The U.S. Biofuel Mandate and World Food Prices: An Econometric Analysis of the Demand and Supply of Calories

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Abstract

We show how yield shocks (deviations from a time trend), which are likely attributable to random weather fluctuations, can facilitate estimation of both demand and supply elasticities of agricultural commodities. We identify demand using current-period shocks that give rise to exogenous shifts in supply. We identify supply using past yield shocks, which affect expected price through inventory accretion or depletion.

We use our estimated elasticities to evaluate the impact of ethanol subsidies and mandates on food commodity prices, quantities, and food consumers' surplus. The current U.S. ethanol mandate requires that about 5 percent of world caloric production from corn, wheat, rice, and soybeans be used for ethanol generation (assuming no recycling of the corn used in biofuels as feed stock). As a result, world food prices are predicted to increase by roughly 30 percent and global consumer surplus from food consumption is predicted to decrease by 155 billion dollars annually. If a third of the biofuel calories are recycled as feed stock for livestock, the predicted price increase scales back to 20 percent. The agricultural growing area is expected to increase, potentially offsetting the CO_2 benefits from biofuels through increased land use change.

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Between the summers of 2006 and 2008, corn prices more than tripled from roughly $2.50 per bushel to nearly $8.00 per bushel. Prices for rice, soybeans, and wheat rose by similar or greater amounts. High prices for staple grains can cause hunger, malnutrition, and riots in developing nations. It has also been shown that weather induced income shocks increase civil conflict in Africa (Miguel et al. 2004, Burke et al. 2009). Since many countries in Africa are net importers of food, an increase in food prices is equivalent to a decrease in real income. It is therefore important to have empirical evidence of the elasticities of food commodity supply and demand, because these indicate how policies that shift supply or demand, like ethanol subsidies, affect world food prices.

Land used for crop production competes with other land uses like forests. Deforestation, on the other hand, results in significant CO_2 emissions. This has brought about an active debate about the potential benefits of using biofuels to reduce CO_2 emissions. For example, the Washington Post reported on February 4, 2010 that "The Environmental Protection Agency said new data showed that, even after taking into account increased fertilizer and land use, corn-based ethanol can yield significant climate benefits by displacing conventional gasoline or diesel fuel." On the other hand, the newspaper article cites Tim Searchinger as "The numbers are inconsistent with the great bulk of analyses by others, which consistently find that emissions from indirect land-use change for crops grown on productive land cancel out the bulk or all of the greenhouse gas reductions, but I will have to study the results." A crucial point of disagreement in the literature is how much the biofuel standard increases food prices and in turn the growing area. The latter will result in additional CO_2 emissions, as land use change (mainly deforestation) accounts for about 20 percent of worldwide CO_2 emissions (IPCC 2007).

A related application of commodity demand and supply involves so-called "leakage" from carbon offsets programs that pay farmers to either forestall deforestation or reforest land that would otherwise be dedicated to crop production. Offset programs shift supply inward, but this causes commodity prices to rise, and thus an offsetting increase in the quantity of cropland supplied elsewhere. The net offset can therefore be much less than the offset purchased in a particular location. The amount of leakage depends on the size of the supply elasticity relative to the demand elasticity.

In this article we exploit yield shocks – deviations from country and crop-specific yield trends that appear to stem from random weather shocks – to estimate world supply and demand for the sum of edible calories derived from corn, soybeans, wheat, and rice. These four crops comprise about 75 percent of the caloric content of food production worldwide.[1] We aggregate all four major commodities crops based on their caloric content.

Agricultural commodity markets are often cited as the archetypal example of competitive markets, having many price-taking producers and buyers and well-developed spot and futures markets. The empirical challenge is to separate supply and demand curves in the market's formation of prices and quantities. Correct identification requires instruments that shift price ways that are plausibly unrelated to unobservables shifts in each curve. Since Wright's (1928) introduction of instrumental-variable estimation, weather has been considered a natural instrument for supply shifts, which can be used to facilitate unbiased demand estimation. The idea is that weather shifts supply in a way that is unrelated to demand shifts. Surprisingly, the literature in agricultural economics that uses weather-based instruments for supply shocks to identify demand curves is extremely thin.

Futures prices in a standard supply equation are also endogenous, even if they are traded prior to potential delivery. Futures prices reflect the intersection of anticipated supply and anticipated demand. However, the existing literature on supply response, following the seminal work by Nerlove, assumes futures prices are exogenous to supply. A recent example from the United States illustrates how this assumption is questionable. In the spring of 2004 soybean rust (a fungus) was first detected in the United States. Although soybean rust is manageable, fungicides used to control it are expensive, its arrival in the United States (the world's largest soybean producer) disrupted commodity markets. In the next growing season, fear of the pest caused some farmers to switch from planting soybeans to planting corn. These supply shifts were anticipated in advance, causing prices for soybeans to rise and prices for corn to fall–movements along the demand curves for these key crops. In other words, the planted area did not decrease because prices went up, but prices went up because there was an unobserved error component (soybeans rust) that lowered area planted and expected harvest. In subsequent years the perceived threat of this new pest abated, causing additional supply fluctuations as relative prices returned to normal. A naive econometrician regressing quantity supplied on futures prices would find a supply elasticity that is biased towards zero due to the soybean rust phenomenon because the potential pest threat (part of the error term) was correlated with the expected future price. While this is just one example, it should be clear that any number of anticipated supply shifts that either are not observable or not measurable to the econometrician, causing downward bias in estimated

[1] Cassman (1999) attributes two-thirds of world calories to corn, wheat, and rice. Adding soybean calories brings the share to 75 percent.

supply response.

Our first contribution is to show how weather-induced yield shocks can be used to identify the supply curve as well as the demand curve. The basic idea is that past weather shocks affect inventories and thus expected futures prices via storage. Competitive farmers will see this price signal and expand supply. Since weather shocks are exogenous, and widely varying over time and geography, past weather shocks result in anticipated price shifts that facilitate identification of supply. We find these estimates to be robust and statistically significant. While the majority of previous studies do not worry about the endogeneity of prices, Nerlove (1958) was the first to use lagged prices or futures prices, yet he found an inelastic supply. However, futures prices are still endogenous. We replicate the analysis of Nerlove (1958) using our data and also find an inelastic supply, suggesting that our significant supply elasticity is not driven by the aggregation of crops or a new data set, but likely due to a more refined instrument. Askari and Cummings (1977) provide a survey of supply estimates using the Nerlove model for various crops and regions and report a wide range of estimates.

We then use the demand and supply model of world commodity calories to examine the effect of biofuel mandates on food prices. The exceptionally large and unanticipated rise in prices between 2006 and 2008 has been attributed to ethanol as well as several other factors. It is important for policy makers to know the extend to which the price increase is attributable to the ethanol policy to accurately assess the impacts of the policy. We find that the current ethanol mandate, which is diverting roughly 5 percent of world caloric production of maize, rice, soybeans, and wheat for ethanol generation, is predicted to increase food prices by 30 percent and significantly increase world production area. This baseline estimate does not incorporate any recycling of the corn used to produce biofuels as feedstock, which will reduce the predicted price increase proportionally. For example, if one third of the calories used to produce biofuel are contained in the waste product that is fed to animals, the price increase would be 20 percent.

Factors besides ethanol policies likely contributed to the threefold price increase. First, rising oil prices accelerated the demand for biofuels as an alternative fuel source. Second, there was a sharp increase in the demand for basic calories from emerging economies like China. This demand growth has accelerated through demand for meat and other animal-based foods, which are highly income elastic. While population doubled in China between 1961 and 2006, meat consumption grew 33-fold (FAO), and comprised a little less than a third of the world's meat consumption in 2006. Meat requires between 5-10 times the agricultural area to obtain the same amount of calories as a vegetarian diet as corn and soybeans are used as feedstock. A third reason for the threefold price increase is a decrease in supply due to detrimental weather, such as the prolonged drought in Australia. Fourth, the United States is the largest exporter of agricultural commodities and many commodity markets are denominated in US dollars. The devaluation of the dollar therefore increased the price for commodities in dollars. Fifth, some have argued that the commodity price boom, much like earlier housing and stock market booms, were due to a speculative bubble. However, recorded inventories of all major commodities declined throughout most the boom, and it is difficult to reconcile a bubble with an absence of inventory growth. Finally, prices, particularly those for rice, were likely influenced by temporary export bans in Vietnam and India, as well as speculation led by Thailand about a possible formation of rice exporters' cartel. Since the Fall of 2008, prices have fallen precipitously, at least partly due to a large inward shift in demand stemming from the global economic slowdown.

1 A Simple Model of Supply and Demand

Consider a basic model of supply and demand for food commodity calories derived from maize, wheat, rice, and soybeans. These four commodities are responsible for 75 percent of the calories produced. To make production quantities comparable we transform the amount produced into calories. The number of people that could be fed on a 2000 calories per day diet are shown in the top panel of Figure 1. Since these four crops are substitutes in production and/or demand, the per-calorie prices are similar and tend to vary synchronously over time. Note that with storage opportunities, supply or demand substitutions possible in the long run can be reflected in short-run price fluctuations. Aggregating crops on a caloric basis facilitates a simple yet broad-scale analysis of the supply and demand of staple food commodities. While rice and wheat are primarily used as a direct food source, corn and soybeans are used mainly as feed stock. In sensitivity check below (Table 5) we test whether the yield shock from corn and soybeans has a different influence on aggregate price than rice and wheat shocks, but find no evidence for this, suggesting that our assumption of a pooled model for all four commodities is valid.

1.1 Theoretical Motivation

Storage is a characteristic feature of the markets for maize, wheat, rice, and soybeans. All four commodities can be stored to smooth out production shocks. As a result, equilibrium does not require a price where supply in the current period equals demand in the current period, but a price where the amount consumed c_t equals food supply at the beginning of the period z_t minus what is placed in storage (denoted x_t), i.e.,

$$c_t = z_t - x_t \tag{1}$$

There is an extensive literature on competitive storage and the resulting price path. Scheinkman and Schechtman (1983) and Bobenrieth H. et al. (2002) set up a model in which profit-maximizing agricultural producers have to make two decisions. The first is how much to store into the next period x_t. Storage has convex cost $\phi(x_t)$. The amount not stored $z_t - x_t$ is consumed and gives consumers utility $u(z_t - x_t)$. The second decision is how much "effort" λ_t to put into new production, which is subject to a multiplicative i.i.d. random weather shock ω_{t+1} that is unknown at the time of planting. One possible interpretation of λ_t is that it specifies the number of acres a farmer plants. Production in the coming harvest season is $s_{t+1} = \lambda_t \omega_{t+1}$, where ω_{t+1} is the distribution of yields due to random weather shocks. The production cost $g(\lambda_t)$ are assumed to be convex, as land of heterogenous quality is consecutively more expensive to farm.

The Bellman equation for the social maximization problem becomes

$$\begin{aligned} v(z_t) \quad = \quad & \max_{x_t \lambda_t} \left\{ u(z_t - x_t) - \phi(x_t) - g(\lambda_t) + \delta \mathbb{E}\left[v(z_{t+1}) \right] \right\} \quad \text{subject to} \\ & z_{t+1} = x_t + \lambda_t \omega_{t+1} \\ & x_t \geq 0, \quad z_t - x_t \geq 0, \quad \lambda_t \geq 0 \end{aligned}$$

Competitive producers will achieve the socially optimal outcome by balancing the cost of storing agricultural goods and exercising effort against payoffs in the next period. Storage can be profitable if the weather shock ω_{t+1} is detrimental and the reduced food supply $z_{t+1} = x_t + \lambda_t \omega_{t+1}$ results in an increase in the price. If ω_{t+1} is allowed to have a mass point at zero, i.e., a non-zero probability that the entire harvest is wiped out and $\lim_{c \to 0} u'(c) = \infty$, the long-run distribution has a finite price and positive storage amount with probability one, yet the mean of the price distribution is infinite (Bobenrieth H. et al. 2002). While low inventory levels (and high prices) will almost surely result in a price drop, the expected price is still increasing. The rational is that if another bad shock would hit, the already strained market would result in a very large price jump. While this outcome is unlikely, the resulting payoff is so large that it still justifies holding stock. Hence, a sequence of bad weather shocks will drive down inventor levels and increase prices. We observe this behavior empirically: price spikes are exceptionally steep if inventory levels remain low for several periods.

Similarly, when storage levels are low and the expected price is the next period is high, farmer increase the amount planted λ_t. Marginal land with higher production cost will enter production as the payoffs are high enough to cover expenses. Scheinkman and Schechtman (1983) show that in a competitive equilibrium

(i) consumption $c_t = z_t - x_t$ is strictly increasing in z_t

(ii) storage x_t is weakly increasing in z_t

(iii) effort λ_t is weakly decreasing in z_t

We will utilize these three points in our empirical implementation below. The fact that bad weather shocks ω_{t+1} in a given period reduce food production and therefore available food supply z_{t+1} has often been used to empirically estimate demand elasticities. However, the above model suggests that a weather shock not only impacts demand in the current period, but also production in the next period via expected price. We are not aware of any paper who has used this result to empirically estimate a supply elasticity using past weather shocks as an instrument for the expected price.

1.2 Empirical Implementation

Our empirical model becomes

$$\begin{aligned}
\text{Supply:} \quad & log(s_t) &=& \; \alpha_s + \beta_s log\left(\mathbb{E}[p_t|_{t-1}]\right) + \gamma_s \omega_t + f(t) + u_t & (2)\\
\text{Demand:} \quad & log(z_t - x_t) &=& \; \alpha_d + \beta_d log(p_t) + g(t) + v_t & (3)
\end{aligned}$$

Quantities supplied and demanded are denoted by s_t and $z_t - x_t$, respectively; p_t is price; the parameters β_s and β_d are supply and demand elasticites; ω_t is the random weather-induced yield shock; α_s and α_d are intercepts; and $f(t)$ and $g(t)$ capture time trends in supply and demand, stemming from technological change, population, and income growth. Finally, u_t and v_t are other unobserved factors that shift supply and demand.

