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Author(s): Michael J. Roberts and WOLFRAM SCHLENKER
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Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate†

By Michael J. Roberts and Wolfram Schlenker*

We present a new framework to identify supply elasticities of storable commodities where past shocks are used as exogenous price shifters. In the agricultural context, past yield shocks change inventory levels and futures prices of agricultural commodities. We use our estimated elasticities to evaluate the impact of the 2009 Renewable Fuel Standard on commodity prices, quantities, and food consumers' surplus for the four basic staples: corn, rice, soybeans, and wheat. Prices increase 20 percent if one-third of commodities used to produce ethanol are recycled as feedstock, with a positively skewed 95 percent confidence interval that ranges from 14 to 35 percent. (*JEL* Q11, Q16, Q42, Q48)

The rapid ascent of commodity prices between late 2005 and 2008 led to renewed debate about what drives the demand and supply for basic food commodities. Corn prices nearly quadrupled from about \$2 per bushel to almost \$8 per bushel, and prices for rice, soybeans, and wheat rose by similar amounts. These prices briefly dropped in 2009–2010 due to the recession, but corn again broke \$8 in 2011. High prices for these staple grains caused hunger, malnutrition, and riots in a number of developing nations, as was vividly reported in the popular press.[1] The price spike was attributed to a number of factors, including the prolonged drought in Australia, accelerating demand growth due to the broad scale economic development in Asia, and a shift in demand stemming from the United States' ethanol policy. The combination of ethanol subsidies, restrictions on ethanol imports, and high oil prices caused a formerly nascent ethanol industry to quickly grow into one that consumes approximately one third of US corn production and about 5 percent of the world's combined caloric production of corn, soybeans, wheat, and rice. Evaluating how

* Roberts: Department of Agricultural and Resource Economics, North Carolina State University, Box 8109, Raleigh, NC 27695 (e-mail: michael_roberts@ncsu.edu); Schlenker: School of International and Public Affairs, Columbia University, 420 W 118th St., New York, NY 10027, and NBER (e-mail: wolfram.schlenker@columbia.edu). We would like to thank three anonymous referees, Jim Hamilton, Randall Walsh, three anonymous referees, and seminar participants at Berkeley, Cornell, Iowa State University, NBER Agricultural Economics Conference, Stanford, University of British Columbia, University of Calgary, and the University of Maryland for very useful comments. All remaining errors are ours. Financial support from Department of Energy Grant DE-FG02-08ER64640 and National Science Foundation Grant SES-0962559 is thankfully acknowledged. The authors have no relevant or financial interests related to this project to disclose.

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[1] Two examples are "Fuel Choices, Food Crises and Finger Pointing" on April 15, 2008 and "Across Globe, Empty Bellies Bring Rising Anger" on April 18, 2008, both published in the *New York Times*.

much the biofuel mandate contributed to higher prices requires estimates of the underlying supply and demand elasticities.

A closely connected issue is land use change. Commodity production, pasture, and forests sequester substantially different amounts of carbon. This has sparked a debate about the potential benefits of using biofuels to reduce CO_2 emissions. Diversion of food into fuel raises the price of food and induces farmers to produce more. Crucial points of disagreement concern the size and nature of this supply response, as the potential size of the CO_2 effect depends on how much additional production comes from the extensive margin. Land use change (mainly deforestation) is thought to account for about 20 percent of worldwide CO_2 emissions (IPCC 2007).[2]

Another discussion that requires estimates of agricultural demand and supply elasticities involves "leakage" from carbon offset programs that pay farmers to either forestall deforestation or reforest land that would otherwise be used in crop production. Carbon offset programs shift the supply of cropland inward, causing commodity prices to rise, and potentially an offsetting increase in the quantity of cropland supplied elsewhere. The global net offset can therefore be much less than the offset purchased in any particular location. The amount of leakage depends on the size of the supply elasticity relative to the demand elasticity.

With these applications in mind, this article develops a new framework to empirically identify both supply and demand elasticities of storable commodities where prices are linked between periods via storage. We apply this framework to the world's four most important staple food commodities: corn, wheat, rice, and soybeans. These commodities make up about 75 percent of the caloric content of food production worldwide.[3] While many other commodities matter for food consumption, and the particular mix of foods varies across locations, we limit ourselves to these four crops. The prices and quantities of other staple food items are inextricably linked to these four commodities. As we will show below, the prices of the four commodities tend to fluctuate closely together. In our baseline specification we simplify matters further by aggregating these four key crops on either a caloric or value-weighted basis.

Agricultural commodity markets, with their many price-taking producers and buyers and well-developed spot and futures markets, are often cited as the archetype of perfect competition. The key empirical challenge is to separate supply and demand in the market's formation of prices and quantities. Correct identification requires instruments that shift prices in ways that are plausibly unrelated to unobservable shifts in each curve. Since Wright's (1928) introduction of instrumental-variable estimation, weather has been considered a natural instrument for agricultural supply shifts, which can be used to facilitate unbiased demand estimation. The idea is that weather shifts supply in a manner that is unrelated to unobserved demand shifts. Given this idea was established long ago we find it surprising that the literature in

[2] A similar concept considers market feedback in fuel consumption instead of agriculture. A standard that limits the carbon intensity of fuels via a subsidy for low-carbon fuels increases fuel quantity demanded. Thus, CO_2 emissions will decline by less than the reduction in carbon intensity. In an extreme case, such a standard could theoretically increase total emissions. However, Holland, Hughes, and Knittel (2009) show that this counterintuitive result does not hold under reasonable parameter assumptions.

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

agricultural economics that uses weather-based instruments to identify demand is extremely thin.[4]

Here we show how yield shocks that are due to random weather shocks can also be used to identify supply. The idea follows naturally from the theory of competitive storage: past shocks exogenously shift inventories, which affect futures prices and the demand for storage, which in turn cause production responses in the future. Past shocks can serve as instruments for futures prices. The same methodology could in principle be applied to any storable commodity, where prices are linked between periods through storage, and past shocks shift the demand to hold inventory.

Our approach to supply estimation differs from a large existing literature that stems from the seminal work of Nerlove (1958). In this literature, supply is estimated by regressing quantities against uninstrumented futures prices, lagged prices, or prices predicted from an autoregressive model. Nerlove's approach purges endogeneity stemming from current *unanticipated* supply shocks that are, for example, due to current weather shocks. However, this does not account for endogeneity stemming from *anticipated* supply shifts that are unobserved to the econometrician, since futures prices reflect the intersection of anticipated supply and anticipated demand. Endogeneity remains a serious concern since these unobserved supply shifts are part of the error in a supply equation with futures prices on the right-hand side of the regression. This is perhaps one reason why this substantial literature on agricultural supply response finds widely varying supply elasticities that often lack statistical significance (Askari and Cummings 1977).

A recent example from the United States illustrates the endogeneity of futures prices in the supply equation. 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. In the subsequent 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 futures prices for soybeans to rise and futures prices for corn to fall, clearly 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 shift in supply (stemming from fear of soybean 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 naïve econometrician, regressing quantity supplied of either corn or soybeans on futures prices, would estimate a supply elasticity biased toward zero due to the soybean rust phenomenon. While this is just one example, it should be clear that, when using the standard approach to supply estimation, any number of anticipated supply shifts that are either unobservable or immeasurable to the econometrician would cause downward bias in the estimated supply response.

Our baseline approach to estimate supply and demand exploits yield shocks—deviations from country and crop-specific yield trends that appear to stem mainly from random weather shocks. A potential shortcoming of this approach is that yields themselves may be endogenous to price. We explore this potential issue in detail and argue that any short-run causal links going from price to yield are likely

[4] For example, Angrist, Graddy, and Imbens (2000) use weather to instrument the supply of fish to the Fulton Fish market in New York.

minimal. When we regress futures prices on past weather shocks, which are more defensibly exogenous than yield shocks, we obtain similar point estimates that are less precisely estimated. The obvious trade-offs between using yield shocks and weather variables as instruments are between statistical power, endogeneity bias and weak-instruments bias. Despite these trade-offs, a wide variety of estimates using different specifications and instruments show remarkable consistency, and most estimates have strong statistical significance.

We use the demand and supply model of world commodity calories to examine the effect of the current US biofuel mandate on food prices. This analysis provides some perspective on rapid price increase between 2005 and 2008 and how much of it might have been attributable to ethanol policy. Our estimates indicate that supply is more elastic than demand, with almost all of the supply response coming from the extensive margin, i.e., an expansion of land area. Both supply and demand elasticities are significantly larger, both economically and statistically, than uninstrumented estimates derived using traditional techniques. The estimates suggest that the US ethanol mandate increased food prices about 30 percent and increased world production area by 2 percent. The baseline estimate for the price increase 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 remain in the byproduct that is fed to animals, and this feedstock is a perfect substitute for other grains, the price increase would be 20 percent. On the other hand, if feedstock is not a perfect substitute, the effect will lie in between. While these predicted effects are substantial, they suggest that other factors likely played a larger role in the 2005–2008 price boom.[5] The 95 percent confidence interval of the predicted price increase is positively skewed and stretches from 14 percent to 35 percent if one-third of commodities used to produce ethanol are recycled as feedstock, suggesting that significantly larger price increases are possible even if the byproducts of ethanol generation are recycled.

At the same time, a 30 percent price increase implies an annual loss of 180 billion in consumer surplus. While most of this is offset with an increase in producer surplus, the US ethanol policy results in transfers from net food importers to net food exporters. Since most developing countries are net food importers, they are especially affected. Moreover, an increase in world food prices for a food importer is equivalent to a reduction in income, which has been shown to increase civil conflict (Miguel, Satyanath, and Sergenti 2004; Burke et al. 2009). The US biofuel policy therefore has significant distributional consequences. This result is in line with earlier research about other policies that purportedly reduce CO_2 emissions. Bento et al. (2009) examine the markets for new and used cars and find that the distributional consequences of a gasoline tax crucially depend on how the revenues are recycled. Similarly, Li, Timmins, and von Haefen (2009) find that higher gasoline taxes not only change the fuel economy of new cars, but also lead to increased scrappage of old inefficient cars, which are primarily owned by the less affluent.

