Identifying Agricultural Demand and Supply Elasticities: Implications for Food Price Volatility

Steven T. Berry♣, Michael J. Roberts♠ and Wolfram Schlenker♡

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Abstract

We extend the reduced-form framework of Roberts & Schlenker (2012) to identify demand and supply elasticities to allow for unobservables that can potentially be serially correlated. Demand and supply elasticities for calories remain rather robust at -0.05 and 0.11, respectively. We use these elasticities to discuss the effect of the ethanol mandate on steady state food prices, which are expected to raise commodity prices by 30% without adjusting for feedbacks from distillers grains. Second, we present statistical estimates of the production shortfall in 2012. US maize production is predicted to decrease by 14%, or a bit less than half the amount used to meet the mandate. While 2012 was hot and dry, it is predicted to become the new normal fairly soon under global climate models. Third, we discuss how bankable permits to meet the ethanol mandate can be used to smooth production shocks.

♣ Yale University and NBER. Email: steven.berry@yale.edu

♠ University of Hawaii. Email: mjrobert@hawaii.edu

♡ University of California at Berkeley and NBER. Email: schlenker@berkeley.edu

The summer of 2012 has seen continued press coverage of the extremely hot and dry conditions in the Midwestern United States. Commodity prices, especially corn, have risen sharply. Since corn is a feedstock for many animals, meats and eggs are projected to become more expensive according to USDA.[1]

The recent price spike is on top of a significant increase in commodity prices since 2005. Many factors have been attributed to this trend, e.g., the increased demand for calorie-intensive meats as emerging countries become richer, an increased demand for basic commodities to meet biofuel mandates, as well as supply shocks due to weather events (drought in Australia or Russian wildfires). Simulating the effect of shifts in both demand and supply and the effect on food commodity prices requires an estimate of demand and supply elasticities of commodities. Since these commodities are traded internationally, it is the global supply and demand elasticity that matter.

There have been various approaches to identify demand and supply elasticities. Hausmann, Auffhammer & Berck (Forthcoming) and Carter, Rausser & Smith (2012) use vector auto-regression to estimate the effect of the US ethanol mandate on US corn prices. The former finds that the US ethanol mandate is responsible for roughly 27% of the observed price increase in the 2006/2007 boom year, while the latter finds that the US ethanol mandate resulted in prices that are roughly 30% higher corn price than they would have been without the mandate. In both approaches, lagged variables are allowed to influence futures prices. One potential concern behind the VARs is that some shocks are anticipated (e.g., pest outbreaks), and hence both lagged price and past futures prices can be endogenous.

In earlier work, we used an IV approach where futures prices were instrumented using yield shocks (deviation from a deterministic trend) or observable lagged weather variables (Roberts & Schlenker 2009, Roberts & Schlenker 2012). Instead of zooming in on one crop in one country (e.g., the United States), we examine the global demand and supply of the four major staple commodities (maize, rice, soybeans, and wheat), which together account for roughly 75% of the calories humans consume. The idea behind our identification is to use *past* shocks, which shift past inventories and thereby the combined market demand curve in the current period (through the demand to refill / deplete inventory levels). These "shifts" in the demand curve can be used to trace out the supply curve. This is the mirror image of the work by Wright (1928), who used weather-induced supply shifts to identify demand. While the use of lagged weather variables is more defensibly exogenous, the first stage is less

[1] Meat prices might initially fall as livestock producers are selling of their herds, leading to an increase in supply.

significant than if we use deviations from a trend. Our baseline specification therefore relies on country-and-crop specific deviations from a trend and argues that they are predominately due to weather. One potential concern of this approach is that there might be unobserved demand or supply shifts that are serially correlated, which would undermine the IV strategy.

The first major contribution of this paper is to extend the reduced-form IV approach and allow for serially correlated unobservables in Section 1. We introduce recent advances in the IO literature, that use observed decisions as proxies for the unobserved serially correlated states (Olley & Pakes 1996). Different modeling strategies are discussed in Section 1.1. The data is briefly summarized in Section 1.2 and the results are shown in Section 1.3.

The second contribution is to examine the effect of the 2012 heat wave on predicted US production in Section 2. While it has been hot and dry, climate change predict a new normal that will be much warmer. Predicted yield declines are slightly less than in 1988, the year with the largest production decline in the last 60 years.

The third and final contribution in Section 3 is to discuss how supply shortfalls will interact with the ethanol mandate. On the one hand, the ethanol mandate requires that corn be diverted for fuel, thereby limiting the amount that is available for food which can amplify production shocks. On the other hand, a portion of the ethanol mandate (up to 20%) can be banked between periods, which allows for smoothing of shocks. Finally, Section 4 concludes.

1 Identifying Demand and Supply Elasticities

A basic model of demand and supply tells us that an outward shift in demand by Δq (in percent) will increase the equilibrium price by $\frac{1}{\beta_s - \beta_d}\Delta q$ percent, where β_s and β_d are the supply and demand elasticity, respectively. An estimate of the demand and supply elasticity is hence all we need to obtain the multiplier $\frac{1}{\beta_s - \beta_d}$, which translates quantity shifts in demand into equilibrium price shifts.

In the following we generalize the model of Roberts & Schlenker (2012) to obtain estimates of β_s and β_d that are consistent under a weaker set of assumptions. We simplify our characterization of world food commodity market by transforming quantities of maize, wheat, rice, and soybeans into caloric equivalents and then aggregating them (Roberts & Schlenker 2009).[2] Aggregating crops facilitates a simple yet broad-scale analysis of the supply

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

and demand of staple food commodities on a worldwide scale. Prices for all four commodities tend to vary synchronously. For example, the recent Russian wildfires that impacted global wheat production influenced maize prices almost as much as wheat prices.

1.1 Model

In the following we introduce three models of yields that become successively less restrictive. Roberts & Schlenker (2012) relied on Model 1 to obtain yield shocks, while we will follow Model 3 below in this paper.

1.1.1 Model 1: Yield as a Function of Trend and Weather

The first model is the simplest model of technology and weather. In this model yields are given by

$$y_{it} = h_i(t, \theta) + \epsilon_{it} \tag{1}$$

where y_{it} is log yield in country i at time t, $h_i(t, \theta)$ is a flexible time-trend parameterized by θ (capturing the effects of technology) and ϵ_{it} represents the unmeasured effects of weather that causes fluctuations around the mean. It seems plausible to assume that weather is difficult to predict at time $t-1$ and we might assume formally that

$$\mathbb{E}[\epsilon_{it} \ |\mathcal{J}_{t-1}] = 0, \tag{2}$$

where $\mathcal{J}_{t-1}$ is a set of lagged variables that do not predict next year's weather.

Equation (1) can be estimated by a standard OLS regression of log-yields on a flexible time trend, recovering "weather" as the residual of the equation. This is the approach we follow in Roberts & Schlenker (2012). Restriction (2) can be tested, and we find no evidence that past (estimated) weather does predict future weather. While we were unable to reject the simple technology/weather model, a lack of a rejection is not a proof of absence.

1.1.2 Model 2: Yield as a Function of a Trend, Price, and Weather

The second model includes price as an additional explanatory variable besides the trend. This model is

$$y_{it} = h_i(t, \theta) + \eta p^e_t + \epsilon_{it}, \tag{3}$$

where p^e_t is the log of the expected harvest price at the time farmers are making planting decisions. The parameter η is the yield-price elasticity, which is to be estimated. In this model, we still assume that ϵ_{it} is serially uncorrelated weather.

There are several classic ways of estimating (3), which are sensitive to particular timing assumptions. One is to assume that the uncorrelated weather term is not observed until after p^e_t is observed. This would justify OLS estimation of (3). Obviously, this is incorrect if farmers make yield-influencing decisions late in the crop-year, so that weather is at least partly observed or predictable. It would also be problematic if there are know supply states that influence both futures prices and yields, e.g., the presence of soybean rust in the early 2000s.

A second classic assumption is that assume that ϵ_{it} is at least partly predictable when p^e_t is observed, but that a *lagged* price p^e_{t-1} is [a] uncorrelated with ϵ_{it} but [b] correlated with p^e_{t-1}. In this case, lagged price can be used as an instrument for current price. Note that if ϵ_{it} was serially correlated, this approach would not work as lagged price would be likely correlated with current ϵ_{it}. Again, technological breakthroughs or persistent pest problems could induce such correlation. The classic "lagged price as instrument" is justified by assuming that lagged price is an element of the set $\mathcal{J}_{t-1}$ in (2).