The supply equation includes last period's futures price. Farmers make planting decisions before a year's weather shock or other supply or demand shocks are realized. The supply in the next period therefore depends on expected prices. We use futures prices one year in advance to measure farmer's expectations. More specifically, we use future prices for corn in December of period $t-1$ for a December delivery in period t. For soybeans we use futures prices in November, and for wheat we use futures prices in September. Each month constitutes the end of the growing season in the Northern hemisphere.

Prices p_t are the key endogenous variables on the right-hand side of both supply and demand. The crux of the identification problem is to identify supply and demand elasticities given that unobserved shifts in supply and demand (u_t and v_t) influence prices via the equilibrium identity. Without correcting for the endogeneity of prices, the supply elasticity would be biased negatively, since unobserved positive supply shifts (u_t) would tend to reduce price all else the same, creating a negative correlation between u_t and price. A naive demand elasticity (without correcting for the endogeneity of prices) would tend to be biased positively, since unobserved positive demand shifts (v_t) would tend to increase price all else the same, creating a positive correlation between v_t and price. If unobserved supply and demand shifters u_t and v_t are correlated, biases could go in either direction.

We utilize either concurrent or lagged yield shocks to identify demand and supply. Our baseline proxy for weather-induced yield shocks are deviations from country-specific trends in yield (tons per hectare) for each crop. Country-and-crop-specific deviations are then converted to calories and aggregated to obtain a world supply shock. Our premise is that these deviations from yield trends are exogenous as they largely due to random weather. One potential concern is that yields themselves might be a function of prices. For example, higher prices could induce farmers to choose higher sowing densities, thereby increasing average yields. On the other hand, higher prices might induce farmers to expand their production to marginal, less productive, land, thereby lowering average yields. It is hence unclear a priori which way the bias would go. We believe that endogenous yield responses are not important in our paper for several reasons: First, farm and county-level data show considerable variability in deviations from a yield trend but have almost no autocorrelation (Roberts and Key 2002, Roberts et al. 2006), while prices have a very high degree of autocorrelation. If yields endogenously respond to prices, than yields should show autocorrelation as well. Second, if yields were responsive to price levels, we should observe that yield shocks are correlated between various countries in a given year as all countries face the same world price. In Figure 4 below, we show scatter plots of yield deviations for the two biggest producers of our four commodities. These plots show no systematic correlation: two of the four even have negative correlation coefficients. While this is not to say there is no endogenous yield response, we believe it to be small compared to variation induced by weather shocks. Finally, in a sensitivity check we directly instrument for yield shocks with weather variables below. The challenge behind such an analysis is to obtain world-wide fine-scaled weather data sets that result in a strong first stage.

1.3 Identification of Demand

Demand for our four basic commodities comes from various sources. These commodities are a primary source of food, especially rice and wheat. Corn and soybeans are also used as feed for livestock and dairy operations, among many other uses. Finally, there is an emerging market for ethanol, which uses a rapidly growing share of corn production in the United States.

Identifying the demand elasticity β_d requires an instrument that shifts supply in a way that is plausibly unrelated to unobserved shifts in demand. Technically, the instrument is a component unrelated to v_t. For short-run demand, weather-induced yield shocks are a natural choice for three reasons. First, they are clearly exogenous as weather affects farmers, but farmers cannot affect weather. Second, they are almost random and unpredictable at planting time except for some cycles like El Nino, which are difficult to forecast. There is no evidence that farmers grow systematically different crops in the United States, the largest producer of calories, in anticipation of El Nino trends. Third, weather is likely to have little or no influence on demand itself, except via its influence on price. The last point stems from the fact that there are well-established international markets with a significant share of production traded internationally.[2] Demand is derived from world markets comprised of firms and individuals that often reside far from the locations experiencing specific weather and production outcomes.

Wright (1928) was first to use weather as an instrument for demand identification when he introduced the instrumental variables technique. A key difference from Wright is that we simultaneously consider the four key commodities that are substitutes in supply and demand. It is important to consider these crops simultaneously to ensure that weather effects on crops that are substitutes in production do not confound own-price elasticities with cross-price elasticities. We aggregate the caloric value of all four crops. Future research might simultaneously estimate equations for all crops, including cross-price elasticities, but identification could be more challenging given the limited number of observations.

It may be tempting to use deviations from the trend in world production as a proxy for aggregate weather shocks. Such an approach can be misleading because it still confounds

[2]Weather shocks would be a problematic instrument with local production as the weather event (i.e., extreme heat) could not only decrease supply but directly impact humans, e.g., via sickness, and therefore influence demand.

supply and demand responses to price, such as adjustments in growing area. Production shocks depend on changes in (i) average yields (output per acre) and (ii) growing area. While the former, weather-induced yield shocks, are arguably exogenous, the latter, expansion in the production areas, are known before harvest is realized and hence interlinked with expected prices. We provide empirical evidence of this below. We hence derive shocks solely from component (i), i.e., country and crop specific yield shocks. As discussed below, they have a much stronger (negative) association with price than aggregate production shocks.

In a second step we use weather data from around the world to link yearly country-specific yields to weather outcomes including time trends to capture technological innovations. Once the link between weather outcomes and yields is established, yield shocks are constructed by multiplying the estimated weather coefficients with weather shocks, which we define to be deviations from average weather outcomes. The advantage of using weather-instrumented yield shocks instead of yield deviations from trends is that the latter might be endogenous, i.e., yields might predicably differ from the long-run trend if prices change.

1.4 Identification of Supply

A novelty of our approach is that we also use yield shocks to identify the supply elasticity β_s in addition to the demand elasticity. This is feasible as past weather shocks impact storage levels and thereby expected price. Negative yield-shocks reduce supply and inventories while increasing the price, thereby exogenously increasing the incentives for new production. These past weather shocks are unlikely to be associated with current supply shifters, such as pest infestations or technological change as weather shocks between years show no autocorrelation.

Unlike transitory yield shocks, commodity price shocks are well known to have a large degree of persistence that stem from storage (Deaton and Laroque 1992, Deaton and Laroque 1996, Williams and Wright 1991). Within the aggregate supply and demand framework above, past weather shocks affect future price by changing future inventories via storage x_t. Using past yield shocks as an instrument for current expected prices would seem to be a useful extension of the standard approach following Nerlove (1958), which estimates supply response using futures prices, lagged prices, or time-series forecasted prices as a proxy for expected prices at planting time. Previous studies which emphasized that prices are endogenous used futures prices or lagged prices. However, the potential concern with using uninstrumented lagged prices is that there might be supply shifters u_t that are correlated with expected price. Recall the example of soybean rust in the introduction. Changes in production come from two sources: (i) changes in output per acre, and (ii) changes in the planting area. While most of the variation of the former is due to exogenous weather effects, the latter is often known in advance. Rational market participants will incorporate area expansions in the expected price, thereby making the expected price endogenous to future supply shifts. As pointed out in the discussion of how to identify demand, area expansions and contractions are predictable and directly influence price. Our extension in the spirit of previous research is to further purge the expected prices from such predictable area expansions and utilize price variation that is due to exogenous yield shocks.

Our own approach of using past yield deviations from a trend as an instrument for expected price is not without its own potential pitfalls: Are prices anticipating yield changes in the next period? However, as mentioned above, the fact that both farm-level data as well as aggregated data show little or no autocorrelation in yields suggests that in practice such problems are likely small, especially when compared to the large variation that is induced by weather shocks. Moreover, yields of the largest producers show no correlation although they are subject to the same price shocks. In summary: supply response to price appears to occur largely via acreage changes, not yield changes. Moreover, small locally-persistent yield shocks are likely dominated by aggregate transitory variation in weather.

2 Data

World production and storage data are publicly available from the Food and Agriculture Organization (FAO) of the United Nations (http://faostat.fao.org/) for the years 1961-2007. The data include production, area harvested, yields (ratio of total production divided by area harvested), and stock variation (change in inventories) for each of the four key crops. The last variable is only available until 2003. In our model estimates below, we stop all series in 2003 for consistency because quantity demanded (which depends on changes in storage) is not available after 2003 and because it precedes the recent boom and bust in commodity prices. Variables are converted into edible calories using conversion factors by Williamson and Williamson (1942), which specify the caloric input per output quantity of various crops. Consumption (quantity demanded) is calculated as production minus the net change in inventories.

Data on quantities are displayed in Figure 1. The top panel displays the number of billion people that could be fed on a 2000 calories per day basis and how much each of the four commodities contributed to total caloric production. Maize has the biggest share while soybeans has the smallest share. Wheat and rice are in the middle and have roughly equal shares. One noteworthy fact is that the overall year-to-year fluctuations (top line) are predominantly due to fluctuations in maize. As will be discussed below, more than half of all corn was traditionally produced in the United States within a confined area (corn belt) that is susceptible to the same weather shocks.[3] Other crops are less concentrated and hence local weather shocks average out when production is summed over the world. One country might have a good year while another has a bad year.

The bottom panel of Figure 1 shows production and consumption quantities. Two features are noteworthy: First, production and consumption have been trending up steadily, almost linearly. They both appear trend stationary. Second, fluctuations around the trend in production are small in proportion to the trend. Consumption fluctuations are even smaller due to smoothing from storage accumulation and depletion. The FAO series on stock variation, necessary for derivation of consumption, ends in 2003 and hence so does our demand estimate.

Yield shocks in our baseline model were calculated by taking jackknifed residuals from fitting separate yield trends for each crop in each country.[4] Trends and shocks were estimated for any country with an average of 1 percent or more of world production for each of our four crops. The average share of world production between 1961-2007 is shown in Table 1. Remaining rest-of-world yields were pooled and treated as a single country for each crop. Yield shocks were derived from both linear and quadratic trends and showed small and statistically insignificant autocorrelation. Figure 2 displays fitted quadratic yield trends to all countries, while the fitted jackknifed residuals are shown in Figure 3. Figure 4 shows scatter plots of yield deviations of the two largest producers of each crop. The lack of significant correlation suggests that yields do not endogenously respond to price, which would induce correlation between countries as everybody faces the same world price, or at least that the endogenous yield response is swamped by the much larger variation induced by weather shocks.

We derive caloric shocks for each country and crop using the product of: (1) country-and-crop-specific yield shocks; (2) hectares harvested; and (3) the ratio of calories per production unit. The world caloric shock is simply the sum of all country-specific shocks of all crops, which is then scaled relative to the world trend in total caloric production. Aggregating country and crop specific yield shocks purges production variation stemming from endogenous land expansion or contraction. As emphasized in the modeling section, land expansions

[3]Today, the US still accounts for roughly 40 percent of world corn production.

[4]OLS residuals give biased estimates of the errors. Jackknifed residuals, derived by excluding the current observation when determining the current residual, give unbiased estimates of the error.

are often correlated with components of the error (e.g., a pest outbreak) and incorporated in next period's expected price, while yield shocks should be primarily due to exogenous weather shocks.[5]

As mentioned above, there is concern that yields might endogenously respond to price changes. In a sensitivity check we therefore construct yield shocks that can be explained through observed weather fluctuations. We fit regressions of log yields on various weather measures as well as a quadratic time trend. Yield shocks are derived as predicted changes in yields that are attributable to deviations in the weather variables from historic averages. For example, if the average temperature in a country is 15°C, the yield shock attributable to a year with an average temperature of 16.5°C is 1.5 times the coefficient on average temperature. For the United States we use the fine-scale weather data set of Schlenker and Roberts (2009) with a piecewise linear function in temperature (degree days) and a quadratic in total precipitation for maize and soybeans. We model rice and wheat using a quadratic in average temperature as there is less agreement on the optimal bounds in the agronomic literature as well as a quadratic in total precipitation during the growing season. For all other countries in the world we use a quadratic in average temperature as well as total precipitation for each of the four crops in a panel setting, i.e., we include all countries that produce at least one percent of a crop as well as the rest of the world in one equation and include country fixed effects. Weather data from the Climate Research Unit (CRU) at the University of East Anglica gives monthly temperature and precipitation readings on a 0.5 degree grid for the entire world for the years 1901-2002 (Mitchell and Jones 2005).[6] The growing season for each country was obtained from Sacks et al. (2010).[7] Weather outcomes in a country are the area-weighted average of all grids that fall in a country, where the crop-specific area weights from Monfreda et al. (2008) are displayed in Figure 7.[8]

We obtain two price series. Our baseline model uses futures prices from the Chicago Board of Trade with a delivery month of December for maize, November for soybeans, and September for wheat.[9] We construct the price p_t as the average futures price during the month when

[5]We divide world yield shocks and inventories by the trend in production, estimated using a quadratic trend in our baseline. The estimated trend is close to being linear and a sensitivity check with a linear trends shows similar results.

[6]http://www.cru.uea.ac.uk/~timm/grid/CRU_TS_2_1.html (accessed November 2008)

[7]The authors provide planting and harvest dates on a 5 minute grid. http://www.sage.wisc.edu/download/sacks/crop_calendar.html (accessed January 2010). We include the entire months between planting and harvest. For example, if average planting is on April 8th and harvest on September 12th, we use weather data from April through September.

[8]The authors provide the fraction of each 5 minute grid cell that is used for various crops. http://www.geog.mcgill.ca/landuse/pub/Data/175crops2000/NetCDF/ (accessed November 2008).

[9]We use futures price for "No.2 yellow" for corn, "No.1 yellow" for soybeans, and "No.2 soft shell" for

the delivery occurred, i.e., in December of the delivery year for corn. The expected price $\mathbb{E}[p_t|_{t-1}]$ is the average futures price in the delivery month one year prior to delivery.[10] All prices are deflated by the Consumer Price Index. Prices for each commodity are converted to their caloric equivalent, with the world calorie price taken as world-production-weighted averages of the four commodities. Unfortunately, the futures price series for rice does not extend before 1985 and we hence use the production-weighted price of the three commodities.

