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 current expected price through inventory accretion or depletion, thereby exogenously shifting the demand for new production. Our estimated supply elasticities are larger than the standard approach taken in the literature, which uses past prices to instrument for current prices. The problem with the standard approach is that past prices are endogenous to anticipated shifts in supply. Our instrument separates exogenous weather-induced price fluctuations from those stemming from forecastable variations in growing area. 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. As a result, world food prices are predicted to increase by 30 percent and global consumer surplus from food consumption is predicted to decrease by 156 billion dollars annually.

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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). Since many countries in Africa are net food importers, an increase in the price of food is equivalent to a decrease in real income. It is hence important for policy makers to know the drivers of rising food prices.

In this article we exploit yield shocks – deviations from country and crop-specific yield trends that are arguably due to 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 one curve (supply or demand) in a way that is plausibly unrelated to shifts in the other 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. In this paper we also show how weather-induced yield shocks can be used to identify the supply curve. Past weather shocks affect current inventories and thus expected future prices via storage. If past yield-shocks are bad and inventories are at low levels, the demand for new production goes up. In other words past weather shocks exogenously shift demand for current production in a way that is plausibly unrelated to current supply.

In a second step, we 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 to the following other factors: First, rising oil prices have accelerated the demand for biofuels as an alternative fuel source. Second, there has been a sharp increase in the demand for basic

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

calories, especially through the increased demand for meat, which is highly income elastic. China showed a more than 33-fold increase in per-capita meat consumption between 1961 and 2006 (FAO) and consumed a little less than a third of the world's meat in 2006. Meat requires roughly 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 potential reason for the threefold price increase is a decrease in supply due to detrimental weather, such as the prolonged drought in Australia. Fourth, while some have argued that the commodity price boom, much like earlier housing and stock market booms, were due to a speculative bubble, it is difficult to reconcile a bubble with an absence of inventory growth. Yet, inventories of all major commodities remained at historically low levels throughout the boom. Finally, prices have fallen precipitously 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 top 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 as shown in the top panel of Figure 4. Aggregating crops on a caloric basis facilitates a simple yet broad-scale analysis of the supply and demand of staple food commodities.

$$\text{Supply:} \quad log(S_t) = \alpha_s + \beta_s log(P_{t-1}) + f(t) + u_t \tag{1}$$

$$\text{Demand:} \quad log(D_t) = \alpha_d + \beta_d log(P_t) + g(t) + v_t \tag{2}$$

Quantities supplied and demanded are denoted by S_t and D_t, respectively; P_t is price; the parameters β_s and β_d are supply and demand elasticites; α_s and α_d are intercepts; $f(t)$ 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 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 for the next period. Since prices are close to random walks, the current period price is a good forecast for next period's expected price. The empirical section below presents evidence that a unit root cannot be rejected for our price series.[2]

Storage is a characteristic feature of all four commodity markets. Maize, wheat, rice, and soybeans 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 supply equals demand plus the net change in storage (denoted N_t)

$$\text{Equilibrium:} \quad S_t = D_t + N_t \tag{3}$$

In our estimation below we do not focus on the theoretical underpinnings of speculative storage, which is a dynamic and forward-looking decision. However, we do account for storage and the fact that storage, like prices and quantity supplied and demanded, are endogenous. Since we aggregate commodities over all countries, there is no need to consider exports or imports as they would cancel out in the sum.

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.

1.1 Identification of Demand

Demand for the 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

[2] A common econometric model of agricultural supply follows Nerlove (1958), which derives supply response as an adaptive function of expected price, and expected price follows from an autoregressive process. The reduced form of the Nerlove model regresses quantity against lagged price and two lags of quantity. In our application, lagged quantities are far from statistically significant so the Nerlove model reduces to our model. The difference is that we account for the endogeneity of expected prices.

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 of v_t plausibly unrelated to u_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. 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.

Our 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 largely due to weather. This premise is supported by the fact that 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). Such a pattern is consistent with random weather shocks but less consistent with structural shifts or technological innovations that would likely display a higher degree of autocorrelation. A more advanced study might rely on specific weather variables as instruments. However, incomplete global weather data may limit the practicability and statistical power of this approach.

1.2 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. We can do this by looking at inventory levels and storage, which links demand for new production with past weather shocks. Negative yield-shocks reduce supply and inventories while increasing the price, thereby shifting demand for new production. These past weather shocks are unlikely to be associated with current supply shifters, such as pest infestations or technological change. Put another way, past weather-induced yield shocks, via storage, exogenously shift demand for future production, allowing for clear identification of supply.

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 (N_t). Thus, we can think of these past weather shocks as shifters in the demand for current supply ($D_t + N_t$) on the right-hand side of the equilibrium condition (1), and not as component of the raw demand shifters (v_t). Because N_t is linked to past yield shocks, demand for current supply (and expected prices) shifts with past yield shocks.

Using past yield shocks as an instrument for current expected prices would seem to be a useful improvement over 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. The problem with the standard approach is that expected prices are still confounded by non-weather components of unobserved supply shifters (u_t). 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 random weather effects (see next paragraph), 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.