[5] Hausman, Auffhammer, and Berck (2012) use a vector autoregression price process to estimate how corn and soybean prices respond to shocks in the United States. They find that US ethanol production was responsible for roughly 27 percent of the recent corn price increase. Similar to Nerlove (1958), lagged variables are allowed to influence futures prices. While we follow a similar time structure of using lagged variables, we only use past yield shocks, not area changes, as an instrument.

I. A Model of Supply and Demand

We simplify our characterization of the world food commodity market by transforming quantities of corn, wheat, rice, and soybeans into caloric equivalents and then aggregating them (Roberts and Schlenker 2009). In sensitivity checks we also present results for a disaggregate analysis as well as an aggregate analysis on the basis of average price. Aggregating crops facilitates a simple yet broad-scale analysis of the supply and demand of staple food commodities on a worldwide scale. A practical reason for aggregation is that prices for all four commodities tend to vary synchronously, which seriously impedes identification of multiple cross-price elasticities and separating cross-price elasticities from own-price elasticities. The strong correlation of prices over time also suggests that substitution possibilities are large enough that the aggregate outcomes likely characterize all four markets reasonably well. For example, the recent Russian wildfires that impacted global wheat production influenced corn prices almost as much as wheat prices.

A. *Theoretical Motivation*

Having reduced the staple food commodity market to a single caloric measure, we need a model that characterizes supply, demand, and inventories and how random shocks facilitate identification of the supply and demand elasticities. The theory of competitive storage sits at the heart of this approach. Storage is a characteristic feature of all four commodities we consider. It allows for substitution of consumption over time by transferring commodities from periods of relative plenty to periods of relative scarcity. Consumption is smoother than production, and prices are less variable and more autocorrelated than they would be without storage opportunities. Equilibrium in each period does not require a price where supply in the current period equals consumption 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 the amount stored for the next period (denoted x_t).

$$c_t = z_t - x_t.$$

An extensive literature on the rational competitive storage model characterizes demand for inventories and the resulting price path of commodities. Our focus differs from this literature, but we do exploit the above identity and other essential characteristics of storage models.

Scheinkman and Schechtman (1983) and Bobenrieth H., Bobenrieth H., and Wright (2002) set up a model in which profit-maximizing agricultural producers make two decisions. The first is how much to store and carry over to 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 is that λ_t specifies the number of acres a farmer plants, and ω_{t+1} is the random yield, which is driven by exogenous weather shocks. Production in the coming harvest season is

$\lambda_t\,\omega_{t+1}$. Production costs $g(\lambda_t)$ are assumed to be convex, as land of heterogeneous quality becomes progressively more expensive to farm.

The Bellman equation for the social maximization problem is

$$v(z_t) \;=\; \max_{x_t \lambda_t} \left\{u(z_t - x_t) - \phi(x_t) - g(\lambda_t) + \delta \mathbb{E}\left[v(z_{t+1})\right]\right\} \quad \text{subject to}$$

$$z_{t+1} \;=\; x_t + \lambda_t \omega_{t+1}$$

$$x_t \geq 0, \qquad z_t - x_t \geq 0, \qquad \lambda_t \geq 0.$$

Competitive price-taking producers and storers achieve the socially optimal outcome by optimally balancing the marginal cost of effort against futures prices and the marginal cost of storing agricultural goods against the change in futures prices. In the social planner's problem, price is reflected by the marginal utility of consumption. Increasing storage is profitable in years when availability z_t is sufficiently large, which causes the current price to be low. By shifting some of the current availability into the next period, current price rises and price in the next period falls. This process continues up to the point when the discounted futures price net of storage cost equals current price. For the same reason, prices rise if availability z_t decreases. If the weather shock is sufficiently negative, inventories theoretically may be drawn to zero, even though this is rarely observed in practice.[6] 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.

For our purposes, the key result from this model is that it implies exogenous shocks are optimally divided between current consumption and inventory adjustments. We can infer this because random shocks randomly shift z_t. Thus, bad weather shocks exogenously reduce z_t and by point (i) reduce consumption and increase price. This captures movement along the demand curve. The same negative weather shocks also draw down inventories by point (ii), thereby increasing the price in subsequent periods. When storage levels are low and the futures price in the next period is high, farmers increase effort λ_t by point (iii) through higher acreage or yields. This captures movement along the supply curve.

[6] In the absence of convenience yield, a stockout theoretically occurs when prices are high enough that the subsequent futures price change becomes negative. If, however, ω_{t+1} is allowed to have a mass point at zero, i.e., a nonzero probability that the entire harvest is wiped out, and $\lim_{c \to 0} u'(c) = \infty$, then the long-run distribution has a finite price, inventories will be positive with probability one, and the mean of the price distribution is infinite (Bobenrieth H., Bobenrieth H., and Wright 2002). While low inventory levels (and high prices) will almost surely result in subsequent price declines, the futures price is still increasing. The rationale is that if another bad shock occurs, the already strained market would result in a very large price jump. The resulting payoff is so large that it always justifies holding positive inventories.

B. *Empirical Model*

The empirical model is

$$(1)\qquad \text{Supply:}\quad q_{st} = \alpha_s + \beta_s p_{st} + \gamma_s \omega_t + f_{s2}(t) + u_t$$

$$(2)\qquad p_{st} = \delta_s + \mu_{s0}\omega_t + \mu_{s1}\omega_{t-1} + f_{s1}(t) + \epsilon_t$$

$$(3)\qquad \text{Demand:}\quad q_{dt} = \alpha_d + \beta_d p_{dt} + f_{d2}(t) + v_t$$

$$(4)\qquad p_{dt} = \delta_d + \mu_{d0}\omega_t + f_{d1}(t) + \eta_t.$$

Log quantity supplied is denoted by $q_{st} = \log(\lambda_{t-1}\omega_t)$, while log quantity demanded is $q_{dt} = \log(\lambda_{t-1}\omega_t + x_{t-1} - x_t)$, which is new production minus the change in inventories. The supply equation uses the log of future price $p_{st} = \log(p_t|_{t-1})$[7], while the demand equation uses log futures prices during the month of delivery $p_{dt} = \log(p_t)$. Intercepts α_s, α_d, δ_s, and δ_d are allowed to evolve over time according to time a trend $f_i(t)$ in all of the four above equations $(i \in \{s1, s2, d1, d2\})$.

Prices are the key endogenous variables on the right-hand side of both supply and demand. The crux of the identification problem is that shifts in supply and demand that are unobserved to the econometrician (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 naïve 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.[8]

Our baseline model uses yield deviations ξ_{cit} for crops c in country i in year t. We fit crop-and-country specific time trends $g_{ci}(t)$ in regressions of log yields y_{cit}, i.e., $y_{cit} = g_{ci}(t) + \xi_{cit}$. The annual shock ω_t is a weighted average of all shocks. The weights ρ_{cit} depend on predicted yields $\hat{y}_{cit} = e^{g_{ci}(t) + \frac{\sigma^2}{2}}$ (where σ^2 is the estimated variance of the error terms), growing area a_{cit}, and the caloric content of one production unit of crop c, κ_c.

$$\omega_t = \frac{\sum_c \sum_i \hat{\xi}_{cit} \times \hat{y}_{cit} \times a_{cit} \times \kappa_c}{\sum_c \sum_i \hat{y}_{cit} \times a_{cit} \times \kappa_c} = \sum_c \sum_i \hat{\xi}_{cit}\,\rho_{cit}$$

$$\rho_{cit} = \frac{\hat{y}_{cit} \times a_{cit} \times \kappa_c}{\sum_c \sum_i \hat{y}_{cit} \times a_{cit} \times \kappa_c}.$$

[7] We use futures prices in December of period $t-1$ with a delivery in December of year t for corn and wheat and a November delivery for soybeans and rice. We present sensitivity checks in the online Appendix where we vary the months, but the results are generally robust.

[8] Carter, Rausser, and Smith (2011) argue that there were two big commodity price spikes—1974 and 2008—that resulted from several correlated macroeconomic factors. It is therefore crucial to use exogenous instruments.

In our baseline model we use the *actual* growing area a_{cit}. While the growing area is endogenous, it enters only as a weighting factor of the exogenous percentage shocks $\hat{\xi}_{cit}$ that are primarily caused by weather. If production increases in a country because of an increase in the area but yields do not deviate from the trend, it will not be appear in our shock ω_t. Weighting by the actual area gives the accurate global exposure to exogenous shocks, which is still a valid exogenous instrument (see online Appendix Section A1.1 for a formal derivation). If one is worried about the endogeneity of the weights, we present a robustness check where we use predicted area along the same country-and-crop-specific time trend we use in the yield regression and get very similar results.

Another, and potentially more worrisome concern is that yields might themselves be endogenous, which would make yield deviations an invalid instrument. We therefore present an analysis where we replace yield shocks $\hat{\xi}_{cit}$ with observed weather outcomes: a quadratic in average temperature and total precipitation. While these instruments are more defensibly exogenous, they are less efficient: the point estimates for the supply elasticity remain robust, but the first-stage results are not as significant, and standard errors are larger.

The price in the demand equation is identified through the exogenous shock ω_t. The exclusion restriction requires that these shocks do not directly affect demand. While it is in principle possible that yield shocks or weather outcomes could shift tastes, hunger, or general caloric need, it seems unlikely that these could matter in a global context. Well-established international markets trade a significant share of production within and between regions and nations. Thus, weather affecting crop production tends to be far removed from demand centers. For example, most of the feed grains used for hog and poultry production in North Carolina come from the Midwest where weather fluctuations are quite unrelated.

