AMIS: IG-12/4

AMIS

2nd SESSION OF THE AMIS GLOBAL FOOD MARKET INFORMATION GROUP

ROME, FAO HEADQUARTERS

Wednesday, 3 October 2012

STOCKS-TO-USE RATIOS AS INDICATORS OF VULNERABILITY TO SPIKES IN GLOBAL CEREAL MARKETS

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Introduction

1. In 2011, the FAO, IFAD, OECD, UNCTAD WFP, World Bank, WTO, IFPRI, and the UN HLTF established an **Agricultural Market Information System (AMIS)** in order to enhance the quality, timeliness and reliability of food market outlook information. One objective was to provide the basis for global food market alerts to price surges and more timely and effective policy responses to market developments. Another was to build data collection capacity in developing countries. This paper addresses the challenge of how best to utilize available global information (in particular the imperfect information on global stocks) in order to strengthen global capacity to issue early warnings of possible price volatility, and thus enhance food security and emergency policy responses to threats to food security.

2. The basic goal of this study is to provide information and a methodological approach to identify critical stocks-to-use ratios (SURs) for major grains and total cereals. The study is oriented towards information relevant to significant policy response. For speculators, anticipation of relevant news about supply-demand balance shortly before it becomes public (for example, early information predicting a WASDE report of the USDA) can be more rewarding when the news relates to a market with little flexibility of response in production or consumption, for then the resulting price reaction to the news will be greater. Here, on the other hand, we focus on information when it is useful for informing policy decisions that might alleviate a shortage. Flexibility of response declines as the time for response decreases. Here we focus on information relevant to the next harvest at the start of the crop year.

3. One year in advance, a host of variables are potentially relevant to the prospects at the end of the crop year. They include interest rates, exchange rates, macroeconomic conditions, anticipated number of animals on feed, prospects for pests and diseases, long run weather forecasts, and costs of inputs such as fertilizers, as well as government agricultural and trade policy interventions. Here we focus on just four types of data, prices, production, consumption (broadly defined) and stocks of the three major grains, wheat, maize and rice. We investigate the use of ratio of stocks to consumption as an advance indicator of "abnormal market conditions" when price data are already available.

4. Information on the behavior of the world's grain markets is scarce and of highly variable quality. The dominant indicators are prices, generally measured in an organized market at a specified location for a specified grade of the product. Most consumers live far from that market, and many of them might consume a type of grain quite different from that traded on the exchange, and at quite different prices. Especially in developing countries, reported prices frequently differ markedly from the reported global price (Gilbert 2011, Jones and Kwiecinski et al. 2010, Rapsomanikis 2011, Porteus 2012). Though frequently unrepresentative of the cost of grain to consumers, and deflated by an often problematic index, global prices are often by far the best available measures of the state of the world's grain markets.

5. The nominal price data used in our estimation are from World Bank/GEM Commodities, for the marketing years ending in 1961 through 2007.[1] The marketing years for wheat, maize, and rice end in May, August, and July, respectively.[2] We take the annual price to be the monthly price observed in the last month of the marketing year.

6. We also study the market for the three grains together as a market for aggregate calories. The calories price is constructed as the average of wheat, maize, and rice annual prices with world wheat, maize, and rice production in calories as weights. World wheat, maize (corn), and rice (milled) production data are from USDA/FAS/PSDO. The weight-calories conversion rates are from USDA/National Nutrient Database.

7. All annual price data are deflated into real price indices using the annual Manufactures Unit Value Index (MUV) from World Bank/GEM Commodities. Note that this index behaves very differently from the United States Consumer Price Index, especially in recent decades; results using the latter could be substantially different.

8. The real (deflated) prices of wheat, maize and rice are shown in Figures 1, 2 and 3, respectively.

1 We take the marketing year definition from USDA/FAS, recognizing that the definition of the marketing year is problematic, since the grains are produced in both hemispheres, and multiple annual rice crops are grown in some countries. See for example Greenfield and Abbassian 2011 for a discussion of this issue.

2 See http://www.fas.usda.gov/export-sales/myfi_rpt.htm. Details and sources are presented in Appendix A.

Figure 1. Wheat real price index

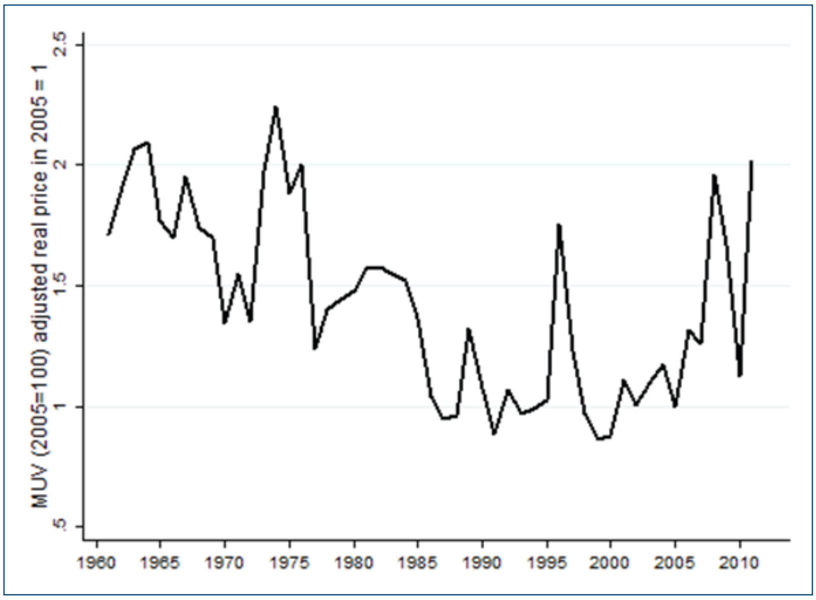


Figure 2. Maize real price index

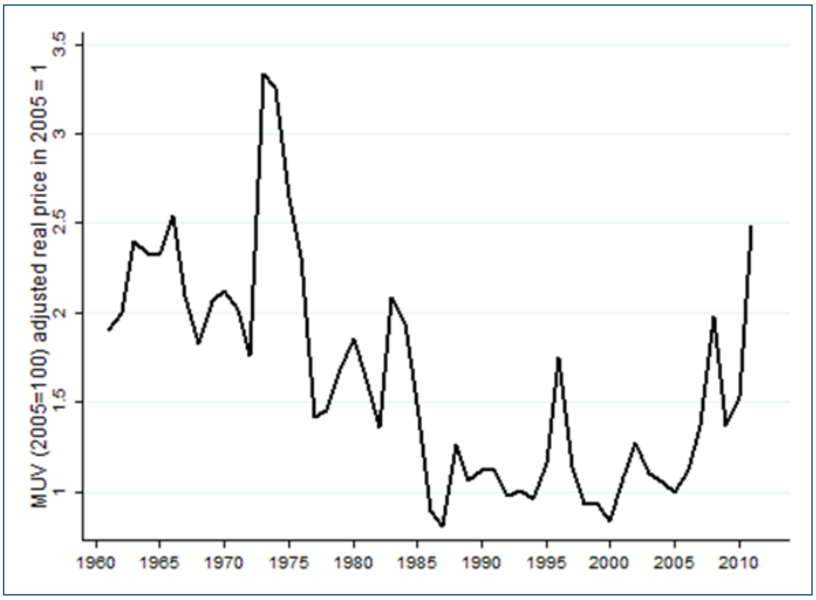


Figure 3. Rice real price index

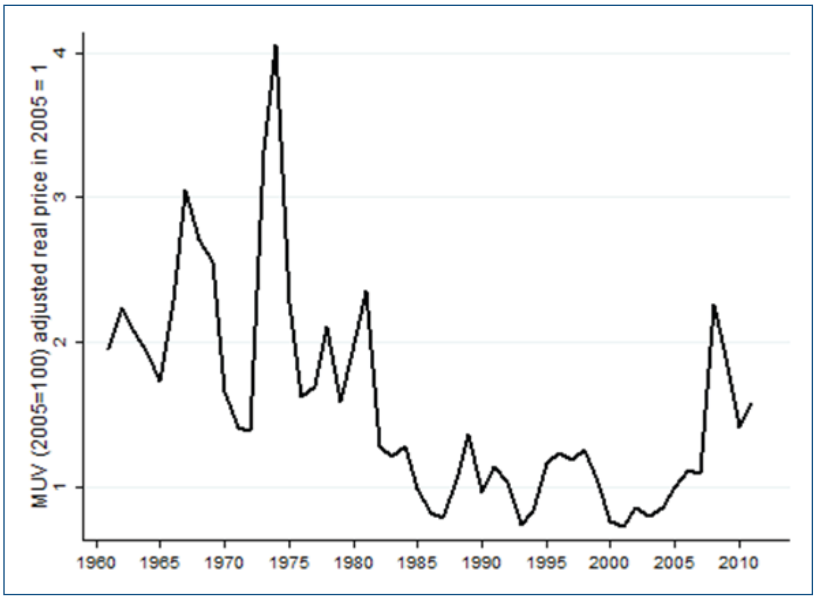


Figure 4. Wheat de-trended production and de-trended real price in log scale

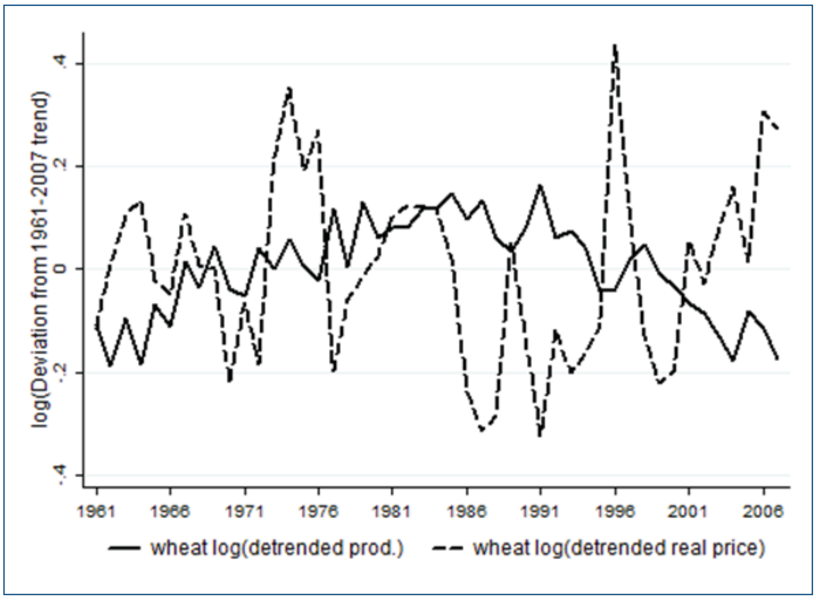


Figure 5. Maize de-trended production and de-trended real price in log scale

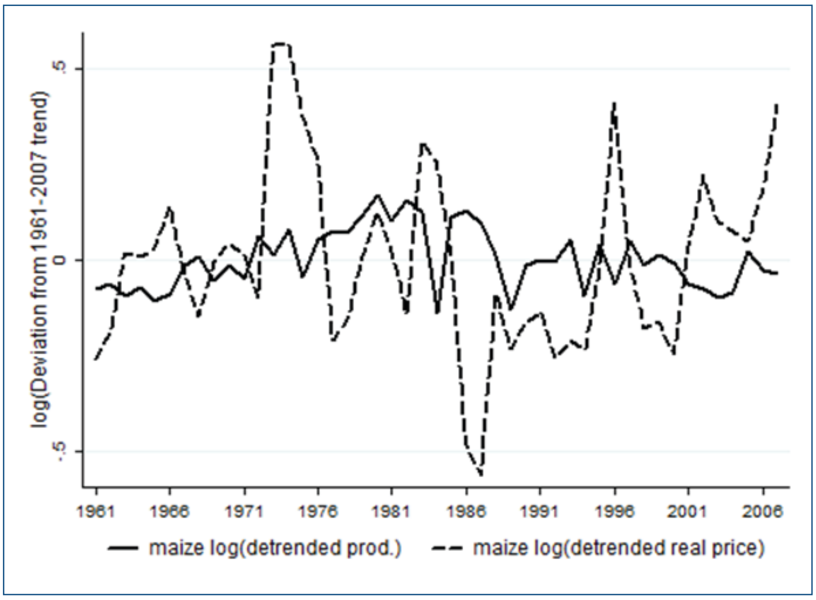
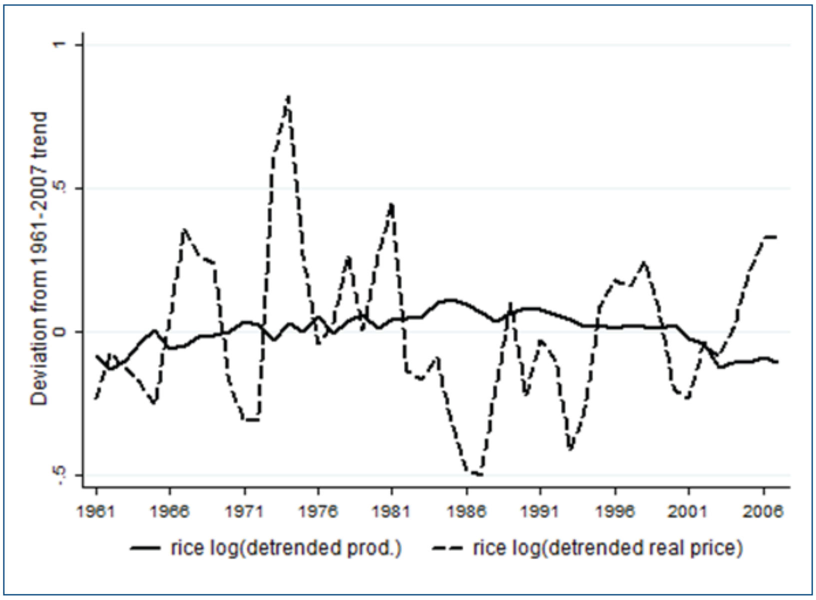


Figure 6. Rice de-trended production and de-trended real price in log scale



9. Aspects of real price behavior that get policymakers' attention are exemplified in the global price of wheat, in Figure 1. Deflated price has trended downward since the 1950s, as wheat production has outpaced demand growth. Maize and rice prices follow similar downward trends. These are their most important dynamic features from the perspective of human welfare. The strength and persistence of these trends is a recent historical aberration. It is principally due to the remarkable success of plant breeders and farmers in continually developing and adopting new crop varieties with enhanced response to increased application of fertilizers, and to innovations in production and transportation of fertilizers that have greatly reduced their cost.

10. As prices of these grains trend downward, they generally fluctuate moderately, within a reasonably well-defined range. However, episodes of higher "volatility," more informatively characterized as intervals with steep jumps in price, followed by precipitous falls back to the trend, are prominent features of the data. These fluctuations are asymmetric, there being no equally prominent troughs to match spikes, and at locally low prices the probability of sudden falls is negligible. In contrast to the recent downward trends, episodes of high volatility of prices have been a feature of grain markets throughout their recorded history.

Do Current Supply and Demand Shocks Explain Price Spikes?

