prices in the future.

Looking at the county level regressions, we see that the coefficient of interest in front of Quantity Purchased is a statistically significant  $-0.018$  and statistically significant at the 1% level. A one standard deviation increase Quantity Purchased is associated a 25% fall in prices (or mean reversion) from May to July of 2008.

We obtain even stronger results when we use the Excess Hoarding measure. The coefficient is  $-0.025$  and implies that a one standard deviation increase in Excess Hoarding is associated with a 30% fall in prices from May to July of 2008. In Table 7, we show an analogous set of placebo regressions using 2007 and 2009 and find no results. So we can use the mean reversion in rice prices as a measure of the over-valuation caused by hoarding.

## 6. Conclusion

Using US supermarket scanner data on household purchases during the 2008 Rice Bubble, we provide an estimate of household hoarding when export bans led to a spike in prices worldwide in the first half of 2008. We provide two strategies to distinguish hoarding from rational precautionary demand. First, we compare the timing of purchases with the expectations implied from futures markets for US rice. Even as futures traders expected in early May little risk of shortages, households nonetheless doubled their purchases into June. We estimate that around 36% of the extra quantities of rice purchased in these three months (i.e. those purchased from the latter half of May to June) was driven by hoarding.

Second, for quantities purchased in April and May, we find that around 15% of these are from households with no previous purchases or taste for rice. These households presumably do not have any precautionary demand. Since futures markets indicated mean reversion in prices starting in early April, their purchases could also not have been *ex ante* profitable. We can hence identify their purchases as also hoarding.

We then estimate the effect of hoarding on prices by documenting greater mean reversion in prices in counties with the most hoarding. Our estimate is that one standard deviation increase in quantities purchased led to around a 25-30% subsequent reversion rice prices from the peak of the crisis in May to July of 2008.



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# Appendix

To motivate our regression specifications, we consider the following static inventory problem for a household given the household's subjective expectations about price increases. As we have argued in the paper, these subjective expectations were likely over-extrapolative in the months of mid-May to June. We assume that the risk-free rate is zero and each household simply maximizes expected utility over the consumption of a good (i.e., rice) tomorrow.  $b$  is the household budget for the good to be consumed.<sup>8</sup> Each household can choose a level of inventory  $I$  by purchasing the good at  $p_0$ , the price of the good today. The household faces an uncertain  $p_1$  for the good tomorrow. The quantity of the good the household can afford at time 1 is  $q_1 = (b - Ip_0)/p_1$ . We assume  $p_1$  is uniformly distributed between  $\underline{\mu}$  and  $\bar{\mu}$  (i.e.,  $p_1 \sim U[\underline{\mu}, \bar{\mu}]$ ). Each household's expectation of the price tomorrow is then  $E[p_1] = (\underline{\mu} + \bar{\mu})/2$ .<sup>9</sup> We further express the upper bound  $\bar{\mu}$  as  $\bar{\mu} = \mu + \alpha p_0$ . So the household's expectation of the price at  $t = 1$  can potentially be affected by the price at  $t = 0$  when  $\alpha$  is non-zero.

The household problem is then

$$\text{Max}_I E[u(I + (b - Ip_0)/p_1)] \quad (3)$$

subject to the constraints that  $I \geq 0$  and the budget constraint  $Ip_0 \leq b$ . The first-order condition w.r.t.  $I$  is given by (assuming an interior solution which occurs for  $\bar{\mu} \gg p_0$ ):

$$E[(1 - p_0/p_1)u'(I^* + (b - I^*p_0)/p_1)] = 0, \quad (4)$$

where  $I^*$  is the optimal hoarding level.

Otherwise, when  $\bar{\mu}$  is sufficiently low, for example,  $I^* = 0$ . This first-order condition then gives  $I^* = g(\mu, p_0)$  as an implicit function of two key parameters of interest  $\mu$ , which controls the expected price appreciation of the good, and  $p_0$  the price of the good today.

We can then derive some key comparative statics using this implicit function to motivate our regression specifications. For simplicity, assume initially that  $\alpha = 0$  (so that  $\bar{\mu} = \mu$ ) and that  $p_0 < \bar{\mu} = \mu$ .

**Proposition 1.**  $I^*$  increases with the expected price at time 1,  $E[p_1]$ .

<sup>8</sup>We assume that the budget  $b$  is invariant to prices. One may fear that the budget would be reduced in face of increases in current prices or expected future prices. We do not observe this in the data (in fact, monthly expenditures on rice increase during the crisis) and hence abstract away from this possibility for simplicity.

<sup>9</sup>The possibility of stock-outs in the second period can be accommodated by setting  $p_1 = \infty$  with positive probability. In this case, a higher probability of stock-outs acts on hoarding like an increase expected price in the second period. We abstract from this as we do not have information on stock-outs in our data.

**Proof of Proposition 1.** First note that since  $E[p_1] = (\mu + \underline{\mu})/2$  and  $\text{Var}[p_1] = (\mu - \underline{\mu})^2/12$ , we can write  $\mu = E[p_1] + \sqrt{3\text{Var}[p_1]}$  and  $\underline{\mu} = E[p_1] - \sqrt{3\text{Var}[p_1]}$ . For a given inventory level  $I$ , by Leibniz's Rule,

$$\begin{aligned} \frac{\partial E[(1 - p_0/p_1)u'(I + (b - Ip_0)/p_1)]}{\partial E[p_1]} &= (1 - p_0/\mu)u'(I + (b - Ip_0)/\mu)/(\mu - \underline{\mu}) \\ &\quad - (1 - p_0/\underline{\mu})u'(I + (b - Ip_0)/\underline{\mu})/(\mu - \underline{\mu}). \end{aligned} \quad (5)$$

If  $\mu > p_0 \geq \underline{\mu}$ , the first term in the expression above is positive and  $(1 - p_0/\underline{\mu})u'(I + (b - Ip_0)/\underline{\mu})/(\mu - \underline{\mu}) < 0$ . Consequently, this difference is positive. On the other hand, if  $p_0 \leq \underline{\mu}$ ,  $(1 - p_0/x)u'(I + (b - Ip_0)/x)/(\mu - \underline{\mu})$  is decreasing in  $x$  (for  $x > p_0$ ). Hence the difference is also positive. Then by the Implicit Function Theorem,

$$\frac{\partial I^*}{\partial \mu} = -\frac{\partial E[(1 - p_0/p_1)u'(I + (b - Ip_0)/p_1)]/\partial E[p_1]}{E[(1 - p_0/p_1)^2 u''(I^* + (b - Ip_0)/p_1)]} > 0 \quad (6)$$

if  $p_0 < \mu$  since  $u''(\cdot) < 0$ . QED

The second comparative static of the optimal hoarding rule is with respect to price  $p_0$ .