Our "uncorrelated weather" test can be thought of as following from an assumption that lagged weather is an element of $\mathcal{J}_{t-1}$. Since ϵ_{t-1} is assumed to be unobserved, this does not lead to a simple IV strategy. However, it does lead to a natural "moment" restriction in a GMM context (Hansen 1982). In particular, one can impose the moment

$$\mathbb{E}[\epsilon_{it}, \epsilon_{i(t-1)}] = \mathbb{E}\left[y_{it} - h_i(t,\theta) - \eta p^e_t, y_{i(t-1)} - h_i(t-1,\theta) - \eta p^e_{t-1}\right] = 0 \tag{4}$$

One could identify the price-coefficient η either by using (4) alone, or by combining that restriction with other IV-style restrictions (such as the "lagged price as instrument restriction.") Combining restrictions would tend to result in more precise estimates.

1.1.3 Model 3: Correlated (Non-weather) Errors

The relatively simple models of the prior discussion all rely on the idea that the "true" error is serially uncorrelated. We now introduce two explicit sources of serial correlation. The idea will be to isolate the "weather" shock even in the presence of the serially correlated errors. As in the Olley-Pakes production function literature (Olley & Pakes 1996), we will use observed decisions as proxies for the unobserved serially correlated states. This is also closely related to the working paper by Ackerberg, Caves & Frazer (2006).

At the time of supply, there are known states of demand and supply, denoted ν_t and ω_t

respectively. We assume that that the relavent state variables in the market are these states of demand and supply together with the amount of land area cultivated in the prior period, $a_{i(t-1)}$, any observed exogenous input prices r_t, and the trending level of technology, τ. As usual τ is modeled as a smooth function of time t.

The states (ν_t, ω_t) can be arbitrary serially correlated. Assume that all market participants, including the farmers and traders in futures markets, observe ν_t and ω_t at the time of planting, although the econometrician does not.

The futures market observes all the state variables and sets the futures price (using $\mathbf{a}_t = \{a_{1t}, a_{2t}, \ldots, a_{nt}\}$, i.e., the set of planting areas of all countries i)

$$p_t^e = f(\mathbf{a}_{t-1}, \mathbf{a}_t, r_t, \nu_t, \omega_t, t) \tag{5}$$

Farmers make two decisions based on these states: they first choose land area, a_{it}, and then non-land inputs, k_{it} according to the decision rules:

$$\begin{aligned} a_{it} &= h(\mathbf{a}_{t-1}, r_t, \nu_t, \omega_t, t) & (6) \\ k_{it} &= g(\mathbf{a}_t, r_t, \nu_t, \omega_t, t) & (7) \end{aligned}$$

Note that a_{it} and k_{it} depend on all the states that determine p_t^e, so this model nests a model where the inputs (a_{it}, k_{it}) depend directly on price.

The land and non-land inputs, together with the technology shock determine expected yield:

$$\mathbb{E}[y_{it}|\ a_{it}, r_t, \omega_t] = \bar{y}_i(a_{it}, k_{it}, \omega_t, t). \tag{8}$$

After planting, weather (and any deviation of tecnology from trend) is realized and actual observed yields are

$$y_{it} = \bar{y}_i(a_{it}, k_{it}, \omega_t, t) + \epsilon_{it} \tag{9}$$

where ϵ_{it} is by construction uncorrelated with the states at planting time t. Furthermore, we assume that while the states (ω, ν) can be arbitrarily serially correlated, ϵ_{it} is itself uncorrelated with the future evolution of the market. This is consistent with the interpretation of ϵ as weather, but ϵ could also include other transitory supply shocks.

The problem with estimating (9) is that [i] we don't see the persistent supply state, ω_t and [ii] we don't necessarily see all the non-land inputs k_{it}. To get around the latter problem, we substitute the non-land input equation (7) into the expected yield equation (8) and get

$$y_{it} = \bar{y}_i(\mathbf{a}_t, r_t, \nu_t, \omega_t, t) + \epsilon_{it} \tag{10}$$

Now the problem is that we don't observe ω_t and t, but we will solve for the unobserved demand and supply shocks via a generalization of Olley & Pakes (1996).

In particular, we treat the observed futures price and the land choice as two equations in the (two) unknown demand and supply states. Specifically, we assume that (5) and (6) can be inverted to solve for the two unknown states:

$$\omega_t = z_1(\mathbf{a}_{t-1}, \mathbf{a}_t, p_t^e, r_t, t) \tag{11}$$

$$\nu_t = z_2(\mathbf{a}_{t-1}, \mathbf{a}_t, p_t^e, r_t, t) \tag{12}$$

Plugging these two back into the yield equation (10) gives

$$y_{it} = \tilde{y}_i\left(\mathbf{a}_{t-1}, \mathbf{a}_t, p_t^e, r_t, t\right) + \epsilon_{it} \tag{13}$$

Because ϵ_{it} is unpredictable from the arguments of $\tilde{y}$, we can estimate (13) to uncover ϵ_{it} as the residual from the regression. The function $\tilde{y}$ has no particular interpretation, it is a kind of reduced-form equation. The important point is that residual ϵ_{it} has the properties of our earlier "deviation from yield" weather variable under a weaker set of assumptions, specifically allowing for serially correlated supply and demand states. The residual can be used as an instrument in the same way.

Specifically, we run a regression for each country and crop that on averages produces at least 0.005percent of global supply (countries are given in Tables 1 and 2).

$$y_{it} = \beta_0 + \beta_1 a_{i(t-1)} + \beta_2 a_{it} + \beta_3 p_t^e + \beta_4 r_t + f(t) + \epsilon_{it} \tag{14}$$

where y_{it} is the log yield in country i in year t, $a_{i(t-1)}$ and a_{it} are the lagged and concurrent log growing area of the crop in country i, p_t^e is the futures prices at the Chicago Board of trade at the beginning of the growing season,[3] and r_t is an index of fertilizer prices in the United States in March/April of year t.

The whole argument of this subsection allows us to carry forward exactly in the manner

[3]The months in which the futures prices are evaluated are given in the first column of Tables 1 and 2. In case the month is September, e.g., the case of winter wheat or other crops grown in the Southern hemisphere, we evaluate the futures contract in September of the year preceding the harvest.

of Roberts & Schlenker (2012), except that instead of using yield "deviations from trend" as the "weather" variable, we use the residuals of the (explicitly motivated) "kitchen sink" regression in (14). The observed variables $(\mathbf{a}_{t-1}, \mathbf{a}_t, p_t^e)$ have both [a] potential direct (causal) effects on yield together with [b] "proxy" effects in controlling for the serially correlated shocks. I.e., once we obtained the global production shock ω_t by summing over all ϵ_{it} (countries and crops) in (14), we run:

$$
\begin{aligned}
\text{Supply:} \quad q_{st} &= \alpha_s + \beta_s p_{st} + \gamma_s \omega_t + f_{s2}(t) + u_t && (15) \\
p_{st} &= \delta_s + \mu_{s0}\omega_t + \mu_{s1}\omega_{t-1} + f_{s1}(t) + \xi_t && (16) \\
\text{Demand:} \quad q_{dt} &= \alpha_d + \beta_d p_{dt} + f_{d2}(t) + v_t && (17) \\
p_{dt} &= \delta_d + \mu_{d0}\omega_t + f_{d1}(t) + \eta_t && (18)
\end{aligned}
$$

Log quantities supplied and demanded are denoted by $q_{st} = log(s_t)$ and $q_{dt} = log(s_{t-1}+x_{t-1}-x_t)$, respectively. The amount consumed (demanded) is the difference between carryover from last period (new production s_{t-1} plus the amount stored x_{t-1}) and the amount x_t that is stored for the next period. The supply equation uses the log of future price $p_{st} = log\,(p_t|_{t-1})$[4], while the demand equation uses log futures prices during the month of delivery $p_{dt} = log(p_t)$. Intercepts $\alpha_s, \alpha_d, \delta_s$, and δ_d are allowed to evolve over time according to time a trend $f_i(t)$.

1.2 Data

We use the same data as in Roberts & Schlenker (2012): World production and storage data are publicly available from the Food and Agriculture Organization (FAO) of the United Nations (http://faostat.fao.org/) for the years 1961-2010. 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 only available 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 (http://http://www.fas.usda.gov/) that has data for 1961-2010 for all variables, including stocks.[5] Variables are converted into edible calories using conversion factors by Williamson & Williamson (1942), which specify edible calories per output quantity of various

[4] 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.

[5] FAS reports production for marketing years.

crops. Consumption (quantity demanded) is calculated as production minus the net change in inventories.

Our 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.[6] 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 $p_{st} = p_t|_{t-1}$ is the log of the average futures price in December one year prior to delivery.[7] All prices are deflated by the Consumer Price Index.[8] 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.

1.3 Empirical Results

We will first replicate the analysis of Roberts & Schlenker (2012) before we present the new revised results.