Our own approach of using past yield shocks as an instrument for expected price is not without its own potential pitfalls: Are prices anticipating yield changes in the next period? Pest infestations or technology shocks that persist for multiple years may shift both expected prices and future supply. 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 (Roberts and Key 2002, Roberts et al. 2006), especially when compared to the large variation that is induced by weather 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. These variables are converted into edible calories using conversion factors by Williamson and Williamson (1942). 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. In our model estimates below, we stop all series in 2003 for consistency because quantity demanded is not available after 2003 and because it precedes the recent boom and

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

bust in commodity prices.

Yield shocks 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. 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. Shocks derived from both linear and quadratic trends give similar results, so we only report data and results from quadratic trends. Figure 2 displays fitted quadratic yield trends to all countries that on average had more than 1 percent of yearly world production in 1961-2007. The fitted jackknifed residuals are shown in Figure 3.

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, 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 are often forecastable and incorporated in next period's expected price, while yield shocks should be primarily due to unanticipated weather shocks.[5]

Prices are those received by U.S. farmers in the month of December of each year, publicly available from the U.S. Department of Agricultural, which were then 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. The top panel of Figure 4 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.

[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.

[5] We divide world yield shocks and inventories by the trend in production, estimated using again a quadratic trend. The estimated trend is very nearly linear.

The bottom of panel of Figure 4 displays log prices as well as production shocks (deviation from the quadratic production trend in percent). This 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.

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 5 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 6.[6] 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

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

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.

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.[7] The supply of approximately 8 percent of U.S. gasoline consumption requires roughly 5 percent of world caloric production.

4 Empirical Estimates

4.1 Estimating Equations

We first regress aggregate caloric production on a quadratic time trend to get predicted production. This is needed for our first-stage instrument W_t, which is the relative yield shock (caloric yield shock divided by predicted production), which is sometimes interacted with the inverse relative inventory level (inventory level divided by predicted production). 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 W_t up to lag K, plus a polynomial time trend up to order I. The first-stage regression model is:

$$log(P_t) = \pi_0 + \sum_{k=0}^{K} \mu_k W_{t-k} + \sum_{i=1}^{I} \rho_i t^i + \epsilon_t$$

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

We consider both the raw yield shocks and yield shocks interacted with inverse pre-shock inventory levels. Both give similar results, but standard errors are smaller when shocks are interacted with inverse inventories, so those are the results we report below. Results using the raw shocks are available on request.

In the second stage we estimate the structural equations (1) and (2), substituting the predicted values of price from the first stage in place of actual prices. For the supply equation (1) we regress the natural log of production quantity against the predicted lag price, a polynomial time trend up to order I as a proxy for $f(t)$ and the supply shifter in the current period, yield shock (W_t). Stage-one variables excluded from the stage-two supply equation are lagged yields shocks which act as instruments. The stage-two regression model of supply is:

$$log(S_t) = \alpha_s + \beta_s \widehat{log(P_{t-1})} + \underbrace{\sum_{i=1}^{I} \gamma_i t^i}_{f(t)} + \eta W_t + u_t$$

For the demand equation (2) we regress the natural log of quantity consumed ($S_t - N_t$, the quantity produced minus the net-change in storage) on predicted price, a polynomial time trend up to order I as a proxy for $g(t)$ and the demand shifter (past yield shocks ($W_{t-k}, k > 1$). The stage-one variable excluded from the stage-two demand equation is the current supply shock (W_t). The stage-two regression model of demand is:

$$log(S_t - N_t) = \alpha_d + \beta_d \widehat{log(P_t)} + \underbrace{\sum_{i=1}^{I} \tau_i t^i}_{g(t)} + \sum_{k=1}^{K} \lambda_k W_{t-k} + v_t$$

It may be tempting to use deviations from the trend in world production as a proxy for aggregate weather shocks. As discussed in the modeling section, such an approach can be misleading because it still confounds 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 random, the latter, expansion in the production areas, are known before harvest is realized and hence interlinked with expected prices. 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.

4.2 Empirical Results

Our rational for using the current price as a proxy for next period's expected price (which in turn impacts next period's supply) was the fact that log prices resemble a random walk. We test this hypothesis formally. Both the augmented Dickey-Fuller test (p-value= 0.70) and the augmented Dickey-Fuller test with a time trend (p-value = 0.25) fail to reject the null hypothesis of a unit root in log prices as do the Phillips-Perron test (p-value=0.73) as well as the Phillips-Barron test with a time trend (p-value 0.23). This validates our assumption of including the instrumented lagged price in the supply equation, as it is last period's proxy of the expected price in the current period.