**Proposition 2.** *Assuming  $u''(x)$  is bounded for high  $x$  and  $\lim_{x \rightarrow 0} u'(x) = \infty$ ,  $I^*$  decreases with the price at time 0,  $p_0$ , for sufficiently low  $b$ .*

**Proof of Proposition 2.** For a given inventory level  $I$ , notice that

$$\begin{aligned} \frac{\partial E[(1 - p_0/p_1)u'(I + (b - Ip_0)/p_1)]}{\partial p_0} &= \int_{\underline{\mu}}^{\mu} \left[ -\frac{u'(I + (b - Ip_0)/p_1)}{p_1(\mu - \underline{\mu})} \right. \\ &\quad \left. - \frac{(1 - p_0/p_1)u''(I + (b - Ip_0)/p_1)I}{p_1(\mu - \underline{\mu})} \right] dp_1. \end{aligned} \quad (7)$$

Whereas the first term in the integrand above is always negative, the second term is only negative for  $p_1 \in [\underline{\mu}, p_0]$ . To establish that the above expression is negative, consider then the integral between  $p_0$  and  $\mu$ .

If  $|u''(x)| < k$  if  $x \in [p_0, \infty)$  and noticing that  $I \leq b/p_0$  for feasible  $I$ , we have that  $-(1 - p_0/p_1)u''(I + (b - Ip_0)/p_1)I < kb/p_0$  as long as  $p_1 \geq p_0$ . Furthermore, since  $-u'(I + (b - Ip_0)/p_1)$  is decreasing in  $p_1$ , we also have that  $-u'(I + (b - Ip_0)/p_1) < -u'(b/p_0)$  as long as  $p_1 \geq p_0$ . Hence,

$$\begin{aligned} &\int_{p_0}^{\mu} \left[ -\frac{u'(I + (b - Ip_0)/p_1) + (1 - p_0/p_1)u''(I + (b - Ip_0)/p_1)I}{p_1(\mu - \underline{\mu})} \right] dp_1 \\ &\leq \frac{-u'(b) + kb/p_0}{(\mu - \underline{\mu})} (\ln \mu - \ln p_0) \end{aligned} \quad (8)$$

Because  $-u'(b) + kb/p_0$  is increasing in  $b$  and  $\lim_{x \rightarrow 0} u'(x) = \infty$ , we can find  $\underline{b}$  such that  $-u'(\underline{b}) + k\underline{b}/p_0 < 0$ . Given that  $\ln \mu - \ln p_0 > 0$ , the expression in (8) is negative for  $b = \underline{b}$  (or, in fact,  $b \leq \underline{b}$ ). This establishes

that  $\partial E[(1 - p_0/p_1)u'(I^* + (b - I^*p_0)/p_1)]/\partial p_0$  is negative if  $b \leq \underline{b}$ .

By the Implicit Function Theorem, provided  $b \leq \underline{b}$ ,

$$\frac{\partial I^*}{\partial p_0} = -\frac{\partial E[(1 - p_0/p_1)u'(I^* + (b - I^*p_0)/p_1)]/\partial p_0}{E[(1 - p_0/p_1)^2 u''(I^* + (b - I^*p_0)/p_1)]} < 0 \quad (9)$$

if  $p_0 < \mu$  since  $u'(\cdot) > 0$  and  $u''(\cdot) < 0$ . QED

Notice that in this analysis, we have not made any assumptions about the correlation between  $p_0$  and  $\bar{\mu}$  (i.e.,  $\alpha = 0$ ). Nevertheless, evidence given our paper suggest that higher  $p_0$  is correlated with higher expected value for  $p_1$  as households are likely to be over-extrapolative (see, e.g., [Shiller \(2000\)](#)) (i.e.,  $\alpha > 0$ ). In this instance, the conclusion of Proposition 2 need not hold as the effects from Proposition 1 can dominate. We can establish that when price increase expectations are sufficiently high and initial prices sufficiently low, an increase in the initial prices can lead to an increase in hoarding:

**Proposition 3.** *Assuming  $\alpha \geq \ln(\bar{\mu}/\underline{\mu}) = \ln[(\mu + \alpha p_0)/\underline{\mu}]$ ,  $I^*$  increases with the price at time 0,  $p_0$  for sufficiently low  $p_0$ .*

**Proof of Proposition 3.** The result is once again established using the Implicit Function Theorem. To apply this result, the numerator in equation (9) is now

$$\begin{aligned} & \int_{\underline{\mu}}^{\bar{\mu}} \left[ -\frac{u'(I + (b - Ip_0)/p_1) + (1 - p_0/p_1)u''(I + (b - Ip_0)/p_1)I}{p_1(\bar{\mu} - \underline{\mu})} \right] dp_1 \\ & + \alpha(1 - p_0/\bar{\mu})u'(I + (b - Ip_0)/\bar{\mu})/(\bar{\mu} - \underline{\mu}) \\ \geq & \int_{\underline{\mu}}^{\bar{\mu}} \frac{u'(I + (b - Ip_0)/\bar{\mu}) - u'(I + (b - Ip_0)/p_1)}{p_1(\bar{\mu} - \underline{\mu})} dp_1 (\equiv A) \\ & - \underbrace{\int_{\underline{\mu}}^{\bar{\mu}} (1 - p_0/p_1) \frac{u''(I + (b - Ip_0)/p_1)I}{p_1(\bar{\mu} - \underline{\mu})} dp_1}_{(\equiv B)} - \underbrace{\alpha p_0 u'(I + (b - Ip_0)/\bar{\mu})/\bar{\mu}(\bar{\mu} - \underline{\mu})}_{(\equiv C)} \end{aligned}$$

Since  $\bar{\mu} \geq p_1$  and  $u''(\cdot) < 0$ ,  $u'(I + (b - Ip_0)/\bar{\mu}) - u'(I + (b - Ip_0)/p_1) \geq 0$  and  $A > 0$ . As  $p_0 \rightarrow 0$ , the integrand in (B) converges to  $u''(I + b/p_1)I/p_1(\bar{\mu} - \underline{\mu}) < 0$  and (minus) the integral converges to a positive value:  $B > 0$ . Finally, as  $p_0 \rightarrow 0$ , (C) converges to 0. Consequently, as  $p_0 \rightarrow 0$  the bound above ( $= A+B+C$ ) is positive. Since the denominator in equation (9) remains negative, the Implicit Function Theorem gives that  $\partial I^*/\partial p_0 > 0$ . QED.