1.3.1 Replication of Roberts and Schlenker (2012)

Table 3 is taken out of Roberts & Schlenker (2012) for comparison.[9] Results include IV and 3SLS estimates, each with multiple specifications of the time trend. Elasticity estimates are reasonably stable across models, varying between 0.086 and 0.114 for supply and -0.028 and -0.067 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 10. 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

[6] We use futures price for "No. 2 yellow" for corn, "No. 1 yellow" for soybeans, "No. 2 soft red" for wheat, and "Rough Rice #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% of 1986, we set the futures price data in 1980 as 70% of the futures price in 1986.

[7] 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.

[8] We deflate prices before we take logs. We use the CPI for all urban consumers: ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt

[9] Recall that the model used deviations from a trend as yield shocks.

regression. This indicates that shocks are at least partially forecastable.[10]

There is a tradeoff 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 heteroscedasticity 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 iid.

Table 3 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 5.80 to 7.85, which imply that a 5% shift in demand food into fuels increase price of the four staple commodities by 29%-39%. 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% 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.[11] Expected price changes, taken as the 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% confidence interval of the bootstrapped multiplier is positively skewed.

An estimated price increase of 30% implies a decline in food consumers' surplus equal to 180 billion dollars annually. We obtain this number from the trapezoid formed by (i) expected supply (along the trend line) is the equivalent of feeding 7.92 billion people for a year on 2000 calories per day of raw grains and oilseed; (ii) prices in 2010 were 77 dollars per person per year; and (iii) the ethanol mandate had increases prices by 30%. About two thirds of ethanol production come from new production and about one third comes from reduced

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

[11]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.

food consumption, i.e., 1.67% of global production given that the supply elasticity tends to be twice the size of the estimated demand elasticity. The reduction in food consumption is equivalent to the annual caloric requirement of 132 million people.

There will 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). The full welfare analysis therefore requires an assumption on the elasticity of supply of fuels, which is beyond the scope of this paper. Otherwise, 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% rather than 30%.

1.3.2 Revised Estimates Allowing for Serial Correlation

Table 4 replicates Table 3 except that the yield shocks ω_t are no longer deviations from trends but estimated via equation (14). Note how the estimated impacts are roughly comparable. For the three-stage least square results (columns (2a)-(2c)), the estimates supply elasticities are slightly larger, while the estimated demand elasticities are slightly smaller in magnitude. The overall price multiplier $\frac{1}{\beta_s - \beta_d}$ in panel C is very robust. The most notable changes are the drop in the first-stage F-statistic.[12]

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% 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 5. 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

[12] Appendix Table A1 gives the results using the FAS data set.

intensive margin.[13] 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 0.09-0.1, 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. Although our land area elasticity for Brazil is comparable to Barr et al. (2010) in magnitude, our estimate for the US 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 government-mandated set-asides and land-retirement programs on instrumented price (panel C of Table 5), the estimated US elasticity drops sharply. Thus, much of the land supply response in the US derives partly, and perhaps mainly, from agricultural policy responding to prices. During the recent price spike, however, conserved lands declined only modestly.[14] Given the relatively subdued responses of recent US agricultural policy and that the US 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 an elasticity of 0.075 from Table 5 on the predicted 30 percent price change, total acreage is predicted to have increased by 2.3 percent, or 36 million acres,

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

[14]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 & Malcolms 2011).

which is the size of the total land area (not agricultural area) of the US state of Iowa.

Our identification relies on exogenous price variation due to last period's production shock. One concern is whether we are estimating a short-run elasticity that is a lower bound for the long-run elasticity. Two facts speak against this: first, prices show a large degree of persistence, so farmers can expect temporary production shocks to have long-run price effects. This is manifested in the relationship between crop and farmland prices. The recent run-up in commodity prices resulted in an almost proportional increase in farmland prices. Since farmland prices are forward looking, this is only efficient if farmers expect commodity prices to stay high, which would seem unlikely if a longer-run supply response were to erode the price shock. Second, Table 6 replicates the analysis but includes two lags in the supply equation, where prices are again instrumented with last 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 3 where we only consider futures prices in the current period. This suggests our estimates are reasonable proxies for the long-run response.

2 Impact of 2012 Weather on US Corn Supply

There has been significant media coverage of weather outcomes in the Midwestern United States. To put the magnitude of the predicted production shortfall into perspective of the US ethanol mandate, we present a simple regression framework that links yields to weather outcomes (Schlenker & Roberts 2009). Specifically, we estimate a model of the form:

$$y_{it} = c_i + \beta_1 GDD_{it} + \beta_2 HDD_{it} + \beta_3 p_{it} + \beta_4 p_{it}^2 + f_s(t) + \epsilon_{it}$$

where y_{it} are log yields in county i and year t. County fixed effects c_i account for baseline differences between counties. We include four weather variables that are season totals: GDD are growing degree days between 10 and 29°C,[15] HDD are heating degree days above 29°C, and p and p^2 are total precipitation and total precipitation squared. We also include state-specific time trends f_s to capture technological progress.

[15]Degree days are just a truncated temperature variable that only counts temperatures between thresholds for each day of the growing season. For example, degree days 10-29°C counts all temperatures below 10C as zero, temperatures between 10° and 29° as the difference to 10 (e.g., a temperature of 11°C gives 1 degree day, a temperature of 12°C gives 2, etc), and temperatures above 29°C as 19 degree days.

The data underlying these regression is constructed using daily fine-scaled weather measures on a 2.5x2.5 mile grid for the contiguous United States. We follow the same algorithm of Schlenker & Roberts (2009), but update the data until August 6, 2012. We only use counties east of the 100 degree meridian (except Florida) in the regression, as the response function might be different for highly irrigated areas. Our subset of counties account for roughly 85% of the corn that is produced in the US.

Regression results are shown in Table 7, where different columns allow for various time trends. Errors are clustered at the state level to adjust for spatial correlation. The estimated coefficients are insensitive to the chosen time control. Degree days 10-29°C are beneficial for yields as they allow for longer-maturity crops, degree days above 29°C are harmful for yields, and precipitation has a hill-shaped function suggestion that too much or too little precipitation is harmful.

The years 2012 has been exceptionally warm and dry. This had both good and bad effects. First, Figure 1 shows cumulative degree days 10-29°C over the 184 days of the growing season for the United States. The variable is the weighted average of all counties in the contiguous United States, where the weights are predicted yields along a trend times actual area. Since this variable is non-negative, it can only go up over time. Historic exposures for the years 1960-2011 are shown as grey dashed lines. The outcome for 2012 is shown as a thick red line. Note the early uptick in March 2012, which indicates a warm spring that allowed early planting, which is beneficial.

Second, Figure 2 shows the season total for harmful degree days above 29°C and precipitation. Note the sharp increase in degree days above 29°C in July as well as the low amount of precipitation. The year that has been hottest and driest in the historic 1960-2011 data is 1988.

Anomalies of degree days above 29°C as well as season-total precipitation are shown in Figure 3 for all counties east of the 100 degree meridian (except Florida) that grow corn. There is significant spatial heterogeneity: highly productive areas like Iowa, Illinois, and Indiana were hit hard, while some areas in Minnesota had above normal rainfall.[16]

The predicted yield impacts are shown in Figure 4. They are derived by pairing the observed weather data from March 1st, 2012 - August 6th, 2012 with the average outcomes for the rest of he growing season (August 7th - August 31st). The top panel show relative impact, while the bottom panel shows absolute impacts in million bushels. While some

[16]There are a few outlier that are due to data errors, i.e., the one county in Texas that shows a very cold summer is likely due to a weather station that is reporting incorrectly and has not been flagged. However, since this county produces so little corn, the results on the overall impact are negligible.

countries see declines of up to 80 log points, overall total production is predicted decrease is 1.6 billion bushels, a 14% decline for the study area. The estimate needs to be updated once the remaining data for August is in. If it continues to stay warmer and drier han usual, the impact will be even larger.

Hansen, Sato & Ruedy (2012) look at the frequency of extreme temperatures around the world and argue that it is predicted to increase significantly with climate change. The paper finds that the United States is one of the few areas that has been "lucky" so far, in the sense that it has not seen a significant increase in observed extremes. The current year might hence be soon the new normal. This is consistent with earlier work, where we found using the same statistical model and data that climate change will result in overall production reduction by much more than the 14% that is predicted to occur this year (Schlenker & Roberts 2009).

3 Policy Implications

The ethanol mandate has direct implications for the food prices. First, the additional calories needed to meet the mandate will drive up steady state equilibrium prices. Second, the mandate will also impact price volatility due to random production shocks to the system.

The predicted production shortfall in the previous Section is a little less than half of the maize production used to meet the ethanol mandate. Future climate change is predicted to lead to increased yield variation (Diffenbaug et al. 2012), which will translate into increased price volatility. The authors argue that the link to the fuel market will dampen volatility if the mandate is not binding and exacerbate it if the mandate is binding. If a certain fraction of the maize production has to be used for ethanol, the (smaller) remaining fraction has to be used to counterbalance production shocks.