A second price series with longer temporal coverage are those received by U.S. farmers in the month of December of each year, publicly available from the U.S. Department of Agricultural. The top panel of Figure 5 displays real price (annual cost of a 2000 calories per day diet in 2007 dollars). There has been a general downward trend of food prices. Prices per calorie move together for all four commodities, most notably maize, wheat and soybeans. This is not surprising, given that those three are close substitutes in production and consumption. For example, maize and soybeans (and to some degree wheat) are used as feed for livestock. If one were cheaper per calorie than the others, profit-maximizing farmers should switch to the cheaper input. Price fluctuations are proportionately much larger than quantity fluctuations in Figure 1. This suggests that both demand and supply are inelastic.

The bottom of panel of Figure 5 displays our two price series in black as well as production shocks (deviation from the quadratic production trend in percent) in grey. The solid black line shows the production-weighted average December price of all four commodities. The black dashed line shows the production-weighted average futures price at delivery for maize, soybeans, and wheat. Leaving out rice, for which we do not have a futures series dating back to 1961 gives comparable results. The figure demonstrates the first stage of our IV strategy: prices fluctuate negatively in comparison to yield-shocks. The lack of autocorrelation in the yield shocks suggest that these yield shocks are due to weather and not technological advances, which would result in deviations from the trend that are less transient.

Table 2 reports descriptive summary statistics on caloric prices, production, consumption, our constructed world aggregate yield shocks, and yield shocks interacting with inverse inventories.

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wheat.

[10] In some cases the time series of a contract does not extend 12 months back and we hence take the average price in months closest to 12 months prior.

3 U.S. Ethanol Subsidies and Mandates

Ethanol has a long history as a car fuel. Ford's Model-T was designed to run both on ethanol and petroleum, or arbitrary mixes of the two. Declining petroleum prices led to a slow phase out of ethanol as a fuel. Recent concerns about anthropogenic CO_2 emissions have renewed interest in ethanol as a fuel substitute, even though the net effect is highly debated (Searchinger et al. 2008). Ethanol is currently being mixed with traditional petroleum in ratios up to 10 percent. Most cars can run on such fuel mixes. Modern flex-fuel cars are designed to run on fuel that is up to 85 percent ethanol.

One might wonder why U.S. ethanol subsidies and mandates can have a measurable effect of world food prices? The answer is simply the size of the U.S. market share. Figure 6 shows the U.S. share of world caloric production over time. Yearly observation are shown as crosses, and a locally weighted regression (bandwidth of 10 years) is added in grey. The yearly ratio fluctuates somewhat due to weather-induced yield shocks, but the average share stays rather constant around 23 percent. There is a slight uptick during the boom years (late 1970s) before the U.S. share falls again after the 1980-1982 recession that heavily impacted the agricultural sector as well. Farmland prices fell roughly one third between the 1982 and 1987 Census.

Given the dominant share of world caloric production, any policy that impacts US production might lead to repercussions on world markets. Ethanol production has risen rapidly over the last couple of years as shown in Figure 9.[11] Ethanol subsidies and biofuel mandates require that a certain amount of fuel is derived from ethanol. The 2005 U.S. energy bill mandated that 7.5 billion gallons of ethanol be used by 2012. The 2007 energy bill increased the mandate to 36 billion by 2022. Moreover, under the 2009 U.S. Renewable Fuels Standard, refiners and fuel blenders are required to blend roughly 11 billion gallons of ethanol into gasoline. Currently, most of the ethanol is produced from corn, and 11 billion gallons of ethanol would require roughly 4.23 billion bushels of corn (assuming an average of 2.6 gallons of ethanol per bushel of corn). This translates into roughly one third of U.S. maize production in 2007 (13 billion bushels), or about 5 percent of world caloric production in 2007. The remains of corn that is used in ethanol production can still be used as feed stock for livestock, which is often labeled distiller's grain. While estimates vary, up to one third of the caloric input is said to be recoverable, but the nutritional content is debated. We therefore present two estimates: our baseline model uses a five percent increase in world

[11] http://www.ethanolrfa.org/industry/statistics/

caloric production (assuming that nothing is recycled) as well as a scenario where we assume that one third of the calories is recycled as feed stock.

While 5 percent of world caloric production would be required for 11 billion gallons of ethanol, the average daily U.S. motor gasoline consumption is 0.39 billion barrels per day.[12] The supply of approximately 8 percent of U.S. gasoline consumption requires roughly 5 percent of world caloric production.

4 Empirical Results

Given the large trends in overall production due to population growth and technological change in Figure 1, all shocks are normalized around the upward production trend. Predicted production is obtained by regressing aggregate caloric production on a time trend of the same order used to derive jackknifed residuals. The default is a quadratic time trend, but we present sensitivity checks for a model with a linear trend below.

Our first-stage instrument ω_t is the relative yield shock (caloric yield shock divided by predicted production), which is interacted with the inverse relative inventory level (inventory level divided by predicted production) in all cases unless otherwise noted. Prices are well known to be more volatile when inventories are low as compared to when they are high. This follows from storage theory and can be observed empirically. Prominent examples include the recent price spike and the one in the 1970s, both of which occurred in an environment with unusually low inventories. Interacting aggregate yield shocks with aggregate inventory levels therefore increases the statistical power of the instrument. If yield shocks are linearly independent of other supply or demand shifters, then multiplying yield shocks with inventory levels is also linearly independent of those shifters. In the first stage we regress the natural log of price against current and lagged yield shocks ω_t up to lag K, plus a polynomial time

[12]Energy Information Administration: http://www.eia.doe.gov/basics/quickoil.html

trend up to order I.[13] The first-stage regression model for the demand and supply price are:

$$\begin{aligned} log(p_t) &= \pi_{d0} + \sum_{k=0}^{K-1} \mu_{dk}\omega_{t-k} + \sum_{i=1}^{I} \rho_{di} t^i + \epsilon_{dt} \\ log\left(\mathbb{E}[p_t|_{t-1}]\right) &= \pi_{s0} + \sum_{k=0}^{K} \mu_{sk}\omega_{t-k} + \sum_{i=1}^{I} \rho_{si} t^i + \epsilon_{st} \end{aligned}$$

In the second stage we estimate the structural equations (2) and (3), substituting the predicted values of price from the first stage in place of actual prices. For the supply equation (2) we regress the natural log of production quantity against the predicted futures price $log\,(\widehat{\mathbb{E}[p_t|}_{t-1}])$, a polynomial time trend up to order I as a proxy for $f(t)$ and the supply shifter in the current period ω_t. Stage-one variables excluded from the stage-two supply equation are lagged yields shocks $\omega_{t,t=t-K-1,\ldots,t-1}$ which act as instruments. The stage-two regression model of supply is:

$$log(s_t) = \alpha_s + \beta_s log\,(\widehat{\mathbb{E}[p_t|}_{t-1}]) + \lambda_{s0}\omega_t + \underbrace{\sum_{i=1}^{I} \tau_{si} t^i}_{f(t)} + u_t$$

For the demand equation (3) we regress the natural log of quantity consumed ($s_t - x_t$, the quantity produced minus the net-change in storage) on predicted price, a polynomial time trend up to order I as a proxy for $g(t)$. The stage-one variable excluded from the stage-two demand equation are the supply shocks $\omega_{t,t=t-K,\ldots,t}$. The stage-two regression model of demand is:

$$log(s_t - x_t) = \alpha_d + \beta_d \widehat{log(P_t)} + \underbrace{\sum_{i=1}^{I} \tau_{di} t^i}_{g(t)} + v_t$$

Regression results of the two-stage least squares as well as three-stage least squares results are summarized in Table 3. Columns differ by the number of lagged shocks as well as the number of polynomials used in the time trend. The first stage regression reveals highly significant instruments ω_t for both the current price p_t in the demand equation and the expected price $log\,(\mathbb{E}[p_t|_{t-1}])$ in the supply equation as shown in Table 4. One particularity

[13] The first stage of expected price used in the supply equation includes the shock ω_t as it is included as a supplier shifter in the second stage. Since the expected price is traded in period $t-1$, K lags runs from $t-1$ to $t-K-1$.

is that the first stage instrumenting the expected price in the supply equation includes the shock ω_t which happens in the *next* period. The coefficient is significant, suggesting that the market already has production signals from the Southern hemisphere or expectations about yield shocks.

Elasticity estimates in Table 3 are reasonably stable across models in Table 3, varying between 0.08 and 0.13 for supply and -0.05 and -0.08 for demand. The top panel summarizes the demand and supply elasticity, as well as the predicted price increase from a ethanol mandate that puts 5 percent of current world caloric production into biofuels. The second panel displays the regression results. Adding additional lagged weather shocks in the last two columns changes the results by very little. The results differ more if we move from a second-order time polynomial (first two columns) to a third order time polynomial (last four columns).

We most prefer estimates in the first two columns because the additional lagged yield shocks are statistically insignificant in the last two columns. Moreover, small-sample bias is known to be smallest in two stage least squares when there are fewer instruments (Nelson and Startz 1990). Unsurprisingly, the trend estimates show that demand has grown more slowly than supply, which accords with the general downward trend in prices and the increase in storage over time.

The supply and demand elasticities imply that the U.S. ethanol mandates (which requires 5 percent of world caloric production to be diverted for ethanol) will increase prices by $\frac{0.05}{\beta_s - \beta_d}$. Since the predicted ratio includes the inverse of the predicted parameters, it will be convex and the expected value will be greater than the ratio evaluated at the expected values. We therefore take 1 million random draws from the joint distribution of the demand and supply elasticity. The mean impact as well as the 95% confidence interval are given in rows 5 and 6 of Table 3. The mean impact is fairly stable between various specification at stays around 30 percent. However, it should also be noted that the distribution is right skewed and the 95% confidence interval extends further to the right than to the left of the mean impact. The mean price increase implies a decrease in consumer surplus from food consumption equal to 155 billion dollars annually.[14] As noted above, the baseline scenario assumes that the waste products from ethanol reduction are not fed to animals. Since studies differ in what fraction can be recycled, we report estimates assuming zero recycling, which can easily be scaled by the assumed recycling ratio as the ultimate price increase is linear in this recycling ratio. For

[14]The expected supply (along the trend line) is the equivalent of feeding 7.06 billion people for a year on 2000 calories per day, prices in 2007 were 74.12 dollars per person per year, and the 30 percent price increase will reduce consumption by 1.5 percent.

example, in case one third of the calories could be recovered as feed stock, the price increase would scale to 20%. There will also be a partially offsetting increase in producer surplus. On top of that, some authors have argued that the ethanol mandate increases fuel supply, thereby lowering fuel cost, which in turn benefits consumers (Rajagopal et al. 2007). The full welfare analysis therefore also requires assumption on the elasticity of supply of fuels that are beyond the scope of this paper. It is worth noting that the policy is a larger shift from consumer surplus to producer surplus.

Table 5 conducts a sensitivity analysis which includes separate yield shocks for corn and soybeans (index by subscript MS) and rice and wheat (indexed by subscript RW). The rational is that the latter are primarily used as food, while the former are also used as feed stock. One might hence wonder whether yield shocks from all four commodities can be pooled together. On the margin, calory demand should equate the price per calory produced or it would be better to substitute to another crop. While there are of course regional preferences for various food sources (rice is predominant in Southeast Asia while Europeans rely much more on wheat), all we need for the prices to move together in equilibrium is that some demanders (feed lots, food processing plants) are willing to substitute various crops on the margin. We find no evidence that shocks are different for the two sets of commodities as all Wald tests (reported in the last three columns of each panel) are not significantly different. Since we have a limited number of observations (43 years), we pool all shocks to limited then number of variables in our analysis.

Table 6 presents various sensitivity checks. Panel A reports the baseline results from Table 3. Panel B uses a linear time trend to obtain jackknifed residuals as well a linear trend in production. The results are insensitive whether we use a linear time trend or a quadratic time trend in the baseline results. The predicted price increase remains robust around 30 percent.

Panel C derives caloric shocks as the product of the jackknifed yield residuals and the *predicted* (as opposed to actual) harvested area along a quadratic time trend. The effect on the estimated results is very minor though as we are dealing with a second order effect, i.e., the product of changes in yield times changes in areas.

Panel D rescales the caloric conversions factors so that the average price between 1961 and 2003 is the same for all commodities. If various goods are substitutes in production, relative conversion factors are given by the price ratios. This allows us to back out the implicit conversation factors set by the market instead of using the ones by Williamson and Williamson (1942). The results change again very little supporting our hypothesis that it is feasible to aggregate all four crops based on caloric conversion factors.

Panel E uses a sensitivity check where the caloric shock ω_t is *not* normalized by the inventory levels. The results seem to become a bit more sensitive to the order of the time polynomial, which is picking up that there was a time period in the 1970s when inventory levels were low and prices spiked.

Panel F focuses on the planting dates in the Northern hemisphere: As before, expected futures prices for wheat with a September delivery are are averaged in the previous September. However, we no longer use soybeans and maize price a year in advance (i.e., in November and December of the previous, respectively), but the average price in March of the delivery year, the month when planting decisions are made in most of the Northern hemisphere. These March prices can incorporate information about the harvest in the Southern hemisphere that farmers in the North can incorporate at the time of planting. Again, the results are robust to this change.