A novelty of our approach is that we use *past* yield (or weather) shocks ω_{t-1} to identify the supply elasticity β_s in addition to the demand elasticity. As described in detail above, this is possible because past weather-induced supply shocks affect inventories, and inventories affect the futures price in subsequent periods. The key assumption for consistent identification of the supply elasticity is that past weather-induced supply shocks have zero covariance with unobserved supply shifters in the current period. Unobserved supply shifters might stem from recurrent or anticipated pest problems, like the example of soybean rust in the introduction, broad macroeconomic phenomena, governmental policies, or perhaps other factors. One concern may be that agronomic or weather factors are correlated over time. We address this potential concern in two ways. First, we show yields and weather shocks display little autocorrelation.[9] Second, we estimate MA models in a sensitivity check and use only innovations in a period, and the results remain robust. Third, we include current weather shocks in the supply equation. While current shocks must be excluded from the demand equation, including them in the supply equation increases precision by reducing the error variance while accounting for current supply shifts that may have been associated with past shocks. Thus, conditional on the current weather or yield shock, it's not clear how or why past weather or yield shocks might be related to unobserved supply shifters.

[9] Rice is an exception; however, the other three commodities and aggregate yield shocks show little autocorrelation.

II. Data

World production and storage data are publicly available from the Food and Agriculture Organization (FAO) of the United Nations (FAO Statistics Division 1960–2010). 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 available only until 2007. In our model estimates below, we stop all series in 2007 because quantity demanded (which depends on changes in inventory) is not available after 2007. In a sensitivity check, we also use data from the Foreign Agricultural Service (FAS) by the United States Department of Agriculture (FAS 1960–2010) that has data for all variables, including stocks.[10] Variables are converted into edible calories using conversion factors by Williamson and Williamson (1942), which specify edible calories 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 people that could be fed on a 2,000-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 overall year-to-year fluctuations (top line) are predominantly due to fluctuations in corn. More than half of all corn, sometimes also called maize, was traditionally produced in the United States, and the bulk of that production is geographically concentrated in one region, the Midwestern corn belt.[11] Other crops are less geographically concentrated, and local weather shocks average close to zero when summed over the whole world. Maize may contribute a larger share of world caloric variability simply because its production is more geographically concentrated and therefore more likely to experience correlated weather outcomes.

The bottom panel of Figure 1 shows production and consumption quantities. Two features are noteworthy: first, production and consumption have been steadily trending upward, almost linearly. Both appear trend stationary. Second, fluctuations around trend 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 2007, and, hence, so does our demand estimate.

Yield shocks in our baseline model are calculated by taking jackknifed residuals from fitting separate yield trends for each crop in each country. Trends and shocks were estimated separately for each country with an average of 0.5 percent or more of world production for a given crop.[12] Remaining rest-of-world yields were pooled and treated as a single country for each crop. Yield shocks in the baseline model

[10] FAS reports production for marketing years. The exact procedure by which marketing years are linked to calendar years is given in Section A2.1 of the online Appendix.

[11] Today, the United States still accounts for roughly 40 percent of world maize production.

[12] The average share of world production between 1961 and 2010 in both the FAO and FAS data are listed in online Appendix Tables A1–A2. Countries that on average produced at least 0.5 percent of a crop are shown in the bottom map in online Appendix Figures A1–A4.

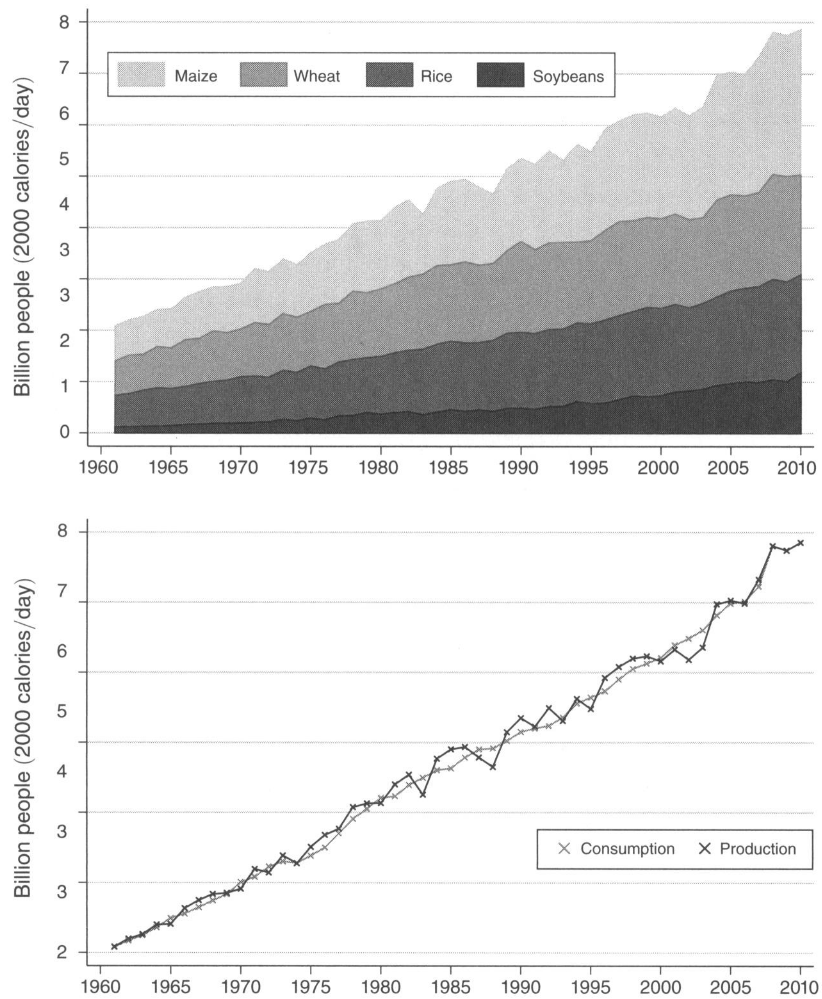

FIGURE 1. WORLD PRODUCTION AND CONSUMPTION OF CALORIES (*FAO Data*)

Notes: The top panel shows world production of calories from maize, wheat, rice, and soybeans for 1961–2010. The bottom panel shows combined production and consumption. Storage allows consumption to be smoothed over periods. The *y*-axis in both panels gives the number of people who could be fed on a 2,000 calories/day diet by hypothetically only consuming the four commodities.

were derived from a trend that is approximated by a restricted cubic spline with three knots,[13] i.e., two variables.[14]

Our premise is that these deviations from yield trends are exogenous as they are 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

[13] The fitted trends and residuals are displayed in online Appendix Figures A5–A7.

[14] Restricted cubic splines are more flexible than quadratic time trends. To access the sensitivity of the results to the chosen trend specification, Table A15 in the online Appendix fits yield trends ranging from a linear time trend to splines with five knots with little effect on the estimated results. While we use generated variables as instruments, Wooldridge (2002) points out that this will still give consistent estimates of the standard errors in the second stage.

hand, higher prices might induce farmers to expand their production to marginal, less productive land, thereby lowering average yields. It is a priori unclear which way the bias would go. We believe that endogenous yield responses are not important in our article for two stylized facts. First, if yields were responsive to price levels, we would observe that yield shocks are correlated between various countries in a given year, as all countries face the same world price.[15] Idiosyncratic yield shocks for various countries get averaged out in aggregate except when regions that account for a significant share of production get hit by the same shock. Accordingly, aggregate shocks vary much less than country- and crop-specific shocks. Our baseline log deviations vary between -0.057 and 0.044 in the FAO data.[16] A value of -0.05 implies that global production was roughly 5 percent below predicted yields.

Second, aggregate yield shocks ω_t have almost no autocorrelation, while prices have a high degree of autocorrelation.[17] If yields endogenously respond to prices, than aggregate yield shocks would show autocorrelation as well. While some endogenous yield response is likely present, these stylized facts suggest it is small relative to variation induced by weather.

To further address the concern of endogenous yield responses, we conduct a sensitivity check where we replace yield shocks with observed weather variables. Since global production and consumption data are annual aggregates, we construct annual weather aggregates for a quadratic in average temperature as well as total precipitation. Weather data from Center for Climatic Research at the University of Delaware (version 2.01) gives monthly temperature and precipitation readings on a 0.5 degree grid for the entire world for the years 1901–2008. Weather outcomes in a country are the area-weighted average of all grids that fall in a country. See online Appendix A2.2 for a more detailed description. The weather for corn in the United States is therefore different for rice in the United States in a given year as they are grown in different areas and different time periods. The global average is simply the area weighted average of all crops and countries. Since the FAS data provides production quantities for all countries with significant production, we take the weighted average of each weather variable and country for all countries in the FAS data, i.e., we omit small countries in the FAO data as they tend to add noise to the measure.

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 and wheat, and November for soybeans and rice.[18] We construct the demand price p_{dt} as the log of the average futures price during the month when delivery occurred, e.g., in December of the delivery year for corn. Futures price in the supply equation

[15] Figure A8 in the online Appendix shows scatterplots of yield deviations for the two biggest exporters for each of our four commodities. These plots show no systematic correlation; one even has a negative correlation coefficient.

[16] Shocks vary between -0.070 and 0.051 in the FAS data, which averages over fewer countries.

[17] The Durbin-Watson statistic when we regress our baseline shock ω_t on various time trends in Tables 1 (FAO data) and Table A8 (FAS data) is 1.68–1.87, suggesting there is no autocorrelation. On the other hand, the statistic is 0.43–0.99 if we use prices, which is below the critical value at the 1 percent level.

[18] We use futures price for "No. 2 yellow" for corn, "No. 1 yellow" for soybeans, "No. 2 soft red" for wheat, and "Rough Rice No. 2" for rice. Rice futures did not trade before 1986, so we prorate the price of rice by the change in rice spot data. For example, if the spot data in 1980 was 70 percent of 1986, we set the futures price data in 1980 as 70 percent of the futures price in 1986. Since the price data are interpolated for rice, we do not use it when we derive the average price of all crops.

