Futures Prices in Supply Analysis Reconsidered

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Abstract

Are futures prices exogenous to agricultural supply? It depends. We argue that crop yield shocks were predictable during the 1961-2007 period because high planting-time futures prices tended to indicate that yield would be below trend. This feature of the data implies that regressions of production on futures prices would underestimate the supply elasticity, i.e., endogeneity in the futures price biases the regression coefficient down. However, this predictability has only a small effect on planted acreage. Thus, estimating supply models with regressions of planted acreage on futures prices entails a small endogeneity bias. Moreover, this small bias is mitigated by adding the realized yield shock as a control variable to such a model as a proxy for the expected yield shock. The marginal contribution of an instrumental variable to bias reduction is thus small.

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1 Introduction

Since the seminal work of Wright (1928), weather has been recognized as an exogenous supply shifter that can be used to identify the demand elasticity. It has been less common to use demand shifters to identify the supply elasticity—perhaps because demand shifters can explain little of the variation in agricultural prices between years. Instead, agricultural supply analysis has typically used a planting-time measure of the price farmers expect to receive and assumed that these expected prices are exogenous to supply. In his seminal work, Nerlove (1958) motivates including a lagged price and a lagged dependent variable as explanatory variables based on a supply model with adaptive expectations. Since the work of Gardner (1976), it has become standard practice to use planting-time (or pre-planting) futures prices of contracts for post-harvest delivery in econometric models of supply with the rationalization that the futures price equals the farmer's rational expectation of post-harvest prices.

The plausible exogeneity of the futures price received little scrutiny until recent work by Roberts and Schlenker (2013; henceforth RS), who argue that futures traders have some expectation of production that affects the futures price and thereby makes the futures price endogenous to supply. They propose using weather in the previous year as an instrumental variable on the grounds that it affects the futures price through an inventory channel. They approximate weather shocks using deviations of yield from trend and apply their model to the world supply of calories from maize, soybeans, wheat, and rice from 1961-2007. Their results indicate substantial endogeneity bias. They estimate supply elasticities in the range of 0.020–0.051 using ordinary least squares (OLS) compared with 0.087–0.102 using two-stage least squares (2SLS).

Choi and Helmberger (1993) also raise concerns about the endogeneity of the futures price in supply analysis. They estimate a system of equations for demand for consumption, demand for inventory, the futures price, acreage, and demand for seed, which they apply to the U.S. soybean market. In apparent contrast to RS, Choi and Helmberger (1993) find little difference in OLS and three-stage least squares estimates of acreage response to price.

Endogeneity bias in a regression model can be conceptualized as an omitted variables problem. The omitted variables in a supply model are predictable factors that affect production. Unpredictable weather and pest shocks do not bias coefficient estimates because they are unknown to futures traders prior to planting and are therefore uncorrelated with the futures price. Only factors that are predictable prior to planting must be included in the regression to obtain unbiased estimates of the supply elasticity.

Instead of using supply shifters as control variables, researchers can mitigate endogeneity bias by finding instrumental variables that isolate demand shocks. Although the novelty in their work is the proposed instrument, RS use both approaches simultaneously. They use the current-year realized yield shock as a control variable and the prior-year realized yield shock as an instrument in their regressions. We show that the control variable does all the work. When we estimate their model using OLS with the control variable, we obtain almost identical results to those from 2SLS.

We also decompose the supply elasticity into components due to changes in (i) total growing area, (ii) the composition of acreage across crops and countries, and (iii) deviations of yield from trend. This decomposition reveals that the futures price is endogenous to total production due to predictable yield shocks, but this predictability has little effect on growing area. This result resolves the apparent contrast between the results of Choi and Helmberger (1993), who model acreage, and RS, who model production.

To interpret our results, we derive expressions for the bias in the relevant OLS and 2SLS estimators. We show that if endogeneity comes from predictable yield shocks, then using prior-year yield shocks as an instrument produces no bias reduction once the current-year yield shock is controlled for, and it could even increase bias. RS recognize that predictable yield shocks (autocorrelation in yields) would invalidate their instrument, which is why they control for the current-year yield shock. However, the realized yield shock is a noisy proxy for the *predictable* component of the yield shock, which is the omitted variable in the regression. Thus, the control doesn't eliminate the bias (Wooldridge 2002) and, because it reduces the amount of noise in the model, it could magnify importance of the predictable component of the yield shock in the model error thereby increasing bias. We conclude that, in the application to world caloric supply, the instrument is mostly innocuous, although it results in a much wider confidence interval than the preferred OLS estimate.

2 Bias in Econometric Models of Global Caloric Supply

2.1 Model Setup

RS model world production of calories from maize, soybeans, wheat and rice using a simple regression equation. They regress the log of total caloric production on the log of a calorie-weighted index of U.S. futures prices while controlling for deterministic trends and an index of yield shocks.

A myriad of complexity underlies this supply equation. When a demand shock changes the futures price index, farmers throughout the world respond to a greater or lesser extent by altering the number of acres planted to these crops and changing the mix of crops within those acres. When making these decisions, they take into account the heterogeneous productivity of the land they operate and predictions about growing season weather. Moreover, differing seasons across the globe mean that farmers may have some information about the likely size of the crop in other parts of the world when making these decisions.

To understand the role of these various components, we decompose world caloric production in year t into three components: (i) total growing area (A_t), (ii) average trend caloric production per unit of land (trend yield; Y_t), and (iii) the average proportional deviation from trend yield (Ψ_t). These components are weighted averages of their country-crop counterparts. For crop c in country i in year t, we write the growing area as A_{cit}, the trend yield as Y_{cit}, and the proportional deviation from trend yield as Ψ_{cit}. Caloric production from crop c in country i is $Q_{cit} = A_{cit}\kappa_c Y_{cit}\Psi_{cit}$, where κ_c denotes the number of calories in one unit of crop c. We write world caloric production as $Q_t = A_t Y_t \Psi_t$, where

$$A_t = \sum_i \sum_c A_{cit}, \tag{1}$$

$$Y_t = \frac{\sum_i \sum_c A_{cit} \kappa_c Y_{cit}}{\sum_i \sum_c A_{cit}}, \tag{2}$$

$$\Psi_t = \frac{\sum_i \sum_c A_{cit} \kappa_c Y_{cit} \Psi_{cit}}{\sum_i \sum_c A_{cit} \kappa_c Y_{cit}}. \tag{3}$$

With this representation, we can decompose the supply response to a price shock into components related to total growing area (equation 1), a component related to the composition of that growing area (equation 2), and a component related to deviations of yield from trend (equation 3). Using the notation that lower case objects represent the logarithm of upper case objects, we work in the remainder of the paper with $q_t \equiv ln(Q_t)$, $a_t \equiv ln(A_t)$, $y_t \equiv ln(Y_t)$, and $\psi_t \equiv ln\left(\Psi_t\right)$.