Regression results of the two-stage least squares as well as three-stage least squares results, where we jointly estimate the demand and supply equation in the second stage using seemingly unrelated regression models (SUR), are summarized in Table 3. Columns differ by the number of lagged yield shocks as well as the number of polynomials used in the time trend. Elasticity estimates are reasonably stable across models, varying between 0.093 and 0.116 for supply and -0.060 and -0.082 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 both the first stage and second/third stage regressions. Note how our constructed instrument W_t is a highly significant predictor of current price in the first stage.[8]

We most prefer estimates in columns 1 and 2 because the additional variables used in other estimates (additional lagged yield shocks or higher order polynomial for a time trend) are statistically insignificant in columns 3-6 in most cases. 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. Additional specifications (not reported), which include lagged prices as controls or yield shocks without inverse inventory interactions as instruments, also give results similar to those reported in columns 1 and 2. If we limit the sample so that it begins in 1978, after the last major spike in prices, supply and demand estimates are still similar but become somewhat more inelastic.

The supply and demand elasticities imply that the U.S. ethanol mandates (which requires

[8] If we use the current price regressed on past, *not concurrent*, yield shocks $W_{t-i,i>0}$ we do not observe a significant relationship. Lagged yield shocks are hence a weak instrument for price changes. If we instrument current predicted price in the supply equation with past yield shocks, we do observe a larger supply elasticity, but error terms increase due to the weak instrument.

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 distribution of the demand and supply elasticity (the joint distribution in the case of SUR). 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 156 billion dollars annually.[9] On the other hand, there will 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, etc.

For comparison, we also present other approaches in Table 4. 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. The do account for observed supply and demand 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, 0.078 for supply and -0.005 for demand. While the demand elasticity is not statistically significant, the standard errors are small and (if assumptions are accepted, which is dubious) rule out elasticities less than -0.025 with 97.5 percent confidence. The supply is statistically significant, and the high end of the 95 percent confidence interval is 0.105. The predicted price increase of an ethanol mandate (diverting 5 percent of world production) would be 60 percent if we use the point estimates of the elasticities.

Columns 3 and 4 of Table 4 follow the approach of Nerlove (1958) and include lagged price which is *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 56 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.

[9]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 1.86 percent.

Table 5 demonstrates this further by regressing the log of the total world growing area for each of the four crops on the combined lagged production shock W_{t-1} of all four commodities. The coefficient is negative and significant in most specifications, 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 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.

All models in Table 4 give smaller supply 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. Our estimated elasticities imply that total caloric production would increase by roughly 3.1 percent, or 162 trillion calories. Table 6 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 17 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.

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. 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 lagged 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. Recent empirical research in the United States suggests such an approach may be feasible (Schlenker and Roberts 2008).