Given the predicted decrease in maize production, both academics (Carter & Miller 2012) and the directorgeneral of the Food and Agricultural Organization (da Silva 2012) have recently advocated to temporarily lift the mandate. On the other hand, Scott Irvin and Darrell Good point out that some ethanol is required in gasoline to meet octane requirements as well as a substitute of MTBE,[17] i.e., even without the mandate there would be a demand for ethanol, although at a lower level of less than half.[18]

The particular way the ethanol mandate is implemented has further interesting impli-

[17] http://www.farmdocdaily.illinois.edu/2012/08/ethanoldoes_the_rfs_matter.html

[18] We are grateful to Barrett Kirwan who pointed us towards their blog post.

cations: refiners and ethanol producers can trade Renewable Identification Numbers (RIN) to meet the mandate. Up to 20% can be banked between years, and it is estimated that currently we are at that limit.[19] The ethanol mandate can be met by relying on "permits" that were previously produced. As long as these excess permits are used to clear the market, production shocks can be offset with banked RINs. There are now two "storable" commodities: physically storing corn as well as storing RINs to meet the ethanol mandate. It is not clear to us at this point where the 20% banking limit comes from.

It might be desirable to increase it to allow for better smoothing of production shocks. Banking excess RINs implies that ethanol production occurred before the mandate required it. While there is an active discussion whether ethanol does indeed reduce CO_2 emissions, if we assume for now that it does at least somewhat, obtaining the "CO_2 reduction" earlier would be desirable. Moreover, unlike carrying crops year-to-year, which results is loss and inventory cost, the cost of carrying RINs is limited. Using RINS to smooth production shocks might hence reduce price volatility and be desirable.

4 Conclusions

This paper makes three contributions. First, we extend the reduced-form IV approach of Roberts & Schlenker (2012) by allowing for serially correlated unobservables. Our model relies on recent advances in the IO literature that use observed decisions as proxies for the unobserved serially correlated states (Olley & Pakes 1996). While the model requires much less stringent assumptions, it does result in comparable estimates of the demand and supply elasticities. The 2009 Renewable Fuel Standard is predicted to have increased commodity prices by roughly 30%, not counting the recycling of distillers grains. If one third can recycled, the price increase is 20%.

Second, we model the impact of the 2012 heat wave / drought. While some areas are severely hit, the overall predicted impact is a 14% decline in production, or a little less than 50% of the corn that is required to meet the ethanol mandate. This estimate is preliminary and assumes that weather in August equals historic averages - if the year continues to be warmer than usual, the predicted impacts will be more severe.

Finally, we briefly outline how bankable RIN permits can be used to smooth production shocks between years, i.e., a RIN (or permit) from a previous year can be used to satisfy this year's ethanol mandate. There is currently a 20% limit on bankable RINs. Lifting this

[19] http://www.farmdocdaily.illinois.edu/2012/08/an_update_on_rin_stocks_and_im.html

limit might be an easy way to reduce price volatility.

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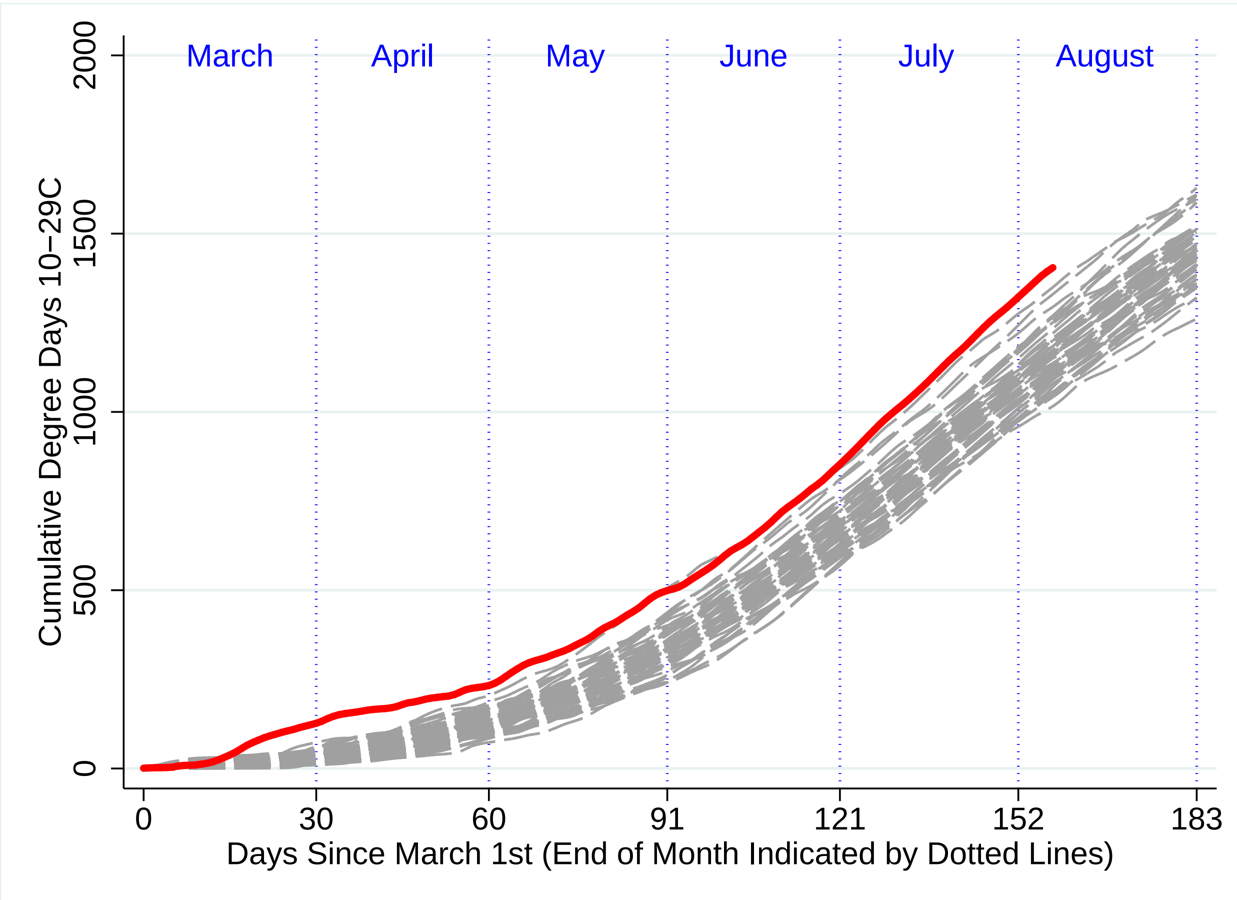
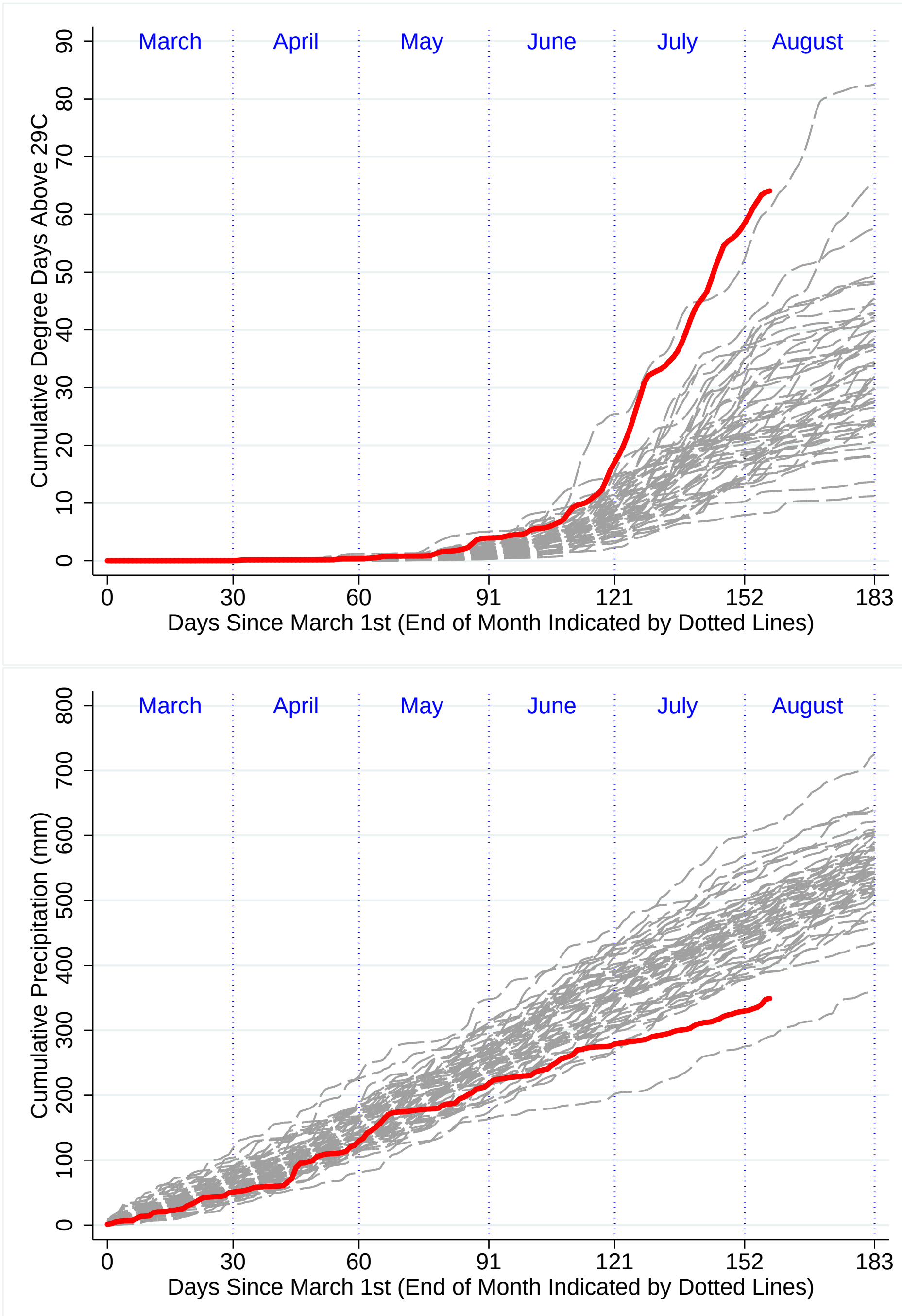
Figure 1: Degree Days 10-29°C in 2012 Relative to 1960-2011