The final component of this decomposition is almost identical to the yield shock variable (ω_t) used by RS. They construct ω_t as the average across countries of log yield deviations from trend, whereas we define ψ_t as the log of average yield deviations from trend. The difference between ω_t and ψ_t does not matter much, empirically. The correlation between the two proxies in our dataset is 0.997, and we show that estimates of the supply elasticity are essentially identical using either proxy. We choose to work with ψ_t because it allows us to use the decomposition in (1)–(3), which in turn allows us to decompose the channels through which price affects caloric production.[1]

RS specify the country-level trend yield for each crop to be a deterministic function of time. Even though trend yield for a particular crop in a particular country does not depend on price, average trend yield (Y_t) may be affected by price if the spatial variation in acreage response to price is correlated with the spatial variation in yields. For example, if countries with more productive climates and soils have a larger growing area response to price, then average trend yield increases when price increases. Similarly, if countries that specialize in

[1] Because the average of a logarithm does not equal the log of an average, $q_t \neq a_t + y_t + \omega_t$.

higher yielding crops have a larger growing area response to price, then average trend yield increases when prices increase.

Log yield shocks (ψ_{cit}) are determined mostly by weather. An exceptionally hot and/or dry growing season causes yield to be far below trend. RS assume that ψ_{cit} is independent of growing area (a_{cit}) and trend yields (y_{cit}), so the average deviation from trend yield (ψ_t) is not affected by price. This assumption would fail if farmers respond to output price shocks by changing inputs such as fertilizer and labor in ways that affect yield. It would also fail if shocks to output prices cause expansion onto cropland of different-than-average quality thereby causing country-level yield to deviate from trend. RS provide some evidence to suggest that any yield response to price is likely negligible compared to yield variation due to weather.[2]

With the exogeneity of ψ_{cit}, aggregate production responds to price only through changes in the amount and composition of growing area. Farmers make growing area decisions based on expectations of prices and expectations of yields at harvest, so these two expectations affect total growing area directly, and they affect trend yield through their effects on the compostion of growing area. We write linear regression equations for a_t and y_t as follows:

$$a_t = \alpha^a + \beta^a p_{\tau t} + \gamma^a \psi_{\tau t} + f^a(t) + u_t^a, \tag{4}$$

$$y_t = \alpha^y + \beta^y p_{\tau t} + \gamma^y \psi_{\tau t} + f^y(t) + u_t^y, \tag{5}$$

where $p_{\tau t} \equiv ln\left(E_\tau\left[p_t\right]\right)$, $\psi_{\tau t} \equiv ln\left(E_\tau\left[\psi_t\right]\right)$, E_τ denotes expectations conditional on the information available at Northern Hemisphere planting time, and $f(t)$ is a trend. Thus, $p_{\tau t}$ is the log of the expected harvest price and $\psi_{\tau t}$ is the log of the expected yield shock at time τ. Following RS, we assume that the futures market provides an unbiased expectation of harvest prices, thus $p_{\tau t}$ denotes the log of a calorie-weighted average of harvest-time futures

[2]See their appendix section A1.1

contracts trading at time τ. If yield shocks are not forecastable, then $\psi_{\tau t} = 0$ and the associated term drops out of equations (4) and (5).

Total log production equals the sum of the logs of the three components in (1)–(3), i.e., $q_t = a_t + y_t + \psi_t$. Exogeneity of the yield shock combined with equations (4) and (5) implies that a model for world caloric supply is:

$$q_t = \alpha + \beta p_{\tau t} + \gamma \psi_{\tau t} + \psi_t + f(t) + u_t, \tag{6}$$

where $\beta = \beta^a + \beta^y$ and similarly for other parameters of supply equation.

The supply elasticity parameter (β) in equation (6) could be estimated consistently by OLS if two conditions were to hold: (i) the supply shocks embedded in u_t were unpredictable by futures traders ($E_\tau [u_t] = 0$), and (ii) yield shocks are either unpredictable ($\psi_{\tau t} = 0$) or a suitable proxy exists for the predictable component of yield shocks. Neither of these conditions are likely to hold exactly. Southern Hemisphere planted acreage is known at time τ, as is the Northern Hemisphere planted acreage of winter wheat, so the supply shocks embedded in u_t are partially predictable. We show in this paper that yield shocks are predictable, but have only small effects on growing area (i.e., γ is small).

2.2 Bias of IV and OLS Estimators

Predictability of u_t and ψ_t and the implied OLS bias suggest that instrumental variables may provide an alternative estimation strategy. RS argue that the previous year's yield shock affects the futures price through interannual storage but should not directly affect production decisions. They suggest using the lagged yield shock as an instrument for the futures price. An alternative, or complementary, approach would be to use the observed yield shock ψ_t to proxy for $\psi_{\tau t}$.

We thus have three possible regression equations with which to estimate β in equation (6):

$$q_t = \alpha_1 + \beta_1 p_{\tau t} + f_1(t) + u_{1t}, \tag{7}$$

$$q_t = \alpha_2 + \beta_2 p_{\tau t} + \gamma_2 \psi_t + f_2(t) + u_{2t}, \tag{8}$$

$$q_t = \alpha_3 + \beta_3 p_{\tau t} + \gamma_3 \psi_t + \delta_3 \varepsilon_{\tau t} + f_3(t) + u_{3t}, \tag{9}$$

where $\varepsilon_{\tau t}$ denotes errors from the first stage regression

$$p_{\tau t} = \theta_0 + \theta_1 \psi_{t-1} + \theta_2 \psi_t + g(t) + \varepsilon_{\tau t} \tag{10}$$

Equations (7)–(9) are defined such that the errors u_{jt} are uncorrelated with the right hand side variables, and therefore that the parameters represent the probability limit of the OLS estimator. Equation (9) is the second stage of a 2SLS estimation procedure, for which (10) is the first stage, i.e., it is an instrumental variables estimator that uses ψ_{t-1} as an instrument for price. We assume that the exclusion restriction holds to make ψ_{t-1} as RS define it, i.e., $E[\psi_{t-1} u_t | \psi_t] = 0$.

We derive the conditions under which each β_1, β_2, and β_3 equal β. We define ν_t such that $E[\varepsilon_{\tau t} \nu_t]$ in the equation $u_t \equiv \delta \varepsilon_{\tau t} + \nu_t$, where $\delta < 0$. This condition implies that we can write the equation of interest (6) as

$$q_t = \alpha + \beta p_{\tau t} + \gamma \psi_{\tau t} + \psi_t + \delta \varepsilon_{\tau t} + f(t) + \nu_t, \tag{11}$$

where ν_t is uncorrelated with the right hand side variables. We can now treat (7)–(9) as regressions with omitted variables relative to (11) and apply standard omitted variable bias formulas. Specifically, the bias in β_1, β_2, and β_3 equals the dot product of coefficients in (11) on any omitted variables with the coefficients on $p_{\tau t}$ in auxiliary regressions of each omitted variable on the included variables.