11. To explain large price spikes, it is natural to look to large shocks to supply and/or demand. Indeed, many assessments of recent periods of volatility have ignored storage, focusing on factors such as weather shocks, global warming and/or technology slowdowns that reduce yields and increase production costs. News mentions of climate-related production problems have proliferated during the past decade. For example, droughts in Australia, fires in Russia, and increased reliance on more volatile production in the Caucasus have been mentioned as causes of recent gyrations in wheat prices. In the United States, summer heat and drought have been widely `recognized as the causes of the current spike in corn price. Relative to stocks, it might seem intuitive that these factors are much more directly related to periods of high volatility of global price behavior. In fact, the link between production variations and grain prices is less easy to establish than one might expect (Greenfield and Abbassian 2011).

12. To obtain an accurate view of price volatility, we need to remove the influence of the strong trends from measures of variation in real grain prices. We de-trend real prices assuming a log-linear trend.[3] This trend is estimated from 1961 through 2007, when grain markets entered a new period of high volatility, which we have not been asked to address here. We use this trend below to de-trend the data for estimation of a model that will address some sources of this recent volatility. We use a similar method to de-trend production of each grain. Figures 4, 5 and 6 display the logarithms of the de-trended real price and de-trended production of wheat, maize and rice, respectively, from 1961 through 2007.

13. Obviously, production is not closely correlated with price, and price peaks do not necessarily coincide with the worst harvest years. Consider the four most prominent shortfalls in corn production between 1960 and 2007, as shown in Figure 5. In 1973 a large percentage shortfall from expected production was associated with the largest real price spike in this time interval. The1983 shortfall was even higher, due to cold and wet early conditions followed by a hot and dry summer, and to a low planted acreage, but the real price spike was much smaller than in 1973. The largest percentage shortfall occurred in 1988, but price barely move beyond average levels. Another shortfall in 1993 hardly moved price at all. A few years later, a smaller relative shortfall caused the second largest spike in the chosen interval. These observations establish that a significant production shortfall is neither necessary nor sufficient to cause a price spike. Figures 4 and 6, for wheat and rice, tell similar stories.

14. Although production fluctuation can have serious effects on agricultural markets, these effects are not as simple and direct as many studies assume. First, they depend on the responses in markets for substitutes in consumption. Global production of major grains is more stable than global production of wheat; a bad maize harvest in the United States can be offset by a good wheat harvest in Canada or India. The poor 1975 corn harvest in the United States, discussed above, occurred when global wheat and rice supplies were also low, so the usual substitutes could not fill the global yield gap in corn.

15. A second important factor relates to an extremely useful attribute of the major grains: they can be stored for years without excessive deterioration. When stocks are available, an output shortfall can be cushioned by

3 See Appendix B for a description of the de-trending methodology.

Figure 7. Wheat SURs

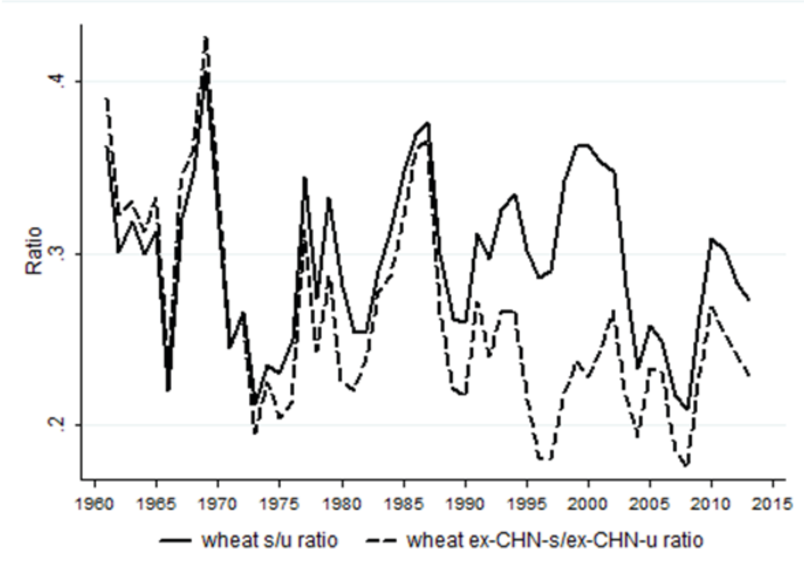


Figure 8. Maize SURs

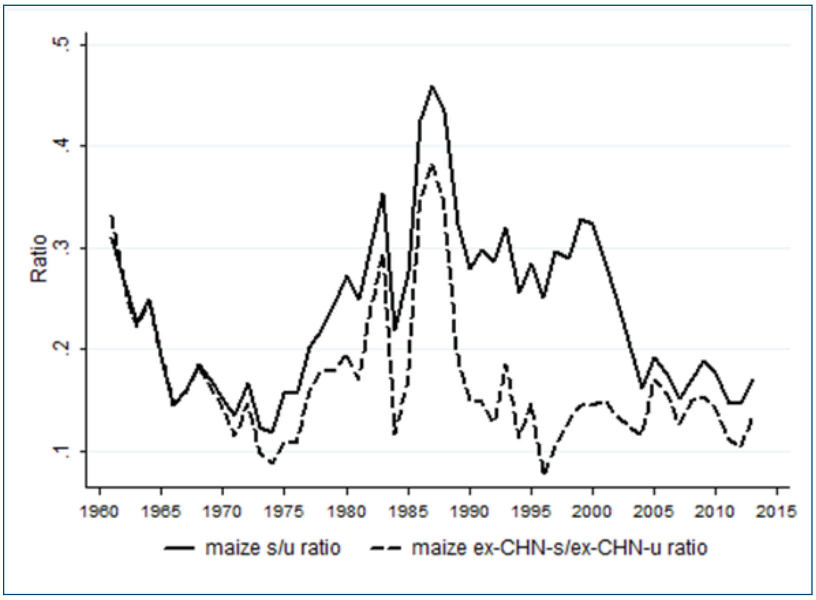
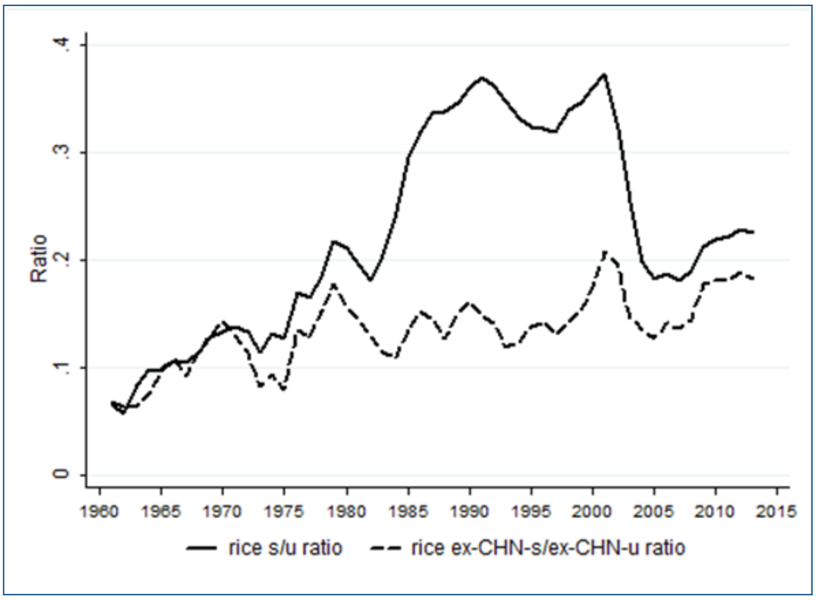


Figure 9. Rice SURs



a drawdown of those stocks. But storability is not always useful in moderating a shock to demand or supply. When stocks are already minimal, their cushion is not available – markets in aggregate cannot borrow food from future production, so price must rise to cause current consumption to fully accommodate a shortfall. Storage greatly affects price behavior. Consider again the production and price history of maize as illustrated in Figure 5, discussed above. The 1975 maize production shortfall had a huge effect on the market not only because it occurred at a time of low yields of wheat and rice, but also because the stocks of all three were too low to buffer these shortfalls.

16. A convenient measure of the adequacy of stocks is to normalize them in the form of the stocks-to-use ratio (SUR), the ratio of stocks to consumption, broadly defined. Figures 7, 8 and 9 present SURs for the three major grains, including "working" or "pipeline" stocks needed for operation of the marketing chain.

17. In 1988, the large shortfall of corn production evident in Figure 8 had little effect on price because it was buffered by high corn stocks in that year. The history of the other major grains tells a similar story: production or demand shocks are far more disruptive in the absence of "discretionary" stocks, stocks above levels essential to the operation of the marketing system.

18. The presence of discretionary stocks renders the identification of production shocks and their timing, by inspection of price time series alone, extremely difficult. Indeed the correlations between real production and de-trended real prices, both adjusted to remove log-linear trends, for wheat, maize and rice are only -0.33, -0.09 and -0.21, respectively. Storage can also transmit effects of a shock in one grain market to the price of another in a later period, further complicating inferences about the underlying drivers of price volatility. Finally, a grain price can spike even if stocks of that grain are substantial. When rice had a moderate spike in 1998, stocks appeared adequate (see Figure 9). Low stocks are not necessary for a price spike. On the other hand, around 2004, rice SUR was low, but so was price, because production was around trend. Hence low stocks of a grain are neither necessary nor sufficient for a price spike. But if a drop in the output of grain calories occurs when calorie stocks are low, large spikes in the price of each of the major grains are likely, as seen in 1975. In sum, to understand grain price spikes, one must look at production and consumption disturbances in the context of the current stocks situation.

19. This discussion raises the possibility of using the SUR as an indicator of current volatility, and perhaps as an indicator of increasing exposure to volatility. Though stocks data are notoriously imprecise (see Greenfield and Abbassian 2011 and IGG 1997) they avoid the problems of deflation that plague price data.

20. As a preliminary informal test of whether the SUR systematically relates to price behavior, consider Figures 10 through 12 below. They suggest a generally negative relation between fluctuations in SUR and price for each major grain.

21. In sharp contrast to production, the SUR seems to be a good indicator of vulnerability to shocks in each market. Correlations of SUR and real price support this: they are -0.40, -0.50 and -0.17 for wheat, maize and rice respectively. This does not mean storage drives price. Stocks reflect the history of past production and consumption (and waste), and reflects the past conscious allocative choices of market participants. They forge a link between past consumption and production and current consumption possibilities. They can turn an anticipated shock in output into a more gradual price adjustment. Thus the possibility of storage can change our interpretation of events in the markets for major grains, discussed in the next section.

The Markets For The Major Grains

22. The three major grains markets are quite distinct, though by no means independent. Rice is primarily a human food and is the preferred staple food for large parts of the populations of India and China, most of South East Asia and parts of Africa and Latin America. The top six producers, all Asian (China, India, Indonesia, Bangladesh, Vietnam and Thailand), account for more than three quarters of global output. Rice is largely produced where it is consumed; it is thinly traded, and quality differentiation is important. Thailand, Vietnam and the United States supply almost two thirds of exports. India and Pakistan also are frequently important exporters.

23. More than two thirds of wheat consumption is as human food, where its uses are differentiated by variety and quality. It is a staple food of parts of the populations of China and India, as well as for the Middle East and North Africa, Europe, the United States and other developed countries. It is increasingly preferred in many other

Figure 10. Wheat stocks-to-use ratio (excluding China) vs. de-trended real price

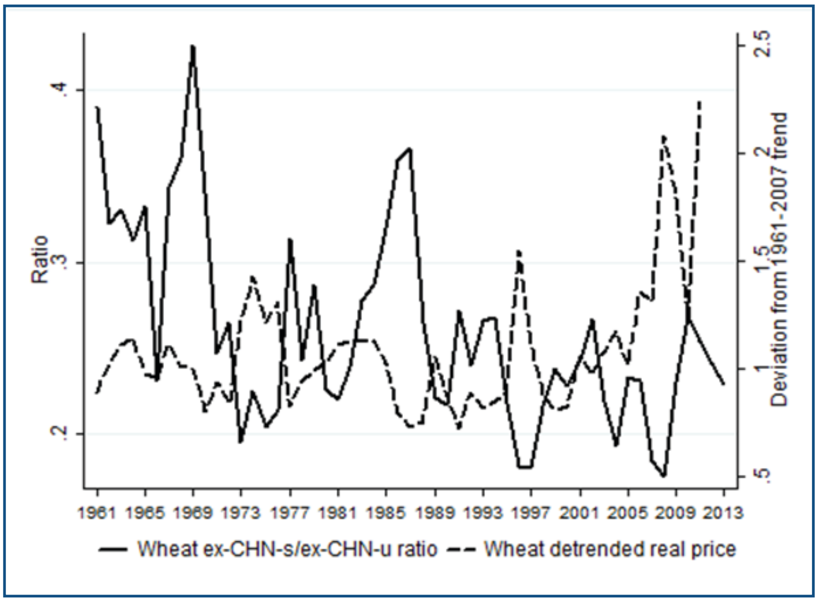


Figure 11. Maize stocks-to-use ratio (excluding China) vs. de-trended real price

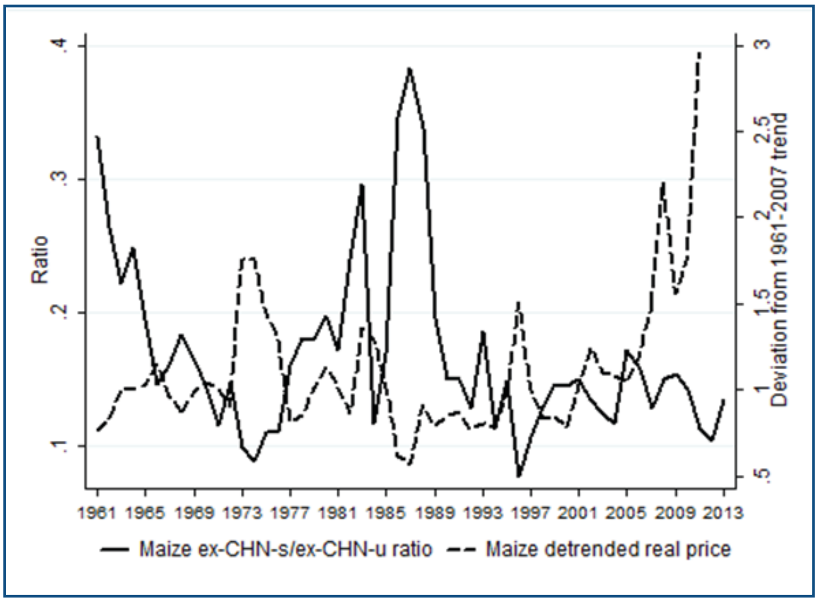
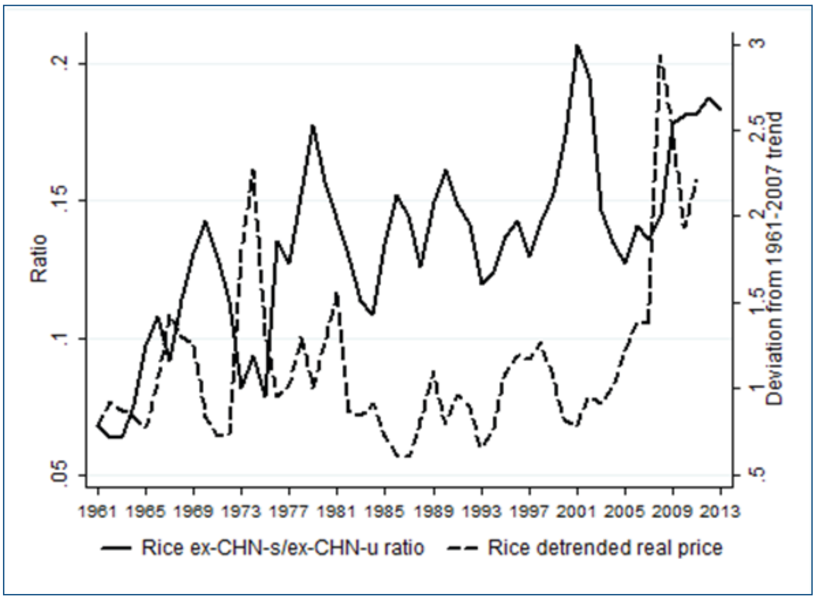


Figure 12. Rice stocks-to-use ratio (excluding China) vs. de-trended real price



countries as they develop. About one sixth (often wheat of inferior quality) is fed to animals. Small amounts are used in industry and for biofuels production in Europe. Its production is widespread, in both developed and developing countries. The major producers, all located in the Northern Hemisphere, are China, the European Union, India, the United States and Russia, which together account for more than two thirds of production. Wheat is widely traded. Major exporters are the United States, the EU, Canada, Argentina and Australia, which supply more than two thirds of exports and one third of world production.