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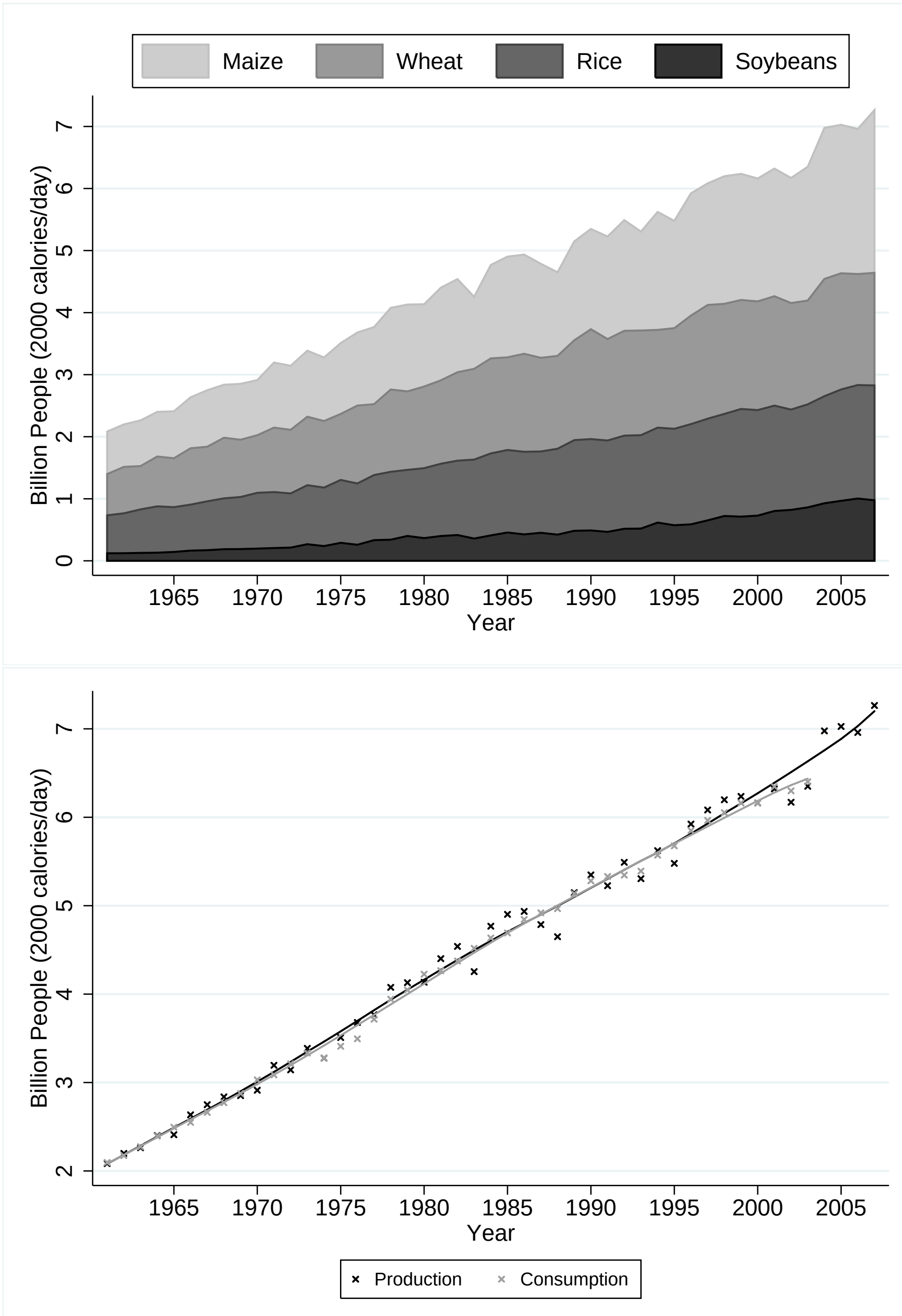
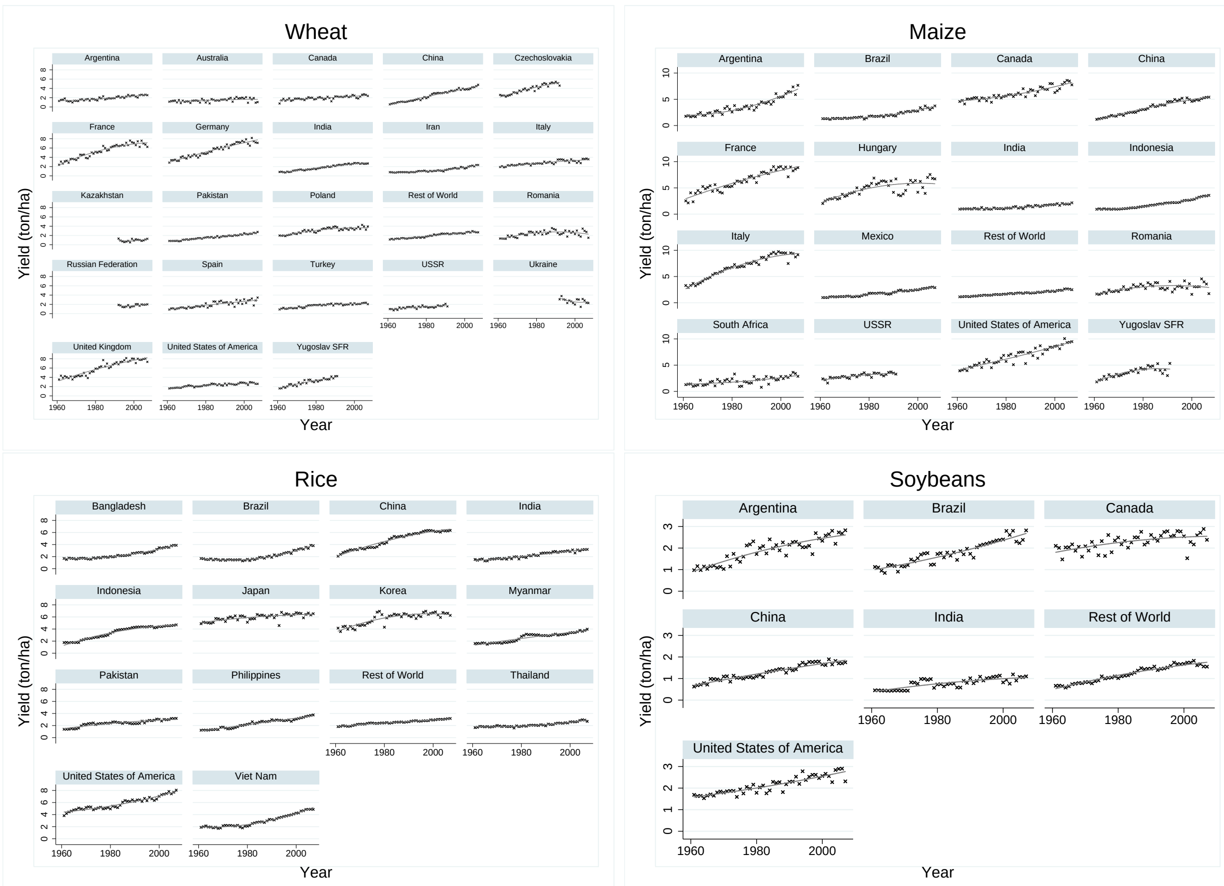
Figure 1: Production and Consumption of Calories from Maize, Wheat, Rice, and Soybeans