We examine this demand curve using standard linear regression models (see, e.g., [Deaton and Muellbauer \(1988\)](#) and [Nevo \(2010\)](#)). Our estimates can be seen as linear approximations to the demand function obtained above. In particular, we estimate the following regression specification for each household  $i$  in

month  $t$  as

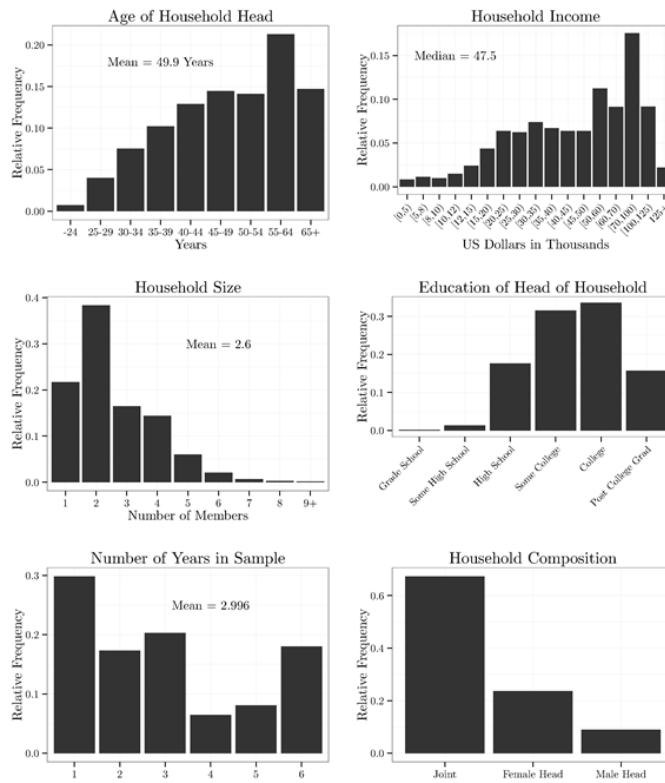
$$I_{i,t} = a_0 + a_1 \times \text{BubblePeriodDummy}_t + \gamma_1 \times p_{i,t} + \gamma_2 \times \text{HouseholdCharacteristics} \quad (10)$$

Linearizing the economic model, a change in expectations  $\Delta\mu$  around the Bubble Period corresponds to a change in inventory  $\Delta I^* = \partial g(\tilde{\mu}, p_0) / \partial \mu \times \Delta\mu$  (controlling for price  $p_0$  and other household characteristics), where  $\tilde{\mu}$  is an intermediary value determined by the change in  $\mu$ .<sup>10</sup> The Bubble Period Dummy hence captures the variation in the expectations of household beliefs  $\mu$ , coinciding with the months around the peak of the Rice Bubble in May of 2008 (from Proposition 2,  $\partial g(\tilde{\mu}, p_0) / \partial \mu > 0$ ). The coefficient  $\gamma_1$  on  $p_{i,t}$  controls for price and captures the usual downward sloping demand curve considerations with normal consumption patterns, so we expect it to be negative. We also introduce a set of household characteristics, i.e., income and size, to soak up variation associated with these normal demand considerations. In some of our specifications we also include household fixed effects and lagged purchases.

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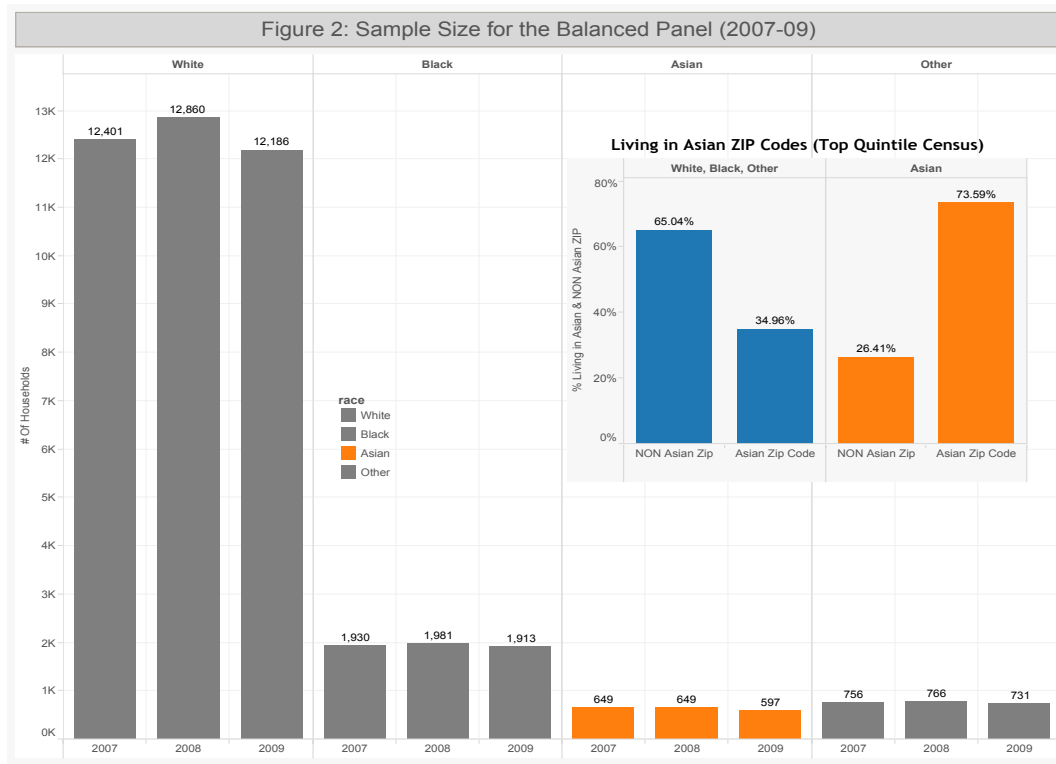
<sup>10</sup>All the hoarding effects are driven by both expectations or changes in expectations and curvature of the utility function. Separating these out requires specific assumptions about the utility function.