24. Maize is used as a staple food in Mexico and Central America, as well as in Sub-Saharan Africa. Such direct human consumption accounts for around ten percent of global maize consumption. Maize is the major commercial animal feed, and this use accounts for about 60% of global maize production. A significant portion of maize is used for biofuels and other industrial purposes. About one sixth of global maize consumption has been for biofuel in recent years. (This is similar to the share of wheat used for animal feed.) This means that the percentage of maize used for biofuels is now greater than the percentage directly consumed by people. In the United States, more than one third of the net calorie value of corn produced (adjusted for byproducts used as feed) is now consumed as feedstock for biofuels. The United States and China produce more than half of the world maize crop. Other significant producers are the European Union and Mexico.

25. Though the global supply of rice is smaller than that of wheat or maize, it supplies a quantity of direct human calories similar to the share supplied by wheat. Rice supplies much of the caloric intake of the world's poor. Because little is fed to animals, and it has few non-food uses, shortfalls in availability directly imply reductions in human rice consumption, in the absence of stocks.

26. The major uses of each of the major grains are distinct, but they overlap in some areas. In major consuming countries such as China and India, parts of the population consume both wheat and rice, and, as rice consumers become wealthier, they tend to substitute some wheat products for rice. In other countries, rice and maize products are staples. Although most wheat is used for food, it has a substantial secondary market as animal feed, and a minor use as a biofuel in Europe. The three major grains also compete for inputs such as fertilizer and land. Hence the possibility arises that an aggregate of the calories supplied by the three grains better reflects the state of the market for the major grains than does any of the three component grains, as explored by Roberts and Schlenker (2009, 2010). Accordingly we include aggregate calories from the grains as a fourth market in what follows.

27. From Figures 4, 5 and 6, it is obvious that the prices of the three major grains are strongly related, even after deflation and removal of their trends. In this study we do not model the complex interaction of grain markets, ignoring the fact that the price of one affects demand for the others. The accurate modeling of this interaction is beyond the scope of this project. In fact, to our knowledge, dynamic modeling of the food demand system as a whole, in a context that recognizes storage as well as income effects, has not been satisfactorily achieved. However, comparison of the annual prices of the three crops, shown together in Figure 13 suggests another, more feasible, approach.

28. Note the similarity of the relative behavior of the three grains over the years included. This is even easier to perceive in the graph of the logarithms of these prices, as shown in Figure 14 where equal movements represent equal relative changes.

29. The dynamics of the deflated price series are very similar, giving empirical support to the hypothesis of strong substitution at the margin. The high level of correlation among de-trended prices for wheat, maize, rice and calories shown in Table 1 is evidence of such similarity, supporting the hypothesis of substitution.

30. Assuming perfect substitution, we can study the market for the three grains together as a market for aggregate calories. The calories price is constructed as the average of wheat, maize, and rice annual prices with the weight being the world wheat, maize, and rice calories production,as shown in Appendix A. World wheat, maize (corn), and rice (milled) production data are from USDA/FAS/PSDO. The weight-calories conversion rates are from the USDA/National Nutrient Database.

31. Considering the market for the three grains together as a market for aggregate calories, Figures 13 and 14 also show the price of this aggregate calorie index. Figure 15

Table 1. Correlation coefficients between wheat, maize, rice, and calories de-trended real price, 1961-2007

	Wheat	Maize	Rice	Calories
Wheat	1.0000			
Maize	0.7875	1.0000		
Rice	0.5803	0.6280	1.0000	
Calories	0.8318	0.8598	0.9133	1.0000

Figure 13. Wheat, rice, maize and calories real price indices

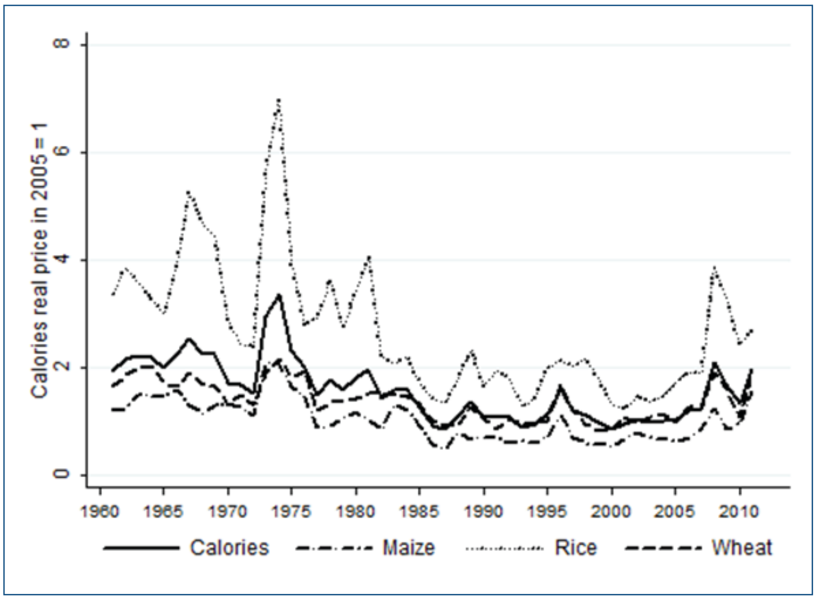
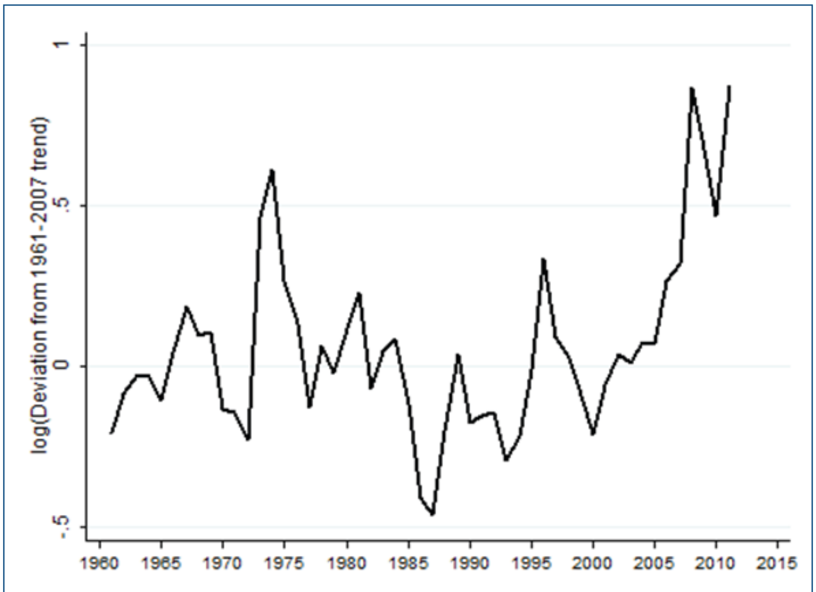


Figure 14. Wheat, rice, maize and calories real price indices in natural log scale

Figure 15. Calories de-trended real price in log scale



shows the deflated de-trended price for the aggregate index. We shall analyze this price series along with the three grain prices below.

POTENTIAL INFLUENCES ON GRAIN MARKET PRICE SPIKES.

Food demand surges

32. Several studies have emphasized increased demand for meat and other animal products due to unprecedented increases of income in developing countries, in particular Chinese and Indian income growth. Alexandratos (2008) reports data that actually seem to imply a slowdown in meat consumption growth dating from the period of the first price spike around 2007/08, but the data may well be unreliable. (See also FAO 2009, Headey and Fan 2008, and Tangerman 2011.) Furthermore, any increase in demand due to higher income would hardly have been a shock to the market by 2007/08, because the income surge, though unprecedented, had already been in place for the entire decade.

Energy and other input prices

33. Reports on food prices frequently claim that oil price led the grain price spikes of the 1970s and in 2007/08. Other analysts appear to believe that energy always leads commodity price surges. Some evidence is presented in Figure 16.

34. Energy prices rose in the 1970s, but equally clearly they trailed grain price surges. Energy prices jumped again after grain price plummeted, then fell and remained fairly constant as grain prices continued to fluctuate during the 1990s. Energy had no role in the 1996 grain price spike. The recent energy price surge was the first to precede a spike in grain prices, a fact not obvious from annual data. (The first commodity embargo of the 1970s was the U.S. soybean export ban, designed to control food price inflation.)

35. Some analysis suggests that energy price raised grain prices via cost increases.[4] While energy costs affect transport and processing costs of food and feed (tending to depress farm gate prices), a positive effect on grain prices at the farm gate could occur only if the cost increase made current grain production levels unprofitable, causing farmers to cut back acreage or chemical inputs, reducing output and driving prices up. Clearly this has not happened. Farm profits are at record levels, as are land prices. Further, as noted above, production has been at record levels in most recent years. Similar arguments that fertilizer prices have raised grain prices suffer from the same fundamental flaw: fertilizer use is high, keeping fertilizer prices high. If fertilizer input is not cut back, how can production be reduced, and thus price increased, via this route?

Biofuels

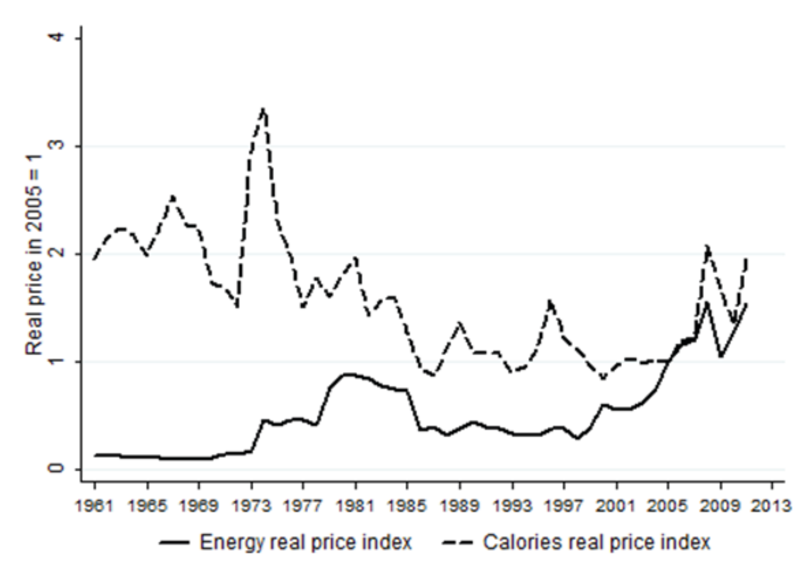
36. Beginning in 2006, introduction of increasing United States federal support for grain bioethanol as a gasoline additive and substitute, and legislation boosting biodiesel based on oilseeds in Europe, have jointly caused an unanticipated rapid increase in biofuel demand, larger and more permanent than any recent weather-related supply shock. This has clearly constituted a huge shock to the global market, and its enduring nature (in contrast to typical supply shocks such as droughts or floods) also has increased the demand for stocks.

37. By agreement with AMIS representatives, we exclude consideration of biofuels here, but not because its effects have been negligible.[5] It is because we want to establish the nature of market behavior before this hugely disruptive influence caused market prices to soar to successive new spikes. This type of demand shock is qualitatively and quantitatively new to global grain markets, and is too recent to be subject to the econometric estimation we conduct here as part of this study. Hence we restrict our estimation to a sample ending in 2007. Although biofuels policy and its anticipation no doubt affect storage behavior in the last few years of our sample, we chose the end date as a compromise between a desire to keep as large a sample size as possible, and the aim of avoiding the influence of a new and different influence on the market. The results of our study will, we hope, help lay the groundwork for later work addressing quantitatively the effects of grain and oilseed biofuels.

4 Baffes and Haniotis (2010) report an elasticity of agricultural prices to energy prices of 0.27, and reference other empirical results.

5 Indeed one of the authors has discussed the key role of biofuels in reducing stocks and making grain markets vulnerable to disruption by otherwise minor shocks (Wright 2011).

Figure 16. Energy and grain calories real price indices



Financial speculation

38. In the years since the boost in biofuels production, much has been written on the disruptive influence of speculation and index trading on the grain markets, among other commodity markets. Some studies (for example Gilbert 2010 and von Braun and Torero 2009) concluded that speculation was a major driver of commodity price volatility. These studies typically lacked a coherent micro-model of how speculation could in fact "drive" the market to high prices without increasing stocks, which were reportedly low for key grains during successive price spikes. Very useful reappraisals of this literature are now available (Aulerich et al. 2012), and we address the issue of claimed "speculative bubbles" in commodity markets elsewhere (Bobenrieth et al. 2012). We shall not pursue it further here, but instead turn to consider the role of stocks in the dynamic behavior of grains markets.

Review of the Storage Model

39. The storage model for agricultural commodity prices is based on the simple logic of "buy low, sell high" by self-consistent, forward looking market participants. Storage decisions implied by this logic will smooth price transitions from one time period to the next when stocks are available, and will generate skewed distributions for prices and stocks-to-use ratios, due to the asymmetric effect of stocks on prices, as a function of the state of the market.

40. For readers interested in technical details, Appendix C presents the structure for the standard storage model. The details presented in Appendix C, however important in the mathematical derivations, are not necessary to understand the basic logic of the model.

41. It is clear that inventory decisions made by private storers and governments do not necessarily follow rational economic purposes. However, agricultural commodity prices at the world level are primarily determined by supply and demand, and inventories are a relevant component of global demand for major agricultural commodities. Here we present a simple closed model of annual supply and demand in the absence of government interventions. It is possible to extend this model to include market interventions and trade, and to incorporate realistic features such as inter-year seasonality, export restrictions, price controls, etc. (See for example Williams and Wright 1991, Miranda and Glauber 1993, Chambers and Bailey 1996, Tomek and Peterson 2005 and Carter et al. 2011.) However, in line with the findings of a close relationship between stocks and prices reviewed by Carter et al. (2011) and many others, the purpose of this paper is to explore the empirical implications of a simple competitive storage model at the world level, focusing on its usefulness in terms of predicting price spikes and price runs. Rather than incorporating more complexity in the model, we focus on the empirical usefulness of the standard model to identify stocks-to-use ratio regions that imply high risk of a price surge.