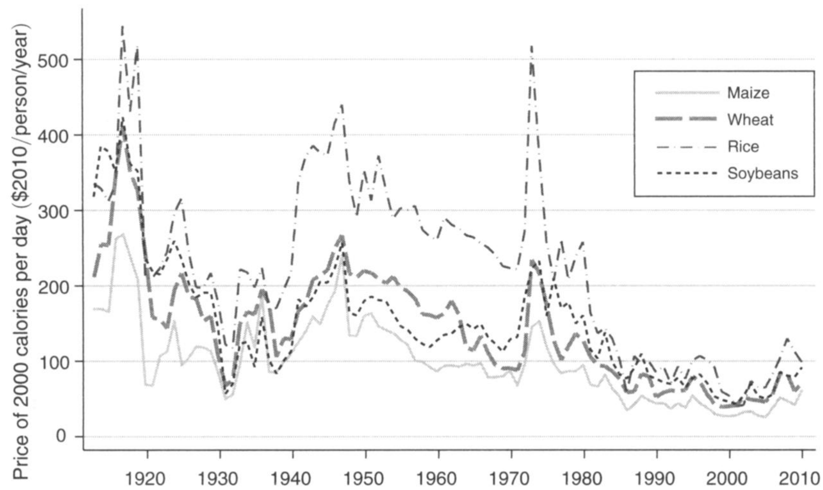

Figure 2. Commodity Prices

Notes: Figure shows caloric prices over time for maize, wheat, rice, and soybeans for 1913–2010. The *y*-axis gives the annual cost of 2,000 calories per day. Price series is taken from National Agricultural Statistics Service.

$p_{st} = p_t|_{t-1}$ is the log of the average futures price in December one year prior to delivery.[19] All prices are deflated by the Consumer Price Index.[20] 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.[21]

A second price series with longer temporal coverage is that received by US farmers, publicly available from the US Department of Agriculture (National Agricultural Statistics Service 1866–2010). Figure 2 displays real price (annual cost of a 2,000-calories-per-day diet in 2010 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.[22] 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

[19] In some cases the time series of a contract does not extend back to the previous December, so we take the average price in months closest to previous December.

[20] We deflate prices before we take logs. We use the CPI for all urban consumers (Bureau of Labor Statistics 1913–2011).

[21] For most commodities one cannot reject a unit root using standard tests (Wang and Tomek 2007), but nor can one reject the hypothesis of a stationary series with significant autocorrelation, as implied by storage theory. The same is true for our data: Augmented Dickey-Fuller tests do *not* reject a unit root for the price series. On the other hand, the first stage of Cochrane-Orcutt regressions of prices on a time trend predict autocorrelation coefficients between 0.50 and 0.81 dependent on whether we use FAO or FAS data and how many spline knots we include to model the time trend. Given that production is clearly trend stationary (a unit root can be rejected), and that production and prices are linked between periods through storage, the evidence points towards a stationary time series with high autocorrelation. Nevertheless, we present a sensitivity check where we control for lagged prices in both the first and second stage, but the results remain robust.

[22] In a sensitivity check we do not use the caloric conversion ratios of Williamson and Williamson (1942), but instead derive them implicitly by forcing the average price of each commodity in 1961–2010 to equal the one for maize. The rescaled price series is shown in online Appendix Figure A9.

cheaper input. Price fluctuations are proportionately much larger than quantity fluctuations in Figure 1. This fact suggests that both demand and supply are inelastic.

III. US 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.

The US ethanol mandate may have a measurable influence on world food prices since it diverts a sizable amount of global production into the fuel market. Since 1960, the US share of combined world caloric production for the four key commodities was about 23 percent (bottom left panel of online Appendix Figure A11), and the majority came from maize. Any mandate that diverts a sizable share of US production into fuel will also be sizable from a global perspective due to the US market share in calorie production.

Ethanol production has risen rapidly over the last couple of years as shown in online Appendix Figure A10. An ethanol tax credit was established in 2005, but it was phased out in January 2012. Mandates, however, are still in effect. The 2005 US Energy Policy Act mandated 7.5 billion gallons of ethanol be used by 2012. The 2007 Energy Independence and Security Act instituted a long-term mandate of using 36 billion by 2022 but limited the share that could be derived from corn-based ethanol. It also accelerated the short-term mandate. In 2009, the US Renewable Fuels Standard (RFS) required refiners and fuel blenders to blend roughly 11 billion gallons of ethanol into gasoline. We examine the effect of the 2009 RFS on world food prices. Currently, nearly all of US ethanol is produced from corn, and 11 billion gallons of ethanol would require roughly 4.07 billion bushels of corn assuming an average of 2.7 gallons of ethanol per bushel of corn (Rajagopal et al. 2007). This translates into roughly one-third of US maize production in 2010 (12.4 billion bushels), or about 5 percent of world caloric production in 2010. Recall that the largest negative historic production shocks was -0.057, so the annual impact of the US ethanol mandate is roughly equivalent to the worst production shock on record, except that the mandate is permanent, not transitory like the weather.

A byproduct from corn ethanol production, called distiller's grains, can be used as feed for livestock. While estimates vary, up to one-third of the caloric input is said to be recoverable, but the nutritional content is debated and generally thought to be inferior. We therefore present two estimates: our baseline model, which assumes that 5 percent of world caloric production is diverted into ethanol generation, 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 US motor gasoline consumption is 0.39 billion barrels per day.[23] Supplying approximately 8 percent of US gasoline consumption requires approximately 5 percent of world caloric food production.

IV. Empirical Results

Here we report results using FAO data. Online Appendix Section A4 reports results using FAS data, which are generally comparable.

A. *Main Results*

We summarize the main results in Table 1. Results include IV and 3SLS estimates, each with multiple specifications of the time trend. Elasticity estimates are reasonably stable across models, varying between 0.087 and 0.116 for supply and -0.028 and -0.066 for demand. F-statistics for first-stage instruments, lagged yield shocks ω_{t-1} for the case of supply, and concurrent yield shocks ω_t for the case of demand are given at the bottom of the table. All F-values are greater than ten, an accepted standard for strong instruments. Comparison of the coefficients on ω_{t-1} in the futures-price regression (panel A) and ω_t in the current-price regression (panel B) imply shocks affect futures prices nearly as much as current prices. This is consistent with storage theory wherein transitory shocks are smoothed over time, giving rise to autocorrelation in prices. It is also interesting that ω_t is statistically significant in some of the futures price regression. This indicates that shocks are at least partially forecastable.[24]

There is a trade-off between the two estimation methods (IV or 3SLS). For IV specifications we report robust standard errors throughout the paper (unless noted otherwise) that account for arbitrary forms of heteroskedasticity and autocorrelation in the error term. The 3SLS results are more efficient than IV estimates, but 3SLS standard errors may be biased if the error terms are not i.i.d. An exercise reported in the online Appendix (Table A12) suggests that 3SLS standard errors may be reasonable approximations. That exercise reports two sets of standard errors for the IV results: uncorrected and robust standard errors. While prices show significant autocorrelation, yield shocks do not: Table A12 presents tests for conditional heteroskedasticity as well as autocorrelation for the yield shocks ω_t, which all fail to reject the that they are i.i.d. Note that the second-stage elasticity estimates, the main parameters of interest, have similar standard errors whether or not they are corrected for heteroskedasticity and autocorrelation. This suggests that multistage standard errors are mainly sensitive to whether the instrument is i.i.d.

Table 1 also includes implied effects of the US ethanol mandate on world commodity prices. A shift in demand Δq changes equilibrium price by $\frac{\Delta q}{\beta_s - \beta_d}$. We therefore define a *price multiplier* $\frac{1}{\widehat{\beta_s} - \widehat{\beta_d}}$ using point estimates for the supply and demand elasticity, which translates outward shifts in demand (changes in quantities) into price changes. Multipliers range from 5.75 to 7.73, which imply that a 5 percent

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

[24] Partial forecastability of current shocks does not create bias in the supply equation because current shocks are not excluded from the second stage.

TABLE 1—SUPPLY AND DEMAND ELASTICITY (*FAO data*)

	Instrumental variables			Three-stage least squares		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. Supply equation						
Supply elast. β_s	0.102***	0.096***	0.087***	0.116***	0.112***	0.097***
	(0.025)	(0.025)	(0.020)	(0.019)	(0.020)	(0.019)
Shock ω_t	1.184***	1.229***	1.211***	1.249***	1.279***	1.241***
	(0.146)	(0.138)	(0.105)	(0.111)	(0.101)	(0.091)
First stage ω_{t-1}	−3.901***	−3.628***	−3.824***	−3.546***	−3.113***	−3.226***
	(1.145)	(0.945)	(0.910)	(0.800)	(0.704)	(0.731)
First stage ω_t	−2.918*	−2.276*	−2.372*	−2.885***	−2.350***	−2.420***
	(1.647)	(1.294)	(1.279)	(0.967)	(0.815)	(0.819)
Panel B. Demand equation						
Demand elast. β_d	−0.028	−0.055**	−0.054**	−0.034	−0.062***	−0.066***
	(0.021)	(0.024)	(0.022)	(0.023)	(0.022)	(0.021)
First stage ω_t	−5.564***	−4.655***	−4.770***	−5.354***	−4.445***	−4.332***
	(1.489)	(1.300)	(1.249)	(1.384)	(1.210)	(1.186)
Panel C. Effect of demand shift						
Multiplier $\frac{1}{\widehat{\beta}_s - \widehat{\beta}_d}$	7.73	6.63	7.06	6.65	5.75	6.12
Exp. multiplier	8.39	7.08	7.42	6.90	5.92	6.31
(95% conf. int.)	(5.2, 15.3)	(4.6, 12.2)	(5.0, 12.0)	(4.9, 10.4)	(4.3, 8.5)	(4.6, 9.1)
$F_{\text{1st-stage}}$ supply	11.61	14.73	17.66			
$F_{\text{1st-stage}}$ demand	13.97	12.81	14.60			
Observations	46	46	46	46	46	46
Spline knots	3	4	5	3	4	5

Notes: Tables show regression results for the supply and demand of calories. The first three columns, 1a–1c, use instrumental variables, while columns 2a–2c use three-stage least squares. Columns a, b, and c include restricted cubic splines in time with three, four, and five knots, respectively. Panel A gives results for the supply equations (1) and (2); i.e., coefficients in the first two rows give the results for log quantity, while coefficients in the third and fourth row give first-stage results of log price. Similarly, panel B gives results for demand equations (3) and (4). Coefficients on time trends are suppressed. Panel C gives the effect of a demand shift on commodity prices: multipliers translate percentage changes in demand into percentage changes in equilibrium price.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

shift from food calories into fuel generation increases the price of the four staple commodities by 29 percent–39 percent. Our preferred estimate uses the more efficient three-stage least squares estimator and more flexible time trends to account for the repeated spikes in the data: the baseline estimate is an approximately 30 percent price increase, which is on the conservative end of the range.