Understanding the bias requires expressions for the parameters in these auxiliary regressions. To this end, we define η_t as the surprise in the yield shock, such that $\Psi_t = E_\tau[\Psi_t]\eta_t$, where $E_\tau[\eta_t] = 1$. It follows that

$$\psi_t = \psi_{\tau t} + ln(\eta_t), \tag{12}$$

where $cov[\psi_{\tau t}, ln(\eta_t)] = 0$ as long as η_t is independent of information available at τ. In addition, because it is an important parameter in characterizing the bias, we define the parameter π as the coefficient on price in the following hypothetical regression

$$\psi_{\tau t} = \mu + \pi p_{\tau t} + h\,(t) + e_t. \tag{13}$$

Replacing $\psi_{\tau t}$ with ψ_t in this regression would produce the same price coefficient π because η_t is independent of information available at τ. We expect $\pi < 0$ because predictable increases in yield will cause the futures price to decrease.

Using these definitions, omitted variables bias formulas (e.g., Wooldridge 2002, p. 64) imply that

$$\beta_1 = \beta + (1+\gamma)\phi_{11} + \delta\phi_{12} \tag{14}$$

$$\beta_2 = \beta + \gamma\phi_{21} + \delta\phi_{22} \tag{15}$$

$$\beta_3 = \beta + \gamma\phi_{31} \tag{16}$$

where

$$\phi_{11} = \pi, \qquad \phi_{12} = \frac{\sigma_\varepsilon^2}{\sigma_{p\tau}^2} \tag{17}$$

$$\phi_{21} = \frac{\pi\sigma_\eta^2}{\sigma_\psi^2 - \sigma_{p\tau}^2\pi^2}, \qquad \phi_{22} = \frac{\sigma_\varepsilon^2\sigma_\psi^2}{\sigma_{p\tau}^2\sigma_\psi^2 - \sigma_{p\tau}^4\pi^2} \tag{18}$$

$$\phi_{31} = \frac{\pi\sigma_\eta^2 - \pi\rho_1\sigma_\psi^2 - \sigma_\eta^2\,(\pi - \pi_1\rho_1)\,(1-\rho_1)^{-1}}{\sigma_\psi^2 - \sigma_{\tau p}^2\pi^2 - \sigma_{\tau p}^{-2}\sigma_\psi^2\sigma_\varepsilon^2}, \tag{19}$$

where $\sigma_\varepsilon^2 \equiv var\left[\varepsilon_{\tau t}\right]$, $\sigma_\eta^2 \equiv var\left[ln(\eta_t)\right]$, $\sigma_\psi^2 \equiv var\left[\psi_t\right]$,$\sigma_{\tau p}^2 \equiv var\left[p_{\tau t}\right]$ is the variance of detrended prices, $\pi_1 \equiv E\left[\tilde{p}_{\tau t}\psi_{t-1}\right]\sigma_{\tau p}^{-2}$ is the coefficient from a regression of ψ_{t-1} on $\tilde{p}_{\tau t}$, and $\rho_1 \equiv E\left[\psi_{t-1}\psi_t\right]\sigma_\psi^{-2} = E\left[\psi_{t-1}\psi_{\tau t}\right]\sigma_\psi^{-2}$ is the first order autocorrelation coefficient for ψ_t.

Equations (14)–(16) reveal that all three estimators underestimate the supply elasticity in general, but are consistent in some special cases. The parameters π, γ, and δ are critical for determining the magnitudes of the bias. First, π equals zero if yield shocks are not predictable by futures traders and is negative if such shocks are partially predictable. If $\pi = 0$, then yield shocks must have zero autocorrelation $\rho_1 = 0$. In this case, the 2SLS estimator in (9) is a consistent estimator and the two OLS estimators in (7) and (8) are biased only if supply shocks embedded in u_t are predictable (i.e., $\delta < 0$). Thus, in this case, the 2SLS framework introduced by RS produces consistent estimates of supply parameters. Moreover, this case implies that controlling for current yield shocks (ψ_t) has no effect on the OLS estimator, i.e., $\beta_1 = \beta_2$ because $\phi_{12} = \phi_{22}$.

If $\gamma = 0$ and $\pi < 0$, then yield shocks are predictable but they have no effect on land allocation. In this case, 2SLS is again consistent but there is a significant difference between the two OLS estimators. When the current yield shock is omitted from the model, the coefficient on price (β_1) has a greater bias because the omitted variable is correlated with price. The difference between β_2 and β_3 in this setting depends on the value of δ. If δ is small, then β_2 and β_3 will be similar. A small δ means that the endogeneity bias comes mostly from correlation between expected yield shocks and prices. Controlling for yields shocks removes this component of bias leaving little bias for 2SLS to correct.

If $\delta = 0$, but $\gamma > 0$ and $\pi < 0$, then 2SLS would have a smaller bias than the OLS estimator that controls for the current yield shock if ϕ_{31} were less negative than ϕ_{21}. On the other hand, if ϕ_{31} were more negative than ϕ_{21}, then 2SLS would have a greater bias than OLS. Comparing, ϕ_{21} and ϕ_{31}, we see that ϕ_{31} has a less negative numerator but also a less positive denominator, so the relative bias is unsigned in general.[3] We also note at this point

[3]The 2SLS bias would be worse than OLS if, after we control for $\varepsilon_{\tau t}$, the correlation between price and the predictable component of yield becomes stronger. Put another way, ψ_{t-1} is not quite a valid instrument

that the bias expressions we derive are for the probability limit of the estimator. Thus, for 2SLS is essentially assumes that the instrument is infinitely strong. The finite sample bias of the 2SLS estimator is likely worse than the asymptotic bias.

The assumed exogeneity of yield shocks implies that we interpret $\pi < 0$ as indicating that predicted yield shocks cause prices. Suppose this assumption fails and that the causation runs in the opposite direction, i.e., a negative π reflects the response of yield shocks to price through substitution between lands of different qualities.[4] The supply elasticity in this case is $\beta + (1 + \gamma)\pi$, which is the sum of the price effects on growing area and on yield. If growing area shocks are exogenous to price ($\delta = 0$), then equation (14) shows that the simple regression in (7) produces a consistent estimate of the supply elasticity. Adding the yield shock control as in (8) or instrumenting using the lagged yield shock as in (9) cause the elasticity to be biased upwards by partialling out the component of the price effect that works through yield. These latter estimators would over-estimate the elasticity by omitting the tendency of yield to decrease when acreage increases. We explore this possibility in our empirical section, along with the other cases discussed above.