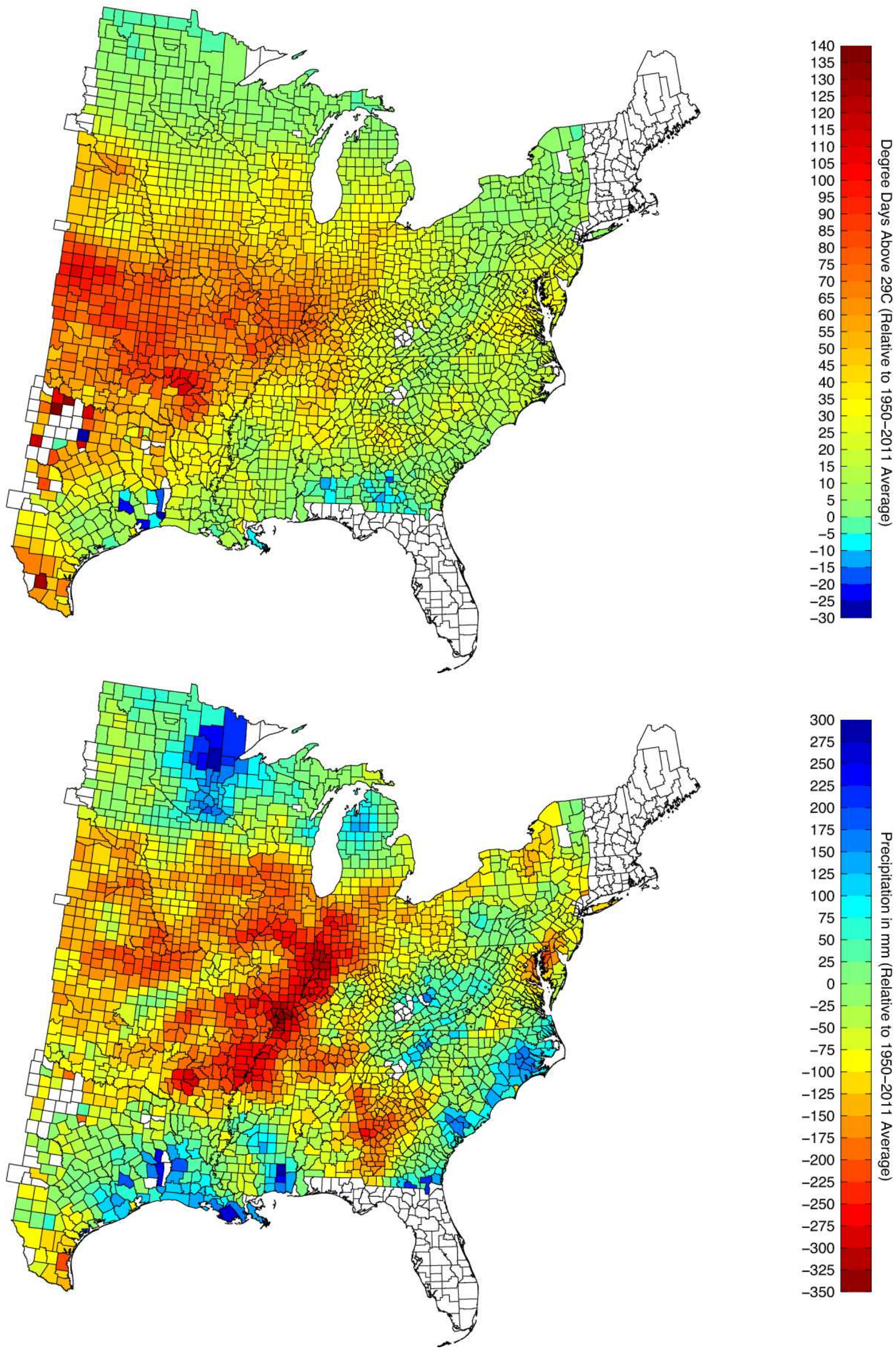
Notes: Panel shows cumulative total of degree days 10-29°C for the United States. The weather measure is the weighted average of all counties in the United States, where the weights are predicted production along a trend line (restricted cubic spline with 3 knots). Cumulative totals for the years 1960-2011 are added as thin dashed lines, while 2012 is shown as a thick solid line.

Figure 2: Degree Days Above 29°C and Precipitation in 2012 Relative to 1960-2011



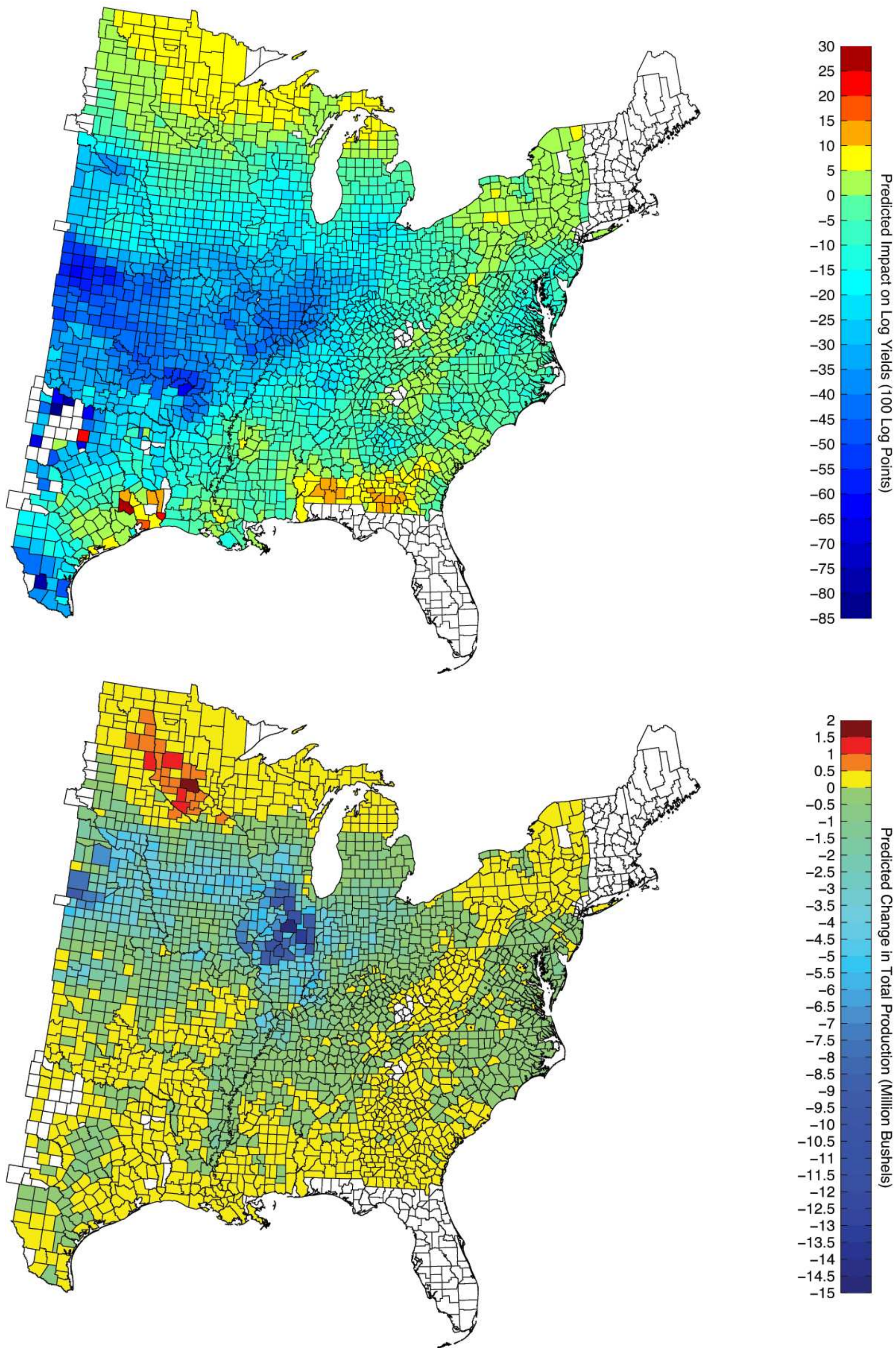
Notes: Top panel show degree days above 29°C, and bottom panel shows precipitation. Both panels show cumulative totals over the growing season for the United States. Weather measures are weighted averages of all counties in the United States, where the weights are predicted production along a trend line (restricted cubic spline with 3 knots). Cumulative totals for the years 1960-2011 are added as thin dashed lines, while 2012 is shown as a thick solid line.