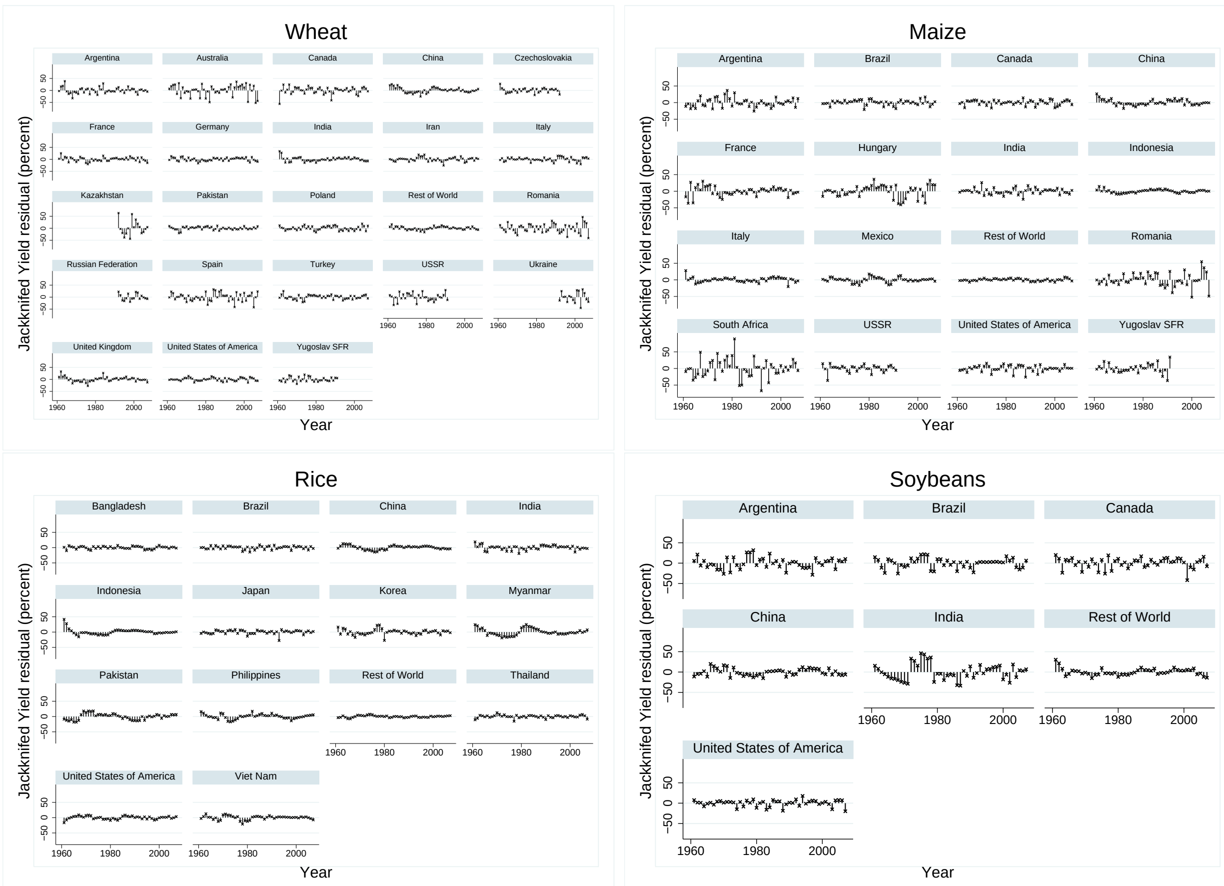
Notes: Top panel displays world production of calories from maize, wheat, rice, and soybeans for 1961-2007. The y-axis are the number of people who could be fed on a 2000 calories/day diet. Bottom level displays production as well as consumption of the same four commodities. A locally weighted regression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