Finally, Table 7 presents results when we use yield residuals that are attributable to observed weather shocks in Panel B. Generally, the significance levels decrease a lot in both the first stage and the second stage. Since the instruments are weak, the results should be considered cautiously. Generally, demand is inelastic, while supply elasticities fluctuate around our baseline estimates, although the confidence intervals are wide as well. Given the added noise in our instrument, the three-stage procedure gives much more concise estimates that two-stage least squares, which are comparable to our baseline estimates if we include one lag of the shock. While the results are in line with our baseline estimates for the parsimonious models using one lag and 3SLS, the results are certainly not as robust as in our baseline case to other modifications. The increase in confidence intervals is due to the fact that we have weather measures of limited accuracy outside the United States. The correlation coefficient between yearly caloric shocks using (i) jackknifed residuals and using (ii) shocks attributable to observed weather shocks is 0.71 in the United States. Since the United States accounts for such a disproportional share of world caloric production, the correlation is still 0.51 if we aggregate shocks over all countries. This is further demonstrated in Figure 8 where we plot yield residuals as deviations from a time trend on the x-axis and yield residuals using weather instruments on the y-axis for the biggest producers. The top left panel shows the United States where the scatter plots aligns reasonably well with the 45-degree line. However, the bottom row shows that our model linking yields to weather is fairly bad for China and Thailand, which both heavily rely on rice.

The main motivation to use weather-induced caloric shocks was to rule out that yields are endogenous to price and hence our caloric shock, which is derived as deviations from a quadratic time trend, might also be endogenous. Figure 8 provides further evidence that this unlikely. We color-coded the scatter plot by the futures prices (traded the year before the yield was realized). If yields are endogenous, we should observe distinct color patterns. For example, if yields respond positively to higher prices as farmers increase sowing densities, our caloric shocks derived as deviations from a time trend should be more positive when prices are high. This would imply that observations with a large x-values should be predominantly shown in red colors, while negative x-values should be shown in blue colors. We find no such distinct color pattern.

Our new estimates are contrasted to other approaches in Table 8. The first two columns report elasticity estimates from seemingly unrelated regressions (SUR) without a first stage. That is, these models use raw endogenous price, *not* predicted price. They do account for observed supply shifters and the correlation of innovations u_t and v_t. We include this regression mainly to illustrate likely endogeneity bias in comparison to 2SLS estimates in Table 3. The SUR regression gives extremely inelastic estimates of supply and demand, 0.016 for supply and -0.017 for demand. While the demand elasticity is statistically significant at the 10% level, the standard errors are small and (if assumptions are accepted, which is dubious) rule out elasticities less than -0.034 with 97.5 percent confidence. The supply is statistically insignificant, and again rule out elasticities greater than 0.34 with 97.5 percent confidence. The predicted price increase of an ethanol mandate (diverting 5 percent of world production) would be 150 percent if we use the point estimates of the elasticities.

Columns 3 to 6 of Table 8 follow the approach of Nerlove (1958) and include futures prices which are *not* instrumented. The estimated supply elasticity becomes lower and insignificant, which is in accordance with the previous literature on supply responses. The predicted price increase of an ethanol mandate (diverting 5 percent of world production) would be around 60 percent if we use the point estimates of the elasticities. Our concern with this approach is that expected price incorporates anticipated area responses and is hence endogenous.

All models in Table 8 give smaller supply elasticities and hence the ethanol policy would lead to larger price increases and lower area expansions. Our model gives a lower predicted reduction in consumer surplus than previous approaches, yet the predicted impact is still sizable. The flip-side of a more elastic supply is that the dampened price increase comes at a potentially other significant effect: A predicted expansion in the agricultural area. Searchinger et al. (2008) and others have emphasized that this land conversion will lead to further CO_2 emissions. Currently, land conversion already accounts for 20% of global CO_2 emissions.

Panel A of Table 9 examines this further by regressing the log of total world growing area (for maize, rice, soybeans, and wheat) on the combined lagged production shock ω_{t-1} of all four commodities in the first two columns. The coefficient is negative and significant at the one percent level, i.e., the planting area moves in the opposite direction of the shocks: A bad yield shock leads to an expansion of the area and vice versa. Rational market participants will incorporate this area-response, as well as all other known information about planting areas, in their expectation of future prices, making the price endogenous. Our approach therefore only uses production shocks that are due to unpredictable yield shocks as an instrument and purges the analysis of possible area responses. We regress the log of total area on instrumented caloric prices in columns (3) through (6), suggesting an area elasticity of roughly 0.06-0.07. While this number is smaller than our supply elasticity estimates, it should be noted that if the more productive countries are the responsive ones, a less than one-to-one response between output and supply is expected. For example, if countries which have twice the average yield increase the area by 6%, total supply will increase by more than 6%. Panels B through F replicate the analysis for individual countries and demonstrate that there are different sensitivities to world caloric shocks and world prices: Major producers and exporters like the United States and Brazil show an even larger elasticity, while more self-sufficient countries like India show smaller elasticities. Our land elasticity for Brazil is comparable to Barr et al. (2010), but larger for the US.[15] Our estimated elasticities imply that total caloric production would increase by roughly 3.5 percent, or 180 trillion calories. Using an elasticity of 0.06 from Table 9 on the predicted 30 percent price change, total acreage is predicted to increase by 2 percent, or 30 million acres. In 2007, total planting area for the four commodities were 1.5 billion acres.

Table 10 shows the range of calories per hectare that can currently be obtained. Using the highest coefficient for maize in the United States, the predicted area increase is 19 million acres. For comparison, the total corn area in the United States is approximately 80 million acres. If the area expansion were to occur in less productive parts of the world, the land conversion would be even greater. For example, Brazil would require an area that is almost three times as large to derive the same amount of calories from maize.[16] As shown

[15]As pointed out above, not instrumenting the price can bias the results towards zero as outlined in the soybean rust example in the introduction.

[16]It should be noted that we are using average calories per acre, yet the correct measure would be the amount of calories obtained on the marginal land. These numbers should hence been seen as a first proxy.

in Table 9, exporting countries like the Unites States and Brazil have been more responsive to fluctuations in world price.

5 Conclusions

We have two basic goals with this analysis. The first is to demonstrate how yield shocks (deviations from a trend), which are likely attributable to random weather fluctuations, can facilitate estimation of both supply and demand of agricultural commodities. The second objective is to estimate elasticities for caloric energy from the world's most predominant food commodities.

Our model is simple. By aggregating crops and countries, we obscure the likely importance of many important factors, especially the imperfect substitutability of crops, transportation costs, tariffs, trade restrictions, and agricultural subsidies. But what the model lacks in complexity, it gains in transparency. We see these estimates as a complement to larger and more sophisticated models, wherein local supply and demand responses are either assumed or estimated individually, and transportation and trade restrictions are carefully accounted for. Our estimates provide a useful reality check for whether micro complexities add up to patterns that are observable in the aggregate data.

With this perspective in mind, we consider price and quantity predictions stemming from the rapid and largely policy-induced expansion of ethanol demand. This policy has diverted (or will soon divert) approximately 5 percent of world caloric production into ethanol production. Since commodities are storable and the current ethanol production trend was largely anticipated since the Energy Policy Act of 2005, it is reasonable to expect that futures prices would have quickly incorporated the shift in demand, even though it has taken several years for ethanol production growth to be realized. Using our preferred estimated supply and demand elasticities, a shift of this magnitude would cause an estimated increase in price equal to 30 percent if none of the corn used for biofuel production can be recycled. If the remains of corn used in biofuels is recycled as feed stock, the price increase would be scaled back accordingly. For example, if one third of the calories can be recovered as feed stock, the price increase would be lowered to 20 percent. Our estimate is smaller than what we obtain using a SUR model that does allow for the endogeneity of prices, or a model that does not instrument futures prices. This prediction is slightly larger than the USDA projected price increase made for corn in 2007, and would suggest that the ethanol subsidy had some role in the threefold price increase, but by no means can account for all of it.

It is surprising that research in agricultural economics has not made greater use of weather-based instruments. One possible reason is the difficulty in linking weather variables to agricultural outcomes, like crop yields. We have circumvented this difficulty by summing local yield deviations from trend. In theory such deviations might be part of the supply response function and therefore endogenous; in practice, however, this appears to be a small issue. Nevertheless, use of weather variables instead of yield shocks may be a promising direction for future research. To make such an approach viable will require rich weather data and a parsimonious model linking weather to yield. Yield shocks attributable to fine scaled weather shocks in the United States shows a correlation coefficient of 0.71 with jackknifed yield residuals suggesting that there is limited endogenous yield response in the United States. However, the lack of fine-scaled weather data outside the United States makes it more difficult to obtain precise yield shocks in other areas. While our results using weather-induced yield shocks are comparable to the ones we obtain in our baseline model for a parsimonious model using one lagged shock and three stage least squares, the results are not very robust.

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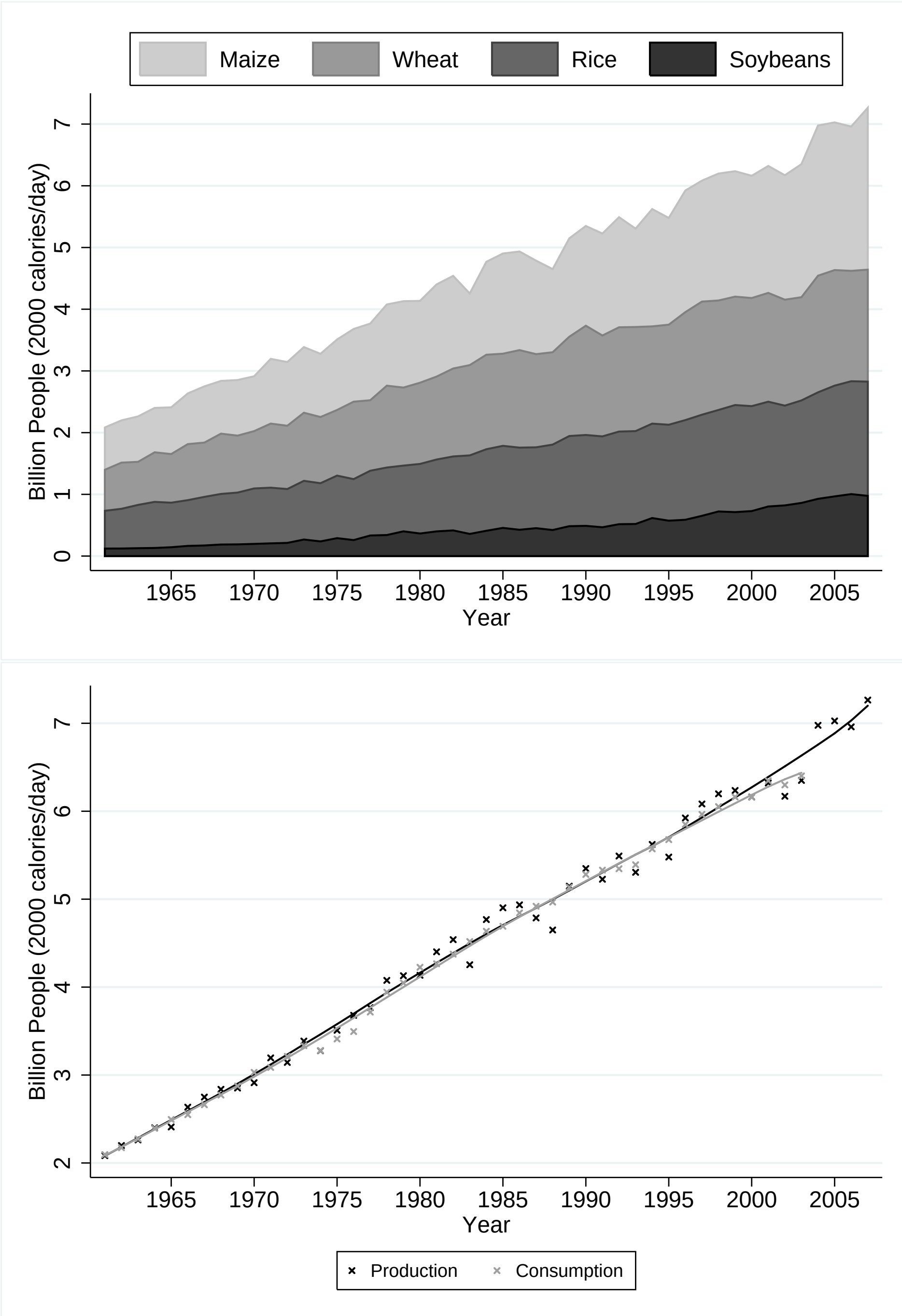
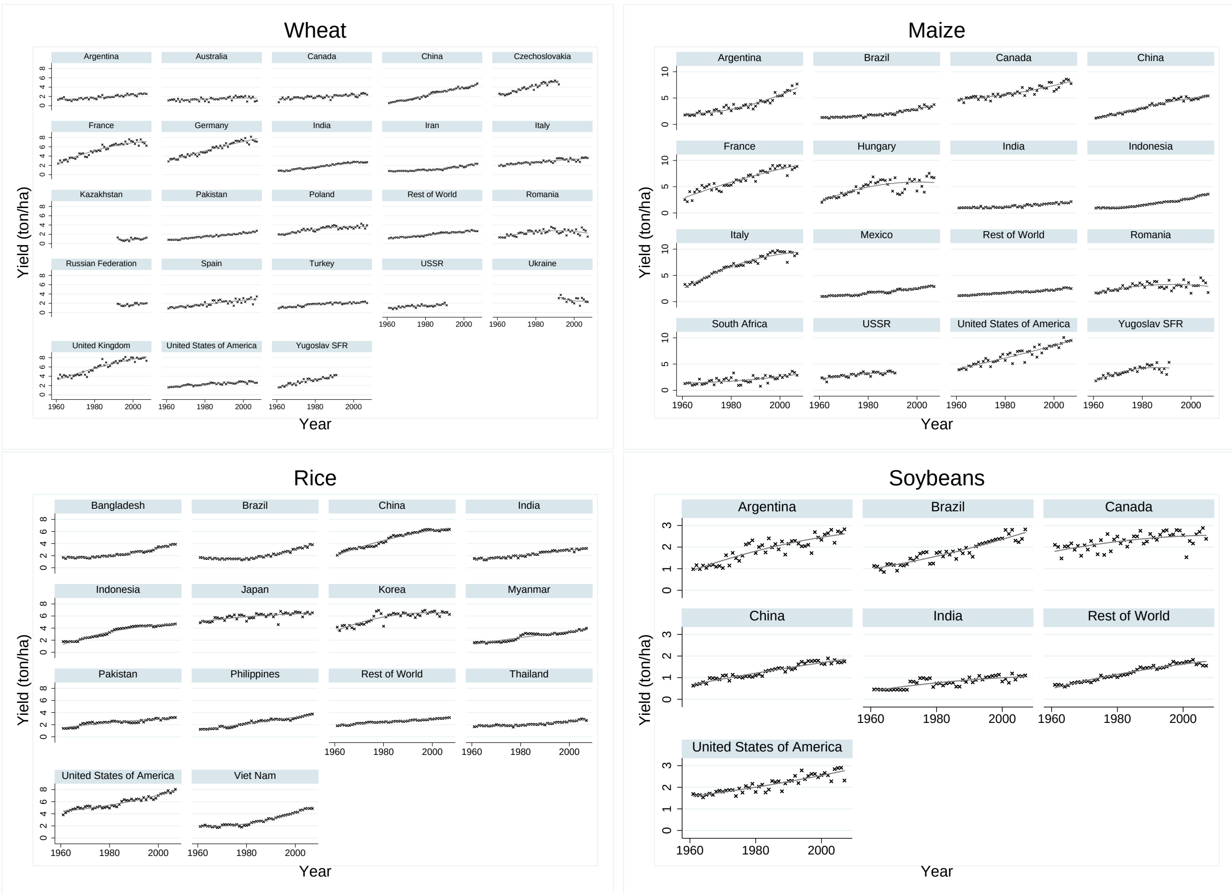
Figure 1: Production and Consumption of Calories from Maize, Wheat, Rice, and Soybeans