Figure 1: Nielsen Panel Demographics



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

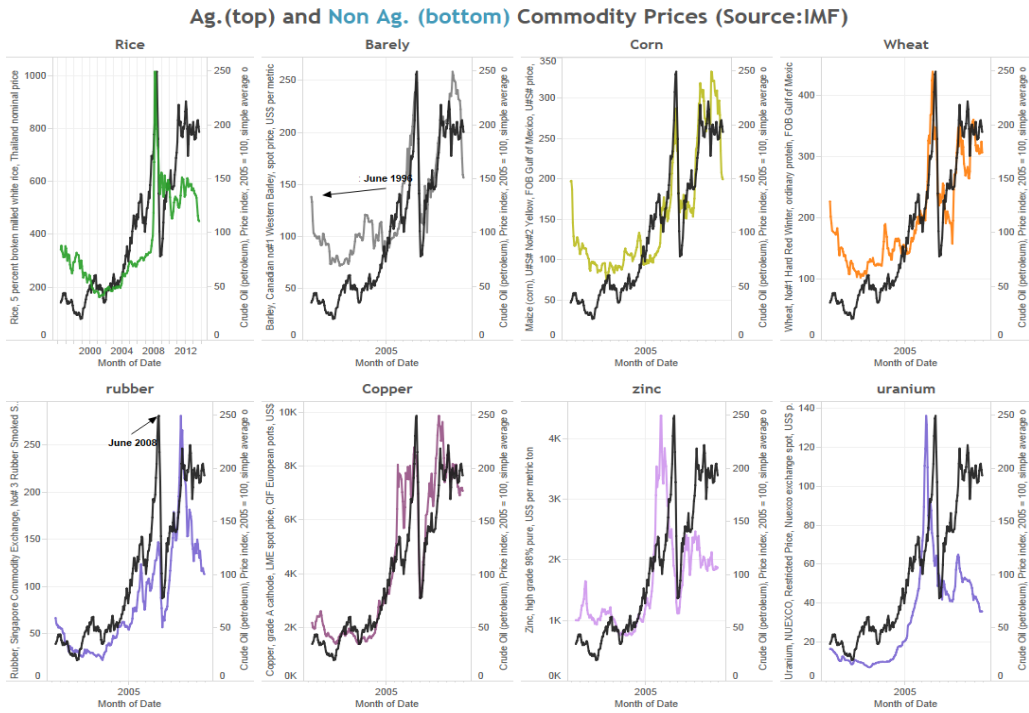
Figure 2: **Balanced Panel Summary Statistics**



This figure plots the distribution of our Sample Size for our balanced panel.

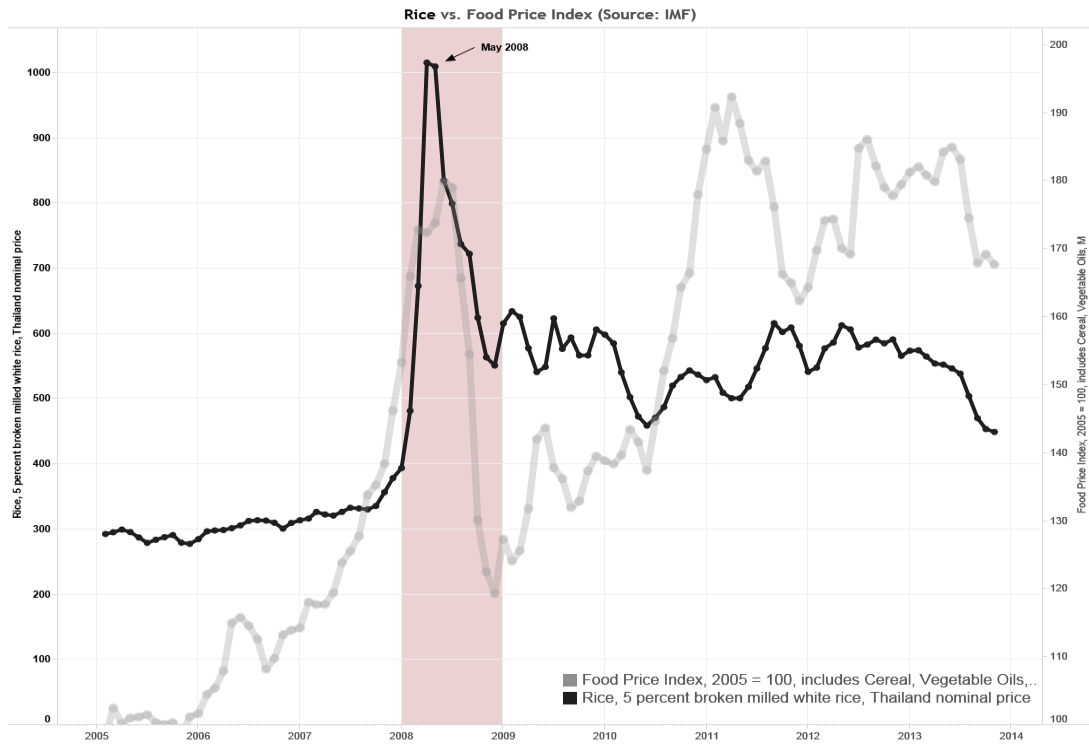


Figure 3: Commodity Prices



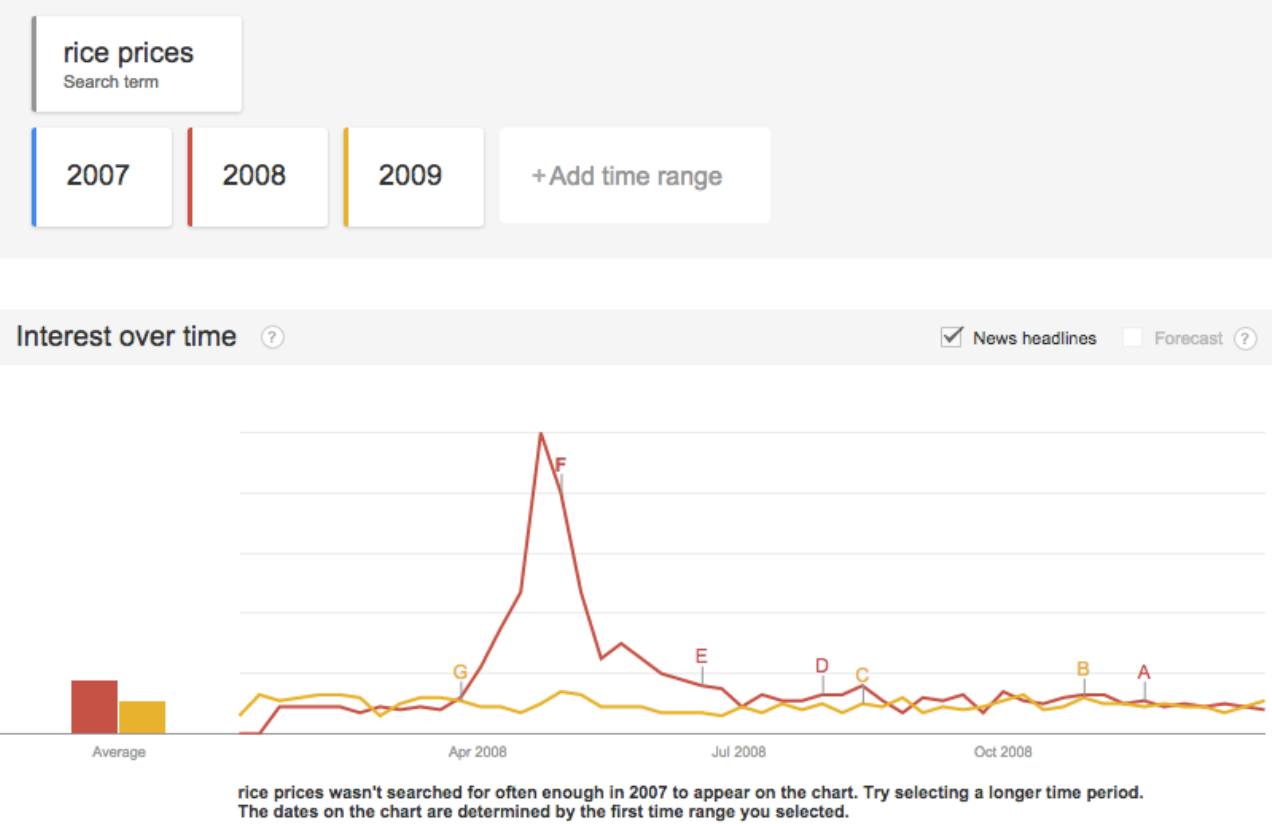
This figure plots the time-series of rice prices versus a food price index.