42. In the model, even independent harvest realizations and stationary demand can be consistent with serially correlated prices; the link in prices is implied by the presence of stocks. Storage decisions buffer random variations in production and demand, smoothing consumption and prices to the extent that discretionary stocks are available. The model was first presented by Gustafson (1958a, 1958b). The model has been extended to address a variety of questions and stylized facts. Methodological contributions have been made by Schechtman and Escudero (1977), Wright and Williams (1982), Scheinkman and Schechtman (1983), Deaton and Laroque (1992, 1995, 1996), Deaton (1991), Bobenrieth, Bobenrieth and Wright (2002, 2004, 2008, 2012) and Carroll (2001, 2009).

43. Figure 17 illustrates a linear consumption demand, as traditionally presented with price and consumption in the vertical and horizontal axes respectively.[6]

44. In a market where all participants share the same information, a self-consistent expectations equilibrium can be described as a function that yields observed prices as prices that are consistent with the beliefs of agents and with their storage decisions. In other words, a self-consistent expectations equilibrium is characterized by forward-looking market participants who make self-consistent economic decisions. This equilibrium concept does not imply that agents know future realizations of market shocks. It only requires that their decisions are made using the information available in a coherent way.

45. In line with the principle that inventories are held in expectation of future shortages in supply, storers compare current price with the price expectation for future periods; their inventory decisions imply a storage demand function, constructed endogenously from the storers´ expectations. Total market demand for the commodity at any given time is then given by the sum of the consumption demand and the storage demand, horizontally at any given price.

46. The total incentive for storage is given by net expected profits. Net expected profits of storing from one year to the next are given by the discounted expected market value of current stocks (in the next time period), minus current market value of stocks, minus total storage costs.

47. As discussed in more detail in Appendix C, if storers decide on a positive level of stocks, then the hypothesis of an "arbitrage-free" competitive equilibrium requires that total net expected profits are equal to zero. Indeed, if expected price for next time period (net of financial and storage costs) were below the current price, and if discretionary stocks were held, then storers would want to maintain negative levels of discretionary stocks. This is unfeasible at the market level.

48. Therefore, in equilibrium, discounted expected price for next period is equal to current price plus current marginal storage cost if discretionary stocks are positive, and discounted expected price for next period is less than current price plus current marginal storage cost if there are no remaining discretionary stocks (a "stockout").

49. This constraint that discretionary stocks cannot be negative induces a sharp discontinuity in the market behavior of inventories: stocks can be a smooth function of prices or of total available supply when stocks are higher than their minimum value, but when stocks hit their lower bound (of essential stocks), this smooth relation to prices is broken. In such circumstances, total available supply goes only to consumption, and, if relevant, shrinkage or depreciation.[7]

50. Figures 18 and 19 show one possible example of storage demand and total market demand[8].

51. The figures show that the implied behavior of prices generated by this model matches what is typically observed for commodity prices: when total available supply is low (to the left of the kink in total demand in Figure 19), the market is unprotected against negative supply shocks. Thus, the logic of the model implies high exposure to price spikes. Alternatively, when available supply is sufficiently high (greater than the kink in Figure 19), storage stabilizes prices. The variance of price in the market is lower when storage is positive than when it is at its lower bound; storage stabilizes price and consumption. Storage reduces the frequency of high prices, and it reduces the frequency of low prices even more effectively. It moves the tails of the distribution toward the center, for both prices and consumption.

52. Because storage is possible, the long-run probability distributions of prices are skewed versions of the inherent distributions of the net harvest shocks. Notably, the sharp nonlinearity of the price function is indicative of the strong skewness observed in empirical commodity price distributions.

6 The functional form and parameter values used in this illustration are those estimated in this study for wheat, using the Maximum Likelihood econometric procedure (see Appendix D for details of the econometric methodology).

7 For simplicity, we have in this section normalized minimum stocks levels at zero. This is an unnecessary, albeit convenient, normalization. What is important is not the arbitrary normalization level, but the sharp curvature change induced by the regime change. Figure 19 for total market demand can be re-scaled conveniently for expositional needs, without altering the essential logic of the exercise. Market level stockpiles cannot be run down below minimum working stocks. The level of such minimum working stocks defines our re-scaled version of the market demand.

8 The example is based on the parameters estimated for the world wheat market.

Figure 17. Inverse consumption demand function (parameters estimated for wheat)

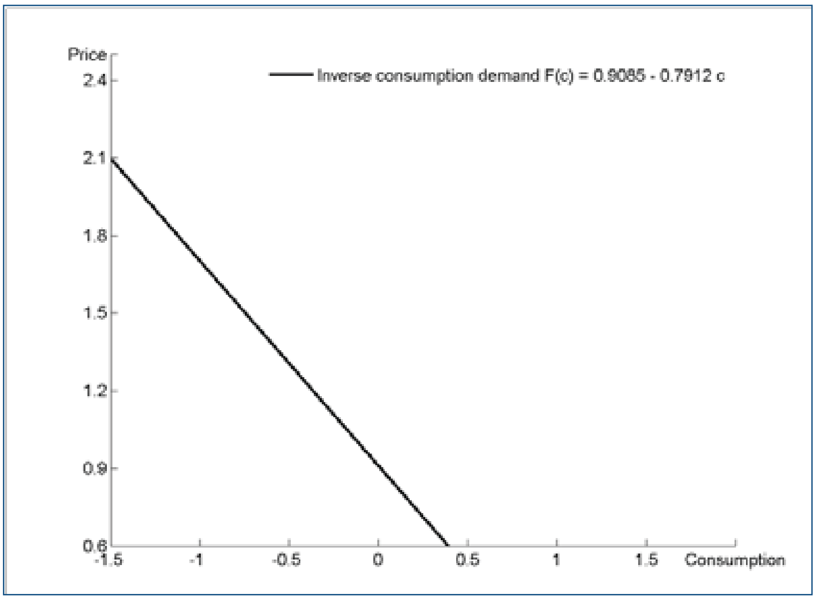


Figure 18. Inverse storage demand function (parameters estimated for wheat)

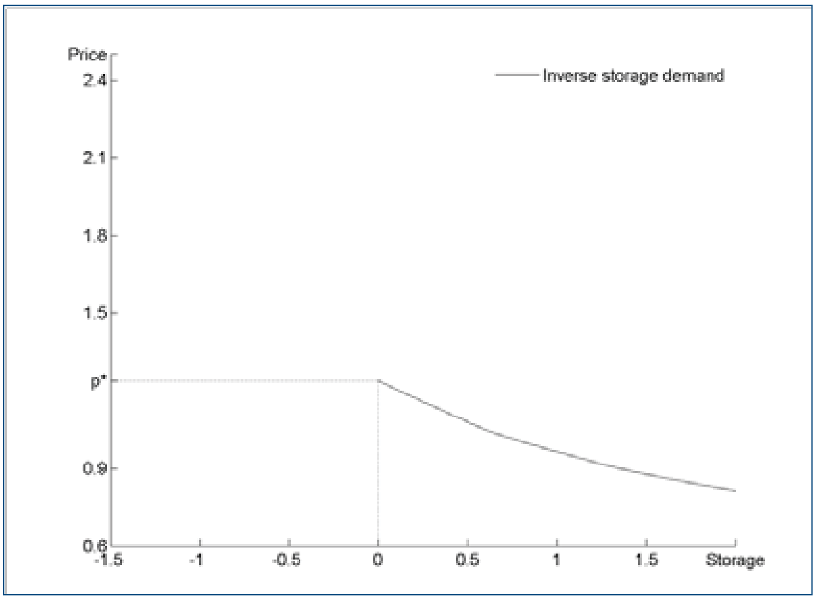
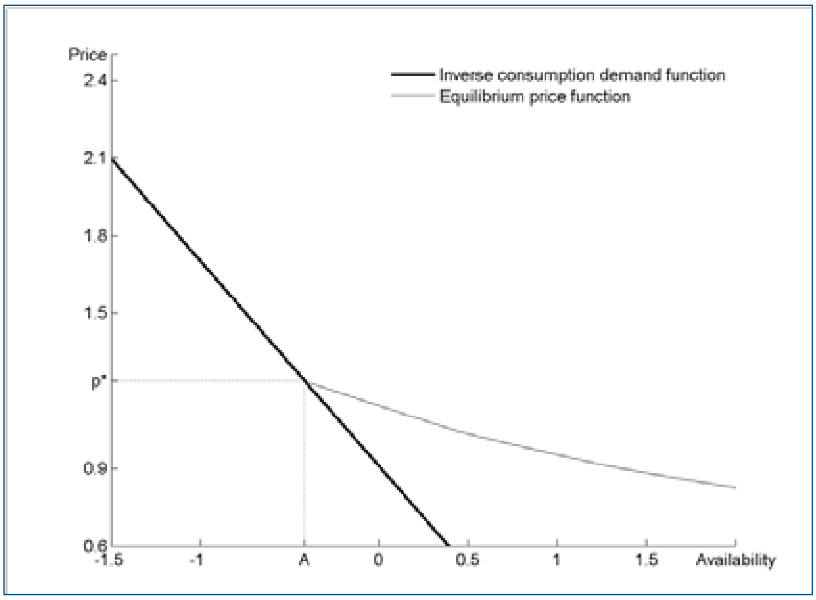


Figure 19. Inverse total market demand function (parameters estimated for wheat)



53. The model presented here assumes a very simple specification for the net supply shock: in particular, no supply response. It is clear that, when supply is not totally inelastic, then storage decisions are not the only way to alter the probability distribution of available supply for future periods. Variable production decisions also affect the likelihood of future realizations of total supply. Solving the model with explicit recognition of supply response changes the details of storage behavior and prices, but it does not change the qualitative behavior of prices implied by our simple model. In particular, it does not change the qualitative behavior in terms of the sharp discontinuity in the slope of the market demand function.

54. To get a sense of the relevance of curvature changes in the equilibrium storage or in the price function, in terms of future volatility of prices, Figure 20 plots forward price volatility (measured as the variance of price) in the subsequent period conditional on current price, for the case of wheat. Complementarily, Figure 21 plots forward price volatility in terms of the current ratio of stocks to consumption, the stocks-to-use ratio.

55. The highly nonlinear behavior of conditional price volatility is striking, as is the sharp slope implied for the function in the neighborhood of the cutoff price. Price volatility increases sharply as the SUR approaches zero. Again, this sharp change in volatility is a reflection of the nonlinear behavior of prices as a function of current conditions. A direct implication of such behavior is that there is a range of the SUR bounded by zero within which the implied volatility of next period's prices changes rapidly.[9]

Econometric Estimation

56. This section discusses our empirical estimation approach. Here we present a general overview of the methods we use. Readers interested in the technical details of the estimation procedures can read Appendix D.

57. Empirical estimation of the standard commodity storage model is complicated by the widely recognized lack of reliable information on crop supply and demand and export (for a discussion on data availability, see Greenfield and Abbasian, 2011). It is also complicated by the fact that data on commodity prices appears to follow trends (deterministic or stochastic), whereas the standard storage model is defined in terms of stationary disturbances, filtered by a structural model of production, consumption and storage.

58. For our estimation, we follow the approach of Deaton and Laroque (1992, 1995, 1996) in using only price data. In light of the standard tradeoff between robustness and accuracy of econometric estimations, we use both limited and full information techniques. Cafiero et al. (2012) show that, conditional on information on the harvest shocks and the consumption demand structure, their Full Information Maximum Likelihood (ML) approach performs better than the other two econometric methods that are by now standard in empirical estimations of dynamic economic models with micro foundations for commodity prices: Generalized Method of Moments (GMM) and Pseudo Maximum Likelihood (PML). In this paper, we implement ML and rely on the results for our analysis of the role or SURs, but we also implement GMM as a method that is less accurate but relies on fewer a priori assumptions. For simplicity, we set direct storage cost at zero.

59. Informed by prior work on the implicit cost of capital in commodity markets, we implement our estimators with a discount rate of 2%. We use a linear inverse demand function relating price to consumption,

$$F(c)=a-b\cdot c$$

where c and F(c) represent normalized consumption and consumption demand price, respectively.

60. The estimates using GMM, a robust method that does not depend upon the informational structure of the model (including the functional form for the consumption demand and the probability distribution of net harvests), are reported in Table 2. The asymptotic standard errors are in parentheses. Comparison across the three grains indicates that the independently estimated (normalized and deflated) mean values of the threshold prices are very similar for maize and rice, and just a little lower for wheat. For aggregate calories, GMM yields a point estimate for the threshold price that implies less stockouts in calories than in each grain separately.

9 We get Figures 20 and 21 in the following way: we first solve the storage model with the parameter values of the world wheat market, and solve for the total market demand function. For each of a set of values of available supply we calculate the corresponding price, SUR, and the variance of the price for next period. We finally plot the generated values.

Figure 20. Forward price volatility in terms of current price (parameters estimated for wheat)

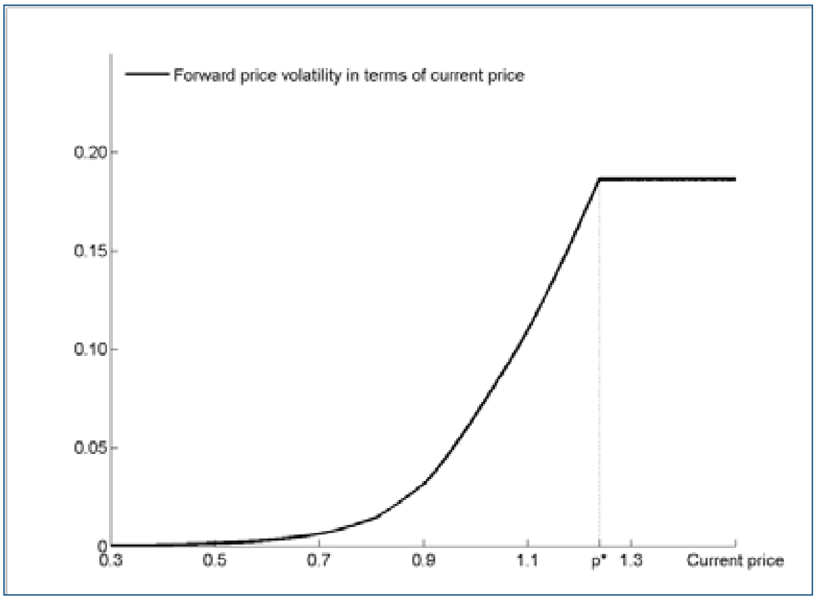
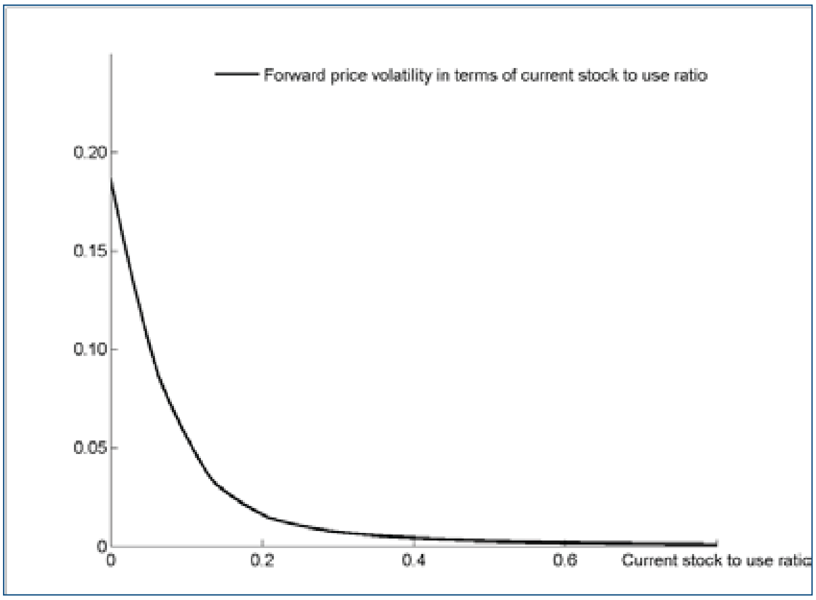


Figure 21. Forward price volatility in terms of current stocks to use ratio (parameters estimated for wheat)



61. Finite sample Monte Carlo experiments presented in Cafiero et al. (2012) show that GMM estimates are much less precise than ML estimates, an implication of the additional structure imposed by ML.