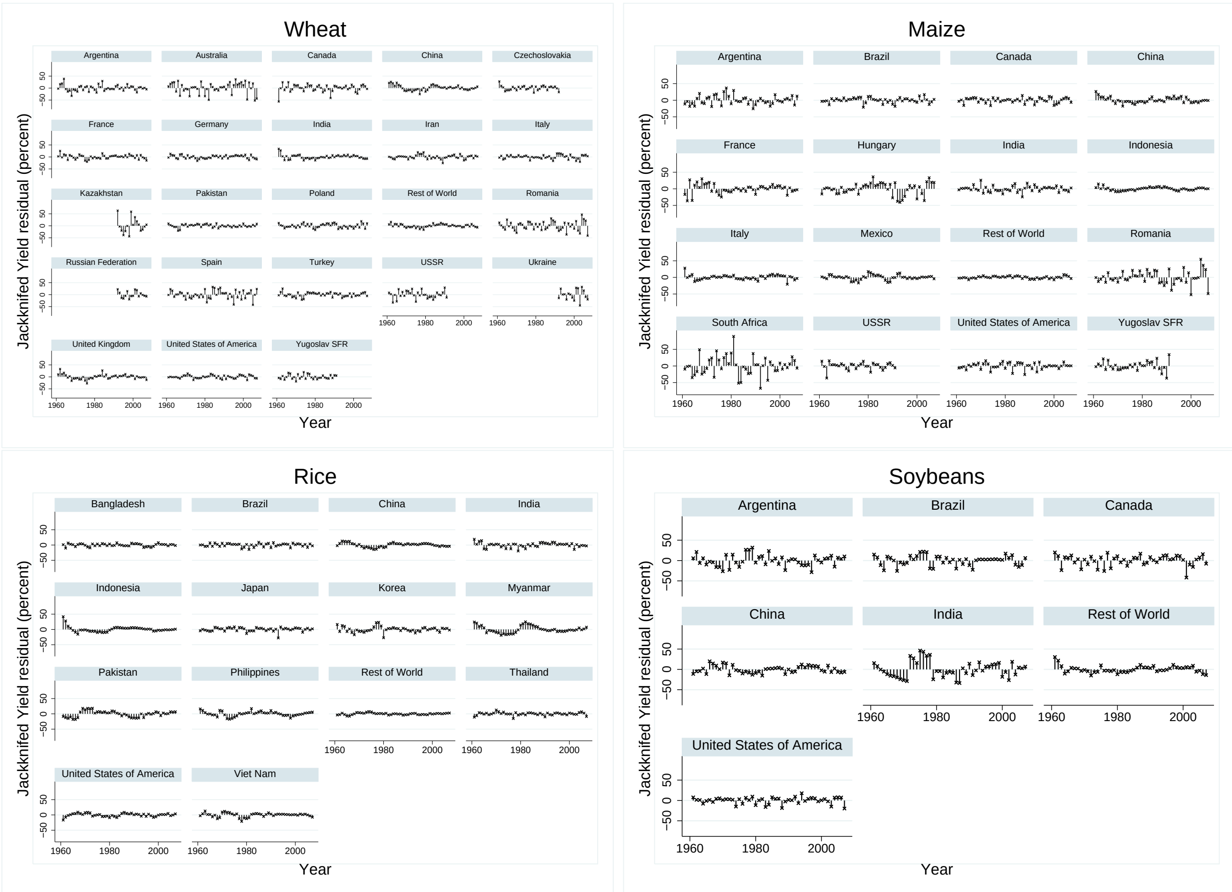
Notes: Top panel displays world production of calories from maize, wheat, rice, and soybeans for 1961-2007. The y-axis are the number of people who could be fed on a 2000 calories/day diet. Bottom level displays production as well as consumption of the same four commodities. A locally weighted regression line (bandwidth of 10 year) is added.

Figure 2: Scatter Plots of Annual Yields (Countries with more than 1 Percent of World Production)



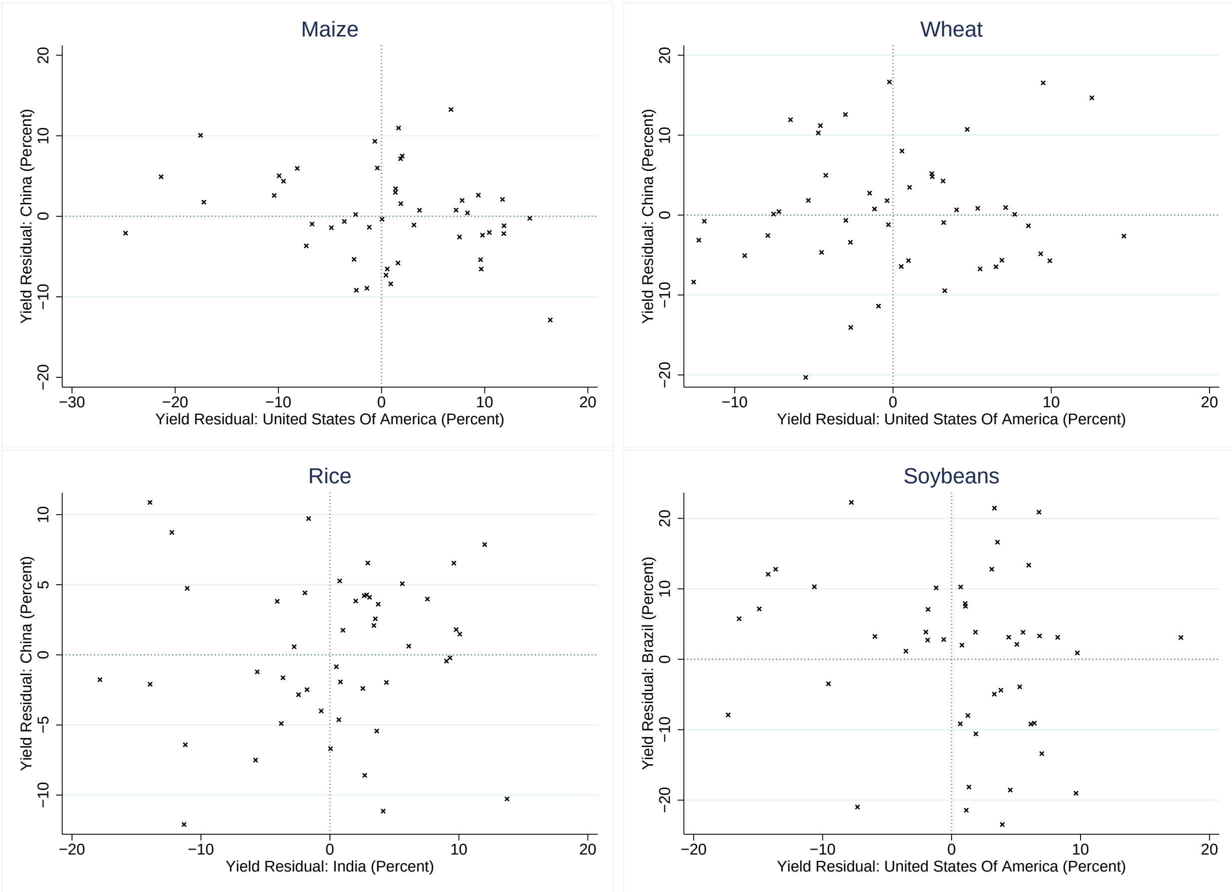
Notes: Scatter plots of yields in each country against time. A quadratic time trend is added as a solid line. Figure shows all countries that produce on average more than 1 percent of world production. All other countries are lumped together as "Rest of World".

Figure 3: Annual Jackknifed Yield Residuals (Countries with more than 1 Percent of World Production)



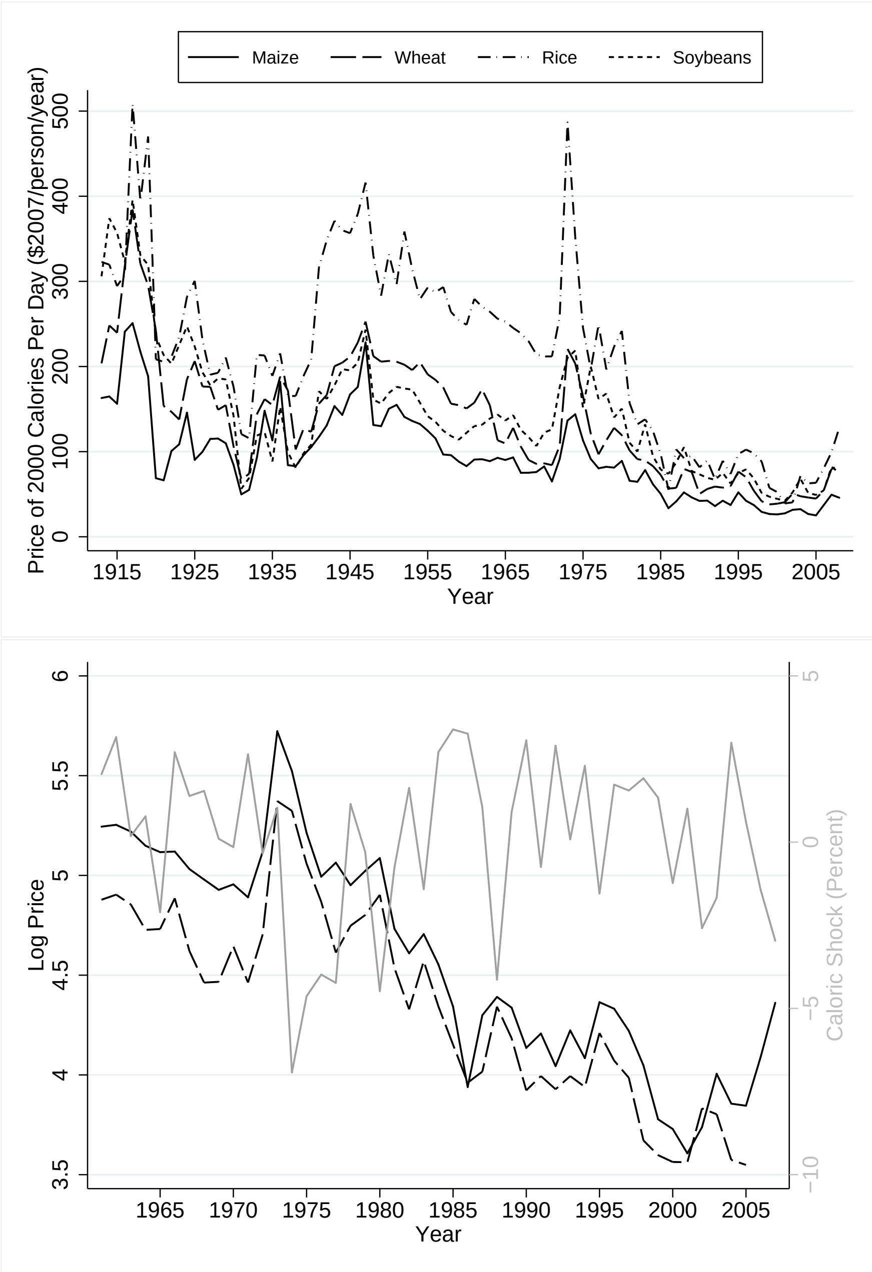
Notes: Scatter plots of jackknifed yield residuals, i.e., the residual is estimated by excluding the observation in question. Figure shows all countries that produce on average more than 1 percent of world production. All other countries are lumped together as "Rest of World".

Figure 4: Correlation of Residuals of Two Largest Producers



Notes: Figure shows scatter plots of yield residuals (deviations from a quadratic trend) of the two largest producers of each crop. The correlation coefficients are -0.24 for maize, 0.12 for wheat, 0.05 for rice, and -0.18 for soybeans.