Figure 4: Price of Rice against Food Price Index



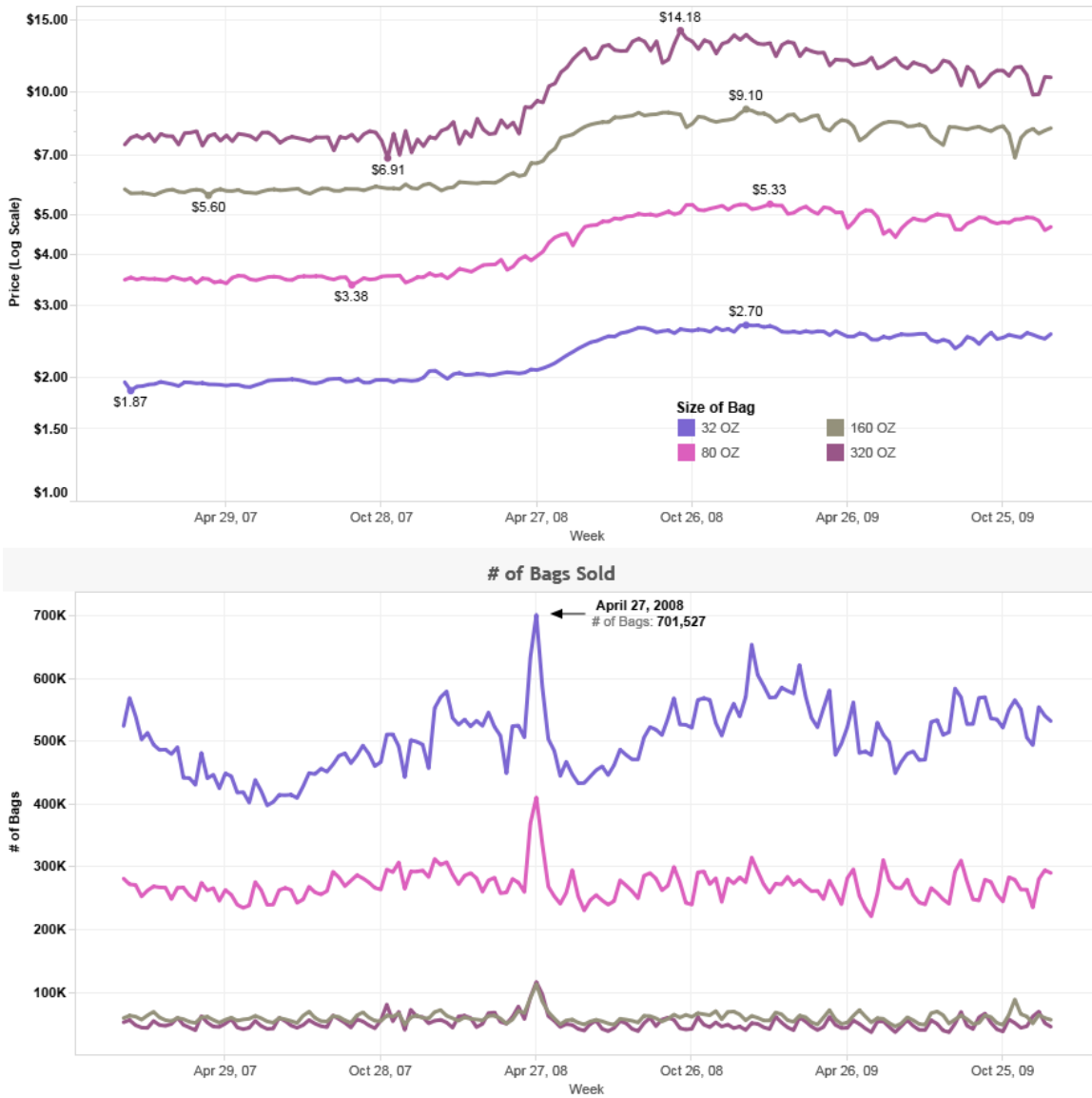
This figure plots the time-series of various agricultural and non-agricultural commodity prices against the price of oil in black.

Figure 5: Google Search Volume for Rice



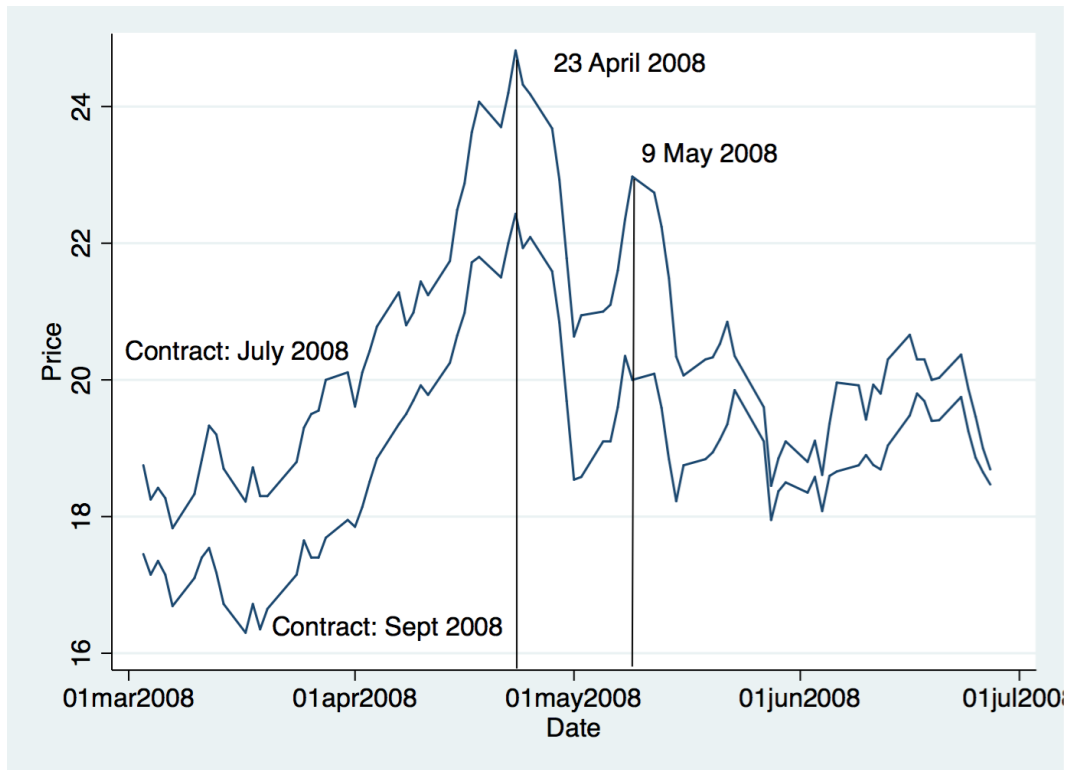
This figure plots the Google Trends Search Volume Index for Rice. The index is normalized at 100 for the period of peak interest.