Figure 3: Spatial Distribution of Degree Days Above 29C and Precipitation in 2012



Notes: Spatial distribution of weather anomalies over the growing season March 1 - August 6, 2012. Top panel shows degree days above 29°C, while the bottom panel shows precipitation totals.

Figure 4: Predicted Yields in 2012



Notes: Predicted yield and production impacts in 2012 by county. Regression uses observed weather data for March 1, 2011 - August 6, 2012 plus the historic average for August 7 - August 31 to get season totals. The top panel shows changes in predicted yields in 100 log points, while the bottom shows predicted changes in total production (using the average area of 2007-2011 as growing area).

Table 1: Countries Used to Derive Maize and Soybean Yield Shocks

	Month	**Data from FAO**						**Data from FAS**					
	Futures	**Production Share**			**Years in Data**			**Production Share**			**Years in Data**		
Country	**Price**	**Avg**	**Min**	**Max**	**N**	**Min**	**Max**	**Avg**	**Min**	**Max**	**N**	**Min**	**Max**
Panel A: Maize Yields													
United States of America	Mar	41.76	30.55	48.11	50	1961	2010	45.09	32.98	50.50	50	1961	2010
China	Mar	15.96	7.95	21.72	50	1961	2010	17.03	9.77	23.56	50	1961	2010
Brazil	Sep	5.29	3.45	7.49	50	1961	2010	5.71	3.66	7.79	50	1961	2010
USSR	Mar	3.52	1.98	8.35	31	1961	1991	3.96	2.11	8.66	26	1961	1986
Mexico	Mar	3.00	2.02	3.94	50	1961	2010	3.06	1.66	4.41	50	1961	2010
Yugoslav SFR	Mar	2.47	1.39	3.25	31	1961	1991	2.65	1.48	3.46	31	1961	1991
Argentina	Sep	2.35	1.03	3.52	50	1961	2010	2.53	1.11	3.78	50	1961	2010
France	Mar	2.29	0.91	3.65	50	1961	2010	.	.	.	.	.	.
Romania	Mar	2.08	0.49	3.29	50	1961	2010	2.61	1.37	3.73	38	1961	1998
South Africa	Sep	1.98	0.61	3.62	50	1961	2010	2.12	0.66	3.88	50	1961	2010
India	Mar	1.93	1.26	2.82	50	1961	2010	2.09	1.35	3.02	50	1961	2010
Italy	Mar	1.51	0.96	1.93	50	1961	2010	.	.	.	.	.	.
Hungary	Mar	1.37	0.51	2.10	50	1961	2010	1.57	0.80	2.19	38	1961	1998
Indonesia	Sep	1.31	0.72	2.17	50	1961	2010	1.14	0.76	1.79	49	1961	2010
Canada	Mar	1.16	0.36	1.71	50	1961	2010	1.23	0.38	1.84	50	1961	2010
Serbia And Montenegro	Mar	0.89	0.50	1.19	14	1992	2005	0.95	0.55	1.20	14	1992	2005
Egypt	Mar	0.89	0.70	1.09	50	1961	2010	0.95	0.78	1.16	49	1961	2010
Ukraine	Mar	0.80	0.27	1.42	19	1992	2010	1.03	0.29	2.34	24	1987	2010
Philippines	Mar	0.77	0.59	1.10	50	1961	2010	0.83	0.61	1.23	50	1961	2010
Thailand	Mar	0.67	0.29	1.16	50	1961	2010	0.71	0.30	1.23	50	1961	2010
Nigeria	Mar	0.65	0.12	1.34	50	1961	2010	0.71	0.32	1.44	50	1961	2010
Spain	Mar	0.58	0.34	0.89	50	1961	2010	.	.	.	.	.	.
North Korea	Mar	0.52	0.14	0.89	50	1961	2010	.	.	.	.	.	.
Bulgaria	Mar	0.50	0.04	0.96	50	1961	2010	0.64	0.18	1.03	38	1961	1998
Kenya	Mar	.	.	.	.	.	.	0.53	0.28	0.78	50	1961	2010
Rest Of World	Mar	9.09	6.95	12.04	50	1961	2010	8.22	6.30	11.64	50	1961	2010
Panel B: Soybeans Yields													
United States of America	Mar	55.55	33.17	73.48	50	1961	2010	58.22	32.88	100.00	50	1961	2010
Brazil	Sep	15.11	1.01	27.23	50	1961	2010	17.29	1.59	29.59	46	1965	2010
China	Mar	12.63	5.77	27.26	50	1961	2010	11.83	5.64	27.47	47	1964	2010
Argentina	Sep	7.31	0.00	21.61	50	1961	2010	8.05	0.05	22.03	46	1965	2010
India	Mar	1.79	0.02	4.99	50	1961	2010	1.89	0.03	4.27	42	1969	2010
Paraguay	Sep	1.09	0.01	2.85	50	1961	2010	1.11	0.03	2.75	46	1965	2010
Canada	Mar	1.07	0.44	1.90	50	1961	2010	1.09	0.44	1.85	47	1964	2010
USSR	Mar	0.94	0.46	1.75	31	1961	1991	0.89	0.48	1.61	23	1964	1986
Indonesia	Sep	0.94	0.27	1.63	50	1961	2010	0.91	0.24	1.65	47	1964	2010
Italy	Mar	.	.	.	.	.	.	0.76	0.01	1.69	10	1981	1990
Rest Of World	Mar	3.93	2.52	6.72	50	1961	2010	3.25	0.01	5.84	48	1963	2010

Notes: Tables displays countries used to derive yield deviations, sorted from largest producer to smallest producer. The first column gives the month when the futures price in equation (14) is evaluated. The next six columns summarize the data from FAO, the last six columns from FAS. Within each data set, the first three give average, minimum, and maximum annual share of global production, respectively, while the last three give the number of years for which we have data as well as the first and last year, respectively.