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



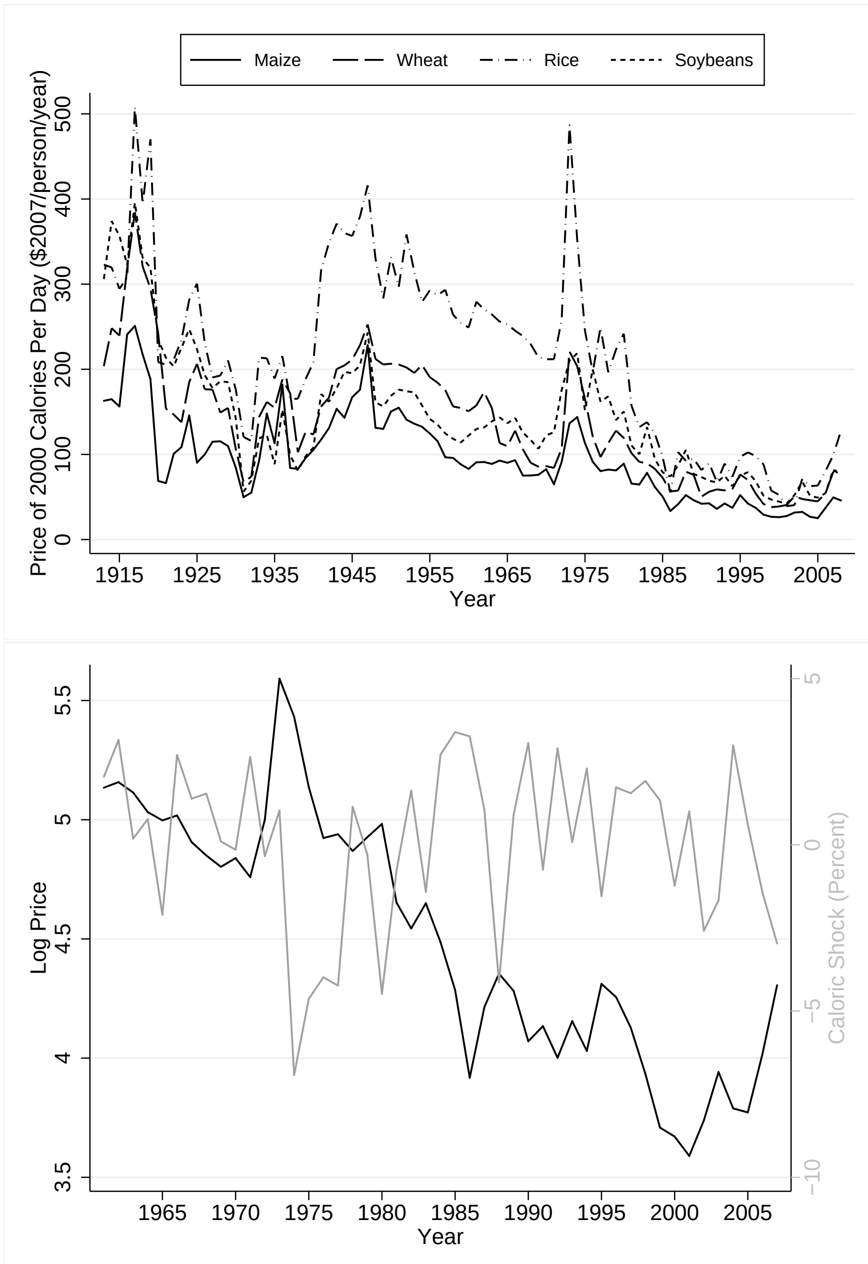
Notes: Scatter plots of yields in each country against time. A quadratic time trend is added as a solid line. Figure shows all countries that produce on average more than 1 percent of world production. All other countries are lumped together as “Rest of World”.

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



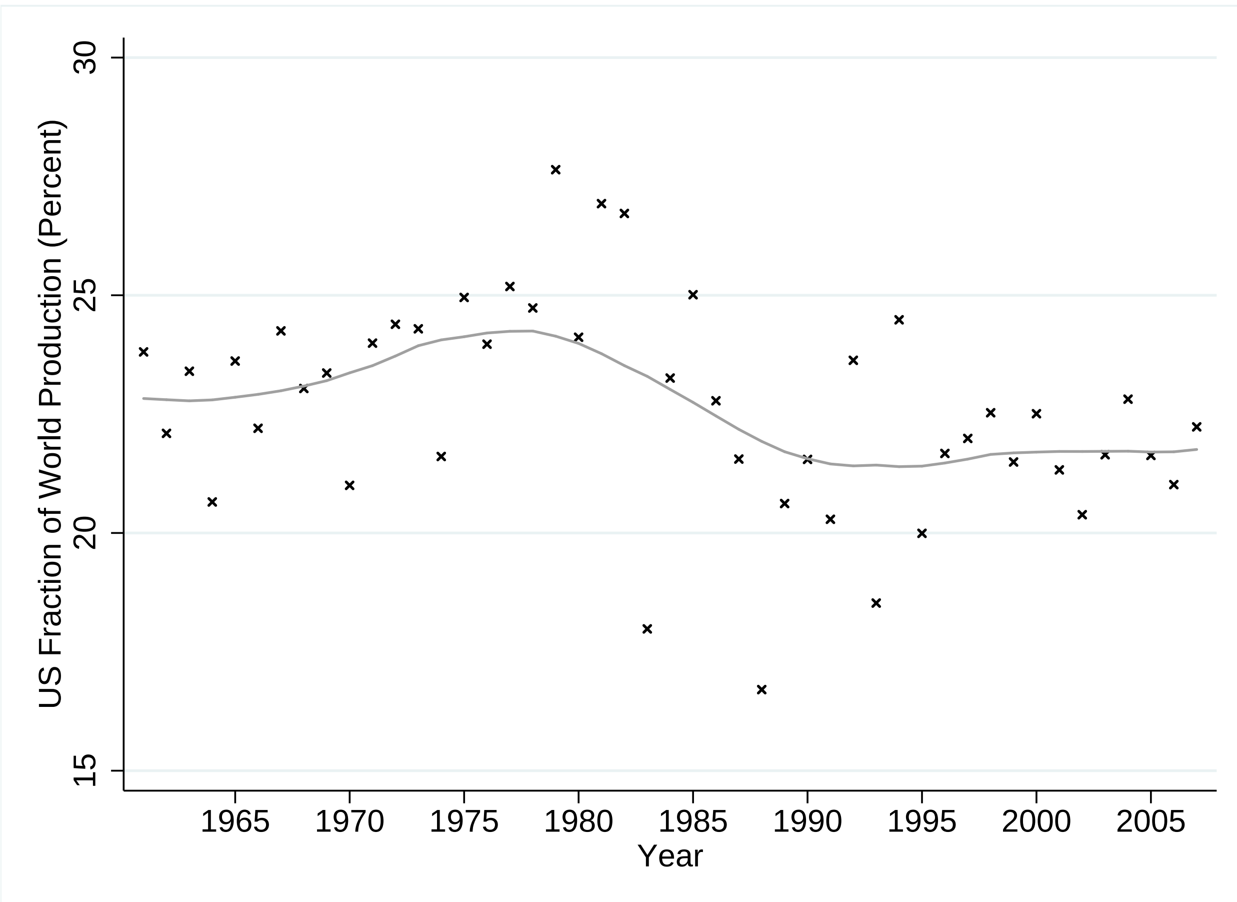
Notes: Scatter plots of jackknifed yield residuals, i.e., the residual is estimated by excluding the observation in question. Figure shows all countries that produce on average more than 1 percent of world production. All other countries are lumped together as "Rest of World".