Figure 6: Price of Rice in US Stores, other size bags



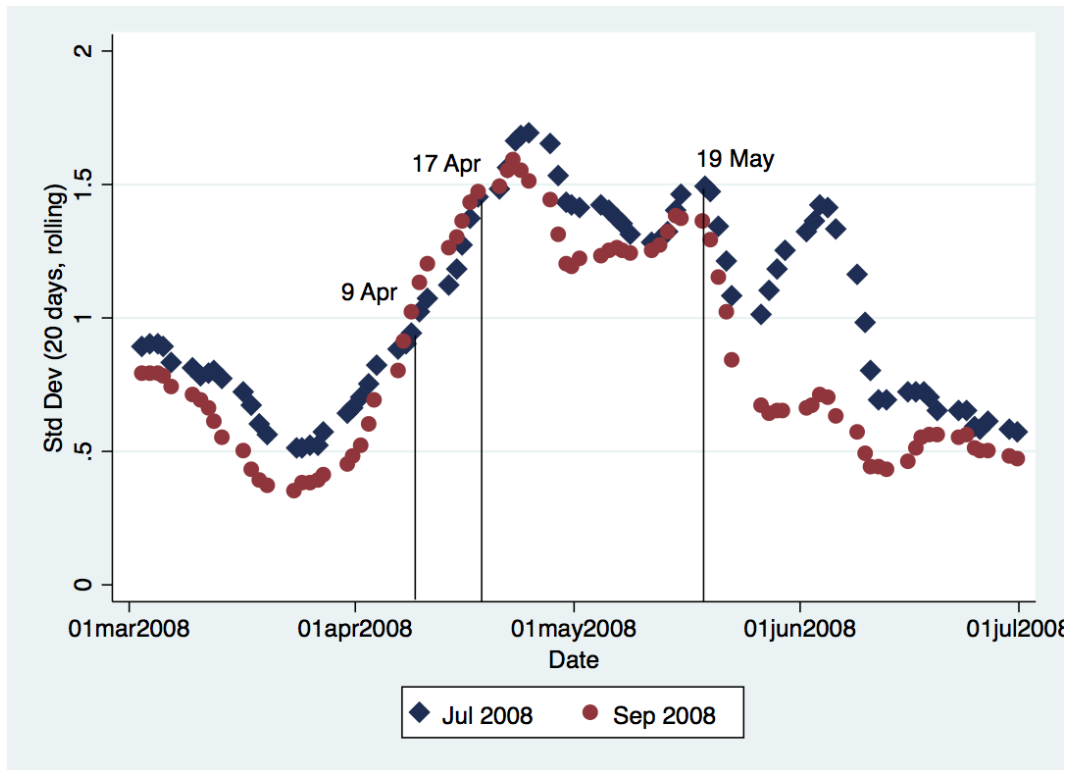
This figure plots the prices of various size bags and volume of sales for the largest and smallest bags.

Figure 7: **Futures Prices**



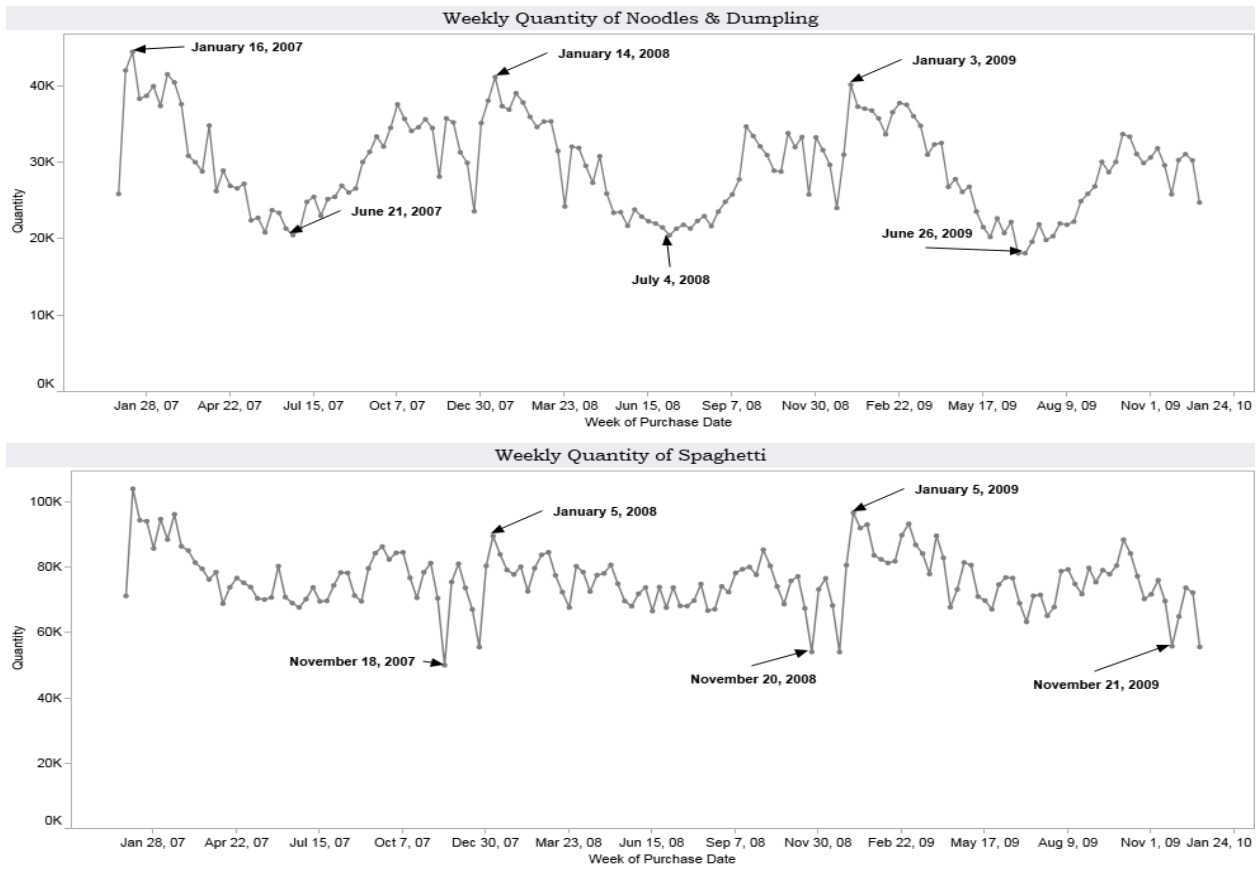
This figure plots the prices for futures contracts for rice with expiration in July 2008 and September 2008. The futures contract is for 2,000 cwt (hundred weight), which corresponds to about 200,000 pounds or circa 91 metric tons, of rough rice, no.2 or better.