62. The ML parameter estimates shown in Table 3 for wheat, maize and rice imply point estimates of the stockout price higher than the GMM estimates. The ML estimates for maize and rice are strikingly similar, as are the implied values of their threshold prices. The slope coefficient on consumption, *b*, is somewhat lower for wheat, so that the graph of the wheat demand curve, as it is usually presented with price on the vertical axis, is less steep. In addition, the stockout price is lower for wheat. The results imply 5 stockouts in the sample for wheat, and 6 for maize and rice in the 47-year sample. For the aggregate of these grains, the results imply only two stockouts for the aggregate stocks. It makes sense that stockouts in aggregate grains should be less frequent than for each grain individually.

63. As discussed in the model section, it is not so much the precise location of the threshold price that matters in terms of forecasted fragility of the market, but the location of a range of prices or SURs with conditional variance that is highly responsive to changes in available supply. The econometric application is useful to support and indentify two separate regimes, characterized by markedly different price volatility levels: one regime is characterized by “stockouts,” the other regime has positive levels of discretionary stocks.

Table 2. GMM Estimates

	Threshold Price p*	over-identifying test statistic	p-value	Number of stockouts
Wheat	1.0581	1.8376	0.3932	17
	(0.0457)			
Maize	1.1939	3.7951	0.7155	10
	(0.1141)			
Rice	1.2201	6.7358	0.9192	12
	(0.1372)			
Calories	1.1815	6.5427	0.9120	8
	(0.1263)			

Table 3. ML Estimates

	a	b	Log-Likelihood	Threshold Price p*	Number of Stockouts
Wheat	0.9085	0.7912	14.1718	1.2360	5
	(0.0398)	(0.0263)			
Maize	0.8917	0.9729	3.1982	1.2977	6
	(0.0312)	(0.0278)			
Rice	0.9132	0.9747	0.3474	1.3053	6
	(0.0230)	(0.0395)			
Calories	1.0072	0.9748	14.7095	1.4005	2
	(0.0339)	(0.0187)			

64. Under the assumption that the markets for the three grains are independent, we can calculate series of implied SURs for wheat, maize, rice and aggregate calories, using their respective prices as data. The idea is that, for each price, the implied normalized stocks and consumption can be calculated from the storage demand at that price, then adjusted to make the implied stocks-to-use ratios comparable to observed trending SURs.

65. More specifically, using the Maximum Likelihood estimation results above to specify the storage demand and the market demand for each grain and for aggregate calories from all three grains, we derive the SUR implied by each observed price, normalized for magnitudes of the mean and variance, and recognizing the trend. Note that time trends in volatility for yields will imply time trends in the SURs implied by our estimations.

66. We construct an implied SUR for each sample year for each of the major grains, net of essential working or "pipeline" stocks. We add an adjustment for these essential stocks, as a fixed fraction of consumption at the stockout price p^*, where this fraction is chosen to match observed minima of the stocks to use data.[10]

67. The upper panel of Figure 22 shows the de-trended observed global prices of wheat from 1961-2007. The implied SURs for wheat are shown in the lower panel of Figure 22. The observed SURs estimated for the world, including essential working stocks, are also shown in the figure. The actual and implied SURs are strongly related, indicating that the model estimated from prices captures a substantial amount of information about consumption and stocks. However the two series also exhibit important differences. In the early 1960s, the reconstructed SUR is substantially below the observed series, and this is also true from 1967 to 1969, and again from1983 to 1985.

68. Figure 23 shows the comparison for maize. Overall, the reconstruction generally tracks the observed SUR better for maize than for wheat; in this case the widest and most persistent gap between the series is between 1980 and 1985, and there is also a notable divergence after 2005, very likely reflecting the early effects of changes in biofuels policies enacted that year.

69. As figure 24 shows, the reconstruction of the SUR for rice does not track the observed SUR nearly as well as do the reconstrctions of SURs for wheat or maize, although movements of the two series are clearly strongly related overall. The reconstruction produces a large overestimate of the SUR from 1961 through 1965, and a large and persistent underestimate after 1994. There are also substantial divergences in the early 1970s, from 1978 to 1981, and from 1985 to 1987. For rice, the observed SUR series appears to be on an increasing trend, in contrast to the reconstruction from the price data. However, variations of the two series for rice do appear to be positively related.

70. The reconstruction for aggregate grain calories offers strong evidence against the assumption that the three major grains have independent markets. The reconstruction tracks the observed aggregate SUR remarkably well, especially in the early 1960s when the reconstruction substantially exceeds the observed SUR for rice, and late in the series (after 1995) when rice SURs surge above their reconstructed values. The reconstruction also tracks the actual SUR much better for calories than it does for maize in 1963 and 1964, and for wheat in the first half of the 1960s. The aggregate measure accounts for substitution between grain calories, and the figure suggests that substitution in stocks can be very important. Large stocks of rice appear to encourage reduced carryover of the competing grains, and vice versa. This suggests that AMIS might consider encouraging further investigation of this possibility.

71. Given that there are serious problems with the accuracy and representativeness of both price data and stocks data, we next explore the possibility that use of both data sources rather than either alone might improve inferences about the danger of oncoming price spikes and supply shortfalls.

10 If there is a trend in the fraction of pipeline stocks we shall not recognize it here. We are interested in exploring this issue further, in consultation with industry experts.