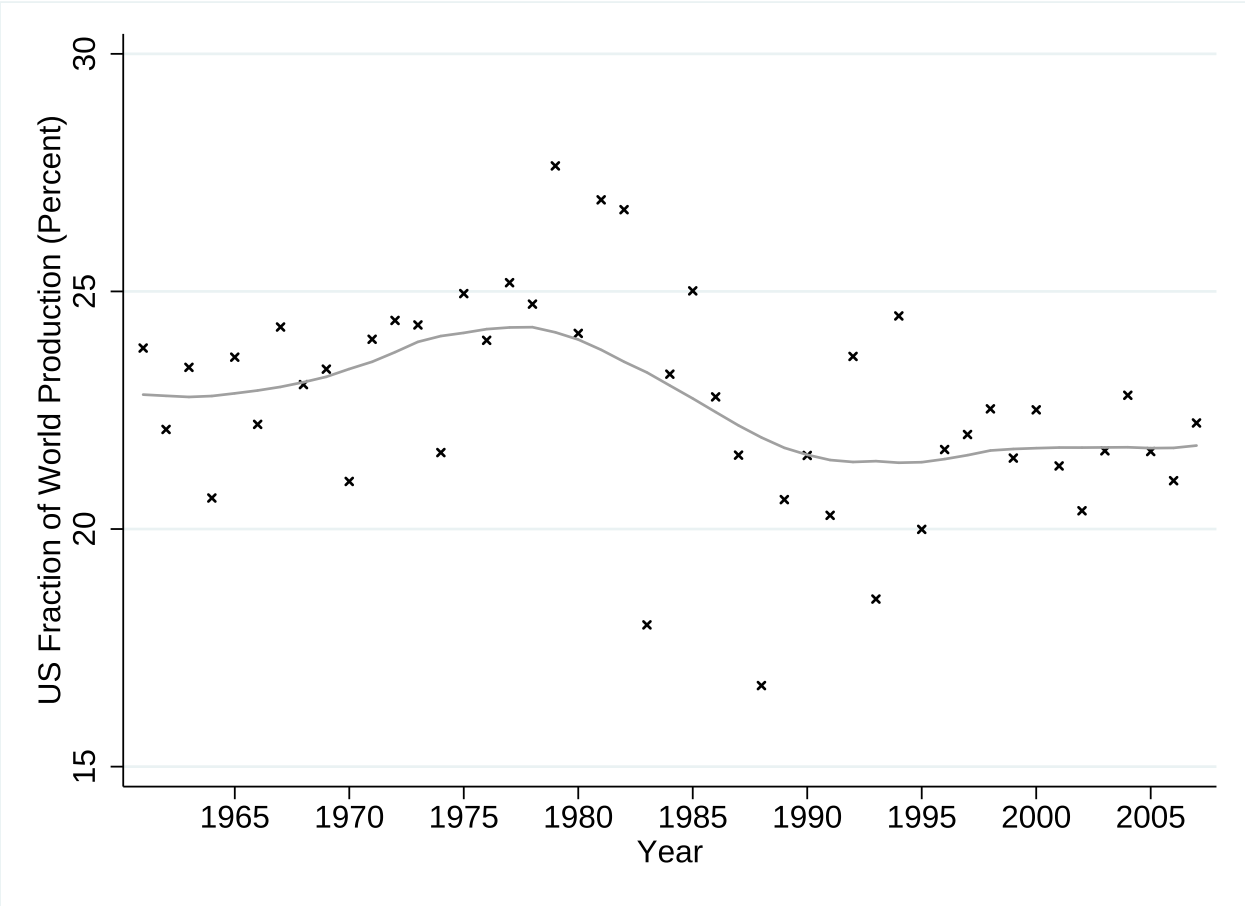
Figure 5: Price and Caloric Shocks



Notes: Top panel displays real annual cost of maize, wheat, rice, and soybeans in 2007 dollars for a 2000 calories per day diet using USDA's December price series. Overall, prices show a downward trend, and the recent spike in food prices in small in absolute terms. However, the spike is large in term of relative increase (threefold increase).

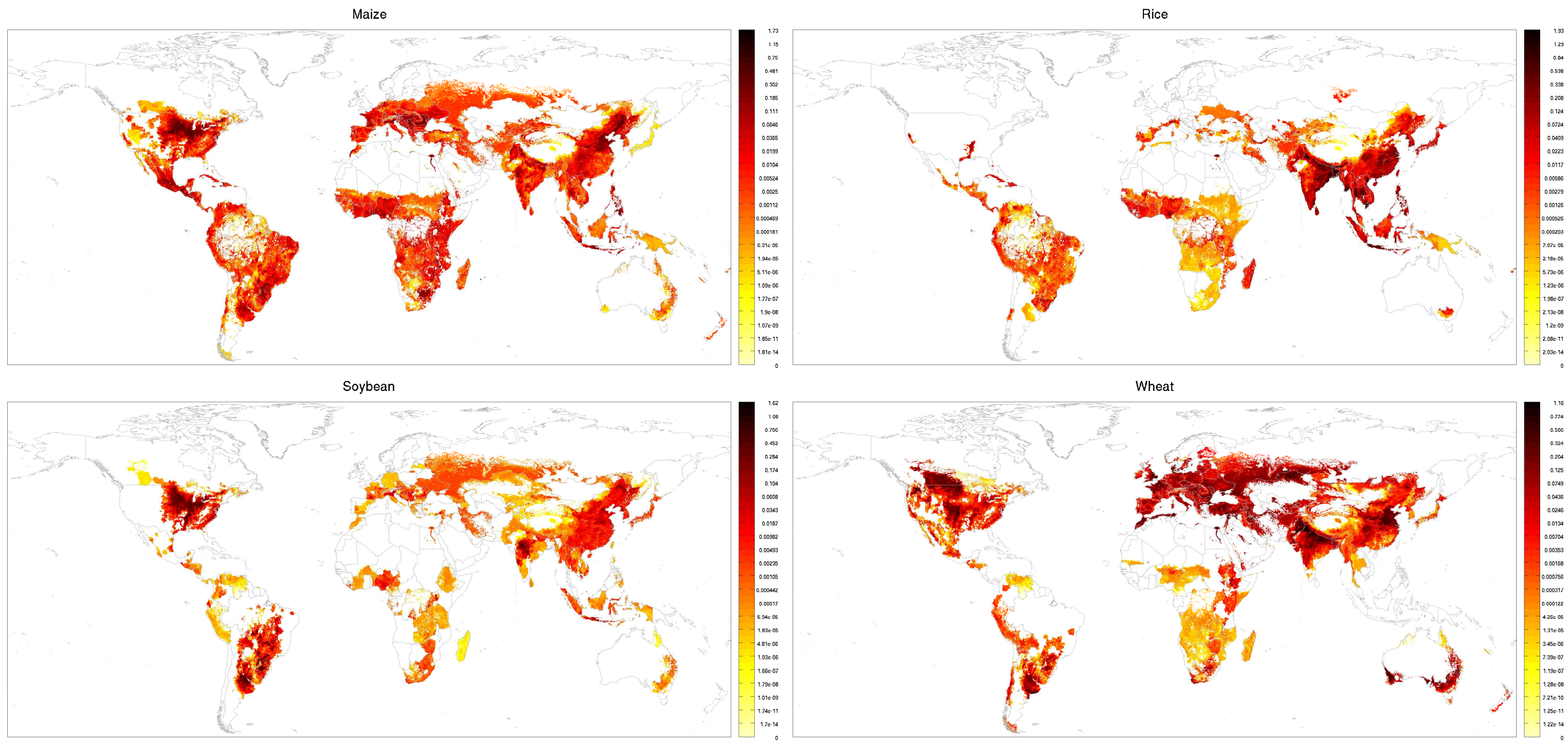
The bottom panel displays log price on the left axis in black and caloric shocks (as percent deviation from production trend) on the right axis in grey for the years 1961-2007. Production-weighted December prices of maize, wheat, rice and soybeans are shown as solid black line, while production-weighted futures prices at delivery (December for maize, November for soybeans, and September for wheat) are shown as dashed line. Shocks are deviations from country-specific yield trends for the same four commodities.

Figure 6: U.S. Share of World Production



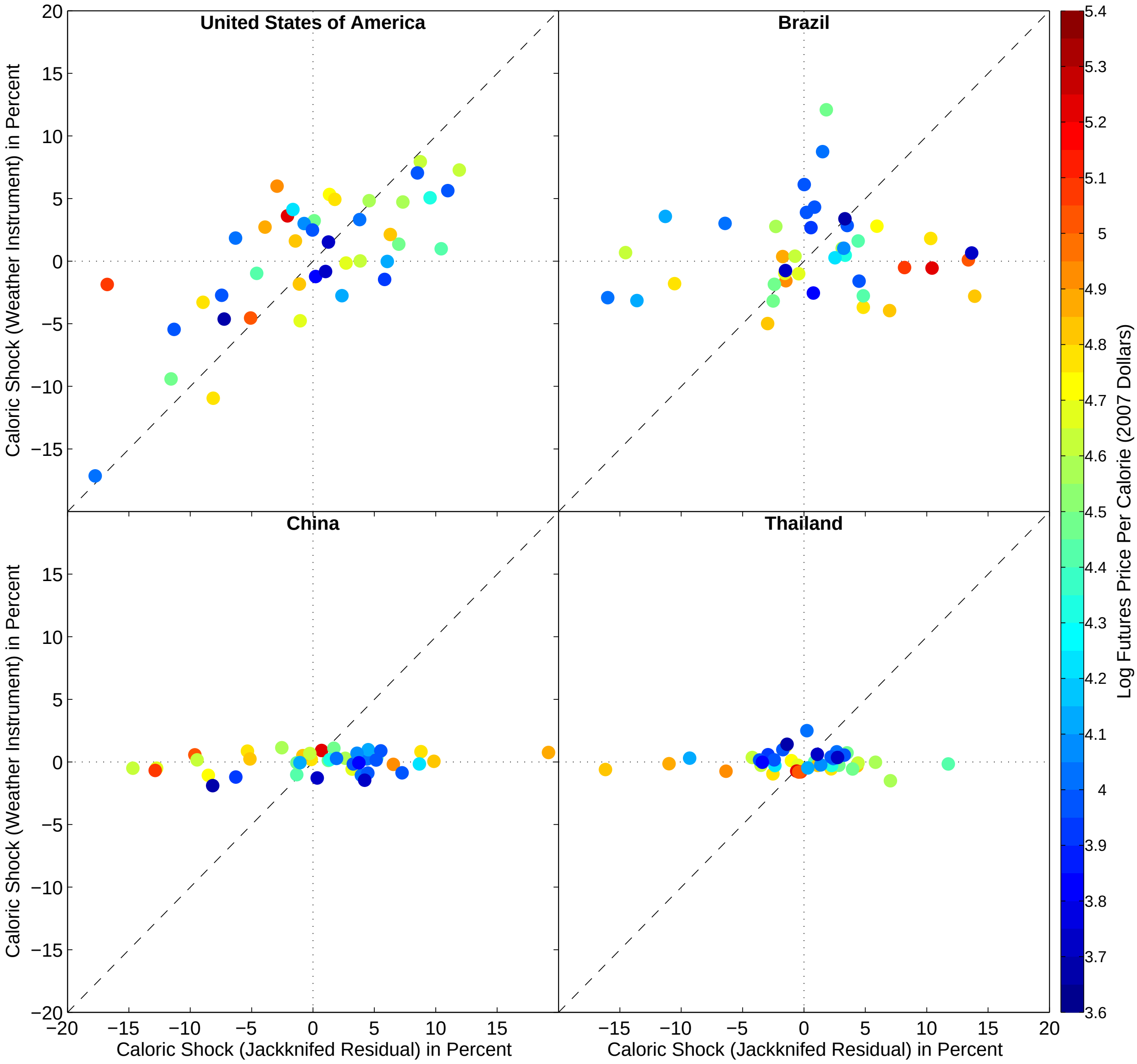
Notes: Graph displays the percent of world wide caloric production from maize, wheat, rice and soybeans that is produced in the United State. Yearly observations are shown as crosses and a locally weighted regression with a bandwidth of 10 years is added in grey.

Figure 7: World Growing Area of Crops



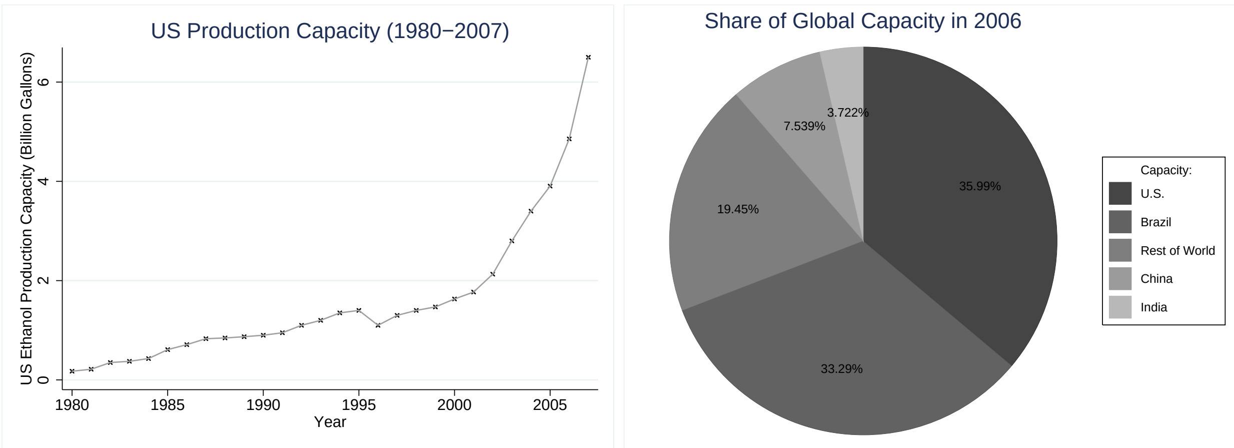
Notes: Panels displays the fraction of each grid cell that is used to grow a crop. A fraction greater than one indicates double cropping.