Figure 8: Volatility for Futures Prices



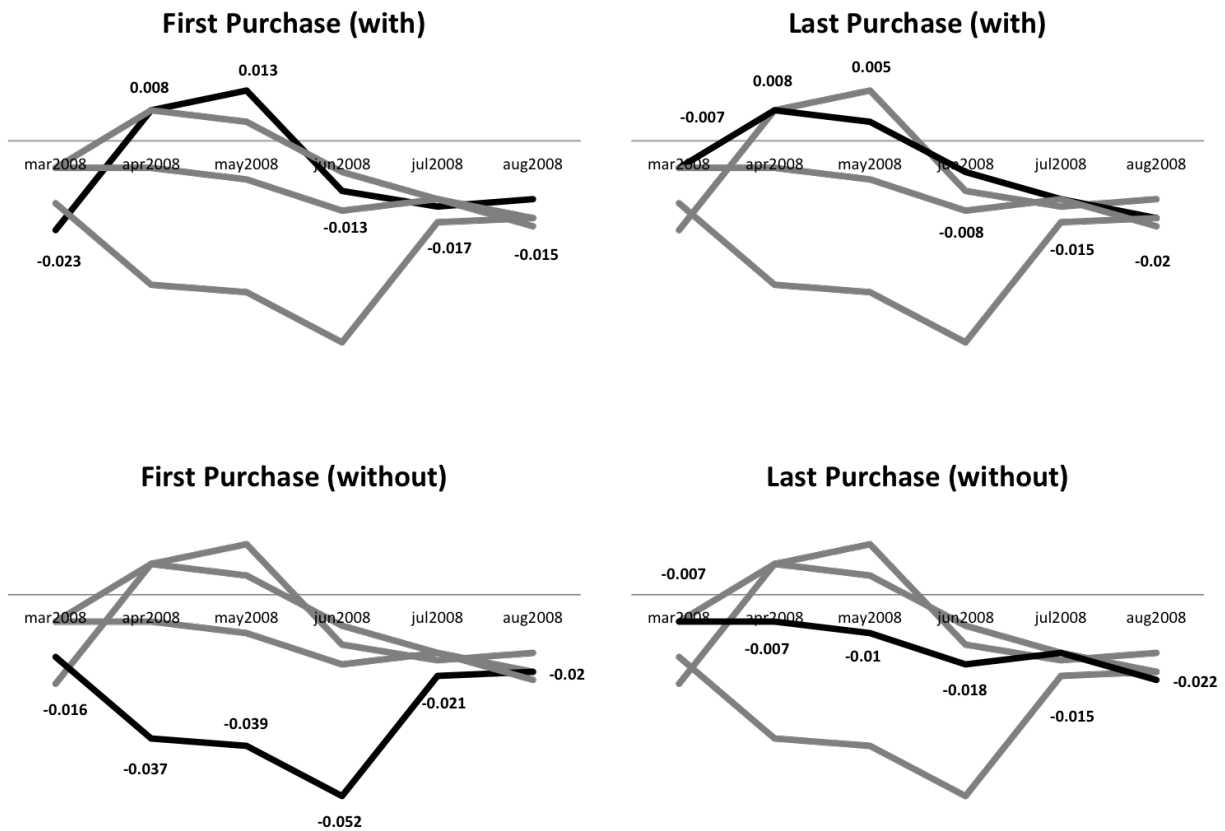
This figure plots the volatility of the futures contracts for rice with expiration in July 2008 and September 2008. The volatility measure is the standard deviation of prices in the last 20 trading days. The futures contract is for 2,000 cwt (hundred weight), which corresponds to about 200,000 pounds or circa 91 metric tons, of rough rice, no.2 or better.

Figure 9: Rice Substitutes: Weekly Quantities of Noodles and Dumplings and Spaghetti



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

Figure 10: First Rice Purchases



This figure plots the coefficients on the LPM hazard model for first and last purchases of rice with and without the sample of individuals who first bought rice in April 2008 or later and last purchased rice in June 2008 or earlier. Each panel displays the same four lines. Each line plots the coefficients for one of the duration models. Each one of the four panels in turn highlights (in black) the line corresponding to the specification in the panel title. For example, the lower left panel highlights in black the line for the estimated coefficients on the duration model for first purchase using all individuals that entered our sample in January 2007 *except* for those that only buy rice between April and June 2008.



Table 1: Summary Statistics. Dependent variables of interest include Quantity, the number of ounces of rice purchased each month and Monthly Frequency, the number of transactions each month. Independent variables of interest include Price, the average price paid each month by household, HH Income, household income and Household Size, the number of persons in household.

<b>Variable</b>	<b>Obs (Million)</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
Quantity (oz)	1,187,057	10.18	57.18	0	10,000
Quantity (oz) (if >0)	154,710	78.09	140.65	2	10,000
Monthly Frequency	1,187,057	0.15	0.42	0	13
Price (USD)	1,465,382	3.51	1.396	0.09	24.34
HH Income (USD '000)	1,524,096	59.59	35.29	3	220
Household Size	1,524,096	2.65	1.353	1	9

Table 2: Baseline Specifications Measuring Hoarding Effect. The dependent variables of interest are Quantity and Monthly Frequency, defined in Table 1. The regression specification is given in Equation (1). The key independent variables of interest are April, May and June 2008 month dummies, with April and May 2008 being the peak of global rice prices. Control variables vary across columns. Robust standard errors in parentheses. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