2.3 Decomposing the Supply Elasticity

Equation (6) essentially includes ψ_t on both the left and right hand sides. On the left hand side, we write total caloric production as $q_t = a_t + y_t + \psi_t$, but then we controlled for ψ_t because of the possibility that it is predictable. Given that this variable is assumed to be exogenous to prices, there seems little reason to include it on the left hand side of the model. It would be cleaner to model the acreage allocation directly using (1) and (2), or the sum

for price because it likely has a small correlation with production through the predictable component of yield shocks. Put another way, $\varepsilon_{\tau t}$ is an imperfect proxy for $\psi_{\tau t}$. This correlation becomes more of an issue after we remove the noise in yield by controlling of the current yield shock. A similar thing happens when comparing β_1 and β_2 for the case with $\delta = 0$ and $\pi > 0$. Adding the current yield shock as a control makes the bias worse ($\phi_{22} > \phi_{12}$) because controlling for ψ_t increases the partial correlation between price and $\varepsilon_{\tau t}$. See (e.g., Wooldridge 2002, p. 64) for more on the conditions under which imperfect proxies can worsen bias.

[4] Price could increase yield deviations from trend (i.e., yield shocks) by changing the use of inputs such as fertilizer, or it could decrease yield shocks by encouraging expansion of acreage onto marginal land thereby causing average yield to deviate from trend. We focus here on the latter case (δ<0) because it matches our empirical finding of a negative correlation between yield and price.

of these two equations, rather than adding the noise induced by ψ_t only to take it back out again. Even if the yield shock does respond to price because farmers adjust inputs in ways that affect deviations of yield from trend, this effect is eliminated from the model once we control for ψ_t.

In the models in (8) and (9), which control for ψ_t, the effect of price on production works partially through its affect on total growing area as in (1) and partially through its effect on trend yield through changing the composition of the growing area as in (2). To estimate the relative importance of these two channels, we estimate the following analogs of (8) and (9):

$$a_t = \alpha_2^a + \beta_2^a p_{\tau t} + \gamma_2^a \psi_t + f_2^a(t) + u_{2t}^a \tag{20}$$

$$a_t = \alpha_3^a + \beta_3^a p_{\tau t} + \gamma_3^a \psi_t + \delta_3^a \varepsilon_{\tau t} + f_3^a(t) + u_{3t}^a \tag{21}$$

$$y_t = \alpha_2^y + \beta_2^y p_{\tau t} + \gamma_2^y \psi_t + f_2^y(t) + u_{2t}^y \tag{22}$$

$$y_t = \alpha_3^y + \beta_3^y p_{\tau t} + \gamma_3^y \psi_t + \delta_3^y \varepsilon_{\tau t} + f_3^y(t) + u_{3t}^y. \tag{23}$$

By construction, the sums of the parameters across dependent variables in these equations equal their analog in (8)–(9), e.g., $\beta_2^a + \beta_2^y = \beta_2$. Thus, these models provide a simple decomposition of the estimated price responses. Analogous bias expressions to those in (15) and (16) can be obtained by replacing β and γ with their analogs from (4) and (5).

The model in (7) does not control for ψ_t so the implied effect on production from this model could work through all three components, a_t, y_t, and ψ_t. To estimate the relative importance of these three channels, we estimate the following analogs of (7) for a_t and y_t:

$$a_t = \alpha_1^a + \beta_1^a p_{\tau t} + f_1^a(t) + u_{1t}^a \tag{24}$$

$$y_t = \alpha_1^y + \beta_1^y p_{\tau t} + f_1^y(t) + u_{1t}^y, \tag{25}$$

along with (13), which is the analogous equation for ψ_t. The relevant bias expressions are those in (14) except with $(1 + \gamma)$ replaced by γ.

It is common for agricultural economists to estimate some form of (24). The potential source of endogeneity in this equation is that futures traders may have knowledge of factors affecting the growing area that will affect the futures price. RS motivate this source of endogeneity with the example of soybean rust in the United States. The discovery of soybean rust in the United States before planting may have caused farmers to reduce their intended planting of soybeans and thus affected the futures price. This discussion applies to the literature that uses panel data where the dependent variable is the share of a region planted to crops (e.g., Wu and Segerson 1995; Hardie and Parks 1997; Holt 1999; Miller and Plantinga 1999) or where the dependent variable is a discrete variable indicating the crop planted (e.g., Wu et al. 2004; Lubowski, Plantinga, and Stavins 2008; Hendricks, Smith, and Sumner 2012).

The estimate of π in (13) provides direct evidence on predictability of the yield shock. Even if the true yield response to price is zero, OLS estimation of π will likely produce negative coefficient on the futures price if yield shocks are forecastable. To some extent, growing-season weather may be predictable before planting. For example, some droughts persist over several years. In addition to predictions of weather, yield forecasts may also reflect other factors such as pest pressure. The discovery of soybean rust in the United States provides one such example. The futures price used by RS reflects expectations of crop yields prior to planting in the Northern Hemisphere, but also reflects realized crop yield shocks in the middle of the growing season in the Southern Hemisphere.

2.4 Which Futures Price to Use?

One issue in specifying the regression is choosing the timing of the futures contract. Several studies use the price of a harvest-time contract traded at planting-time (e.g., Gardner 1976; Choi and Helmberger 1993; Goodwin, Vandeveer, and Deal 2004; Hausman 2012) while others use the price of a harvest-time contract traded prior to planting (e.g., Orazem and Miranowski 1994; Holt 1999; Wu et al. 2004; Hendricks, Smith, and Sumner 2012). Gardner (1976) viewed this choice primarily as an issue of determining when production decisions were made. A more relevant consideration for the econometrician is to choose a price that is subject to fewer endogeneity concerns. Futures traders have greater knowledge of exogenous factors affecting planted area—such as excess rainfall preventing planting—at the time of planting than in the months preceding planting. In the United States, the National Agricultural Statistics Service (NASS) releases a prospective plantings report the last week of March. Based on this consideration it seems preferable to use a futures price traded prior to March to reduce endogeneity concerns in the United States. This point was also made by Orazem and Miranowski (1994).

In their empirical application, RS estimate world supply of calories using the price of a December or November contract (depending on the commodity) traded one year prior to delivery. For example, the futures price for maize in 2007 is the December 2006 price of the December 2007 contract. Their production data is from the Food and Agricultural Organization (FAO), which reports crop production by country according to the calendar year the crop was harvested. For example, Brazilian soybeans planted in October 2006 and harvested in April 2007 would be recorded by FAO as 2007 production. While the RS futures price reflects expectations prior to planting in the Northern Hemisphere, their futures price also reflects realized growing area in the Southern Hemisphere as well as planted winter-wheat acreage in the Northern Hemisphere.

3 Results

3.1 Comparison of IV and OLS Estimates

We replicate the supply results of RS to better understand the sources of endogeneity that they find. We do not replicate their demand analysis since we are only concerned with the supply analysis for this paper. We also only replicate results using production data from the Food and Agriculture Organization (FAO) of the United Nations.

Total caloric production is the sum of the production of maize, rice, soybeans, and wheat using the caloric conversion factors from Williamson and Williamson (1942). Two-stage least squares estimates use data for the period 1961–2007. One period is lost because the lagged yield shock is used an an instrument, so there are 46 observations. In OLS regressions we use the same 46 years, 1962–2007. We construct the RS yield shock ω_t as the weighted average of country and crop-specific log yield shocks as described in their paper. We construct the yield shock ψ_t as the log of the weighted average of country and crop-specific yield shocks as we describe in the previous section.