Figure 8: Contrasting Caloric Shocks: Deviations from Trend versus Weather Induced Residuals



Notes: Figure shows scatter plots of caloric chocks for four countries. The x-axis shows caloric shocks using yield deviations from a quadratic time trend. The y-axis uses yield shocks that are obtained from regressing yields on weather measures. The scatter plots are color coded by the futures price (traded in the previous year).

Figure 9: U.S. Ethanol Production Capacity Over Time and as Share of World Capacity



Notes: Left panel shows ethanol production capacity in billion gallons 1980-2007. The right panel shows the U.S. share of global capacity in 2006 as well as producers with next biggest market shares.

Table 1: Countries with Share of World Production Greater than 1 Percent

Country	**Share**	**Country**	**Share**
Wheat		**Maize**	
USSR	21.23	United States of America	42.00
China	14.05	China	15.66
United States of America	12.07	Brazil	5.21
India	8.53	USSR	3.52
Russian Federation	6.86	Mexico	3.01
France	5.33	Yugoslav SFR	2.47
Canada	4.81	Argentina	2.35
Turkey	3.48	France	2.32
Australia	3.13	Romania	2.15
Germany	2.89	South Africa	2.01
Ukraine	2.69	India	1.91
Pakistan	2.49	Italy	1.54
Argentina	2.23	Hungary	1.41
Italy	2.06	Indonesia	1.26
United Kingdom	2.01	Canada	1.15
Kazakhstan	1.87	Rest of World	14.07
Iran, Islamic Republic of	1.54		
Poland	1.38		
Yugoslav SFR	1.29		
Romania	1.27		
Spain	1.16		
Czechoslovakia	1.05		
Rest of World	12.12		
Rice		**Soybeans**	
China	34.44	United States of America	56.73
India	20.64	Brazil	14.43
Indonesia	7.50	China	13.05
Bangladesh	5.48	Argentina	6.62
Thailand	4.27	India	1.63
Vietnam	3.97	Canada	1.04
Japan	3.67	Rest of World	6.49
Myanmar	3.12		
Brazil	2.08		
Philippines	1.87		
Korea, Republic of	1.59		
United States of America	1.44		
Pakistan	1.07		
Rest of World	8.86		

Notes: Table reports all countries with an average yearly share of world production (1961-2007) above one percent for each crop. All other countries are lumped together as "Rest of World".

Table 2: Descriptive Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Year		1982	12.56	1961	2003
Caloric Production	billion people	4.32	1.34	2.08	6.35
Caloric Storage	million people	15.9	118	-317	210
Caloric Stock	million people	982	339	445	1564
Caloric Shock - Dev. from Linear Trend	million people	2.97	104	-226	175
Caloric Shock - Dev. from Quadratic Trend	million people	4.67	107	-240	159
Caloric Shock - Weather Inst. Linear Trend	million people	-0.00	0	-0	0
Caloric Shock - Weather Inst. Quadratic Trend	million people	0.00	0	-0	0
Caloric Price - Futures at Delivery	US$2007 per year	89.43	42.96	35.25	215.44
Caloric Price - Futures one Year Before	US$2007 per year	87.98	37.24	38.62	189.60
Caloric Price - Dec. USDA Prices	US$2007 per year	117.29	60.95	36.85	305.76
Log Caloric Supply	Log billion people	1.412	0.337	0.734	1.849
Log Caloric Demand	Log billion people	4.060	1.261	1.495	5.775
Log Caloric Price - Futures at Delivery	Log US$2007 per year	4.385	0.474	3.563	5.373
Log Caloric Price - Futures one Year Before	Log US$2007 per year	4.388	0.430	3.654	5.245
Log Caloric Price - Dec. USDA Prices	Log US$2007 per year	4.628	0.540	3.607	5.723

Notes: Descriptive Statistics of the 43 annual observations used in the demand/supply equation. Quantities are in the number of people that could be fed on a 2000 calories a day diet. Prices are the annual cost of a daily diet of 2000 calories in US$2007.

Table 3: Demand and Supply Elasticities of Calories using Jackknifed Yield Residuals

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
Demand Elasticity	-0.0505***	-0.0554***	-0.0641**	-0.0797***	-0.0668***	-0.0634***
(s.e.)	(0.0190)	(0.0167)	(0.0243)	(0.0215)	(0.0241)	(0.0226)
Supply Elasticity	0.1165***	0.1337***	0.0826***	0.0951***	0.0957***	0.0979***
(s.e.)	(0.0286)	(0.0241)	(0.0217)	(0.0189)	(0.0208)	(0.0189)
Price Increase	31.41	27.01	36.10	29.31	32.14	32.16
95% Conf. Int.	(21.32,50.14)	(20.69,36.62)	(23.75,60.31)	(22.01,40.80)	(22.23,50.00)	(22.79,48.40)
	Demand					
Price p_t	-5.05e-02***	-5.54e-02***	-6.41e-02**	-7.97e-02***	-6.68e-02***	-6.34e-02***
	(1.90e-02)	(1.67e-02)	(2.43e-02)	(2.15e-02)	(2.41e-02)	(2.26e-02)
Time Trend	4.26e-02***	4.26e-02***	4.56e-02***	4.77e-02***	4.69e-02***	4.77e-02***
	(8.32e-04)	(8.57e-04)	(2.50e-03)	(2.81e-03)	(3.03e-03)	(3.44e-03)
Time Trend^2	-4.18e-04***	-4.23e-04***	-6.12e-04***	-7.34e-04***	-6.74e-04***	-7.07e-04***
	(2.34e-05)	(2.28e-05)	(1.53e-04)	(1.63e-04)	(1.77e-04)	(1.93e-04)
Time Trend^3			2.93e-06	4.56e-06*	3.78e-06	4.23e-06
			(2.26e-06)	(2.37e-06)	(2.57e-06)	(2.74e-06)
	Supply					
$\mathbb{E}[p_t \vert_{t-1}]$	1.17e-01***	1.34e-01***	8.26e-02***	9.51e-02***	9.57e-02***	9.79e-02***
	(2.86e-02)	(2.41e-02)	(2.17e-02)	(1.89e-02)	(2.08e-02)	(1.89e-02)
Shock ω_t	2.46e-01***	2.62e-01***	2.61e-01***	2.72e-01***	2.71e-01***	2.73e-01***
	(3.37e-02)	(2.94e-02)	(2.65e-02)	(2.38e-02)	(2.56e-02)	(2.35e-02)
Time Trend	4.46e-02***	4.46e-02***	5.41e-02***	5.40e-02***	5.27e-02***	5.26e-02***
	(9.34e-04)	(8.74e-04)	(2.04e-03)	(1.89e-03)	(2.32e-03)	(2.14e-03)
Time Trend^2	-3.54e-04***	-3.44e-04***	-9.23e-04***	-9.11e-04***	-8.48e-04***	-8.43e-04***
	(2.66e-05)	(2.40e-05)	(1.12e-04)	(1.04e-04)	(1.26e-04)	(1.16e-04)
Time Trend^3			8.45e-06***	8.37e-06***	7.52e-06***	7.46e-06***
			(1.68e-06)	(1.55e-06)	(1.81e-06)	(1.68e-06)
Observations	42	42	42	42	41	41
Time Trend I	2	2	3	3	3	3
Shock Lags K	1	1	1	1	2	2

Notes: Top panel displays the demand and supply elasticity as well as the predicted price increase from an ethanol mandate that requires 5 percent of world production calories to be diverted for biofuel use (assuming none of the corn used for biofuel production is recycled as feed stock, otherwise the predicted price increase would scale accordingly). The bottom panel displays the second stage regressions in more detail. The first stage results are given in Table 4.

Table 4: First-Stage Results for Demand and Supply Equation

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
			Demand: First-Stage Instrumenting Price p_t			
Shock ω_t	-1.19e+00***	-1.16e+00***	-1.12e+00***	-9.92e-01***	-1.04e+00***	-1.07e+00***
	(2.62e-01)	(2.47e-01)	(2.93e-01)	(2.65e-01)	(2.97e-01)	(2.57e-01)
Shock ω_{t-1}					-3.99e-01	-3.30e-01
					(2.95e-01)	(2.02e-01)
Time Trend	-8.43e-03	-6.49e-03	4.64e-03	2.03e-02	7.05e-04	2.32e-02
	(9.73e-03)	(1.01e-02)	(2.64e-02)	(2.84e-02)	(3.22e-02)	(3.28e-02)
Time Trend^2	-5.49e-04**	-5.88e-04***	-1.32e-03	-2.10e-03	-1.08e-03	-2.12e-03
	(2.24e-04)	(2.28e-04)	(1.47e-03)	(1.53e-03)	(1.72e-03)	(1.71e-03)
Time Trend^3			1.22e-05	2.32e-05	8.68e-06	2.26e-05
			(2.27e-05)	(2.33e-05)	(2.60e-05)	(2.54e-05)
			Supply: First-Stage Instrumenting Expected Price $\mathbb{E}[p_t\|_{t-1}]$			
Shock ω_{t-1}	-8.60e-01***	-7.52e-01***	-9.18e-01***	-8.17e-01***	-8.33e-01***	-8.45e-01***
	(2.14e-01)	(1.91e-01)	(2.26e-01)	(1.98e-01)	(2.20e-01)	(1.96e-01)
Shock ω_{t-2}					-3.53e-01	-3.41e-01*
					(2.21e-01)	(1.89e-01)
Shock ω_t	-6.10e-01***	-6.35e-01***	-6.82e-01***	-6.75e-01***	-6.39e-01***	-6.45e-01***
	(2.10e-01)	(1.97e-01)	(2.27e-01)	(2.09e-01)	(2.20e-01)	(1.99e-01)
Time Trend	-1.04e-02	-9.64e-03	-3.01e-02	-2.54e-02	-2.14e-02	-2.17e-02
	(8.15e-03)	(7.64e-03)	(2.46e-02)	(2.26e-02)	(2.77e-02)	(2.51e-02)
Time Trend^2	-4.39e-04**	-4.57e-04***	6.72e-04	4.25e-04	2.55e-04	2.76e-04
	(1.85e-04)	(1.73e-04)	(1.32e-03)	(1.21e-03)	(1.43e-03)	(1.30e-03)
Time Trend^3			-1.69e-05	-1.34e-05	-1.07e-05	-1.11e-05
			(1.99e-05)	(1.83e-05)	(2.10e-05)	(1.91e-05)
Observations	42	42	42	42	41	41
Time Trend I	2	2	3	3	3	3
Shock Lags K	1	1	1	1	2	2

Notes: Table displays the first stage regressions for the results in Table 3.

Table 5: First-Stage Results separating Maize/Soybeans and Rice/Wheat Shocks

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
	Demand: First-Stage Instrumenting Price p_t					
Shock $\omega_{t,MS}$	-1.14e+00**	-1.18e+00***	-1.18e+00**	-1.01e+00***	-1.04e+00**	-1.09e+00***
	(4.71e-01)	(4.03e-01)	(4.79e-01)	(3.87e-01)	(4.83e-01)	(3.74e-01)
Shock $\omega_{t,RW}$	-1.22e+00***	-1.21e+00***	-1.08e+00**	-1.15e+00***	-9.78e-01**	-1.18e+00***
	(3.51e-01)	(3.10e-01)	(4.41e-01)	(3.59e-01)	(4.58e-01)	(3.54e-01)
Shock $\omega_{t-1,MS}$					1.95e-01	-5.16e-02
					(4.90e-01)	(3.38e-01)
Shock $\omega_{t-1,RW}$					-9.29e-01**	-6.74e-01**
					(4.35e-01)	(3.34e-01)
Time Trend	-8.75e-03	-6.82e-03	6.87e-03	1.25e-02	-2.52e-02	-3.95e-03
	(1.02e-02)	(1.03e-02)	(3.11e-02)	(3.17e-02)	(4.25e-02)	(3.96e-02)
Time Trend^2	-5.41e-04**	-5.79e-04**	-1.44e-03	-1.69e-03	1.98e-04	-7.55e-04
	(2.37e-04)	(2.34e-04)	(1.71e-03)	(1.69e-03)	(2.23e-03)	(2.04e-03)
Time Trend^3			1.38e-05	1.72e-05	-8.88e-06	3.61e-06
			(2.60e-05)	(2.54e-05)	(3.26e-05)	(2.97e-05)
F-stat	0.0146		0.0195		1.3904	
χ^2-stat		0.0039		0.0627		1.5022
p-value	0.9040	0.9505	0.8892	0.8023	0.2557	0.4719
	Supply: First-Stage Instrumenting Expected Price $\mathbb{E}[p_t\|_{t-1}]$					
Shock $\omega_{t-1,MS}$	-6.88e-01*	-6.25e-01**	-4.91e-01	-5.43e-01*	-5.03e-01	-5.43e-01*
	(3.67e-01)	(3.15e-01)	(3.66e-01)	(3.03e-01)	(3.64e-01)	(3.11e-01)
Shock $\omega_{t-1,RW}$	-8.56e-01***	-7.00e-01***	-1.15e+00***	-9.46e-01***	-1.01e+00***	-9.97e-01***
	(3.00e-01)	(2.59e-01)	(3.25e-01)	(2.76e-01)	(3.37e-01)	(2.88e-01)
Shock $\omega_{t-2,MS}$					7.62e-03	7.44e-02
					(3.61e-01)	(2.88e-01)
Shock $\omega_{t-2,RW}$					-5.75e-01*	-6.07e-01**
					(3.28e-01)	(2.64e-01)
Shock $\omega_{t,MS}$	-2.63e-01	-2.64e-01	-9.26e-02	-9.33e-02	-1.28e-01	-1.38e-01
	(3.64e-01)	(3.32e-01)	(3.61e-01)	(3.20e-01)	(3.50e-01)	(3.01e-01)
Shock $\omega_{t,RW}$	-8.22e-01***	-8.89e-01***	-1.20e+00***	-1.23e+00***	-1.03e+00***	-1.06e+00***
	(2.94e-01)	(2.66e-01)	(3.42e-01)	(3.03e-01)	(3.45e-01)	(2.96e-01)
Time Trend	-1.31e-02	-1.22e-02	-7.37e-02**	-6.49e-02**	-7.10e-02*	-7.35e-02**
	(8.75e-03)	(7.94e-03)	(3.18e-02)	(2.78e-02)	(3.77e-02)	(3.22e-02)
Time Trend^2	-3.73e-04*	-3.95e-04**	2.90e-03*	2.45e-03*	2.72e-03	2.85e-03*
	(2.00e-04)	(1.81e-04)	(1.66e-03)	(1.46e-03)	(1.90e-03)	(1.63e-03)
Time Trend^3			-4.82e-05*	-4.21e-05**	-4.48e-05	-4.66e-05**
			(2.43e-05)	(2.14e-05)	(2.72e-05)	(2.33e-05)
F-stat	0.1179		1.5607		0.8349	
χ^2-stat		0.0326		0.8421		2.9795
p-value	0.7323	0.8568	0.2158	0.3588	0.4385	0.2254
Observations	42	42	42	42	41	41
Time Trend I	2	2	3	3	3	3
Shock Lags K	1	1	1	1	2	2

Notes: Table displays first stage regressions results when we separate caloric shocks from maize and soybeans (subscript MS) and rice and wheat (subscript RW). Table includes Wald tests in the last three rows of each panel to check whether coefficients for maize and soybeans are different from coefficients for rice and wheat in the first four rows of each panel. None of the p-values is below 0.1, suggesting that pooling the four crops is adequate.