An unbiased estimate of the price increase needs to adjust for the fact that the expectation of an inverse of a random variable does not equal the inverse of its expectation. To find the expected price increase we take one million random draws from the estimated joint distribution of estimated supply and demand elasticities and find the price multiplier for each one.[25] Expected price changes, taken as the

[25] Another approach would be to use shrinkage estimators to obtain more efficient estimates of the inverse ratio. Since the elasticities are interesting in their own right, we decided to stick with standard OLS estimates, as a shrinkage estimator would result in biased estimates of these elasticities.

average of the one million simulated multipliers, are larger, because the price multiplier is a convex function of the sum of two elasticities, and the expected value of a convex function is larger than the function evaluated at the argument's expected level. For the same reason, the 95 percent confidence interval of the multiplier is positively skewed.

An estimated price increase of 30 percent implies a decline in food consumers' surplus equal to 180 billion dollars annually. We obtain this number assuming (i) expected supply (along the trend line) is the equivalent of feeding 7.92 billion people per year on 2,000 calories per day of raw grains and oilseed; (ii) prices in 2010 were 77 dollars per person per year; and (iii) the ethanol mandate increases prices by 30 percent. About two-thirds of ethanol production comes from new production, and about one-third comes from reduced food consumption, i.e., 1.67 percent of global production, given the supply elasticity tends to be about twice the size of the estimated demand elasticity. The reduction in food consumption is equivalent to the annual caloric requirement of about 132 million people.

There might also be an offsetting increase in producer surplus. Some argue that the ethanol mandate increases fuel supply, thereby lowering fuel cost, which in turn benefits consumers (Rajagopal et al. 2007). Alternatively, if past ethanol subsidies were insufficient to achieve the current mandate, it could increase the cost of gasoline production. A full welfare analysis would require an account of this supply shift, plus assumptions about the elasticities of supply and demand of fuels, which is beyond the scope of this article. Otherwise, if the net effect on fuel costs is small, in the agricultural market the policy largely amounts to a shift from consumer surplus to producer surplus.

The baseline scenario assumes byproducts from ethanol production are not fed to animals. We report estimates assuming zero recycling because studies differ in what fraction can be recycled, and the demand shift can be easily adjusted to any assumed recycling ratio. For example, if one-third of the calories could be recovered as feed stock, the demand shift and price increase would be multiplied by two-thirds, dropping the price increase to 20 percent rather than 30 percent. For our preferred 3SLS estimates in Table 1, the positively skewed 95 percent confidence interval ranges from 14 to 35 percent.

B. *Using Weather as an Instrument*

While an absence of autocorrelation in aggregate yield shocks and an absence of correlation in shocks between countries suggests that a random weather component is much larger than possible endogenous yield responses to price, a more defensibly exogenous instrument is weather itself. In Table 2 we present results when weather variables rather than yield shocks are used as instruments. We now use four instruments instead of one: a quadratic in both average temperature and total precipitation.[26] Coefficients from the log quantity regressions are given in columns a, while

[26] These weather variables are weighted averages of the University of Delaware gridded weather data, where we weight grids in a county over the areas a crop is grown and the time during which it is grown. Annual weather variables for each country and crop are aggregated using the growing area in a country. See the online data Appendix A2.2 for more detail.

TABLE 2—SUPPLY AND DEMAND ELASTICITY: WEATHER AS INSTRUMENT (*FAO Data*)

	log Q (1a)	log P (1b)	log Q (2a)	log P (2b)	log Q (3a)	log P (3b)
Panel A. Supply equation						
Supply elast. β_s	0.085*		0.089		0.091*	
	(0.048)		(0.055)		(0.053)	
Temperature T_{t-1}		3.252***		3.080***		3.050***
		(0.863)		(0.738)		(0.768)
Temperature T^2_{t-1}		−0.084***		−0.080***		−0.078***
		(0.022)		(0.019)		(0.019)
Precipitation P_{t-1}		2.937		2.597		3.174
		(2.249)		(1.923)		(2.097)
Precipitation P^2_{t-1}		0.130		−0.193		−0.497
		(1.072)		(0.922)		(0.982)
Temperature T_t	0.037	1.776**	−0.015	1.413**	−0.041	1.259*
	(0.184)	(0.750)	(0.201)	(0.669)	(0.195)	(0.691)
Temperature T^2_t	−0.002	−0.045**	−0.000	−0.035**	0.000	−0.031*
	(0.005)	(0.019)	(0.005)	(0.017)	(0.005)	(0.018)
Precipitation P_t	0.547	2.274	0.498	1.952	0.610*	2.847
	(0.332)	(1.805)	(0.363)	(1.611)	(0.371)	(1.742)
Precipitation P^2_t	−0.426***	−0.694	−0.431***	−0.952	−0.464***	−1.233
	(0.143)	(0.829)	(0.156)	(0.737)	(0.157)	(0.763)
Panel B. Demand equation						
Demand elast. β_d	−0.014		−0.056**		−0.047*	
	(0.025)		(0.028)		(0.025)	
Temperature T_t		1.282		1.099		1.305
		(1.209)		(1.003)		(1.038)
Temperature T^2_t		−0.034		−0.030		−0.035
		(0.030)		(0.025)		(0.026)
Precipitation P_t		1.991		1.636		0.759
		(3.227)		(2.675)		(2.853)
Precipitation P^2_t		1.075		0.705		1.015
		(1.460)		(1.211)		(1.266)
Panel C. Effect of demand shift						
Multiplier $\frac{1}{\widehat{\beta}_s - \widehat{\beta}_d}$	10.07		6.91		7.25	
Exp. multiplier	14.13		9.35		7.71	
(95% conf. int.)	(4.8, 52.9)		(3.8, 25.7)		(4.0, 27.4)	
Observations	46	46	46	46	46	46
Spline knots	3	3	4	4	5	5

Notes: Table replicates the three-stage least square results in Table 1 except that prices are instrumented with weather (quadratic in average temperature and precipitation) instead of yield shocks. Column pairs a and b present results from one joint regression, where columns a give results for the quantity regression, and columns b the results for the price regressions. Columns 1a–b, 2a–b, and 3a–b include restricted cubic splines in time with three, four, and five knots, respectively.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

results from the log price regressions are given in columns b. Significance levels decrease in both the first stage and the second stage. Coefficients on the instruments in the supply equation seem reasonable. For example, the quadratic in average temperature is hill shaped with an optimal growing season average of 19°C or 67°F. Instruments in the demand equation are neither individually nor jointly significant, and the demand elasticities should, hence, be interpreted with caution.[27] While past weather shocks are more defensible as an instrument, our baseline regression uses past yield shocks due to the large increase in efficiency.

C. *Response on Extensive and Intensive Margins*

Searchinger et al. (2008) and others argue that ethanol production drives up food commodity prices, which, in turn, causes greater conversion of forest and pasture into crop production. Because land use conversion (mainly deforestation) already accounts for up to 20 percent of global CO_2 emissions, these indirect land-use changes might offset or even reverse apparent CO_2 emission savings derived from substituting ethanol for traditional gasoline. Thus, an interesting policy question is whether new corn ethanol supply comes from the intensive or extensive margin. We investigate this issue in Table 3. The first three columns regress the log of growing area (for maize, rice, soybeans, and wheat) on the instrumented price to measure responses on the extensive margin. The last three columns use the log of total fertilizer, one of the major inputs that can be adjusted to increase production on the intensive margin.[28] The regressions are identical to the IV regression in our baseline model, except log growing area or log fertilizer use replaces log quantity. The estimated area elasticity is 0.07–0.08, while there is no significant response for fertilizer use—the point estimate is negative. This suggests that new supply likely comes from the extensive, not the intensive, margin.

The estimated land-area elasticity is slightly smaller than the overall supply elasticity. There will be less than a one-to-one relationship between output increases and land area increases if higher-productivity countries happen to be more responsive to prices than low-productivity countries. For example, if total land area increases by 5 percent, but areas with higher-than-average yield increase area by 6 percent and areas with less-than-average yield increase by 4 percent, total supply will increase by more than 5 percent. We therefore replicate the analysis for individual countries and find different sensitivities to world caloric shocks and world prices. Major producers and exporters like the United States and Brazil show much larger elasticities than the global average.

Although our land area elasticity for Brazil is comparable to Barr et al. (2010) in magnitude, our estimate for the United States is significantly larger. Agricultural programs of the US government have historically driven the US area response. In times of low prices, farmers received subsidies in exchange for setting previously cropped land idle (called *set asides*). At the same time, the US government scaled up programs that pay farmers to idle land for purposes of reducing soil erosion and protecting wildlife, water quality, and addressing other environmental concerns. During periods of high prices, set asides and conservation programs have been scaled back. When we regress the log of the growing area plus

[27] There are two reasons why it is empirically more challenging to estimate demand elasticities. First, the bottom panel of Figure 1 shows that consumption is much smoother through time than production. Second, these small changes in consumption are only indirectly derived using changes in inventories, which are harder to obtain than production numbers.

[28] FAO does not provide crop-specific fertilizer use. The data are, hence, for all crops, not just the four staples. The data are limited to 1961–2002 since reporting practices changed in 2003.