Table 2: Countries Used to Derive Wheat and Rice Yield Shocks

	Month	Data from FAO						Data from FAS					
	Futures	Production Share			Years in Data			Production Share			Years in Data		
Country	**Price**	**Avg**	**Min**	**Max**	**N**	**Min**	**Max**	**Avg**	**Min**	**Max**	**N**	**Min**	**Max**
Panel A: Wheat Yields													
USSR	Sep	21.23	12.68	31.10	31	1961	1991	26.54	15.35	35.94	26	1961	1986
China	Mar	14.23	6.43	20.10	50	1961	2010	17.25	7.71	24.52	50	1961	2010
United States of America	Sep	11.91	7.60	16.86	50	1961	2010	14.52	10.00	19.90	50	1961	2010
India	Sep	8.73	3.42	13.04	50	1961	2010	10.58	4.01	16.92	50	1961	2010
Russian Federation	Sep	7.07	4.55	9.33	19	1992	2010	8.96	5.54	11.99	24	1987	2010
France	Sep	5.35	3.72	6.78	50	1961	2010	.	.	.	.	.	.
Canada	Mar	4.75	2.78	8.44	50	1961	2010	5.80	3.46	10.25	50	1961	2010
Turkey	Sep	3.44	2.60	4.37	50	1961	2010	3.42	2.56	4.12	50	1961	2010
Australia	Mar	3.14	1.70	4.67	50	1961	2010	3.84	2.03	5.87	50	1961	2010
Germany	Sep	2.94	1.99	4.02	50	1961	2010	.	.	.	.	.	.
Ukraine	Sep	2.76	0.64	3.87	19	1992	2010	3.85	0.81	6.12	24	1987	2010
Pakistan	Sep	2.54	1.29	3.80	50	1961	2010	3.09	1.51	4.74	50	1961	2010
Argentina	Mar	2.20	1.25	4.19	50	1961	2010	2.70	1.74	5.10	50	1961	2010
United Kingdom	Sep	2.02	1.06	2.92	50	1961	2010	.	.	.	.	.	.
Italy	Sep	2.00	0.92	3.79	50	1961	2010	.	.	.	.	.	.
Kazakhstan	Sep	1.88	0.80	3.23	19	1992	2010	2.44	0.96	3.85	24	1987	2010
Iran	Sep	1.56	0.98	2.59	50	1961	2010	1.89	1.14	3.23	50	1961	2010
Poland	Sep	1.38	0.93	1.79	50	1961	2010	1.62	1.10	2.16	38	1961	1998
Yugoslav SFR	Sep	1.29	0.90	1.78	31	1961	1991	1.55	1.08	2.16	31	1961	1991
Romania	Sep	1.25	0.44	2.25	50	1961	2010	1.64	0.64	2.79	38	1961	1998
Spain	Sep	1.14	0.58	2.09	50	1961	2010	.	.	.	.	.	.
Czechoslovakia	Sep	1.05	0.66	1.41	32	1961	1992	1.25	0.81	1.71	31	1961	1991
Hungary	Sep	0.96	0.45	1.44	50	1961	2010	1.24	0.64	1.76	38	1961	1998
Bulgaria	Sep	0.76	0.31	1.11	50	1961	2010	1.00	0.37	1.37	38	1961	1998
Egypt	Sep	0.73	0.35	1.37	50	1961	2010	0.90	0.43	1.76	49	1961	2010
Uzbekistan	Sep	0.68	0.16	1.03	19	1992	2010	0.69	0.08	1.26	24	1987	2010
Mexico	Sep	0.67	0.37	1.04	50	1961	2010	0.77	0.50	1.06	50	1961	2010
Czech Republic	Sep	0.66	0.47	0.80	18	1993	2010	.	.	.	.	.	.
Afghanistan	Sep	0.57	0.25	1.02	50	1961	2010	0.70	0.33	1.23	50	1961	2010
Brazil	Mar	0.56	0.17	1.21	50	1961	2010	0.64	0.05	1.45	50	1961	2010
Morocco	Sep	0.56	0.20	1.05	50	1961	2010	0.66	0.23	1.34	50	1961	2010
Serbia And Montenegro	Sep	.	.	.	.	.	.	0.51	0.31	0.74	14	1992	2005
Syria	Sep	.	.	.	.	.	.	0.56	0.19	1.10	50	1961	2010
Rest Of World	Sep	7.04	4.67	9.83	50	1961	2010	4.94	2.86	6.96	50	1961	2010
Panel B: Rice Yields													
China	Sep	34.08	26.07	39.13	50	1961	2010	34.74	25.61	39.66	50	1961	2010
India	Mar	20.59	16.77	24.81	50	1961	2010	20.59	16.52	24.33	50	1961	2010
Indonesia	Sep	7.61	4.68	9.88	50	1961	2010	7.64	5.35	9.03	50	1961	2010
Bangladesh	Mar	5.56	4.66	7.34	50	1961	2010	5.58	4.63	7.40	50	1961	2010
Thailand	Sep	4.33	3.32	5.17	50	1961	2010	4.15	3.27	4.70	50	1961	2010
Vietnam	Sep	4.08	2.54	6.03	50	1961	2010	4.03	2.50	5.86	50	1961	2010
Japan	Mar	3.55	1.55	7.49	50	1961	2010	3.83	1.72	7.71	50	1961	2010
Myanmar	Sep	3.23	2.39	4.94	50	1961	2010	2.50	2.12	3.11	50	1961	2010
Brazil	Sep	2.06	1.33	2.98	50	1961	2010	2.07	1.47	2.87	49	1961	2010
Philippines	Mar	1.90	1.48	2.47	50	1961	2010	1.84	1.36	2.43	50	1961	2010
South Korea	Mar	1.55	0.86	2.26	50	1961	2010	1.68	0.96	2.41	50	1961	2010
United States of America	Mar	1.44	1.01	2.02	50	1961	2010	1.52	1.05	2.16	50	1961	2010
Pakistan	Mar	1.09	0.72	1.51	50	1961	2010	1.08	0.71	1.54	50	1961	2010
Egypt	Sep	0.76	0.44	1.07	50	1961	2010	0.75	0.41	1.14	50	1961	2010
Nepal	Sep	0.68	0.43	0.98	50	1961	2010	0.69	0.44	0.96	49	1961	2010
Cambodia	Sep	0.65	0.14	1.23	50	1961	2010	0.63	0.13	1.18	50	1961	2010
North Korea	Sep	0.58	0.25	0.90	50	1961	2010	0.59	0.31	0.77	50	1961	2010
Madagascar	Sep	0.53	0.41	0.71	50	1961	2010	0.50	0.40	0.68	50	1961	2010
Taiwan	Sep	.	.	.	.	.	.	0.70	0.22	1.34	49	1961	2010
Rest Of World	Mar	5.74	4.54	7.16	50	1961	2010	4.98	3.87	6.42	50	1961	2010

Notes: Table displays countries used to derive yield deviations, sorted from largest producer to smallest producer. The first column gives the month when the futures price in equation (14) is evaluated. The next six columns summarize the data from FAO, the last six columns from FAS. Within each data set, the first three give average, minimum, and maximum annual share of global production, respectively; the last three give the number of years for which we have data as well as the first and last available year.

Table 3: Replication: Supply and Demand Elasticity in Roberts and Schlenker (FAO Data)

	Instrumental Variables			**Three Stage Least Squares**		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
			Panel A: Supply Equation			
Supply Elast. β_s	0.100***	0.094***	0.086***	0.114***	0.109***	0.096***
	(0.024)	(0.024)	(0.019)	(0.019)	(0.020)	(0.018)
Shock ω_t	1.176***	1.222***	1.206***	1.239***	1.270***	1.234***
	(0.141)	(0.133)	(0.103)	(0.108)	(0.098)	(0.089)
First Stage ω_{t-1}	-3.980***	-3.703***	-3.873***	-3.590***	-3.182***	-3.254***
	(1.153)	(0.954)	(0.926)	(0.808)	(0.719)	(0.745)
First Stage ω_t	-2.898*	-2.248*	-2.338*	-2.857***	-2.316***	-2.379***
	(1.656)	(1.302)	(1.302)	(0.981)	(0.830)	(0.837)
			Panel B: Demand Equation			
Demand Elast. β_d	-0.028	-0.055**	-0.055**	-0.035	-0.063***	-0.067***
	(0.021)	(0.025)	(0.023)	(0.023)	(0.023)	(0.021)
First Stage ω_t	-5.547***	-4.626***	-4.732***	-5.312***	-4.388***	-4.264***
	(1.493)	(1.297)	(1.257)	(1.388)	(1.210)	(1.189)
			Panel C: Effect of Demand Shift			
Multiplier $\frac{1}{\widehat{\beta_s}-\widehat{\beta_d}}$	7.85	6.70	7.09	6.75	5.80	6.13
Exp. Multiplier	8.49	7.14	7.46	7.00	5.98	6.31
(95% Conf. Int.)	(5.3,15.4)	(4.6,12.2)	(5.0,12.0)	(5.0,10.5)	(4.4,8.6)	(4.6,9.0)
$F_{\text{1st-stage}}$ Supply	11.91	15.08	17.49			
$F_{\text{1st-stage}}$ Demand	13.81	12.73	14.17			
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 in Roberts & Schlenker (2012). The first three columns (1a)-(1b) use instrumental variables, while columns (2a)-(2c) use three stages least squares. Columns (a), (b), and (c) include restricted cubic splines in time with 3, 4, and 5 knots, respectively. Panel A gives results for the supply equations (15) and (16), i.e., coefficients above the vertical line give the results for log quantity, while coefficients below the line give first stage results of log price. Similarly, panel B gives results for demand equations (17) and (18). 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. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.