The futures price is the caloric weighted average of the price of maize, soybeans, and wheat.[5] We use futures contracts with a delivery month of December for maize and wheat and a delivery month of November for soybeans. The futures price is the average price in December one year prior to delivery. Where price data are missing, we use the monthly average futures price nearest to December of the year prior to the harvest year.

Panel A of table 1 reports 2SLS estimates (equation (9)). Results in columns (1a)–(1c) in table 1 use ω_t as the yield shock while results in columns (2a)–(2c) use ψ_t as the yield shock. Our estimates in columns (1a)–(1c) of panel A are remarkably close to replicating supply estimates in columns (1a)–(1c) of table 1 of RS. Estimates of the supply elasticity differ little whether we use ω_t or ψ_t as the yield shock. In the rest of our discussion, we focus on using ψ_t as the yield shock because it allows us to apply the decomposition in (1)–(3).

Panel B of table 1 reports OLS estimates of equation (8), which includes the yield shock as a control. From the bias expressions in the previous section, we expect a substantial difference between the estimates in panels A and B if growing-area shocks are predictable (i.e., if $\delta < 0$). A natural source of such predictability comes from the fact that Southern Hemisphere planted acreage is known at time τ, as is the Northern Hemisphere planted acreage of winter wheat. The OLS estimates, however, are very similar to 2SLS estimates implying that the effect of such predictability on growing area is small (i.e., γ is close to zero). In fact, OLS estimates are slightly larger than 2SLS estimates in columns (2a) and (2c). We also report the p-value from a Hausman test of endogeneity that tests between the

[5] RS do not use the futures price of rice when constructing an average price because rice futures did not trade before 1986.

models in panel A and panel B. We cannot reject the null hypothesis of exogeneity for any of the specifications of spline knots.

Panel C of table 1 reports OLS estimates of equation (7), which omits the yield shock. Our estimates in columns (1a)–(1c) are again remarkably close to replicating OLS estimates in columns (1a)–(1c) of table 4 from RS. OLS estimates of the supply elasticity that omit the yield shock are much smaller than results in panel A or panel B, indicating that there is substantial predictability in yield shocks. If such predictability were not present ($\pi = 0$), then our bias expressions imply that panels B and C would produce similar estimates. We report the p-value from a test for omitted variable bias that tests between the models in panel B and panel C.[6] We reject the null hypothesis of no omitted variable bias at the 1 percent level for all the specifications of spline knots.

In summary, the futures price is endogenous to total production due to predictable yield shocks ($\pi < 0$), but this predictability has little effect on growing area (γ is small). Predictable shocks to growing area have little influence ($\delta \approx 0$), so there is little need to apply instrumental variables estimation once current yield shocks are controlled for. Moreover, because the 2SLS estimates of standard errors are roughly 75 percent larger than standard errors of OLS, these results argue against using 2SLS. This conclusion holds under the RS assumption that yield shocks do not respond to price. In the next section, we address this assumption and decompose the econometric biases in supply elasticity estimation due to acreage, trend yield, and yield shocks as described in Section 2.3.

3.2 Decomposing the Bias

Table 2 shows our results for decomposing the sources of endogeneity by estimating equations (20)–(25) and (13). The supply elasticity estimates in panel A are 2SLS estimates with the yield shock as a control and the lagged yield shock as an instrument, panel B are OLS

[6] We perform this test by treating (7) and (8) as a pair of seemingly unrelated regressions. We stack the regressions, estimate by OLS, and compute a t-statistic for equality of the β coefficients. We cluster the standard errors by year.

estimates with the yield shock as a control, and panel C are OLS estimates that omit the yield shock as a control.

The difference between estimates in panels A and B of table 2 are small. OLS estimates of growing area response to price that control for the yield shock are slightly smaller than 2SLS estimates, but p-values for a test of endogeneity are between 0.315–0.778. The comparison of results in panels A and B reinforces the notion that predictable supply shocks embedded in u_t are minimal ($\delta \approx 0$). OLS estimates of average trend yield response to price are actually larger than 2SLS estimates.

Comparing columns (1a–1c) to columns (2a–2c) in panel B, we see that 70% of the estimated supply response is due to changes in total growing area ($0.063/(0.063 + 0.026) = 0.7$) and the remainder is due to changes in average trend yield. The effect on average trend yield reveals changes in the composition of growing area. The composition of the growing area may change if area response to price is heterogeneous and correlated with trend yields. Two stage least squares estimates in panel A indicate that roughly 82% of the supply response is due to changes in total growing area.

Table 2 provides some evidence that the futures price is partially endogenous to growing area ($\gamma^a > 0$ and $\gamma^y > 0$). Elasticity estimates of the growing area response to price are about 0.012 smaller (a 13–19% reduction) if the yield shock is omitted as a control (columns 1a–1c of panels B and C) and elasticity estimates of the average trend yield are about 0.005 smaller (columns 2a–2c of panels B and C; a 13–19% reduction). These sources of endogeneity may arise if producers adjust their planted acreage in anticipation of a yield shock and futures prices respond to the anticipated change in planted acreage. We conduct a test for omitted variable bias for each growing area model and obtain p-values in the range of 0.055–0.095. For the average trend yield models, the corresponding p-values lie in the range of 0.102–0.138.

Table 2 indicates roughly 75% of the difference between the supply elasticity estimates with and without the yield shock control (panels B and C) is due to the predictability of yield shocks. Regressing the yield shock on the futures price gives an elasticity estimate of roughly -0.050. This estimate is an order of magnitude too large to be interpreted as a yield response to price. Such an interpretation would require that new land brought into production in response to a price rise has close to zero yield. To see this, note that the estimated growing-area responses in columns (1a–1c) are 0.051–0.070; it is only possible to increase acreage and decrease yield by the same percentage if the marginal land has zero yield. This interpretation becomes even less plausible in the next section, when we report that most of the supply response in these estimates comes from the U.S.

It seems clear that the reason for a negative estimated yield elasticity is because future traders likely have some forecast of the expected yield shock, so the futures price is higher in years with a negative yield shock. Assuming that the true elasticity is zero, a statistical test for endogeneity is simply to test whether the coefficient on log futures price is equal to zero. In table 2 we report p-values for this test in the range of 0.003–0.006.

In summary, these results suggest that regressions of world growing area on futures prices may have a bias of up to 20% that can be mitigated by controlling for realized yield shocks. Regressions of total production on futures prices are subject to a much greater bias because, although yield shocks are predictable, this predictability has a relatively small effect on land allocation.