Figure 4: Price and Caloric Shocks



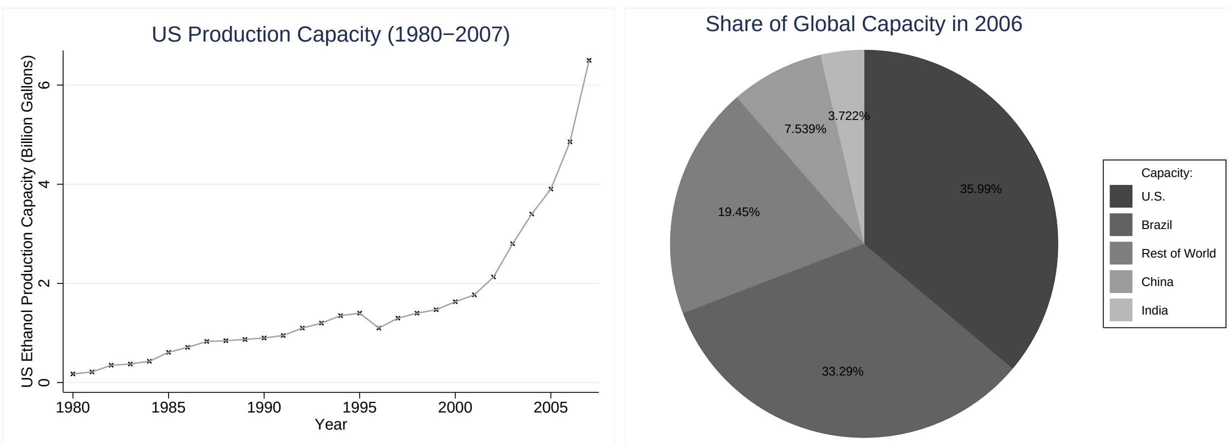
Notes: Top panel displays real annual cost of maize, wheat, rice, and soybeans in 2007 dollars for a 2000 calories per day diet. Overall, prices show a downward trend, and the recent spike in food prices in small in absolute terms. However, the spike is large in term of relative increase (threefold increase). The bottom panel displays log price on the left axis and caloric shocks (as percent deviation from production trend) on the right axis for the years 1961-2007. Price are the production-weighted prices of maize, wheat, rice and soybeans. Shocks are deviations from country-specific yield trends for the same four commodities.

Figure 5: 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 6: 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 Shock	million people	4.67	107	-240	159
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 Price	US$2007 per year	106.83	53.44	36.22	268.26
Log Caloric Supply	Log billion people	1.412	0.337	0.734	1.848
Log Caloric Demand	Log billion people	1.408	0.339	0.740	1.857
Log Caloric Price	Log US$2007 per year	4.546	0.516	3.590	5.592

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: Regression Results: Demand and Supply of Calories