Figure 22. De-trended price vs. SUR for Wheat

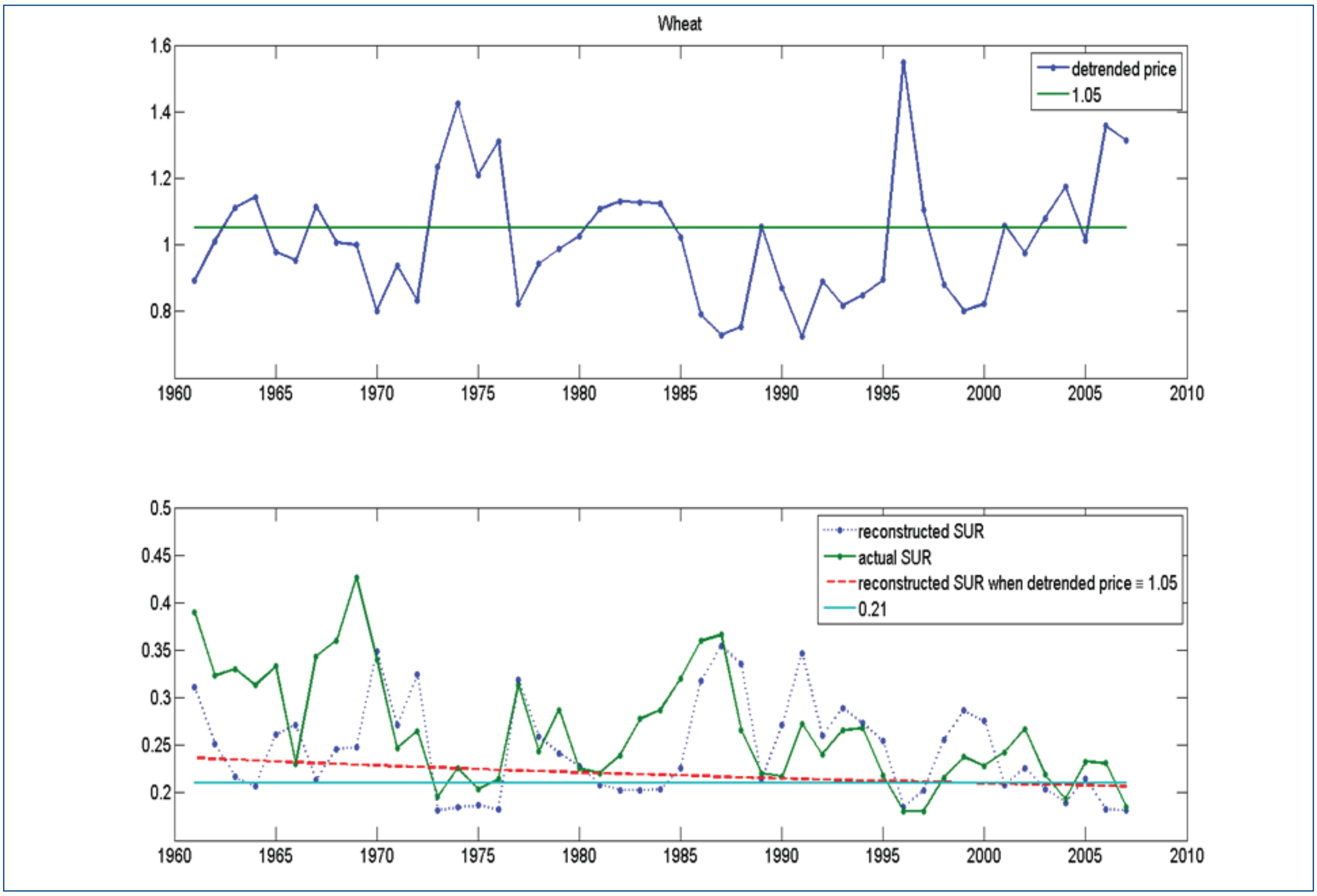


Figure 23. De-trended price vs. SUR for Maize

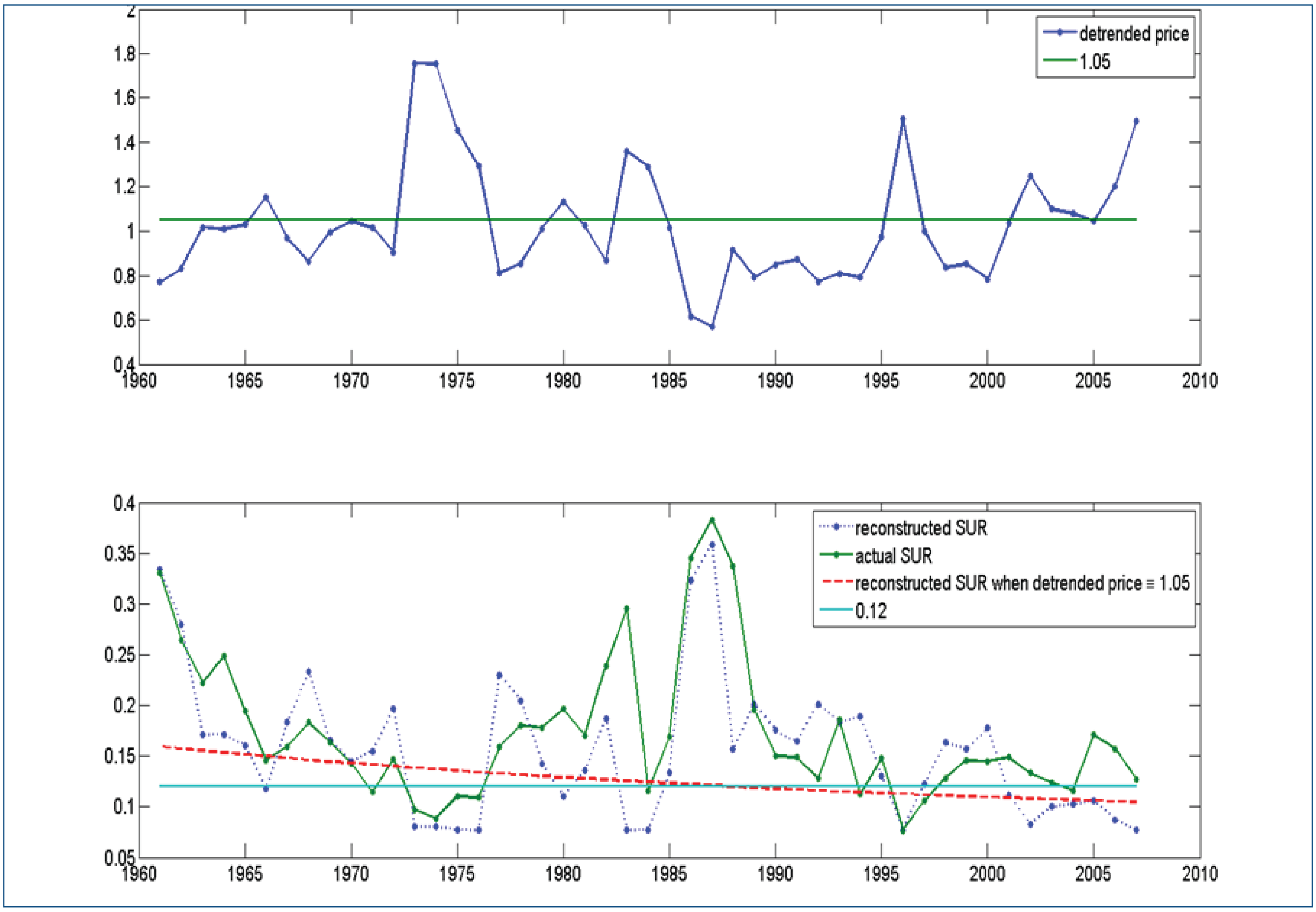


Figure 24. De-trended price vs. SUR for Rice

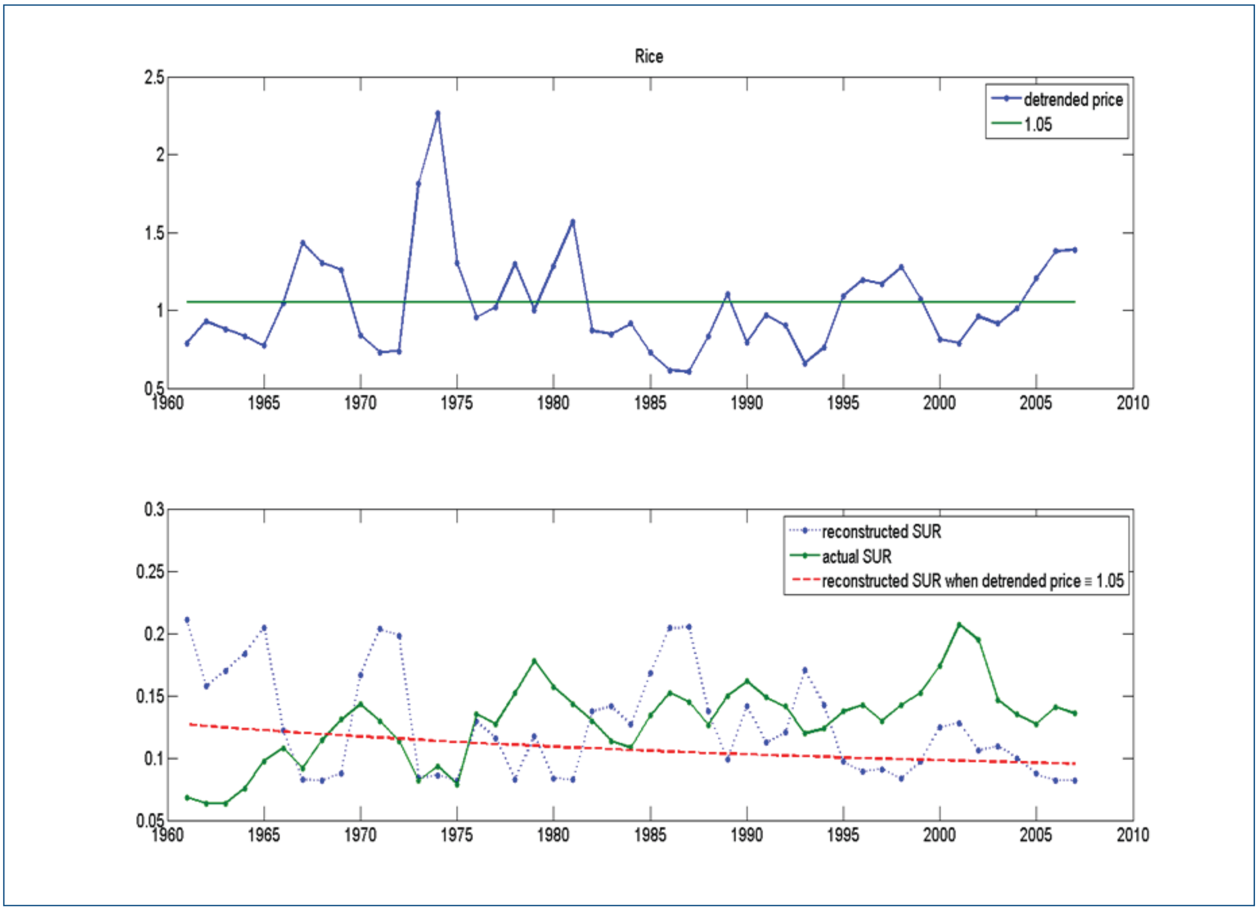
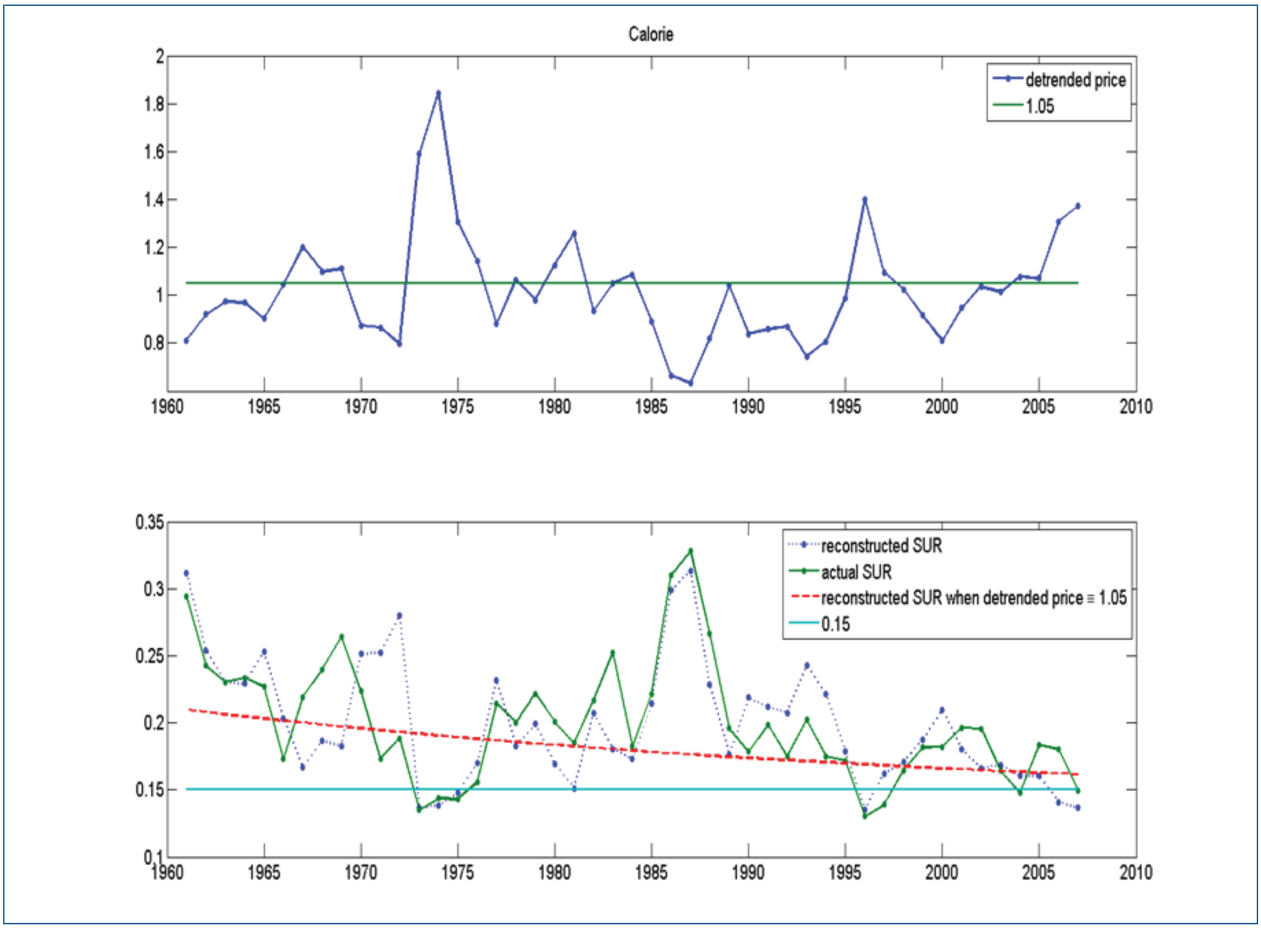


Figure 25. De-trended price vs. SUR for Calorie



72. The discussion of the commodity market model shows that stocks moderate the price-increasing effects of negative shocks to available supply. Price spikes occur after stocks have been depleted. These observations have two implications:

a. Price spikes tend to come after price has already increased to a threshold price region, consistent with low aggregate supply.

b. Price spikes generally come only after stocks have been depleted to a low "critical" region.

73. If each global grain market were independent, and shocks were serially independent, and each market had perfect information, then, as indicators of impending shortages, price and SUR would be two sides of the same coin – either measure would incorporate the same information, and send the same message.

74. However, the theoretical equivalence of prices and stocks as predictors is based on a model in which all information about the market is costlessly aggregated and available to all. Were this currently the case, AMIS should not be concerned with improvement of stocks information and this paper would be pointless.

75. However, in the market for grains in particular, it is very clear that information is incomplete, and that the information about the current situation at any time is difficult and costly to obtain and organize. In the United States, the Department of Agriculture releases WASDE reports of stocks and harvest prospects during the crop year, and these reports, which aim at nothing more than aggregating information in principle observable literally "on the ground," very frequently cause prices on commodity markets to jump upon their release. Hence, before release, stocks estimates must contain information not anticipated and therefore not reflected in current prices or in other accessible data.

76. Further, as emphasized above, prices recorded in the global grain market do not accurately represent the marginal value to global consumers. Prices faced by consumers vary by quality and location, and in some countries they might reflect taxes or trade bans that distort prices. Similarly, stocks data are not accurately reported. Stocks are difficult to measure accurately. Changes in unreported stock holding of subsistence farmers, or of consumers (see Timmer 2010), can be important, but are not measured in available data. Public stocks are often managed in a way that reflects government objectives rather than market reality, and in many cases the size of public stocks is kept secret for strategic purposes. Large private corporations might also see strategic value in keeping the size of their own stocks confidential. This discussion implies that correlations between reported SURs and prices of each grain will be far from perfect. Table 4 shows that this is true. The correlations between SUR for each market and each of the grain prices is negative, but none is above 0.6 in absolute value. Prices and SURs obviously contain some information and/or noise not common to both. The usefulness of the aggregate calorie measure is confirmed by the fact that each grain price is more highly correlated with the SUR for calories than with its own SUR.

Table 4. Correlation coefficient matrix between de-trended real price, excluding-China stock to use ratio, 1961-2007

	Wheat de-trended real price	**Maize de-trended real price**	**Rice de-trended real price**	**Calories de-trended real price**
Wheat excluding-China stock to use ratio	-0.4018	-0.4413	-0.3438	-0.4344
Maize excluding-China stock to use ratio	-0.3971	-0.5034	-0.4356	-0.5156
Rice excluding-China stock to use ratio	-0.2286	-0.2048	-0.1731	-0.2136
Calories excluding-China stock to use ratio	-0.4996	-0.5723	-0.4729	-0.5792

77. We now address the following key question: in a world with unreliable but widely available price data, can unreliable stocks data add valuable, though error-ridden, information about market vulnerability to near-term shortages of supply and spikes in price?

78. Suggestive evidence is provided by transition probabilities constructed from the data for prices and SURs calculated from market observations. Tables 5 and 6 show the transition matrices for prices and stocks of calories, respectively, using five bins in each. Clearly transitions from any bin tend to go to nearby bins. Large jumps in prices are uncommon in general, but there is an 11 percent chance of jumping from the lowest price bin to the highest. On the other hand, there is no jump from lowest to highest in SUR. This suggests that, when price jumps or spikes occur starting at a low price, the SUR is likely to be closer to a warning (low) level.[11] We investigate this possibility in the next section.

Table 5. Transition matrix for de-trended calorie price

		To				
		80-100	68-80	40-60	20-40	0-20
From	80-100	0.500	0.250	0.000	0.250	0.000
	60-80	0.300	0.300	0.200	0.200	0.000
	40-60	0.111	0.222	0.333	0.222	0.111
	20-40	0.000	0.300	0.100	0.200	0.400
	0-20	0.111	0.000	0.333	0.222	0.333

Note. 80 -100 stands for the bin from 80 percentile to 100 percentile.

Table 6. Transition matrix for calorie SUR

		To				
		20-40	40-60	60-80	80-100	
From	0-20	0.625	0.125	0.125	0.125	0.000
	20-40	0.200	0.300	0.300	0.200	0.000
	40-60	0.222	0.333	0.111	0.333	0.000
	60-80	0.000	0.300	0.200	0.100	0.400
	80-100	0.000	0.000	0.222	0.333	0.444

Note. 0 - 20 stands for the bin from the 0 percentile to the 20th percentile.

CAN SURS SIGNAL WARNINGS OF SHORTAGE NOT EVIDENT IN GRAIN PRICE?

i. Wheat

79. Let us initially assume that, even though reported prices and stocks are not highly correlated, severe supply shortages always coincide with "price spikes." Consider the case of wheat shown in Figure 4. It is immediately apparent that, after accounting for trend, two spikes dominate the figure, one in 1973-1976, the other in 1996. In both of these cases, the price the year preceding the spike was well below unity. Thus price gave no warning of the impending shortage. The next largest spike,[12] in 2006-07, occurs after a price close to unity; in this case price gave some indication that the market could well tighten. Other lesser "spikes" of about 10 percent or more above the mean occur around 1963-4, 1967, 1981-1984, and 2004.

80. Large spikes are obviously quite rare in the available data. Even adding lesser spikes does not give us a sample useful for statistical analysis. Hence we must resort to a less formal analysis of the evidence.

81. First and foremost, consider the two largest spikes. Was there evidence of market tightening in the SUR data not available from inspection of price in the previous year?

82. To help answer this question, we would like to focus on a level of SUR that might be chosen as "critical" in the sense that it indicates a threshold of higher volatility.

83. Identification of critical levels or regions of key indicators of vulnerability to price spikes is ultimately for AMIS to decide. Here, for purposes of advancing the discussion of this choice, we propose to focus on an SUR around which the variance of price or the probability of stockout becomes increasingly sensitive to a further fall in SUR.

11 The corresponding matrix generated by the model assuming normal harvest disturbances shows much lower probability of a transition from low to high price. However, the model assumes no errors of price observation.

12 Our arbitrary choice of deflator, MUV, is important in defining the relative magnitudes of spikes. The United States CPI could well lead to different inferences. This issue, and the influence of exchange rates, merits further research.

Figure 26. Forward price volatility for wheat and increase in forward price volatility for increase in current price