3.3 Country-specific Growing Area Results

By construction, the supply response estimated by RS works entirely through growing area response to price. The world supply response to price is not, however, equal to the world area response to price because area response to price changes the composition of the growing area. Our decomposition picks up this component through the log-average-trend-yield term (y_t). An alternative method to estimate the world supply response to price is to calculate a weighted average of country-specific estimates of area response to price, where weights are equal to the trend caloric production of each country ($A_{it}Y_{it}$).[7] Zellner (1969) showed that

[7] An estimate of the world area response to price can also be calculated as a weighted average of country-specific estimates of area response to price, but using growing area of each country (A_{it}) as weights instead.

regression estimates with aggregate time series data and the average of regression estimates with disaggregate data are both consistent estimators of the aggregate coefficient in the case of a linear, static model with heterogeneous coefficients.[8]

We construct a panel dataset of caloric production using the FAO production data. To maintain consistent production regions through the sample period we aggregate production from countries that were formerly part of the Union of Soviet Socialist Republics (USSR) or formerly part of the Socialist Federal Republic of Yugoslavia (Yugoslav SFR). Countries that produced less than 0.5% of world caloric production on average were aggregated into one of two regions—“Rest of North” or “Rest of South”–depending on hemisphere. We assigned each country to the northern or southern hemisphere based on the average planting and harvest dates for maize and rice from Sacks et al. (2010). We group countries into the northern hemisphere if the planting date is earlier than harvest date within a calendar year.[9] Our dataset is a balanced panel of 31 countries or regions during the period 1961–2007.

Table 3 shows estimates of the aggregate supply elasticity using the production-weighted average of country-specific regressions. We estimate country-specific regressions using the same three estimators used previously: 2SLS with ψ_t as a control, OLS with ψ_t as a control, and OLS omitting ψ_t. These regressions are specified exactly the same as before, except that the left-hand-side variable is the growing area in the country or region.[10] Standard errors for the aggregate supply elasticities are generated using a bootstrap, clustered by year, with 1,000 replications.

Estimates of the aggregate supply elasticity in panels A and B of table 3 are similar to estimates in panels A and B of table 1. The weighted-average yield shock coefficients in panels A and B of table 3 are similar to estimates in panels A and B of table 1 *minus one*

[8]Our aggregate regressions are not exactly the sum of country-specific regressions because the sum of logs is not equivalent to the log of a sum, but this is not likely to be a major concern in practice.

[9]In other words, countries are grouped into the northern hemisphere if planting of maize and rice occurs early in the calendar year and harvest occurs late in the calendar year. We use the dates for the crop that represents the largest portion of total production in the few cases where the crop calendar for maize and rice give conflicting results for the hemisphere.

[10]Results are similar if we use the log yield shock of the country or region as a control ψ_{it} instead of the log world average yield shock ψ_t.

because the yield shock is not included in the LHS in the results in table 3. Results in panel C of table 3 that omit the yield shock as a control are much larger than estimates in panel C of table 1. As in table 2, most of the endogeneity of the futures price with respect to caloric production is because yield shocks are forecastable and affect the futures price—estimating area response to price mitigates this endogeneity concern.

The OLS estimates in panel C of table 3 are still smaller than estimates in panel B indicating that, as in table 2, there may still be some endogeneity concerns related to expected yield shocks affecting anticipated growing area. There is also an endogeneity concern that growing area in the southern hemisphere is known at the time the futures price is trading ($\delta < 0$). Two stage least squares estimates may reduce the bias from this endogeneity, but results differ little in panels A and B in table 3.

Figure 1 shows estimates of the supply elasticity for each country or region with 95 percent confidence intervals where the trend in the regressions is specified with 5 spline knots. For some countries 2SLS gives larger estimates of the area response to price, but for others 2SLS gives smaller estimates. Generally, estimates do not differ substantially if we include the yield shock or omit the yield shock from OLS regressions.

The estimates of those countries that produce most of the world's calories are particularly relevant. The top five countries or regions produce roughly 65 percent of the world's calories from these crops: USA (23%), China (20%), India (9%), former USSR (7%), and the Rest of the North (7%). Estimates of supply response in China, India, and the Rest of the North are minimal. Supply response in the former USSR is larger, but the largest estimated supply response is in the United States.

Table 4 shows results for growing area response to price in the United States for the different estimators and different specifications of spline knots. The 2SLS estimates in panel A of our table 4 are very similar to the results reported by RS in panel B of their table 3.[11] OLS estimates that include the yield shock as a control (panel B of table 4) are slightly

[11] One difference in our specification is that we use ψ_t as the yield shock instead of ω_t, but this makes a minor difference in the results.

larger than 2SLS estimates when we use 3 or 5 spline knots in the trend. Hausman tests do not reject the null hypothesis of the exogeneity of the futures price. OLS estimates that omit the yield shock as a control (panel C of table 4) give smaller estimates and we can reject the null hypothesis of no omitted variable bias at the 5 percent level for trend specificiations with 3 or 4 spline knots. Since the dependent variable is growing area in these regressions, all of the omitted variable bias is due to the endogeneity of the futures price with growing area. The world supply elasticity due to area response to price in the United States is the area response multiplied by the proportion of caloric production in the United States ($0.295 \times 0.23 = 0.068$). Therefore, roughly 77 percent ($0.068/0.088 = 0.77$) of the estimated world supply elasticity is due to area response to price in the United States.

We also considered a specification in which we estimated country-specific area response to price using different futures prices for countries in the northern and southern hemispheres (results not reported). The futures price used for each hemisphere is the price of a contract for delivery after harvest trading prior to planting for the respective planting and harvest periods for the northern and southern hemisphere. This futures price should reduce endogeneity concerns for the southern hemisphere because the futures price is trading before growing area is known. Results using different futures prices for each hemisphere differed little with our results in table 3. One explanation for the small difference between these results is that most of the caloric production (87%) occurs in the northern hemisphere.

4 Conclusion

We argue that the aggregate crop supply elasticity can be well estimated by OLS regression of growing area on a futures price with a control for a flexible trend and realized deviations of yield from trend. This recommendation should not be applied without qualification. A regression estimate of supply elasticity is specific to the type of price variation in the sample (annual shocks vs long swings), the location in space of the price measured, and the time period covered.

References

Choi, J.S., and P.G. Helmberger. 1993. "Acreage Response, Expected Price Functions, and Endogenous Price Expectations." *Journal of Agricultural and Resource Economics* 18:37–46.

Gardner, B.L. 1976. "Futures Prices in Supply Analysis." *American Journal of Agricultural Economics* 58:81–84.

Goodwin, B.K., M.L. Vandeveer, and J.L. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86:1058–1077.

Hardie, I.W., and P.J. Parks. 1997. "Land Use with Heterogeneous Land Quality: An Application of an Area Base Model." *American Journal of Agricultural Economics* 79:299–310.

Hausman, C. 2012. "Biofuels and Land Use Change: Sugarcane and Soybean Acreage Response in Brazil." *Environmental and Resource Economics* 51:163–187, 10.1007/s10640-011-9493-7.

Hendricks, N.P., A. Smith, and D.A. Sumner. 2012. "Crop Supply Dynamics and the Illusion of Partial Adjustment." Working paper, Available at `http://nphendricks.wordpress.com/work-in-progress/`.