TABLE 3—GROWING AREA AND FERTILIZER USE AS A FUNCTION OF INSTRUMENTED PRICES (*FAO data*)

	log growing area			log fertilizer		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. World						
Futures price $p_t\|_{t-1}$	0.082***	0.078***	0.071***	−0.070	−0.071	−0.066
	(0.021)	(0.023)	(0.017)	(0.094)	(0.073)	(0.063)
Panel B. United States						
Futures price $p_t\|_{t-1}$	0.289***	0.278***	0.278***	0.026	0.021	0.097
	(0.075)	(0.075)	(0.071)	(0.173)	(0.095)	(0.079)
Panel C. US growing area + set asides						
Futures price $p_t\|_{t-1}$	−0.071	−0.050	−0.095**			
	(0.065)	(0.055)	(0.045)			
Panel D. Brazil						
Futures price $p_t\|_{t-1}$	0.261*	0.217	0.174	−0.150	−0.166	−0.041
	(0.141)	(0.142)	(0.111)	(0.506)	(0.262)	(0.260)
Observations	46	46	46	41	41	41
Spline knots	3	4	5	3	4	5

Notes: Table presents IV regression results. The regressions are equivalent to the IV results in Table 1 except that the second-stage dependent variable is different: columns 1a–1c use log growing area and columns 2a–2c log fertilizer. Columns a, b, and c include restricted cubic splines in time with three, four, and five knots, respectively.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

government-mandated set asides and land-retirement programs on instrumented price (panel C of Table 3), the estimated US elasticity drops sharply. Thus, much of the land supply response in the United States derives partly, and perhaps mainly, from agricultural policy responding to prices. During the recent price spike, however, conserved lands declined only modestly.[29] Given the relatively subdued responses of recent US agricultural policy and that the United States figures so prominently in world production of staple grains and oilseeds, supply response today might be somewhat less than our estimates, which would make the price and welfare impacts larger. However, land in US set aside and conservation programs is thought to be significantly inferior to land under cultivation, so it is not clear how much smaller the supply elasticity may be.

Using our estimated elasticities, total caloric production would increase by roughly 3.3 percent, or 190 trillion calories. In 2010, worldwide planting area for the four commodities was 1.6 billion acres. Using the average elasticity of 0.077 from Table 3 on the predicted 30 percent price change, total acreage is predicted to have increased by 2.3 percent, or 36 million acres, which is the size of the total land area (not agricultural area) of the US state of Iowa.

[29] Set asides ended with the Federal Agriculture Improvement and Reform Act of 1996. Since the first Renewable Fuel Standards in 2005, land enrolled in the Conservation Reserve Program has fallen from about 37 million acres in 2008 to about 29 million acres today (Hellerstein and Malcolm 2011).

TABLE 4—COMPARISON TO UNINSTRUMENTED REGRESSIONS (*FAO data*)

	OLS			SUR		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. Elasticities						
Supply elast. β_s	0.051*	0.020	0.023	0.065***	0.039	0.040*
	(0.028)	(0.031)	(0.029)	(0.020)	(0.025)	(0.024)
Demand elast. β_d	0.012	−0.018*	−0.016*	0.023**	−0.011	−0.010
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)
Panel B. Effect of demand shift						
Multiplier $\frac{1}{\widehat{\beta}_s - \widehat{\beta}_d}$	25.59	26.19	25.55	23.64	19.89	20.04
Exp. multiplier	55.05	22.85	15.26	77.51	37.23	15.51
(95% conf. int.)	(−206,248)	(−227,262)	(−205,247)	(12,120)	(8,122)	(9,118)
Observations	46	46	46	46	46	46
Spline knots	3	4	5	3	4	5

Notes: Table replicates Table 1 except that prices are not instrumented. Columns 1a–1c give results for OLS regressions, and columns 2a–2c from Seemingly Unrelated Regressions (SUR). Columns a, b, and c include restricted cubic splines in time with three, four, and five knots, respectively.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

D. *Comparison to Traditional Methods*

We compare the new estimates to other approaches without a first stage in Table 4. The first three columns report elasticity estimates using OLS, while the last three columns uses seemingly unrelated regressions (SUR). These models use uninstrumented price and futures prices, *not* predicted price in the spirit of Nerlove (1958). The SUR regressions do account for the correlation of innovations u_t and v_t. We include this regression mainly to illustrate likely endogeneity bias in comparison to IV and 3SLS estimates in Table 1. The OLS regressions give extremely inelastic estimates of supply and demand, 0.02 for supply if we include four spline knots and −0.018 for demand. The estimates also become much more sensitive to the flexibility of the time controls. While the demand elasticity is statistically significant at the 10 percent level if we include four spline knots, the standard errors are small and (if assumptions are accepted, which is dubious) rule out elasticities less than −0.038 with 97.5 percent confidence. The supply is statistically significant if we use three spline knots, which rules out elasticities greater than 0.106 with 97.5 percent confidence, or even smaller quantities for other time controls. The predicted price increase of the ethanol mandate (diverting 5 percent of world production) would be much larger, as the price multiplier is at least 25, or four times the baseline. For the seemingly unrelated regressions (SUR), the price multiplier is at least three times as large. Instrumenting prices with yield shocks is therefore crucial; otherwise the predicted price increase would likely be too large. Our concern with the traditional approach is that both futures prices and lagged prices incorporate anticipated area responses and are, hence, endogenous.

E. *World versus Local Prices*

Our baseline model sums over all countries in the world. ADM, Bunge, and Carghill are internationally operating arbitrageurs that work to equate possible price differentials between countries, subject to transportation costs. Prices in countries that have a port seem to be strongly associated with one another. For example, Fackler and Tastan (2008) test whether the law of one price holds for soybeans in the United States, Brazil, and Europe and cannot reject that markets are cointegrated. While landlocked countries might have prices that differ from the world market as arbitrage between prices becomes more costly, most large producers used in this study (see online Appendix Tables A1 and A2) do have ports.

We use price data from the US Chicago Board of Trade, and one might wonder how appropriate it is as a global measure. Table 5 disaggregates yield shocks into those in the United States and the rest of the world (RW). Shocks in both regions are rescaled using the ratio of the predicted production in the region divided by predicted global production. For brevity, the table presents only elasticities and the predicted commodity price increase, while individual coefficients for both the United States and the rest of the world are given in online Appendix Table A4. Panel C presents a test whether the coefficients on the instruments derived from US yield deviations equal those for the rest of the world. In no case can we reject that the coefficients are equal at any conventional significance level; all p-values are above 0.2. In other words, a production shock in Brazil does not have a significantly different effect on US futures prices than an equally sized shock in the United States. The estimated elasticities are also comparable to what we obtained in Table 1.

F. *Long-Run Response to Price*

Identification of our supply response relies on exogenous price variation that is driven by production shocks in the previous period. One concern is whether we are estimating a short-run elasticity that is a lower bound for the long-run elasticity.[30] Two observations speak against this: first, prices are both volatile and show a large degree of persistence, so farmers can expect temporary production shocks to have long-run price effects. There has been an active debate following Deaton and Laroque (1996) surrounding apparently excessive autocorrelation in prices. While our variation stems from short-run weather shocks, farmers can expect price changes from these weather shocks to persist. This persistence is also manifested in the relationship between crop and farmland prices. The run-up in commodity prices resulted in an almost proportional increase in farmland prices in 2005–2008. Since farmland prices are forward looking, this is efficient only if farmers expect commodity prices to stay high, which would seem unlikely if a longer-run supply

[30] It is also possible that the long-run elasticity is smaller than the short-run elasticity. This could happen if, in the short run, farmers respond to higher prices by using practices that boost output temporarily to the detriment of long-run productivity. Specifically, long-run supply response could be diminished by (a) overextracting from aquifers and thereby increasing future costs of irrigation; (b) accumulation of pest problems from an expanded monoculture; (c) reduced soil quality, especially if land that is newly cultivated in response to higher prices is marginal, has thin topsoil and cannot be cropped continuously. Such challenges are well known and have long been pervasive in agriculture.

TABLE 5—SUPPLY AND DEMAND ELASTICITY: SEPARATING SHOCKS IN US FROM REST OF WORLD (*FAO data*)

	Instrumental variables			Three-stage least squares		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. Elasticities						
Supply elast. β_s	0.107***	0.089***	0.083***	0.112***	0.105***	0.091***
	(0.022)	(0.025)	(0.020)	(0.019)	(0.020)	(0.018)
Demand elast. β_d	−0.021	−0.053**	−0.053**	0.003	−0.049**	−0.051***
	(0.020)	(0.022)	(0.021)	(0.017)	(0.019)	(0.017)
Panel B. Effect of demand shift						
Multiplier $\frac{1}{\widehat{\beta}_s - \widehat{\beta}_d}$	7.84	7.07	7.39	9.14	6.50	7.05
Exp. mult. (SE)	8.35	7.44	7.78	9.62	6.71	7.28
(95 percent conf. int.)	(5.3,14.7)	(4.8,13.3)	(5.2,12.6)	(6.5,15.5)	(4.9,9.8)	(5.3,10.6)
Panel C. p-value on equal coefficients						
$S_{\text{1st-stage}}\ \omega_{t-1}$ equal	0.20	0.56	0.77	0.81	0.50	0.61
$D_{\text{1st-stage}}\ \omega_t$ equal	0.42	0.24	0.27	0.77	0.36	0.38
Observations	46	46	46	46	46	46
Spline knots	3	4	5	3	4	5

Notes: Table replicates Table 1 except caloric shocks for the United States and the Rest of the World are considered separately. Both shocks are normalized by the predicted fraction of global production to make the shocks comparable in size. Panel C presents p-values from tests for whether the shock coefficients are the same when used as instruments for price. Coefficients for the United States and the Rest of the World (RW) are given in online Appendix Table A4. Columns a, b, and c include restricted cubic splines in times with three, four, and five knots, respectively.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

response were to erode the price shock. Second, our estimate of the longer-run supply response is consistent with our short-run estimates (Table 6). This longer-run analysis includes two lags in the supply equation, where prices are again instrumented with the previous period's weather shock. The table displays the coefficients on the futures price in the current period $\beta_{s,t}$ and lagged futures prices ($\beta_{s,t-1}$, $\beta_{s,t-2}$) as well as the sum of the three coefficients, which is the combined long-run impact. The sum of coefficients is slightly larger, but very close to our baseline estimate in Table 1 where we consider only futures prices in the current period.