	Model					
	2SLS	**3SLS**	**2SLS**	**3SLS**	**2SLS**	**3SLS**
Supply elasticity	0.115***	0.116***	0.109***	0.110***	0.093***	0.095***
(s.e.)	(0.029)	(0.027)	(0.029)	(0.027)	(0.034)	(0.031)
Demand elasticity	-0.062***	-0.066***	-0.061***	-0.060***	-0.081***	-0.082***
(s.e.)	(0.022)	(0.021)	(0.022)	(0.020)	(0.025)	(0.023)
Price Increase	29.71	28.74	31.08	31.02	30.48	29.94
95% conf. int.	(20.18,47.45)	(19.93,44.57)	(20.72,50.93)	(20.88,50.18)	(19.44,54.78)	(19.60,50.40)
First-stage						
Shock W_t	-0.901***		-0.942***		-0.837***	
(s.e.)	(0.269)		(0.283)		(0.297)	
Shock W_{t-1}	-0.321		-0.331		-0.231	
(s.e.)	(0.274)		(0.285)		(0.297)	
Shock W_{t-2}			0.053		0.118	
(s.e.)			(0.294)		(0.298)	
Time trend	-1.94e-2*		-1.58e-2		2.47e-2	
(s.e.)	(1.04e-2)		(1.18e-2)		(3.73e-2)	
Time trend^2	-4.02e-4*		-4.72e-4**		-2.66e-3	
(s.e.)	(2.36e-4)		(2.63e-4)		(1.93e-3)	
Time trend^3					3.25e-5	
(s.e.)					(2.84e-5)	
Supply						
Lagged Price	0.115***	0.116***	0.109***	0.110***	0.093***	0.095***
(s.e.)	(0.029)	(0.027)	(0.029)	(0.027)	(0.034)	(0.031)
Shock W_t	0.188***	0.188***	0.187***	0.188***	0.215***	0.215***
(s.e.)	(0.030)	(0.028)	(0.030)	(0.028)	(0.031)	(0.028)
Time trend	4.47e-2***	4.48e-2***	4.43e-2***	4.43e-2***	5.10e-2***	5.09e-2***
(s.e.)	(1.22e-3)	(1.14e-3)	(1.34e-4)	(1.26e-3)	(4.64e-3)	(4.28e-3)
Time trend^2	-3.435e-4***	-3.42e-4***	-3.39e-4***	-3.38e-4***	-7.13e-4***	-7.04e-4**
(s.e.)	(3.21e-5)	(3.00e-5)	(3.42e-5)	(3.20e-5)	(2.58e-4)	(2.38e-4)
Time trend^3					5.40e-6	5.29e-6
(s.e.)					(3.59e-6)	(3.31e-6)
Demand						
Price	-0.062***	-0.066***	-0.061***	-0.060***	-0.081***	-0.082***
(s.e.)	(0.022)	(0.021)	(0.022)	(0.020)	(0.025)	(0.023)
Shock W_{t-1}	-4.36e-3	-7.58e-3	-5.66e-3	-7.36e-3	5.79e-3	-3.88e-3
(s.e.)	(2.29e-2)	(2.15e-2)	(2.34e-2)	(2.19e-2)	(2.25e-2)	(2.07e-2)
Shock W_{t-2}			-8.84e-3	1.55e-2	2.16e-2	2.78e-2
(s.e.)			(2.11e-2)	(1.89e-2)	(2.10e-2)	(1.90e-2)
Time trend	4.36e-2***	4.15e-2***	4.19e-2***	4.19e-2***	4.89e-2***	4.97e-2***
(s.e.)	(8.44e-4)	(8.65e-4)	(9.36e-4)	(9.23e-4)	(2.89e-3)	(3.04e-3)
Time trend^2	-4.17e-4***	-4.13e-4***	-4.17e-4***	-4.16e-4***	-8.23e-4***	-8.60e-4***
(s.e.)	(1.97e-5)	(1.90e-5)	(2.13e-5)	(2.07e-5)	(1.69e-4)	(1.72e-4)
Time trend^3					5.89e-6**	6.38e-6***
(s.e.)					(2.40e-6)	(2.41e-6)

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. The bottom panels display the first and second stage regressions in more detail.

Table 4: Replication of Other Approaches: Demand and Supply of Calories

	Model			
	SUR - Price Not Instrumented		**Supply Price Not Instrumented**	
	(1)	**(2)**	**(3)**	**(4)**
Supply elasticity	0.078***	0.074***	0.027	0.025
(s.e.)	(0.014)	(0.012)	(0.022)	(0.023)
Demand elasticity	-0.005	-0.008		
(s.e.)	(0.010)	(0.011)		
Time trend (order I	2	3	2	3
Shocks (highest lag K)	1	2	1	2

Notes: The first two columns do not instrument price (which is arguably endogenous). The last two columns follow the approach of Nerlove (1958) and do not instrument lagged prices in the supply equation.

Table 5: Acreage Changes in Response to Past Caloric Shocks

	Maize	**Wheat**	**Rice**	**Soybeans**
	Panel A: Linear Time Trend			
Shock W_{t-1}	-0.0776***	-0.1004**	-0.1042***	-0.2025**
(s.e.)	(0.0266)	(0.0465)	(0.0317)	(0.0939)
	Panel B: Quadratic Time Trend			
Shock W_{t-1}	-0.0628**	-0.0553	-0.0705***	-0.1473*
(s.e.)	(0.0252)	(0.0335)	(0.0202)	(0.0874)

Notes: Regression of log world growing area on lagged yield shocks including various time trends. Panel A and B use a linear and quadratic time trend, respectively.

Table 6: 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.