Holt, M.T. 1999. "A Linear Approximate Acreage Allocation Model." *Journal of Agricultural and Resource Economics* 24:383–397.

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2008. "What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions." *Land Economics* 84:529–550.

Miller, D.J., and A.J. Plantinga. 1999. "Modeling Land Use Decisions with Aggregate Data." *American Journal of Agricultural Economics* 81:180–194.

Nerlove, M. 1958. *The Dynamics of Supply: Estimation of Farmers' Response to Price*. Baltimore, MD: The Johns Hopkins Press.

Orazem, P.F., and J.A. Miranowski. 1994. "A Dynamic Model of Acreage Allocation with General and Crop-Specific Soil Capital." *American Journal of Agricultural Economics* 76:385–395.

Roberts, M.J., and W. Schlenker. forthcoming. "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate." *American Economic Review* in press, `http://www.wolfram-schlenker.com/ethanol.pdf`.

Sacks, W.J., D. Deryng, J.A. Foley, and N. Ramankutty. 2010. "Crop Planting Dates: An Analysis of Global Patterns." *Global Ecology and Biogeography* 19:607–620.

Williamson, L., and P. Williamson. 1942. "What We Eat." *Journal of Farm Economics* 24:698–703.

Wooldridge, J.M. 2002. *Econometric Analysis of Cross Section and Panel Data*, 1st ed. Cambridge, MA: MIT Press.

Wright, P.G. 1928. *The Tariff on Animal and Vegetable Oils*. New York: Macmillan.

Wu, J., R.M. Adams, C.L. Kling, and K. Tanaka. 2004. "From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies." *American Journal of Agricultural Economics* 86:26–41.

Wu, J., and K. Segerson. 1995. "The Impact of Policies and Land Characteristics on Potential Groundwater Pollution in Wisconsin." *American Journal of Agricultural Economics* 77:1033–1047.

Zellner, A. 1969. "On the Aggregation Problem: A New Approach to a Troublesome Problem." In K. Fox, J. Sengupta, and G. Narasimham, eds. *Economic Models, Estimation and Risk Programming: Essays in Honor of Gerhard Tintner*. Springer-Verlag, pp. 365–374.

Appendix

We derive the conditions under which each of β_1, β_2, and β_3 in (7)–(9) equal β in

$$q_t = \alpha + \beta p_{\tau t} + \gamma \psi_{\tau t} + \psi_t + \delta \varepsilon_{\tau t} + f\left(t\right) + \nu_t,$$

where ν_t is uncorrelated with the right hand side variables.

Bias in (7)

The model is

$$q_t = \alpha_1 + \beta_1 p_{\tau t} + f_1\left(t\right) + u_{1t}.$$

From Wooldridge (2002), we have

$$\beta_1 = \beta + (1+\gamma)\phi_{11} + \delta\phi_{12},$$

where ϕ_{11} and ϕ_{12} are the coefficients on price in the following auxiliary regressions of the excluded on the included variables:

$$\psi_{\tau t} = \phi_{11}\tilde{p}_{\tau t} + e_{11\tau t},$$

$$\psi_t = \phi_{11}\tilde{p}_{\tau t} + e_{11t},$$

$$\varepsilon_{\tau t} = \phi_{12}\tilde{p}_{\tau t} + e_{12t},$$

where $\tilde{p}_{\tau t} \equiv p_{\tau t} - g_p(t)$ is the detrended price. From standard OLS geometry, the coefficient on $p_{\tau t}$ in a multiple regression that includes the trend terms is the same as the coefficient in a simple regression on the detrended price. The first two equations have identical price coefficients because $\psi_t = \psi_{\tau t} + ln(\eta_t)$, where $ln(\eta_t)$ is independent of information available at τ.

By the definition of π in (13), we have $\phi_{11} \equiv \pi$. Defining the variance of detrended prices as $\sigma_{\tau p}^2 \equiv var\left[\tilde{p}_{\tau t}\right]$ we have

$$\begin{aligned}
\phi_{12} &= \frac{E\left[\tilde{p}_{\tau t}\varepsilon_{\tau t}\right]}{\sigma_{\tau p}^2} \\
&= \frac{E\left[\left(\theta_1\psi_{t-1} + \theta_2\psi_t + \varepsilon_{\tau t}\right)\varepsilon_{\tau t}\right]}{\sigma_{\tau p}^2} \\
&= \frac{\sigma_\varepsilon^2}{\sigma_{\tau p}^2},
\end{aligned}$$

where $\sigma_\varepsilon^2 \equiv E\left[\varepsilon_{\tau t}^2\right]$. The second and third lines follow from the fact that the error is uncorrelated with the right-hand-side variables in (10).

Bias in (8)

The model is

$$q_t = \alpha_2 + \beta_2 p_{\tau t} + \gamma_2\psi_t + f_2\left(t\right) + u_{2t}.$$

From Wooldridge (2002), we have

$$\beta_2 = \beta + \gamma\phi_{21} + \delta\phi_{22},$$

where ϕ_{21} and ϕ_{22} are the coefficients on price in the following auxiliary regressions of the excluded on the included variables:

$$\psi_{\tau t} = \phi_{21}\tilde{p}_{\tau t} + \lambda_{21}\psi_t + e_{21t},$$

$$\varepsilon_{\tau t} = \phi_{22}\tilde{p}_{\tau t} + \lambda_{22}\psi_t + e_{22t}.$$

We do not need to detrend ψ_t because by definition it is a deviation from trend.

We have

$$\begin{bmatrix} \phi_{21} & \phi_{22} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} \sigma_{\tau p}^2 & E\left[\tilde{p}_{\tau t}\psi_t\right] \\ E\left[\tilde{p}_{\tau t}\psi_t\right] & \sigma_\psi^2 \end{bmatrix}^{-1} \begin{bmatrix} E\left[\tilde{p}_{\tau t}\psi_{\tau t}\right] & E\left[\tilde{p}_{\tau t}\varepsilon_{\tau t}\right] \\ E\left[\psi_t\psi_{\tau t}\right] & E\left[\psi_t\varepsilon_{\tau t}\right] \end{bmatrix}$$

where $\sigma_\psi^2 \equiv var\left[\psi_t\right]$. Now,

$$\begin{aligned} E\left[\tilde{p}_{\tau t}\psi_t\right] &= E\left[\tilde{p}_{\tau t}\left(\psi_{\tau t} + ln(\eta_t)\right)\right] \\ &= E\left[\tilde{p}_{\tau t}\psi_{\tau t}\right] \\ &= \pi\sigma_{\tau p}^2. \end{aligned}$$

Note also that $E\left[\psi_t\psi_{\tau t}\right] = E\left[\left(\psi_{\tau t} + ln(\eta_t)\psi_{\tau t}\right)\right] = var\left[\psi_{\tau t}\right]$ because $E\left[ln(\eta_t)\psi_{\tau t}\right] = 0$. Defining $\sigma_\eta^2 \equiv var\left[ln(\eta_t)\right]$ and using $\sigma_\psi^2 = var\left[\psi_{\tau t}\right] + \sigma_\eta^2$, we write $E\left[\psi_t\psi_{\tau t}\right] = \sigma_\psi^2 - \sigma_\eta^2$. Also, from above, $E\left[\tilde{p}_{\tau t}\varepsilon_{\tau t}\right] = \sigma_\varepsilon^2$. Finally, the term $E\left[\psi_t\varepsilon_{\tau t}\right]$ because the error in (10) s uncorrelated with the right-hand-side variables, one of which is ψ_t.