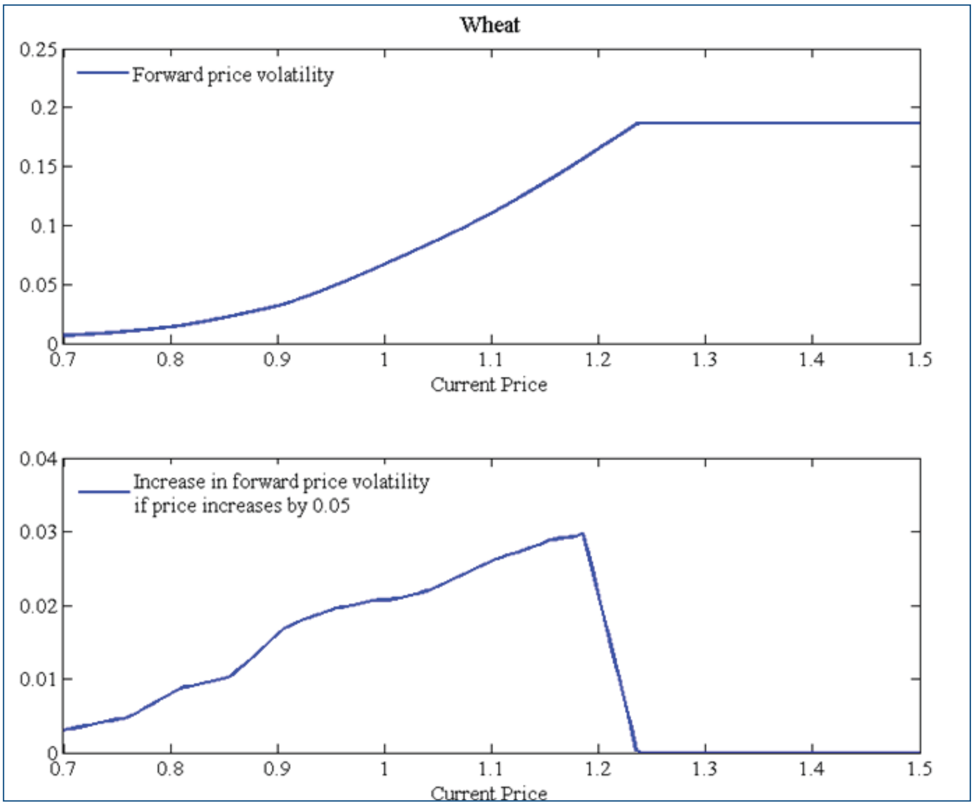
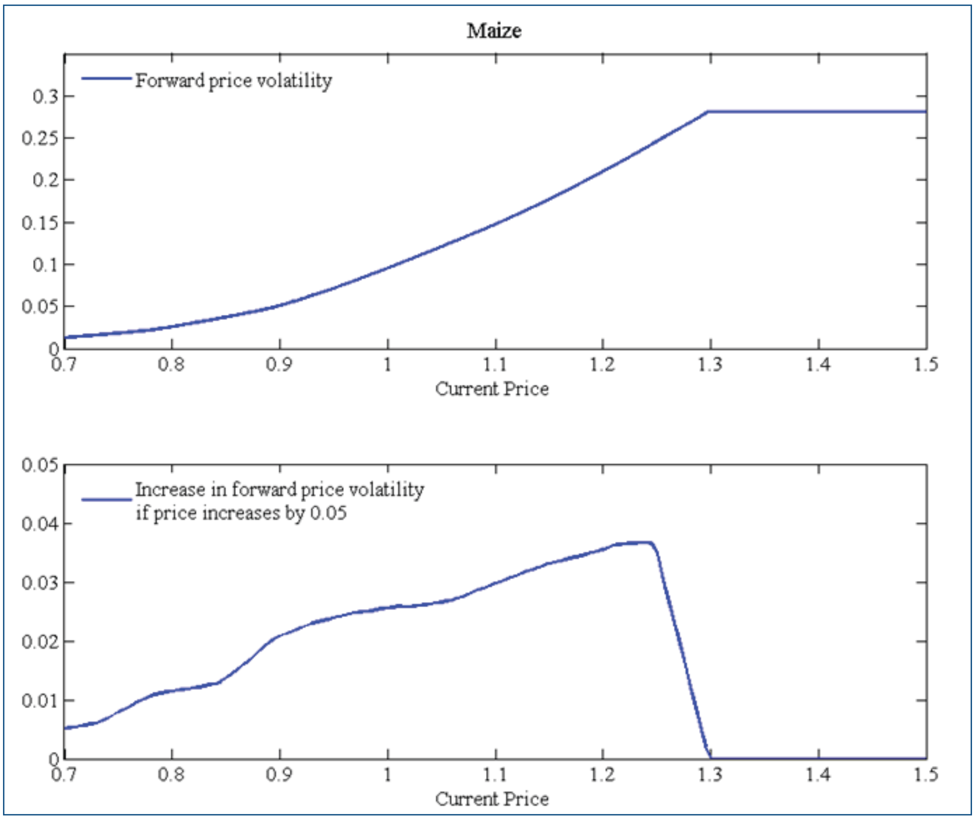


Figure 27. Forward price volatility for maize and increase in forward price volatility for increase in current price



84. To identify such a "threshold" SUR level, we look to our models of the four markets with parameters given by the point ML (Maximum Likelihood) estimates. From each, we derive a relation between price level and the variance of next year's price, conditioned on the price level. Figure 26, panel (a), shows the relation for wheat. The variance of the next year's wheat price is low when current price is low, and rises at an increasing rate as price rises. After entering the stockout region of prices, the variance remains constant and unrelated to further increase of current price.

85. Panel (b) shows the increase in variance from a 0.05 increase in price, as a function of current price. If price passes 1, the rate of increase in variance, measured as described, slows down. But in the neighborhood of 1.05, there is an inflexion point: the rate of increase in variance starts to increase again – it becomes more responsive to a given tightening of the market as measured by a price increase. Figures 27 through 29 show similar measures for maize, rice and aggregate calories. Figures 27 and 28 for maize and rice, respectively, also show inflexion points at around 1.05 in the normalized price distribution generated by the underlying stationary model.

86. From inspection of the wheat price series it is clear that at such a price (given by the horizontal line at 1.05) vigilance about price spikes is warranted. For each grain, we calculate the SUR implied by the critical price of 1.05. For wheat, the values of this critical level are shown in the bottom panel of Figure 22. They follow a negative trend. This reflects the decrease over time in production variance, consistent with our specification of structure of the underlying stationary model. Other specifications choices might well imply different threshold levels. Our specification choice is not

obviously inconsistent with the price history through 2007. This decrease makes a lower critical level appropriate in later years. Choice of specification and the sensitivity of critical indicators to this decision are obvious issues for further investigation.

87. With respect to the first major spike in 1973, in the prior year the SUR was above the constructed "critical" line and in this strict sense not sending a warning. However, comparison of the SUR with its reconstruction in 1972 (a point on the dotted line) shows that the SUR was relatively closer to the critical level than was the price. The wheat SUR was not unusual, but it was less optimistic than the wheat price in 1972.

88. In 1995, before the second large spike, the wheat SUR was at about the critical level, while the price was about 15 percent below its critical line. In this sense, the SUR was indicating a warning, whereas price revealed no serious cause for concern.

89. Of the other smaller spikes, the SUR adds little to the evidence from the price level except in 1966, when it indicates an impending spike in 1967 not signaled by the previous price.

ii. Maize

90. Four major spikes are evident in the maize price in Figure 23, in 1973-1976, 1983-1984, 1996 and at the end of the series in 2007. Before the large 1973 spike, the SUR was around its critical level, whereas price was below its de-trended mean; stocks offered a warning signal not evident in price, before a period of high prices and scarcity.

91. On the other hand, stocks were high before the 1983-84 spike – neither prices nor stocks warned of the price jump.[13] In 1995 neither price nor SUR was at the critical level before the 1996 price jump. In 2004 SUR and price were both only close to their critical levels. However the SUR was indicating increased tightness over the preceding few years, whereas price was weakly suggesting the opposite. For maize, the SUR information added little to information from prices in warning of spikes except in 1972.

iii. Rice

92. The dominant spike in rice price in Figure 24 occurred in 1973-75. There were lesser spikes in 1967-69, 1980-81, and around 2006-07.

Figure 28. Forward price volatility for Rice and increase in forward price volatility for increase in current price

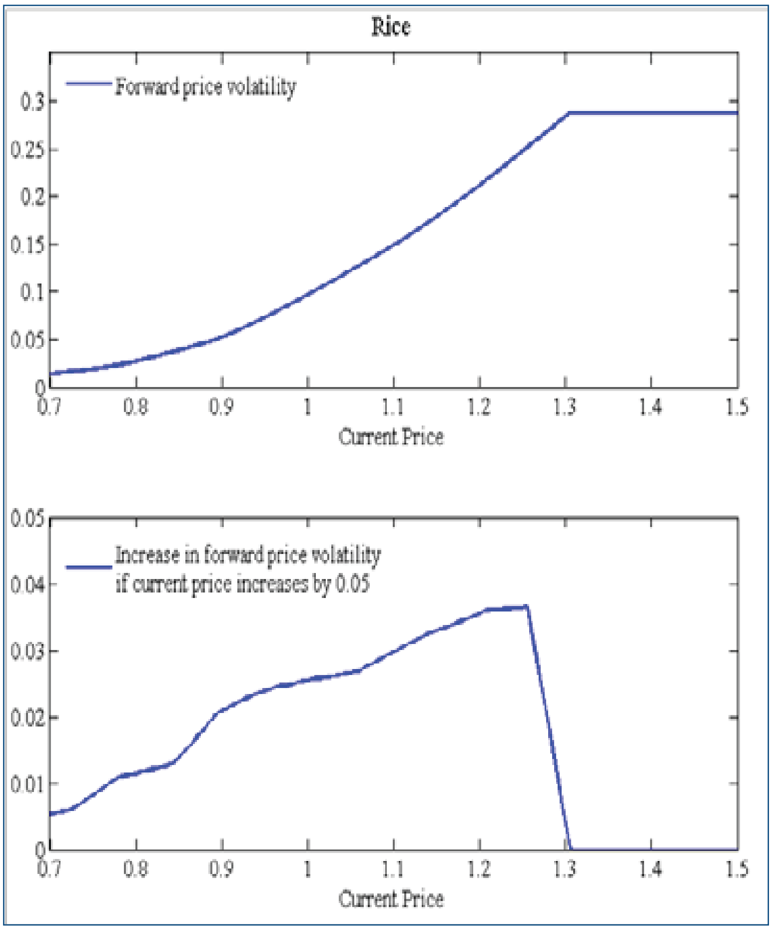
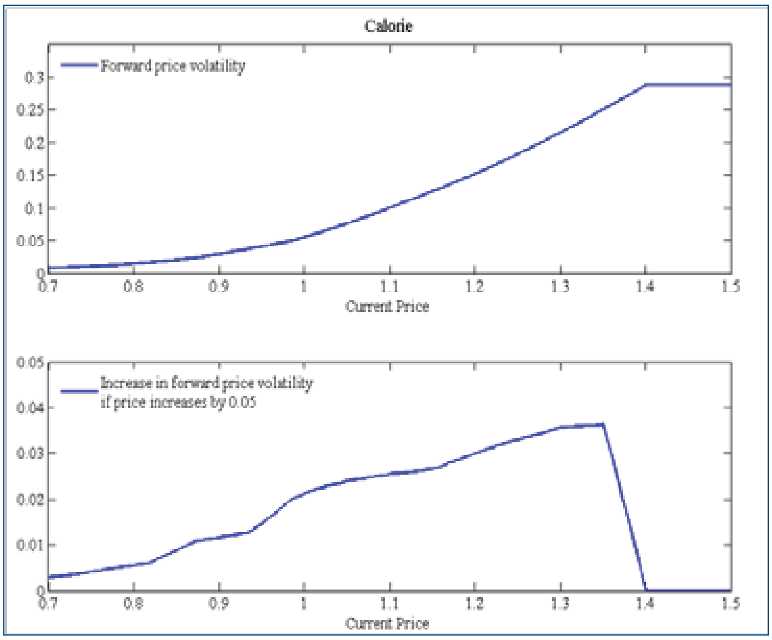


Figure 29. Forward price volatility for calories and increase in forward price volatility for increase in current price



13 Huge United States acreage restrictions meant that stocks data overestimated supply anticipated for 1983.

93. In 1972, before the largest spike, the SUR was at its critical level, adding a warning signal not at all evident in the rice price that year, which was quite low. For the lesser spikes, without further insights into the uptrend in the SUR it is difficult to detect variations that might have been useful as warnings of market tightening.

94. In sum, while recognizing the inevitable hazard of over-interpreting sparse data, we conclude that for each of the major grains the SUR indicates a warning signal of one of the two highest price spikes since 1960, in 1995 in the case of wheat, and in 1972 for maize and rice. Hence there seems to be good reason to consider the SUR in addition to price in interpreting the risk of market tightness and scarcity in grain markets.

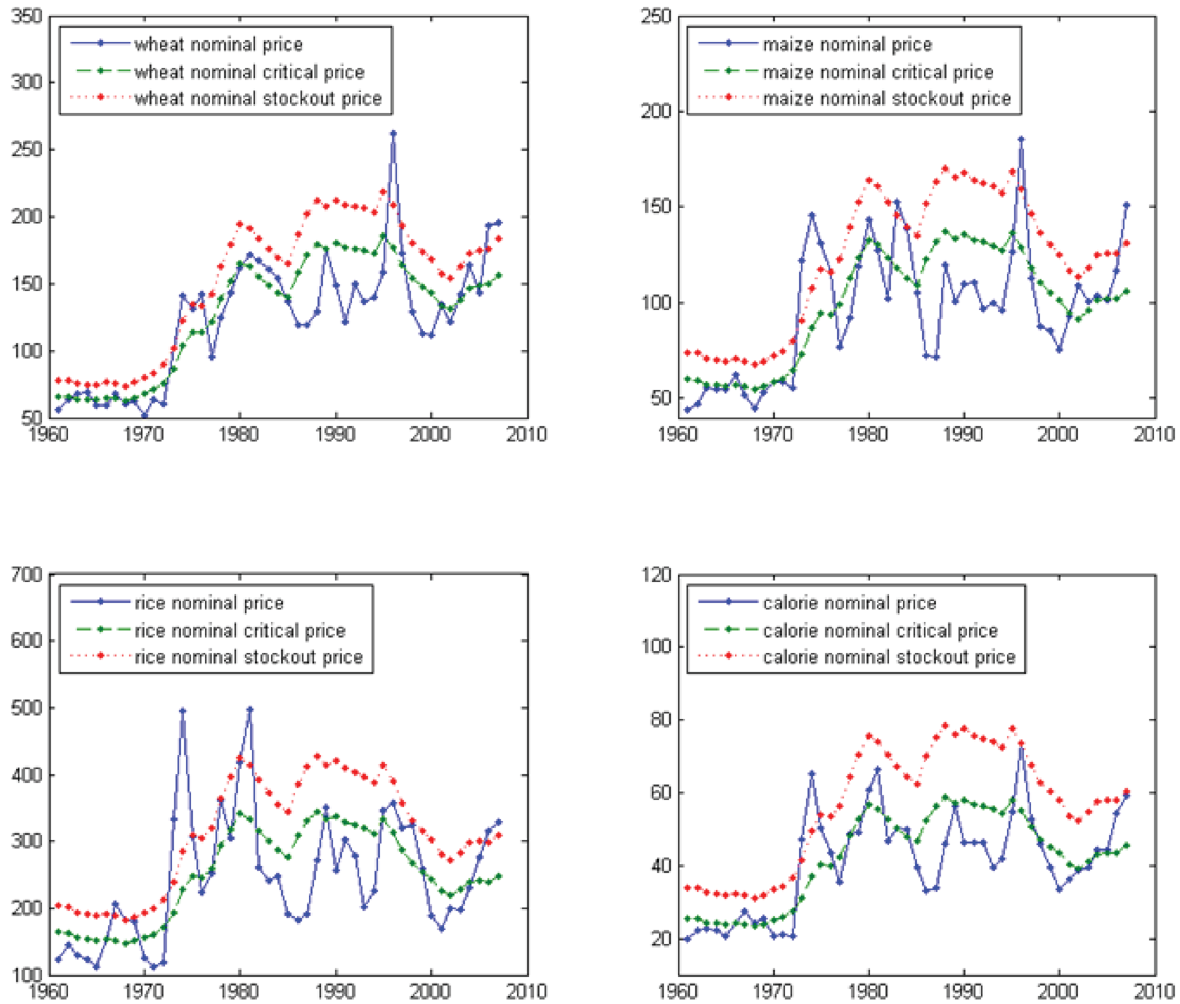
iv. The aggregate market for calories from major grains

95. Figure 25 shows the SUR for calories along with its reconstruction from aggregated calorie prices. Remember that this figure aggregates stocks and consumption excluding China for the three major grains.

96. As noted above, the first and quite remarkable implication of this figure is that the reconstructed SUR traces the observed values much better overall than does the similar figure for rice, and much better in the early years than observed for wheat alone. This suggests our assumption of high substitutability between calories from different grains is justified.