G. *Multicrop Systems*

Our baseline estimates pooled all four basic staples (maize, rice, soybeans, and wheat), while ethanol production relies almost exclusively on maize. If the four commodities are not perfect substitutes, the mandate could cause corn prices to rise more than the other three crops.[31] We therefore consider a 2×2 system of supply and demand equations, where the two commodities are maize and the sum

[31] Online Appendix Table A5 pools quantities and prices for all four commodities but separates yield shocks for each of the four commodities. Panel D of the table presents tests whether the coefficients on the four shocks are the same, and equality cannot be rejected except if we model the time trend least flexible as a restricted cubic spline in time with three knots.

TABLE 6—SUPPLY AND DEMAND ELASTICITY: LAGGED SUPPLY PRICE (*FAO data*)

	Instrumental variables			Three-stage least squares		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. Supply equation						
Supply: $\beta_{s,t}$	0.066*	0.059	0.060**	0.074**	0.086***	0.079***
	(0.039)	(0.037)	(0.031)	(0.031)	(0.030)	(0.027)
Supply: $\beta_{s,t-1}$	0.030	0.024	0.028	0.023	0.004	0.013
	(0.048)	(0.042)	(0.035)	(0.031)	(0.027)	(0.024)
Supply: $\beta_{s,t-2}$	0.041	0.039	0.031	0.025	0.029*	0.026*
	(0.037)	(0.033)	(0.030)	(0.016)	(0.017)	(0.015)
Combined $\sum_{\tau=0} \beta_{s,t-\tau}$	0.137***	0.121***	0.118***	0.123***	0.119***	0.118***
	(0.018)	(0.020)	(0.015)	(0.016)	(0.021)	(0.019)
Panel B. Demand equation						
Demand elast. β_d	−0.019	−0.059**	−0.055**	−0.028	−0.051***	−0.051***
	(0.021)	(0.025)	(0.026)	(0.020)	(0.017)	(0.017)
Panel C. Effect of demand shift						
Multiplier $\frac{1}{\widehat{\beta_s} - \widehat{\beta_d}}$	6.41	5.53	5.75	6.63	5.90	5.91
Exp. multiplier	6.63	5.73	5.94	12.61	7.86	8.20
(95% conf. int.)	(4.8,9.8)	(4.1,8.6)	(4.3,8.7)	(5.9,28.2)	(5.0,13.9)	(5.2,14.4)
Observations	44	44	44	44	44	44
Spline knots	3	4	5	3	4	5

Notes: Table replicates Table 1 except that it includes two lags of the price in the supply equation. Columns a, b, and c include restricted cubic splines in time with three, four, and five knots, respectively.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

of the other three crops (Table 7). We present results for the specification with four spline knots, akin to column 2b of Table 1. The first two columns, 1a and 1b, as well as the last two columns, 2a and 2b, are from a single regression. The only difference is that the last two columns impose symmetry of the cross-price elasticities, which cannot be rejected in the unrestricted version of the model (a p-value of 0.87). Own-price supply elasticities are positive, but statistically significant only if we impose symmetry. Cross-price supply elasticities are never significant, but these have large standard errors. We cannot rule out the possibility that the cross-price elasticity equals the own-price elasticity.[32] Own-price demand elasticities are negative and significant. The size is larger than what we observe when we aggregate all four commodities. This is deceptive as the cross-price demand elasticities are quite large in magnitude, and significant if we impose symmetry. Consumers or agricultural producers that use commodities as inputs (e.g., feedlots) have the option to

[32] In our view, substitutability is reasonably large for relatively small variations in adjustments to global crop mix. For example, wheat, corn, and soybeans are substitutable over many parts of the Midwestern United States. In other parts of the world, e.g., India and China, some land is substitutable between wheat and rice. Especially since aggregate shocks are small and buffered by storage, a chain of substitutions could make aggregate substitutability quite large, at least over the range of aggregate weather shocks. But since prices consequently move together, it is difficult to precisely identify cross-price elasticities.

TABLE 7—SUPPLY AND DEMAND ELASTICITY: TWO-CROP SYSTEM (*FAO data*)

	Unrestricted system		Symmetry imposed	
	log maize (1a)	log other (1b)	log maize (2a)	log other (2b)
Panel A. Supply system				
log maize price	0.086	−0.024	0.136*	−0.001
	(0.118)	(0.078)	(0.070)	(0.047)
log other price	0.040	0.105*	−0.001	0.088**
	(0.088)	(0.058)	(0.047)	(0.036)
Panel B. Demand system				
log maize price	−0.271**	0.221*	−0.269***	0.240**
	(0.123)	(0.124)	(0.099)	(0.102)
log other price	0.248*	−0.336**	0.240**	−0.361***
	(0.136)	(0.132)	(0.102)	(0.113)
Panel C. Effect of maize demand shift				
Multiplier	4.14	2.31	3.63	1.95
Exp. multiplier	4.58	2.57	4.08	1.90
(95 percent conf. int.)	(1.7,15.6)	(−1.0,9.1)	(2.6,7.1)	(0.5,3.6)
p-value (symmetry)	0.870	.	.	.
Observations	46	46	46	46
Spline knots	4	4	4	4

Notes: Table replicates 3SLS results with four knots from Table 1, except that calories from the four crops are split into a 2×2 system: maize (M) and all other crops (O). Columns a and b present results from one joint regression, where columns a give the results for the maize regression and columns b the results for the aggregated crop (rice, soybeans, and wheat). The first two columns do not impose symmetry, while the last two do. The multiplier gives the price increase for a 1 percent outward shift in demand for maize, while baseline results give the multiplier on aggregate demand for maize, rice, soybeans, and wheat. To make the multiplier comparable to the pooled analysis, we derive the production-weighted average multiplier of all commodities, which is 8.37 in the unrestricted system and 7.21 if we impose symmetry.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

switch between commodities as relative prices change. Studies that focus on one commodity might therefore obtain an elasticity that is too high.

To derive price implications of this model, let $\mathbf{q}$ be the (2×1) column vector of the quantity of maize and three-crop aggregate commodity and let $\mathbf{p}$ be corresponding vector of prices. The demand system is $\mathbf{q} = \beta_d \mathbf{p}$, and the supply system is $\mathbf{q} = \beta_s \mathbf{p}$.[33] The effect of the US ethanol mandate, which diverted 5 percent of world caloric production of the four commodities, or 14 percent of the world's maize production, into ethanol, is hence $[\beta_s - \beta_d]^{-1}[1\ 0]'\Delta q$. For the same price increase, the multiplier will be lower as the mandate diverts 14 percent of maize production compared to 5 percent of world caloric production, which is larger by a factor of 2.8.

Panel C of Table 7 displays (i) the multiplier that uses the point estimates of the own-price and cross-price elasticities as well as (ii) the expected multiplier and (iii) the 95 percent confidence interval if we sample one million draws from the joint

[33] For a more detailed model, see online Appendix Section A1.2.

distribution of the parameters. The predicted price increase for corn is 51 percent (3.63×0.14), while the predicted price increase for the other commodities is 27 percent (1.95×0.14). Although the own-price effect for corn is statistically significant at the 95 percent confidence level and 50 percent larger than the cross-price effect for the other commodities, the two multipliers are not significantly different from one another due to the lack of precision in the 2×2 system.[34] The price increases are smaller using FAS data.

We are mainly interested in the ethanol-induced increase in overall expenditures for commodity calories. The baseline model implicitly assumes the four commodities are perfect substitutes, with the overall effect embodied by the price increase of the aggregate commodity, calories. For the disaggregate analyses, the overall price increase is the production-weighted average of individual commodity price increases. Multipliers that translate changes in aggregate demand into predicted changes in the overall price are given in the notes to Table 7.[35] These multipliers are 8.37 in the unrestricted system and 7.21 if we impose symmetry, which is slightly higher than the baseline multiplier of roughly six in the pooled analysis.[36] The 95 percent confidence interval increases to (4.8, 12.6) under the more efficient estimate where we impose symmetry and increases significantly more to (0.6, 31.5) in the less efficient unrestricted system. Since confidence intervals are positively skewed, the upper bound increases more than the lower bound decreases.

Table 8 reports results if we disaggregate the analysis further and estimate a 4×4 system of supply and demand for each of the commodities. Prices of each commodity are instrumented with past yield shocks (supply) or concurrent yield shocks (demand) for each of the four commodities. We switch to using the FAS data, which has three more observations, as the analysis already has limited degrees of freedom. Prices of the four commodities move closely together, which makes it is difficult to identify them separately. Instruments are weak, and results should be interpreted with care. While the point estimates for the price multipliers are roughly comparable to the 2×2 system, the 95 percent confidence interval includes zero for each of the four commodities due to the large standard errors. We take the table as suggestive evidence that our pooled analysis gives numbers that are roughly comparable to a 4×4 system.

The predicted price increase for maize is 59 percent (4.21×0.14) in the unrestricted system and 36 percent (2.54×0.14) if we impose symmetry of cross-price elasticities. At the same time, predicted price increases for other commodities are lower. The multipliers for translating shifts in aggregate demand into changes in the overall price of calories are 7.53 and 3.25, respectively, which is again reasonably similar to our baseline estimate of six.[37] Since the estimates are less precise, the

[34] Results using both four and five spline knots are shown in online Appendix Table A6 for FAO data and online Appendix Table A10 for the FAS data.

[35] We take the production-weighted average of the individual multipliers, where the production weights are the average fraction of world caloric production in 2005–2010 for each of the crops. We then divide the average multiplier by the maize share to transfer units into multiples of aggregate demand instead of maize demand.

[36] The multipliers are 5.48 and 5.19 if we use the FAS data in Table A10.

[37] The multipliers are 6.63 and 4.26 if we use the FAO data in Table A7.