Table 4: Supply and Demand Elasticity (FAO Data) using Model 3

	Instrumental Variables			**Three Stage Least Squares**		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
			Panel A: Supply Equation			
Supply Elast. β_s	0.121**	0.114*	0.097**	0.128***	0.129***	0.117***
	(0.050)	(0.059)	(0.047)	(0.035)	(0.042)	(0.037)
Shock ω_t	1.201***	1.222***	1.211***	1.223***	1.260***	1.265***
	(0.269)	(0.234)	(0.204)	(0.209)	(0.204)	(0.188)
First Stage ω_{t-1}	-3.983**	-3.327**	-3.726***	-3.519***	-3.024***	-3.217***
	(1.477)	(1.286)	(1.270)	(1.088)	(0.921)	(0.966)
First Stage ω_t	-2.958*	-2.090	-2.342*	-3.009**	-2.119*	-2.381**
	(1.693)	(1.251)	(1.268)	(1.359)	(1.145)	(1.130)
			Panel B: Demand Equation			
Demand Elast. β_d	-0.017	-0.052	-0.052	-0.017	-0.053*	-0.056**
	(0.032)	(0.036)	(0.033)	(0.028)	(0.030)	(0.027)
First Stage ω_t	-5.288***	-4.082**	-4.347**	-5.295***	-4.055**	-4.206***
	(1.848)	(1.677)	(1.666)	(1.852)	(1.609)	(1.570)
			Panel C: Effect of Demand Shift			
Multiplier $\frac{1}{\widehat{\beta_s}-\widehat{\beta_d}}$	7.24	6.04	6.71	6.92	5.48	5.77
Exp. Multiplier	14.44	7.56	8.17	7.65	6.07	6.27
(95% Conf. Int.)	(3.8,32.4)	(3.2,25.5)	(3.7,24.7)	(4.4,15.7)	(3.5,12.0)	(3.8,11.7)
$F_{\text{1st-stage}}$ Supply	7.28	6.69	8.61			
$F_{\text{1st-stage}}$ Demand	8.18	5.92	6.81			
Observations	45	45	45	45	45	45
Spline Knots	3	4	5	3	4	5

Notes: Table replicates Table 3 except that the yield shocks ω_t are no longer deviations from trends but estimated via equation (14). The first three columns (1a)-(1b) use instrumental variables, while columns (2a)-(2c) use three stages least squares. Columns (a), (b), and (c) include restricted cubic splines in time with 3, 4, and 5 knots, respectively. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.

Table 5: 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 $p_t\|_{t-1}$	0.101***	0.097***	0.085***	-0.048	-0.042	-0.064
	(0.028)	(0.035)	(0.025)	(0.091)	(0.097)	(0.096)
			Panel B: US			
Futures Price $p_t\|_{t-1}$	0.324***	0.312***	0.313***	0.041	0.033	0.144
	(0.098)	(0.113)	(0.102)	(0.167)	(0.101)	(0.101)
			Panel C: US Growing Area + Set-Asides			
Futures Price $p_t\|_{t-1}$	-0.046	0.001	-0.070			
	(0.080)	(0.080)	(0.049)			
			Panel D: Brazil			
Futures Price $p_t\|_{t-1}$	0.376**	0.301	0.236	-0.268	-0.297	-0.112
	(0.174)	(0.201)	(0.152)	(0.655)	(0.259)	(0.267)
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 4 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 3, 4, and 5 knots, respectively. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.

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: $\beta_{s,t}$	0.039	0.027	0.037	0.072	0.067	0.080
	(0.062)	(0.071)	(0.065)	(0.054)	(0.058)	(0.055)
Supply: $\beta_{s,t-1}$	0.066	0.064	0.061	0.006	-0.007	-0.003
	(0.068)	(0.066)	(0.062)	(0.054)	(0.051)	(0.047)
Supply: $\beta_{s,t-2}$	0.055	0.050	0.037	0.033	0.038	0.036
	(0.083)	(0.079)	(0.080)	(0.027)	(0.032)	(0.029)
Combined $\sum_{\tau=0}^{2} \beta_{s,t-\tau}$	0.160***	0.141***	0.135***	0.112***	0.098**	0.113***
	(0.034)	(0.047)	(0.038)	(0.027)	(0.041)	(0.039)
			Panel B: Demand Equation			
Demand: β_d	-0.001	-0.058	-0.052	-0.020	-0.048**	-0.032
	(0.028)	(0.041)	(0.042)	(0.023)	(0.020)	(0.020)
			Panel C: Effect of Demand Shift			
Multiplier $\frac{1}{\widehat{\beta_s}-\widehat{\beta_d}}$	6.22	5.03	5.36	7.57	6.85	6.90
Exp. Multiplier	6.94	5.87	6.21	8.14	8.14	7.92
(95% Conf. Int.)	(4.0,13.5)	(3.1,12.7)	(3.4,13.1)	(5.1,14.3)	(4.2,17.7)	(4.3,17.3)
Observations	43	43	43	43	43	43
Spline Knots	3	4	5	3	4	5

Notes: Table replicates Table 4 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 3, 4, and 5 knots, respectively. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.

Table 7: The Effect of Weather on Maize Yields 1950-2011

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Degree Days 10-29° C (1000 Degree Days)	0.314***	0.301***	0.303***	0.346***	0.343***	0.361***
	(0.068)	(0.066)	(0.063)	(0.082)	(0.079)	(0.074)
Degree Days Above 29° C (100 Degree Days)	-0.622***	-0.616***	-0.625***	-0.580***	-0.583***	-0.584***
	(0.068)	(0.066)	(0.065)	(0.069)	(0.068)	(0.067)
Precipitation (m)	1.028***	1.016***	1.029***	1.092***	1.061***	1.095***
	(0.212)	(0.208)	(0.198)	(0.217)	(0.216)	(0.209)
Precipitation (m) Squared	-0.806***	-0.800***	-0.818***	-0.807***	-0.787***	-0.814***
	(0.165)	(0.160)	(0.153)	(0.163)	(0.161)	(0.156)
R^2	0.7734	0.7784	0.7810	0.7920	0.7955	0.7972
Observations	115205	115205	115205	115205	115205	115205
Counties	2276	2276	2276	2276	2276	2276
Spline Knots	3	4	5	3	4	5
Year Fixed Effects	No	No	No	Yes	Yes	Yes

Notes: Table regresses county-level log maize yields for areas east of the 100 degree meridian in the year 1950-2011 on four weather variables as well as time controls. Columns (a), (b), and (c) include state-specific restricted cubic splines in time with 3, 4, and 5 knots, respectively. The last three columns also additionally include year fixed effects. Errors are clustered at the state level. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.

A1 Appendix

Table A1: Supply and Demand Elasticity (FAS Data)

	Instrumental Variables			Three Stage Least Squares		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Panel A: Supply Equation					
Supply Elast. β_s	0.146**	0.126	0.132*	0.119**	0.111*	0.113*
	(0.066)	(0.079)	(0.078)	(0.049)	(0.062)	(0.059)
Shock ω_t	1.225***	1.269***	1.256***	1.185***	1.264***	1.247***
	(0.224)	(0.179)	(0.181)	(0.197)	(0.175)	(0.181)
First Stage ω_{t-1}	-2.859*	-2.120*	-2.233*	-2.471**	-2.299**	-2.387**
	(1.616)	(1.168)	(1.179)	(1.082)	(0.987)	(0.994)
First Stage ω_t	-1.182	-0.349	-0.511	-1.291	-0.340	-0.504
	(1.838)	(1.217)	(1.244)	(1.558)	(1.189)	(1.185)
	Panel B: Demand Equation					
Demand Elast. β_d	-0.047	-0.107*	-0.092	-0.039	-0.109	-0.094
	(0.068)	(0.061)	(0.058)	(0.063)	(0.069)	(0.061)
First Stage ω_t	-3.775**	-2.839**	-2.976**	-3.941**	-2.800**	-2.944**
	(1.721)	(1.334)	(1.328)	(1.818)	(1.415)	(1.395)
	Panel C: Effect of Demand Shift					
Multiplier $\frac{1}{\widehat{\beta_s}-\widehat{\beta_d}}$	5.20	4.29	4.46	6.33	4.55	4.84
Exp. Multiplier	6.59	5.27	4.40	7.60	5.75	12.41
(95% Conf. Int.)	(2.2,30.5)	(2.2,19.3)	(2.3,20.6)	(3.1,31.5)	(2.3,22.0)	(2.5,21.1)
$F_{\text{1st-stage}}$ Supply	3.13	3.30	3.59			
$F_{\text{1st-stage}}$ Demand	4.81	4.53	5.02			
Observations	49	49	49	49	49	49
Spline Knots	3	4	5	3	4	5

Notes: Table replicates Table 4 except that it uses FAS data instead of FAO data, which runs through 2010. Columns (a), (b), and (c) include restricted cubic splines in time with 3, 4, and 5 knots, respectively. Stars indicate significance levels: *** : 1%; ** : 5%; * : 10%.