97. For calories, one dominant spike occurs in 1973-75, and other spikes occur in 1967, 1980-81, 1996 and 2006-07. The 1973 spike is preceded by an SUR below its critical level, at a time when price was quite low. Thus overall SUR signaled a warning not evident in calorie prices in 1972. Of the lesser spikes, the SUR gave warnings

Figure 30. Nominal critical and stockout prices



Note. This figure plots the nominal price, together with nominal critical price and stockout price. Stockout price corresponds to the estimate of the cutoff price for the de-trended model. Critical price corresponds to a de-trended normalized price of 1.05.

stronger than information evident in price in 1966, and again in 1995. The spike in 2007 likely reflects at least in part anticipation of higher demand due to new biofuels legislation in the United States and the European Union. Such large unanticipated demand shocks are not in the prior histories of these markets, nor are they reflected in our estimates.[14] The critical SUR for calories gives a warning not matched by information from current price one year before two of the other three spikes.

98. Interestingly, the SUR for calories appears to be superior as an indicator of spikes in prices of wheat, maize and rice than is the SUR for either grain individually. The aggregate measure takes account of interaction between supplies of different grains in determining overall supply-demand balance in each market.

99. Finally, for those interested in interpreting the prices corresponding to critical values of SURs, and the stockout prices in nominal dollars, Figure 30 shows these values for each grain and for aggregate calories. They are not monotonic, but reflect the varying net influence of the MUV and improvements in yield.

Conclusion

100. In this paper we have confirmed the strong relationship between prices and SURs as indicators of the state of grain markets, and of the relevance of the standard storage model for the relations between stocks and prices. Using the underlying stationary model, we are able to estimate the markets with a maximum likelihood procedure, and to derive SURs consistent with the price series that match the observed SURs well. We have also shown evidence of strong substitution between major grains as sources of calories in the relation between SURs for individual grains and for aggregate calories. But both prices and SURs are unreliable data, and the information in SURs is sufficiently distinct from that in prices to render SURs valuable additional indicators of vulnerability. In particular, our example of a series of critical values for SURs for aggregate grains, adjusted for a trend implied by the model, seems to be a good indicator of vulnerability to spikes when the associated price shows no cause for concern, based on the largest spikes observed in the past five decades. Selection of a set of critical values, or a band of critical values, is an obvious topic for further research

101. The results derived here raise an interesting possibility. Economists have traditionally assumed that stocks data are so unreliable that empirical estimation must rely on prices alone. In our results we see some hint that stocks, though no doubt unreliable, may be no worse and perhaps better indicators than prices of the state of grain markets. Ideally, of course, we should try to construct empirical methods that exploit the information in both in estimating grain market behavior.

102. Finally, it is useful to be aware of the limitations of prediction of spikes in stochastic markets. Furthermore, the better our predictions, the less likely are the spikes, because stocks will tend to adjust in a way that moderates the anticipated spike. In this sense, increased success in improving warning indicators is likely to reduce the evidence of their effectiveness.

14 As noted above, truncation of the sample interval at 2007 was a compromise between concern for sample size and desire to avoid as far as possible contamination from the effects of the new policy regime including the large, persistent and unprecedented demand shift.

Price Data: Price at the ending month of each marketing year from 1961 to 2007. According to the Foreign Agricultural Service (FAS) of the United States Department of Agriculture (USDA), the marketing year for wheat, maize and rice ends in May, August and July, respectively.

For details, please see http://www.fas.usda.gov/export-sales/myfi_rpt.htm.

Nominal Prices: Obtained from GEM Commodities of the World Bank. Wheat is priced as US no.1 Hard Red Winter Wheat. Maize is US no. 2 yellow and rice is Thai 5% broken. Price is that of the ending month of each marketing year.

Deflator: Annual Manufactures Unit Value Index (MUV) from GEM Commodities of the World Bank, which is a composite index of prices for manufactured exports from the fifteen major developed and emerging economies to low- and middle-income economies, valued in U.S. dollars. All the real price indices have their 2005 values as 100.

The link to the GEM Commodities of the World Bank is:

http://data.worldbank.org/data-catalog/commodity-price-data.

World Production for World Calorie Price Construction:

Wheat: "Wheat, World" from the Production Supply and Distribution Online (PSD Online) of the USDA;

Maize: "Corn, World" from the PSD Online of the USDA;

Rice: "Rice (milled), World" from the PSD Online of the USDA.

The link to PSD online is http://www.fas.usda.gov/psdonline/psdHome.aspx.

Calorie Content:

The calorie contents for wheat, maize, and rice are obtained from the National Nutrient Database of the USDA: http://ndb.nal.usda.gov/.

Wheat: the arithmetic average of energy contents in hard red spring, hard red winter, soft red winter, hard white, and soft white wheat (i.e., 333.8 kcal per 100g).

Maize: the arithmetic average of energy contents between white and yellow corn (i.e., 365.0kcal per 100g).

Rice: the arithmetic average of energy contents among white long grain regular raw un-enriched, white short grain raw, brown medium grain raw, brown long grain raw, white medium grain raw un-enriched, white short grain raw un-enriched rice (i.e., 362.2kcal per 100g).

Observed Stock-to-Use Ratio:

For wheat, maize (corn), and rice, this ratio is obtained by dividing the corresponding Ending Stocks by the corresponding Domestic Consumption, both obtained from the PSD online of the USDA: http://www.fas.usda.gov/psdonline/psdHome.aspx. These two quantity data are marketing year based. Specifically, the marketing year for wheat is from June to May, for maize is from September to August, and for rice is from August to July.

The calorie ending stocks and consumption are the sum of the ending stocks and consumption, respectively, of the wheat, maize (corn), and rice from the PSD online converted to calorie using the conversion above.

To obtain Stock to Use Ratio excluding China, we subtract China's Ending Stock (Domestic Consumption). from World Ending Stock (Domestic Consumption).

Assume that the annual real price p_t contains an exponential downward trend, and $0 < \lambda < 1$ is its annual decay rate. That is,

$$p_t = \lambda^t \varepsilon_t,$$

where ε_t is a stationary price.

Taking the natural logarithm of both sides of equation above, we have:

$$\ln p_t = E_\infty \ln \varepsilon_t + t \times \ln \lambda + (\ln \varepsilon_t - E_\infty \ln \varepsilon_t),$$

where E_∞ denotes the unconditional mean.

Let $\alpha \equiv E_\infty \ln \varepsilon_t$

and

$\zeta_t = \ln \varepsilon_t - E_\infty \ln \varepsilon_t$.

We have

$$\ln p_t = \alpha + t \times \ln \lambda + \zeta_t.$$

Using Ordinary Least Squares, we can obtain the residuals of the above regression, $\widehat{\zeta}_t$. We define the exponential of the residuals, i.e., $\exp(\widehat{\zeta}_t)$, as the de-trended price for our analysis.

Here we present a stylized version of the basic competitive storage model. We make several simplifying assumptions; however, the model and many results are valid under much more general settings.

Time is discrete. Available supply is the sum of stocks carried from the previous period plus net supply shock (net "harvest"). Total market demand is defined as the sum of consumption plus storage demand. Storers are risk neutral and form self-consistent expectations of prices in subsequent periods. Supply shocks (net of any demand disturbance), denoted by ω_t here, are i.i.d., with a support that has a lower bound. Storers are risk neutral and face a constant discount rate $r > 0$. The cost of storing $x_t \geq 0$ units of discretionary stocks, here normalized at zero, from time t to time $t+1$ is $c(x_t)$.[15]

Implicitly, equilibrium price conveys the information on storage. Inventories are determined by simple market forces: agents store until the expected gain from the last unit stored matches the cost of the storage activity. Note that this cost includes the opportunity cost of the commodity. If storers are risk averse, expected net gains include anticipated variations in their welfare. If storers are risk neutral, expected net gains are simply equal to expected net profits. Total net expected profits of storing x_t units from period t to period $t+1$ are given by

$$\frac{1}{1+r}\left[E_t p(\omega_{t+1} + x_t)\, x_t\right] - p_t x_t - c(x_t).$$

If storers decide on a positive level of stocks, then the hypothesis of an arbitrage-free equilibrium requires that total net expected profits are equal to zero. If net expected profits were positive, the market would provide free profit-making opportunities for speculators, which would not be a sustainable situation. If expected price for next time period (net of financial and storage costs) were below the current price, and if stocks were held, then storers would want to maintain negative levels of stocks. At the individual storers level, this could be done by borrowing units of the commodity. However, this is not feasible for the market as a whole; indeed, the market cannot borrow units from future harvests.

A key element of the model is consumption demand. The inverse consumption demand for the representative consumer, which represents demand price as a decreasing function

[15] We do not wish to claim that the storage cost structure is linear; in practice, however, possible discrepancies from a linear approximation to the average cost of storage are of second order of importance.

of consumption, is denoted by $F: \mathbb{R} \rightarrow \mathbb{R}$. This function is assumed to be continuous and strictly decreasing, with $\frac{1}{1+r} E_t F(\omega_{t+1}) - c'(x_t) > 0$, where E_t denotes the expectation taken with respect to the net supply shock at time $t+1$, that is, ω_{t+1}. Total available supply is denoted z_t. By definition, $z_t \equiv \omega_t + x_{t-1}$. That is, total availability of the commodity in period t is furnished by contemporaneous production in period t, plus previous storage x_{t-1}.

The inverse consumption demand F represents price at any positive amount of consumption ("willingness to pay"). Given the level of total available supply, price is defined to be an equilibrium price, i.e.

$$p_t = F(c_t) = F(z_t - x_t).$$

A Stationary Rational Expectations Equilibrium (SREE) in this model is a price function p which describes the current price p_t as a function of available supply z_t and which satisfies, for all z_t,

$$p_t = p(z_t) = \max\left[F(z_t), \frac{1}{1+r} E_t p(\omega_{t+1} + x_t) - c'(x_t)\right],$$

where $$x_t \equiv \begin{cases} z_t - F^{-1}(p(z_t)), \text{if } z_t < z^* \equiv \inf\{z: p(z) = 0\} \\ z^* - F^{-1}(0), \text{ if } z_t \geq z^* \end{cases}$$

The existence and uniqueness of the SREE as well as several of its properties are proved in Scheinkman and Schechtman (1983), Deaton and Laroque (1992, 1995, 1996), and Bobenrieth, Bobenrieth and Wright (2002, 2012). A set of properties of the SREE and proofs for the cases presented here are to be found in (for example) Cafiero et al. (2011).

In this Appendix we present a description of Generalized Method of Moments (GMM) and Pseudo Maximum Likelihood (PML), the two econometric methods we implement in this work.

Our econometric estimations are implemented using price data only. In using the de-trended prices to fit the storage model, we correct the discount factor in the arbitrage equation in recognition of the fact that storage arbitrage interacts with the trend. Because actual arbitrage is done with prices that might be trending, this correction factor is necessary to adjust the financial cost of storage, in order to calculate the net incentive of the storers. The de-trended series of prices that we use in the estimations are obtained by eliminating from the original series of real prices a log-linear trend component (see Appendix B).

D.1. GMM Estimator

For a sample of commodity prices $\{p_t\}_0^{T-1}$, our GMM estimator is based on the GMM estimator presented by Deaton and Laroque (1992) of the storage model. It fits the following autoregression:

$$u_t = p_t - \gamma \min\{p^*, p_{t-1}\},$$

where $\gamma \equiv (1 + r)$.

Let q_t (a 1 by h vector) be the instrumental variables for u_t, and define W_T to be a positive semi-definite matrix that approaches a constant positive definite matrix as $T \uparrow \infty$.

The GMM estimator for $\theta = (\gamma, p^*)$ of Deaton and Laroque (1992) is defined as:

$$\theta_{GMM} = \operatorname{argmin}_{\theta \in \Theta} \left(\frac{1}{T-1}\sum_{t=1}^{T-1} u_t \otimes q_t\right) W_T \left(\frac{1}{T-1}\sum_{t=1}^{T-1} u_t \otimes q_t\right)^{\prime},$$

where $\otimes$ denotes the Kronecker product. For example, the GMM estimator of Deaton and Laroque (1992) used $q_t^{DL} = [1, p_{t-1}, p_{t-2}, p_{t-3}]$ and $W_T^{DL} = \left((T-1)^{-1}\sum_{t=1}^{T-1} q_t^{\prime}\, q_t\right)^{-1}$. In our GMM implementation, we estimate only p^*.

For given q_t, the GMM estimator uses the weighting matrix

$$W_T^E(\theta_C) = \frac{1}{T-1}\sum_{t=1}^{T-1} u_t^2(\theta_C) \otimes q_t^{\prime}\, q_t,$$

where θ_C is some consistent estimate for θ, and is asymptotically efficient in that its asymptotic variance-covariance matrix is the smallest in matrix sense.

where θ_C is some consistent estimate for θ, and is asymptotically efficient in that its asymptotic variance-covariance matrix is the smallest in matrix sense.

The asymptotic variance-covariance matrix for the efficient GMM estimator can be estimated using:

$$\frac{1}{T-1}\left[\left(\frac{\sum_{t=1}^{T-1}\frac{\partial u_t(\theta_{GMM})}{\partial\theta}\otimes q_t}{T-1}\right)W_T^E(\theta_{GMM})^{-1}\left(\frac{\sum_{t=1}^{T-1}\frac{\partial u_t(\theta_{GMM})}{\partial\theta}\otimes q_t}{T-1}\right)'\right]^{-1}.$$

D.2. ML Estimator

Following Deaton and Laroque (1995, 1996) and Cafiero et al. (2011, 2012), we consider the harvest process ω_t to be i.i.d. normal with zero mean and standard deviation of 1. The inverse discount rate is γ, and the inverse consumption demand function is $F = a + bc$. The parameter vector to be estimated is $\theta = (a, b)$.

Then,

$$\Pr(p \le p_t | p_{t-1}) = \Pr\{\omega \ge p^{-1}(p_t) - [p^{-1}(p_{t-1}) - F^{-1}(p_{t-1})]\}.$$

Given the normality assumption, the implied density for conditional price is:

$$l(p_t|p_{t-1}) = \phi(\omega_t)\left|\frac{dp^{-1}(p_t)}{dp_t}\right|,$$

where $\omega_t = p^{-1}(p_t) - \left(p^{-1}(p_{t-1}) - f^{-1}(p_{t-1})\right)$.

The ML estimates for θ is obtained by maximizing:

$$\ln L_{ML} = \sum_{t=1}^{T}\left(\ln\phi(\omega_t) + \ln\left|\frac{dp^{-1}(p_t)}{dp_t}\right|\right),$$

where $\ln\phi(\omega_t) = -\frac{1}{2}(\ln 2\pi + \omega_t^2)$.

We solve the model for each candidate parameter vector and obtain the implied sequence of harvest shocks. We impose $b < 0$ by programming the likelihood maximization routine in terms of the set of transformed parameters $\eta \equiv \{\eta_1, \eta_2\}$, where $\eta_1 = a$, $\eta_2 = \ln(-b)$. Having identified a maximum, we form an estimate of the asymptotic variance-covariance matrix of the estimated parameters, W, as the outer product of score vectors, evaluated at the estimated values $\widehat{\eta}$. A consistent estimate of the variance-covariance matrix V of the original parameters is obtained using the delta method as $V = DWD'$, where D is a diagonal matrix of the derivatives of the transformation functions:

$$D = \begin{Bmatrix} 1 & 0 \\ 0 & -e^{\widehat{\eta}_2} \end{Bmatrix}$$

ML estimation involves solving the model numerically for each candidate vector of estimates. We approximate the equilibrium price function on 10,000 equally spaced nodes, and discretize the standard normal harvest distribution using a Gauss-Hermit transformation with 20 unevenly distributed nodes.

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