Table 6: Sensitivity Checks: Elasticities Estimated using Jackknifed Yield Residuals

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
			Panel A: Baseline			
Demand Elasticity	-0.0505***	-0.0554***	-0.0641**	-0.0797***	-0.0668***	-0.0634***
(s.e.)	(0.0190)	(0.0167)	(0.0243)	(0.0215)	(0.0241)	(0.0226)
Supply Elasticity	0.1165***	0.1337***	0.0826***	0.0951***	0.0957***	0.0979***
(s.e.)	(0.0286)	(0.0241)	(0.0217)	(0.0189)	(0.0208)	(0.0189)
Price Increase	31.41	27.01	36.10	29.31	32.14	32.16
95% Conf. Int.	(21.32,50.14)	(20.69,36.62)	(23.75,60.31)	(22.01,40.80)	(22.23,50.00)	(22.79,48.40)
			Panel B: Caloric Shock Derived using Linear Time Trend			
Demand Elasticity	-0.0492**	-0.0544***	-0.0590**	-0.0715***	-0.0616**	-0.0575***
(s.e.)	(0.0192)	(0.0169)	(0.0234)	(0.0211)	(0.0234)	(0.0220)
Supply Elasticity	0.1058***	0.1206***	0.0868***	0.1010***	0.1008***	0.1038***
(s.e.)	(0.0261)	(0.0219)	(0.0230)	(0.0194)	(0.0229)	(0.0206)
Price Increase	33.91	29.20	36.43	29.70	32.24	32.21
95% Conf. Int.	(22.88,54.59)	(22.32,39.68)	(23.80,61.39)	(22.33,41.26)	(22.07,50.88)	(22.67,48.94)
			Panel C: Caloric Shock Derived using Quadratic Area Trend			
Demand Elasticity	-0.0489**	-0.0528***	-0.0614**	-0.0740***	-0.0639***	-0.0595***
(s.e.)	(0.0185)	(0.0165)	(0.0233)	(0.0211)	(0.0233)	(0.0216)
Supply Elasticity	0.1171***	0.1318***	0.0856***	0.0970***	0.0988***	0.1013***
(s.e.)	(0.0274)	(0.0230)	(0.0206)	(0.0178)	(0.0199)	(0.0180)
Price Increase	31.51	27.66	35.85	29.95	31.96	32.15
95% Conf. Int.	(21.66,49.45)	(21.23,37.39)	(24.04,58.22)	(22.59,41.46)	(22.44,48.72)	(23.15,47.34)
			Panel D: Rescaled Caloric Conversion Factors to Equalize Average Prices			
Demand Elasticity	-0.0629***	-0.0578***	-0.0803***	-0.0794***	-0.0662***	-0.0655***
(s.e.)	(0.0184)	(0.0151)	(0.0237)	(0.0167)	(0.0200)	(0.0199)
Supply Elasticity	0.1247***	0.1347***	0.0716***	0.0783***	0.0808***	0.0801***
(s.e.)	(0.0362)	(0.0289)	(0.0165)	(0.0142)	(0.0154)	(0.0139)
Price Increase	28.15	26.64	34.27	32.18	35.13	35.38
95% Conf. Int.	(18.71,46.27)	(19.92,37.27)	(23.97,52.50)	(25.63,41.52)	(25.44,51.32)	(25.87,51.01)
			Panel E: Caloric Shock not Divided by Inventory			
Demand Elasticity	-0.0439**	-0.0464***	-0.0555**	-0.0654***	-0.0564**	-0.0535**
(s.e.)	(0.0180)	(0.0158)	(0.0225)	(0.0198)	(0.0218)	(0.0205)
Supply Elasticity	0.1219***	0.1376***	0.0870***	0.1001***	0.0991***	0.1031***
(s.e.)	(0.0285)	(0.0230)	(0.0208)	(0.0172)	(0.0193)	(0.0169)
Price Increase	31.61	27.70	37.01	30.87	33.43	32.89
95% Conf. Int.	(21.55,50.13)	(21.46,36.99)	(24.67,60.68)	(23.65,41.84)	(23.51,50.83)	(24.11,47.24)
			Panel F: Futures Price for Maize and Soybeans Traded in March			
Demand Elasticity	-0.0505***	-0.0554***	-0.0641**	-0.0797***	-0.0668***	-0.0642***
(s.e.)	(0.0190)	(0.0167)	(0.0243)	(0.0215)	(0.0241)	(0.0226)
Supply Elasticity	0.1234***	0.1455***	0.0858***	0.1009***	0.0981***	0.1001***
(s.e.)	(0.0323)	(0.0268)	(0.0232)	(0.0199)	(0.0218)	(0.0197)
Price Increase	30.34	25.45	35.38	28.36	31.68	31.60
95% Conf. Int.	(20.20,49.76)	(19.40,34.71)	(23.18,59.42)	(21.35,39.31)	(21.87,49.45)	(22.33,47.74)
Observations	42	42	42	42	41	41
Time Trend I	2	2	3	3	3	3
Shock Lags K	1	1	1	1	2	2

Notes: Sensitivity checks of results from Table 3 to various modeling assumptions. Panel A displays the baseline results from Table 3 for comparison.

Table 7: Sensitivity Checks: Elasticities Estimated using Yield Shocks Attributable to Observed Weather Shocks

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
			Panel A: Baseline			
Demand Elasticity	-0.0505***	-0.0554***	-0.0641**	-0.0797***	-0.0668***	-0.0634***
(s.e.)	(0.0190)	(0.0167)	(0.0243)	(0.0215)	(0.0241)	(0.0226)
Supply Elasticity	0.1165***	0.1337***	0.0826***	0.0951***	0.0957***	0.0979***
(s.e.)	(0.0286)	(0.0241)	(0.0217)	(0.0189)	(0.0208)	(0.0189)
Price Increase	31.41	27.01	36.10	29.31	32.14	32.16
95% Conf. Int.	(21.32,50.14)	(20.69,36.62)	(23.75,60.31)	(22.01,40.80)	(22.23,50.00)	(22.79,48.40)
			Panel B: Production Shock Derived using Observed Weather			
Demand Elasticity	-0.0315	-0.0591	-0.0324	-0.0682	-0.0404	-0.0569
(s.e.)	(0.1144)	(0.0494)	(0.1197)	(0.0539)	(0.0621)	(0.0347)
Supply Elasticity	-1.8247	0.1532***	1.6023	0.1555***	-0.2373	-0.4045
(s.e.)	(48.0201)	(0.0388)	(32.5143)	(0.0461)	(0.4016)	(0.3542)
Price Increase	0.02	26.98	-0.02	25.39	3.00	-4.77
95% Conf. Int.	(-1.65,1.66)	(14.88,55.91)	(-2.43,2.47)	(13.75,58.30)	(-177.35,170.22)	(-146.83,131.75)
Observations	41	41	41	41	40	40
Time Trend I	2	2	3	3	3	3
Shock Lags K	1	1	1	1	2	2

Notes: Sensitivity checks of results from Table 3 to modeling yield shocks using observed weather outcomes. Caloric shocks in panel B are derived as follows: For the United States we fit a model that uses degree days and a quadratic in total precipitation following Schlenker and Roberts (2009), while rice and wheat are modeled using a quadratic in average temperature and total precipitation during the growing season. We estimate a quadratic in average temperature and total precipitation for a panel of all other countries that produces more than 1 percent of a particular crop. All other countries are lumped together as "Rest of World", where the weather variables are the area-weighted average of all countries. All regressions include a quadratic time trend.

Table 8: Replication of Other Approaches: Demand and Supply of Calories

	SUR - Price Not Instrumented		**Demand Instrumented / Supply Not Instrumented**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Demand Elasticity	-0.0173*	-0.0187*	-0.0489***	-0.0489***	-0.0489***	-0.0655***
(s.e.)	(0.0094)	(0.0098)	(0.0180)	(0.0180)	(0.0180)	(0.0243)
Supply Elasticity	0.0159	0.0136	0.0226	0.0245	0.0238	0.0226
(s.e.)	(0.0182)	(0.0162)	(0.0239)	(0.0251)	(0.0274)	(0.0239)
Price Increase	197.31	191.37	146.21	124.40	75.41	80.69
95% Conf. Int.	(-694.47,1147.67)	(-646.87,1145.45)	(36.94,299.62)	(35.79,294.97)	(34.00,343.52)	(31.62,209.22)
Time Trend I	2	3	2	2	2	3
Shocks Lags K	n.A.	n.A.	1	1	1	2
Supply Lags	n.A.	n.A.	0	1	2	0

Notes: The first two columns do not instrument price (which is arguably endogenous) and simply use the observed price in a year in both the supply and demand equation. The last four columns follow the approach of Nerlove (1958) and do not instrument futures prices in the supply equation. Following the literature, lagged supply quantities are included in some regressions.

Table 9: Acreage Changes in Response to Past Caloric Shocks and Instrumented Price

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
			Panel A: World Growing Area			
Shock ω_{t-1}	-0.0599***	-0.0620***				
	(0.0147)	(0.0186)				
$\mathbb{E}[p_t\|_{t-1}]$			0.0725***	0.0634***	0.0756***	0.0750***
			(0.0146)	(0.0148)	(0.0130)	(0.0140)
			Panel B: Growing Area of United States			
Shock ω_{t-1}	-0.2642***	-0.2512***				
	(0.0654)	(0.0826)				
$\mathbb{E}[p_t\|_{t-1}]$			0.3200***	0.2569***	0.3350***	0.2967***
			(0.0562)	(0.0566)	(0.0504)	(0.0527)
			Panel C: Growing Area of Brazil			
Shock ω_{t-1}	-0.3111***	-0.2304**				
	(0.0731)	(0.0897)				
$\mathbb{E}[p_t\|_{t-1}]$			0.3768***	0.2356**	0.3681***	0.2233**
			(0.1096)	(0.0947)	(0.0986)	(0.0877)
			Panel D: Growing Area of China			
Shock ω_{t-1}	-0.0256	-0.0424				
	(0.0272)	(0.0340)				
$\mathbb{E}[p_t\|_{t-1}]$			0.0311	0.0434	0.0371	0.0713**
			(0.0299)	(0.0311)	(0.0265)	(0.0277)
			Panel E: Growing Area of India			
Shock ω_{t-1}	-0.0124	-0.0049				
	(0.0262)	(0.0331)				
$\mathbb{E}[p_t\|_{t-1}]$			0.0150	0.0050	0.0259	0.0065
			(0.0296)	(0.0315)	(0.0266)	(0.0287)
			Panel F: Growing Area of Thailand			
Shock ω_{t-1}	-0.1078*	-0.1636**				
	(0.0553)	(0.0682)				
$\mathbb{E}[p_t\|_{t-1}]$			0.1306*	0.1673**	0.0979*	0.1020
			(0.0672)	(0.0730)	(0.0591)	(0.0640)
Observation	42	42	42	42	41	41
Time Trend I	2	3	2	3	2	3
Shock Lags K	n.a.	n.a.	1	1	2	2

Notes: First two columns show regression results of log total world growing area (for maize, wheat, rice, and soybeans) on lagged weather shocks using various time trends as controls. The last four columns regress log total area on instrumented lagged prices. Columns (3) and (4) use up to one lag of the weather shock as the instrument, while columns (5) and (6) use up to two lags.

Table 10: Calories per Acre in 2007

Country	Maize	Wheat	Rice	Soybeans
Argentina	16.96	5.82		8.59
Australia		3.61		
Bangladesh			8.16	
Brazil	8.91		8.10	8.83
Canada	20.01	5.37		8.39
China	13.29	9.89	13.6	6.09
France	22.11	15.60		
Germany		16.93		
Hungary	14.14			
India	5.16	6.24	6.82	3.44
Indonesia	8.74		9.64	
Iran		5.04		
Italy	22.93	7.58		
Japan			13.33	
Kazakhstan		2.72		
Korea			13.22	
Mexico	7.30			
Myanmar			7.77	
Pakistan		5.64	6.26	
Philippines			7.44	
Poland		7.92		
Rest of World	6.27	6.22	6.42	5.78
Romania	7.13	4.98		
Russian Federation		4.60		
South Africa	7.43			
Spain		6.31		
Thailand			6.01	
Turkey		4.71		
Ukraine		5.63		
United Kingdom		17.92		
United States of America	23.04	6.00	16.21	9.12
Vietnam			10.74	

Notes: Table gives the number of million calories per hectare using the predicted yield (along the trend) in 2007.