TABLE 8—SUPPLY AND DEMAND ELASTICITY: FOUR-CROP SYSTEM (*FAS data*)

	Unrestricted system				Symmetry imposed			
	log maize (1a)	log rice (1b)	log soybeans (1c)	log wheat (1d)	log maize (2a)	log rice (2b)	log soybeans (2c)	log wheat (2d)
Panel A. Supply system								
log maize price	0.207*	−0.019	−0.734	−0.123	0.270***	−0.016	−0.303*	0.107*
	(0.121)	(0.043)	(0.546)	(0.163)	(0.101)	(0.065)	(0.168)	(0.061)
log rice price	0.043	0.048	0.350	0.111	−0.016	0.032	0.078	0.036
	(0.094)	(0.033)	(0.426)	(0.127)	(0.065)	(0.076)	(0.145)	(0.050)
log soybeans price	−0.252	0.085	0.705	0.010	−0.303*	0.078	0.554	−0.163
	(0.177)	(0.062)	(0.761)	(0.240)	(0.168)	(0.145)	(0.452)	(0.127)
log wheat price	0.088	−0.019	−0.229	0.059	0.107*	0.036	−0.163	0.100
	(0.099)	(0.035)	(0.417)	(0.135)	(0.061)	(0.050)	(0.127)	(0.063)
Panel B. Demand system								
log maize price	−0.244***	0.153***	0.227	−0.065	−0.287***	0.141***	0.078	0.068
	(0.078)	(0.054)	(0.193)	(0.083)	(0.066)	(0.032)	(0.068)	(0.045)
log rice price	0.061	0.007	−0.145	0.014	0.141***	−0.017	−0.114***	−0.071**
	(0.046)	(0.031)	(0.131)	(0.051)	(0.032)	(0.031)	(0.038)	(0.030)
log soybeans price	−0.008	−0.081	−0.329	0.043	0.078	−0.114***	−0.236**	−0.039
	(0.107)	(0.075)	(0.238)	(0.110)	(0.068)	(0.038)	(0.109)	(0.065)
log wheat price	0.199**	−0.152***	−0.063	−0.109	0.068	−0.071**	−0.039	−0.095
	(0.079)	(0.055)	(0.183)	(0.083)	(0.045)	(0.030)	(0.065)	(0.060)
Panel C. Effect of maize demand shift								
Multiplier	4.21	1.99	3.11	0.94	2.54	−1.18	1.70	1.21
Exp. multiplier	3.00	5.41	1.34	1.07	2.77	3.48	1.98	−3.52
(95% conf. int.)	(−20.1,28.1)	(−33.4,40.0)	(−19.7,24.3)	(−17.0,18.9)	(−5.2,11.5)	(−16.6,16.1)	(−3.4,7.1)	(−13.3,14.5)
p-value (symmetry)	0.201	.	.	.	.	.	.	.
Observations	49	49	49	49	49	49	49	49
Spline knots	5	5	5	5	5	5	5	5

Notes: Table replicates 3SLS results with five knots from Table 1 except that each of the four crops is modeled separately. Columns a–d present results from one joint regression. The first four columns do not impose symmetry, while the last four do. The multiplier gives the price increase for a 1 percent outward shift in demand for maize, while baseline results give the multiplier on aggregate demand for maize, rice, soybeans, and wheat. To make the multiplier comparable to the pooled analysis, we derive the production-weighted average multiplier of all commodities, which is 7.53 in the unrestricted system and 3.25 if we impose symmetry.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

95 percent confidence interval increases to (−6.6, 14.5) if we impose symmetry and (−43.8, 61.6) in the unrestricted system.

In summary, even if we relax the assumption of perfect substitutability, the predicted price increase in the overall expenditures for the four commodities remains relatively robust around a multiplier of six. At the same time, we cannot rule out a maize price increase that is twice as large as the overall increase for calories. But this larger price increase for corn is counterbalanced by lower price increases for other commodities. Since the multicrop systems are more flexible and less precisely estimated, the 95 percent confidence intervals increase, with the upper bound rising significantly more than lower bound declines due to positive skewness.

H. *Further Robustness Checks*

An online Appendix reports a number of additional sensitivity checks that we briefly summarize here. Results are generally robust in the sense that the price multiplier is around six in most specifications.

The 2009 Renewable Fuel Standard (RFS) changed fuel supply and gasoline prices and thereby influenced agricultural production costs.[38] If this shift in supply were large enough, it would confound our estimated elasticities. One way to ensure this is not the case is to reestimate the model using only data before the introduction of the ethanol mandate. Table A13 limits the analysis to 1961–2003 or 1961–2005, so the dataset stops before the recent runup in prices and the implementation of the 2007 or 2009 Renewable Fuel standards. Results are similar.

Table A14 varies the timing at which we evaluate futures prices. Final results of a year's production shock are not fully revealed before December. On the other hand, planting decisions for next year's harvest of winter wheat are made in September in the Northern Hemisphere. We therefore consider futures prices in September of the previous year (panel A), or March of the concurrent year (panel B), because production shocks in the Southern Hemisphere are resolved by March of the concurrent year. Panel C again evaluates prices at the end of the year but uses the spot price in the demand equation instead of the futures price during the month of delivery. Results are similar in all cases.

To check the sensitivity of our estimates to the derivation of yield shocks, Table A15 replicates the analysis using linear time trends, restricted cubic splines with four knots (three variables), or restricted cubic splines with five knots (four variables) in the derivation of the yield shocks. Our baseline specification used three spline knots (two variables). The results are again insensitive to the chosen time trend in the derivation of yield shocks.

Table A16 further examines the derivation of yield shocks. Panel A replicates the analysis by using yield shocks that are *not* jackknifed as in our baseline. Panels B and C allow yields to be autocorrelated, which may arise from technological breakthroughs or if weather has autocorrelation. We fit models up to MA(1) or MA(3), respectively, for each country and crop. For example, in panel C, we fit four models.[39] The model with the lowest Bayesian information criterion is chosen, and yield deviations are the innovations in a given period, i.e., the new information that has been revealed. Results remain robust.

Table A17 reports results from three further sensitivity checks. Given that prices show a high degree of persistence, we include the second lag of prices in panel A. Log futures prices for period t that are traded at the end of $t-1$ are instrumented with the yield shock in ω_{t-1} while controlling for the second lag of the dependent variable, i.e., log futures prices with a maturity in $t-1$ that are traded in $t-2$. Panel B uses two lagged shocks ω_{t-1} and ω_{t-2} to instrument

[38] The RFS, which might nominally be considered an implicit cost or tax on gasoline production, formerly included a large subsidy for ethanol production. Now that ethanol plants are in place (fixed costs are largely sunk), it is not clear whether current and past RFS ultimately served to subsidize or tax fuel. Another complicating feature is the substantial size of US demand for gasoline. Since ethanol displaced about 10 percent of oil formerly used in gasoline production, the biofuel mandate may have reduced world oil prices.

[39] MA(0), MA(1), MA(2), and MA(3).

futures prices. The panel also presents results from overidentification tests as we now include two instruments, but none of them has a p-value below 0.40. Panel C rescales the caloric conversion ratios so the average price in 1961–2010 of all four crops equals that of maize.[40] The original as well as the rescaled price series are shown in Figure A9. We do this as the average price of rice is highest, and shifts in production between crops hence alters the overall price. However, the results are insensitive to this rescaling.

V. Conclusions

Our analysis makes two contributions to the literature. We first introduce a new framework on how to identify supply elasticities for storable commodities and apply it in the agricultural setting: weather-induced yield shocks can facilitate estimation of both supply and demand of agricultural commodities. In applying this idea to the available data we found it more practical to use yield shocks (deviations from time trends of output per land unit) instead of using weather directly, which gives a weaker first stage as global annual production has to be linked to aggregate annual weather measures. We obtain similar point estimates using both weather and yield shocks. The 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.

While the idea of using weather to identify demand is an old idea, it has rarely been applied and, to our knowledge, has never been applied on a global scale. Our approach of using past shocks to identify supply is new and results in estimates that are far more elastic than those obtained using traditional methods. 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 computational 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.

The second contribution is to estimate elasticities for caloric energy from the world's most predominant food commodities. With this perspective in mind, we consider price and quantity predictions stemming from the rapid and largely policy-induced expansion of ethanol demand. The 2009 Renewable Fuels Standard diverted approximately 5 percent of world caloric production of the four staple crops into ethanol production. Since commodities are storable and current ethanol production levels were 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

[40] In other words, the price series of wheat, soybeans, and rice are each multiplied by a constant so the average price equals the maize average price.

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 distillers' grains, a byproduct from corn used in ethanol production, are recycled as feed stock, the price increase would be scaled back accordingly. For example, if one third of the calories can be recovered as feedstock, the price increase would be lowered to 20 percent. These predicted price increases are far smaller than those obtained using a SUR model that does not account for the endogeneity of prices. Our prediction is slightly larger than the USDA projected price increase made for corn in 2007 and would suggest that the ethanol mandate had some role in the fourfold price increase, but by no means can account for all of it.

It is also important to consider uncertainty surrounding these baseline estimates. The 95 percent confidence bands around the induced price increase have a large, positive skew. Even taking distillers' grains into account, the ethanol-induced price increase for food commodities as a whole may be as low as 14 percent, just 6 percentage points below the baseline of 20 percent; but it may also be as large as 35 percent, a full 15 percentage points above the baseline.[41] Multicrop models relax the perfect substitutability between the four crops. Price increases may vary across crops, but the point estimates for the increase in total expenditures for the four crops remains comparable. These estimates are less precise, and the 95 percent confidence bands increase more on the upper end than the lower end due to the positive skewness.

Our analysis suggests factors besides the US ethanol policy likely contributed strongly to the rapid price rise between 2005 and 2008. These factors may include rapid growth 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 constituted a little less than a third of the world's meat consumption in 2007. Meat requires between five and ten times the agricultural area to obtain the same amount of calories as a vegetarian diet. This demand growth resumed as the world economy recovers from the financial crisis and subsequent recession, and corn prices jumped to new highs in 2011. Another reason for the large price increase is a decrease in supply due to detrimental weather, such as prolonged drought in Australia, coupled with low worldwide inventories. The implications of increases in demand coupled with the potential of production shortfalls in the face of changing climate will likely add further upward pressure on future prices.

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[41] Using the 3SLS results in Table 1.

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