	<b>Quantity (oz)</b>		<b>Monthly Frequency</b>	
	(FE)	(AB)	(FE)	(AB)
April 2008	6.628 ** ( 0.494 )	8.175 ( 0.443 )	0.050 ** ( 0.003 )	0.048 ** ( 0.003 )
May 2008	5.027 ** ( 0.437 )	7.233 ** ( 0.423 )	0.032 ** ( 0.003 )	0.040 ** ( 0.003 )
June 2008	0.577 ( 0.365 )	2.500 ** ( 0.438 )	-0.000 ( 0.003 )	0.011 ** ( 0.003 )
Price (USD)	-0.221 * ( 0.099 )	-3.269 ** ( 0.248 )	-0.002 ** ( 0.001 )	-0.034 ** ( 0.002 )
Y(t-1)		-0.045 ** ( 0.001 )		-0.013 ** ( 0.001 )
Month FE	YES	YES	YES	YES
HH FE	YES	YES	YES	YES
Obs.	1,140,402	1,058,222	1,140,402	1,058,222

Table 3: Basic IV Specification Measuring Hoarding Effect. The dependent variables of interest are Quantity and Monthly Frequency, defined in Table 1. The regression specification is given in Equation (1). The key independent variables of interest are April, May and June 2008 month dummies, with April and May 2008 being the peak of global rice prices. Control variables vary across columns. The price of rice is instrumented by international rice prices (obtained from the IMF). The FE IV specification is estimated in First-Differences using purchases of rice two months earlier as instrument for the change in purchases in the previous month. The first column presents the first stage estimates for a TSLS estimator (not presented). The pairwise correlation of the price of rice with international rice prices is 0.1865. The F-statistic in the first stage is 110,315 and the Minimum Eigenvalue Statistic is 96,225.7, well above the usual critical values for the hypothesis of weak instruments. The model is exactly identified so no overidentification tests were performed. Robust standard errors in parentheses. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

	<b>Rice Price (USD)</b> (OLS)	<b>Quantity (oz)</b> (FE IV)	<b>Monthly Frequency</b> (FE IV)
April 2008	-2.031 ** ( 0.010 )	5.771 ** ( 0.583 )	0.039 ** ( 0.004 )
May 2008	-1.646 ** ( 0.011 )	6.963 ** ( 0.577 )	0.049 ** ( 0.004 )
June 2008	-0.873 ** ( 0.010 )	2.291 ** ( 0.479 )	0.016 ** ( 0.004 )
Price (USD)		-15.262 ** ( 4.321 )	-0.164 ** ( 0.032 )
HH Inc. ('000)	0.006 ** ( 0.000 )		
HH Size	-0.043 ** ( 0.001 )		
Int Rice Pr ('00 USD/Ton)	0.291 ** ( 0.001 )		
Y(t-1)		-0.047 ** ( 0.002 )	-0.022 ** ( 0.002 )
Month FE	YES	YES	YES
HH FE	NO	YES	YES
Obs.	1,140,402	1,017,554	1,017,554

Table 4: Discrete Time Duration Until First and Last Rice Purchase. The model is estimated by maximum likelihood using Equation (2). The monthly hazard rate for first time purchase of rice is modelled as a linear probability model in columns (1) and (3) and as a logit model in columns (2) and (4). The sample only includes households that entered our sample in January 2007. Standard errors are given in parenthesis. For the logit hazard we also provide Average Partial effects in brackets for each variable. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

	Coefficient Estimates			
	First Purchase		Last Purchase	
	(LPM)	(LOGIT)	(LPM)	(LOGIT)
Apr '08	0.008 * ( 0.004 )	0.086 † ( 0.045 ) [ 0.008 ]	0.008 ** ( 0.002 )	0.238 ** ( 0.045 ) [ 0.010 ]
May '08	0.013 ** ( 0.004 )	0.143 ** ( 0.049 ) [ 0.014 ]	0.005 * ( 0.002 )	0.148 ** ( 0.044 ) [ 0.006 ]
Jun '08	-0.013 ** ( 0.004 )	-0.168 ** ( 0.058 ) [ -0.016 ]	-0.008 ** ( 0.001 )	-0.263 ** ( 0.051 ) [ -0.011 ]
Month Dummies	YES	YES	YES	YES
N of HHs	297,904	297,904	706,508	706,508

Table 5: Fixed Effects specifications. The regressions involve only individuals who purchased rice for the first time in April, May or June (2008). Control variables vary across columns. These regressions only use observations from February to August 2008. Robust standard errors in parentheses. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

	<b>Quantity (oz)</b>	
	<b>(FE)</b>	<b>(AB)</b>
April (2008)	38.012 ** ( 2.183 )	37.418 ** ( 2.189 )
May (2008)	35.240 ** ( 2.488 )	36.494 ** ( 2.101 )
June (2008)	17.515 ** ( 1.526 )	18.118 ** ( 2.140 )
Price (USD)	5.068 ** ( 0.788 )	3.207 ( 2.563 )
Y(t-1)		-0.056 ** ( 0.011 )
HH FE	YES	YES
Obs.	2,970	2,960

Table 6: Ex-Post Price Variation and Excess Hoarding (2008). The regressions have Price Variation from May until July 2008 as dependent variable and hoarding defined as the total quantity purchased from March until May. This is decomposed into “Excess Hoarding” and “Predicted Purchases” using TSLS estimates from a regression of quantity on prices, household income and size and monthly seasonal dummies using international prices as instrument for prices. The estimated coefficients are used to predict the quantity purchased by a household in a given month (“Predicted Purchases”) and the residual is classified as “Excess Hoarding”. The regressors are accumulated values of those variables over March, April and May 2008. The regressions are run using averages at the county level. Robust standard errors are presented for the county level regressions. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

Dependent Variable:	Price Variation (May to July)	
Quantity (oz)	-0.018 ** ( 0.008 )	
Excess Hoarding (IV) (oz)		-0.025 ** ( 0.009 )
Observations	1834	1834
p-value ( $H_0 : \beta > 0$ )	0.012	0.004

Table 7: Ex-Post Price Variation and Excess Hoarding (2007 and 2009). The regressions have Price Variation from May until July as dependent variable and hoarding defined as the total quantity purchased from March until May. This is decomposed into “Excess Hoarding” and “Predicted Purchases” using TSLS estimates from a regression of quantity on prices, household income and size and monthly seasonal dummies using international prices as instrument for prices. The estimated coefficients are used to predict the quantity purchased by a household in a given month (“Predicted Purchases”) and the residual is classified as “Excess Hoarding”. The regressors are accumulated values of those variables over March, April and May. The regressions are run using averages at the county level. Robust standard errors are presented for the county level regressions. Significance levels : † at 10%, \* at 5%, and \*\* at 1%.

Dependent Variable:	Price Variation (May to July)			
	(2007)		(2009)	
Quantity (oz)	0.000 ( 0.000 )		0.001 ( 0.003 )	
Excess Hoarding (IV) (oz)		0.001 ( 0.000 )		0.000 ( 0.003 )
Observations	22398	22398	1818	1818
p-value ( $H_0 : \beta > 0$ )	0.871	0.916	0.684	0.536