We now have

$$\begin{aligned} \begin{bmatrix} \phi_{21} & \phi_{22} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} &= \begin{bmatrix} \sigma_{\tau p}^2 & \pi\sigma_{\tau p}^2 \\ \pi\sigma_{\tau p}^2 & \sigma_\psi^2 \end{bmatrix}^{-1} \begin{bmatrix} \pi\sigma_{\tau p}^2 & \sigma_\varepsilon^2 \\ \sigma_\psi^2 - \sigma_\eta^2 & 0 \end{bmatrix} \\ &= \frac{1}{\sigma_{\tau p}^2\sigma_\psi^2 - \sigma_{\tau p}^4\pi^2} \begin{bmatrix} \sigma_\psi^2 & -\pi\sigma_{\tau p}^2 \\ -\pi\sigma_{\tau p}^2 & \sigma_{\tau p}^2 \end{bmatrix} \begin{bmatrix} \pi\sigma_{\tau p}^2 & \sigma_\varepsilon^2 \\ \sigma_\psi^2 - \sigma_\eta^2 & 0 \end{bmatrix} \\ &= \frac{1}{\sigma_{\tau p}^2\sigma_\psi^2 - \sigma_{\tau p}^4\pi^2} \begin{bmatrix} \pi\sigma_{\tau p}^2\sigma_\eta^2 & \sigma_\varepsilon^2\sigma_\psi^2 \\ \sigma_{\tau p}^2\sigma_\psi^2 - \sigma_{\tau p}^4\pi^2 - \sigma_{\tau p}^2\sigma_\eta^2 & -\pi\sigma_{\tau p}^2\sigma_\varepsilon^2 \end{bmatrix} \end{aligned}$$

Bias in (9)

The model is

$$q_t = \alpha_3 + \beta_3 p_{\tau t} + \gamma_3\psi_t + \delta_3\varepsilon_{\tau t} + f_3\left(t\right) + u_{3t}.$$

From Wooldridge (2002), we have

$$\beta_3 = \beta + \gamma\phi_{31},$$

where ϕ_{31} is the coefficient on price in the following auxiliary regression of the excluded variable on the included variables:

$$\psi_{\tau t} = \phi_{31}\tilde{p}_{\tau t} + \lambda_{31}^{\psi}\psi_t + \lambda_{31}^{\varepsilon}\varepsilon_{\tau t} + e_{31t},$$

We do not need to detrend ψ_t and $\varepsilon_{\tau t}$ because by definition they are deviations from trend.

We have

$$\begin{aligned}
\begin{bmatrix} \phi_{31} \\ \lambda_{31}^{\psi} \\ \lambda_{31}^{\varepsilon} \end{bmatrix} &= \begin{bmatrix} \sigma_{\tau p}^2 & E\left[\tilde{p}_{\tau t}\psi_t\right] & E\left[\tilde{p}_{\tau t}\varepsilon_{\tau t}\right] \\ E\left[\tilde{p}_{\tau t}\psi_t\right] & \sigma_{\psi}^2 & E\left[\psi_t\varepsilon_{\tau t}\right] \\ E\left[\tilde{p}_{\tau t}\varepsilon_{\tau t}\right] & E\left[\psi_t\varepsilon_{\tau t}\right] & \sigma_{\varepsilon}^2 \end{bmatrix}^{-1} \begin{bmatrix} E\left[\tilde{p}_{\tau t}\psi_{\tau t}\right] \\ E\left[\psi_t\psi_{\tau t}\right] \\ E\left[\varepsilon_{\tau t}\psi_{\tau t}\right] \end{bmatrix} \\
&= \begin{bmatrix} \sigma_{\tau p}^2 & \pi\sigma_{\tau p}^2 & \sigma_{\varepsilon}^2 \\ \pi\sigma_{\tau p}^2 & \sigma_{\psi}^2 & 0 \\ \sigma_{\varepsilon}^2 & 0 & \sigma_{\varepsilon}^2 \end{bmatrix}^{-1} \begin{bmatrix} \pi\sigma_{\tau p}^2 \\ \sigma_{\psi}^2 - \sigma_{\eta}^2 \\ E\left[\varepsilon_{\tau t}\psi_{\tau t}\right] \end{bmatrix} \\
&= \frac{1}{\sigma_{\tau p}^2\sigma_{\psi}^2\sigma_{\varepsilon}^2 - \sigma_{\tau p}^4\pi^2\sigma_{\varepsilon}^2 - \sigma_{\psi}^2\sigma_{\varepsilon}^4} \begin{bmatrix} \sigma_{\psi}^2\sigma_{\varepsilon}^2 & -\pi\sigma_{\tau p}^2\sigma_{\varepsilon}^2 & -\sigma_{\psi}^2\sigma_{\varepsilon}^2 \\ -\pi\sigma_{\tau p}^2\sigma_{\varepsilon}^2 & \sigma_{\varepsilon}^2\sigma_{\tau p}^2 - \sigma_{\varepsilon}^4 & \pi\sigma_{\tau p}^2\sigma_{\varepsilon}^2 \\ -\sigma_{\psi}^2\sigma_{\varepsilon}^2 & \pi\sigma_{\tau p}^2\sigma_{\varepsilon}^2 & \sigma_{\tau p}^2\sigma_{\psi}^2 - \sigma_{\tau p}^4\pi^2 \end{bmatrix} \begin{bmatrix} \pi\sigma_{\tau p}^2 \\ \sigma_{\psi}^2 - \sigma_{\eta}^2 \\ E\left[\varepsilon_{\tau t}\psi_{\tau t}\right] \end{bmatrix}
\end{aligned}$$

where we plug in quantities derived above.

Next, we derive an expression for $E\left[\varepsilon_{\tau t}\psi_{\tau t}\right]$.

$$\begin{aligned}
E\left[\varepsilon_{\tau t}\psi_{\tau t}\right] &= E\left[\left(\tilde{p}_{\tau t} - \theta_1\psi_{t-1} - \theta_2\psi_t\right)\psi_{\tau t}\right] \\
&= E\left[\tilde{p}_{\tau t}\psi_{\tau t}\right] - \begin{bmatrix} E\left[\psi_{t-1}\psi_{\tau t}\right] & E\left[\psi_t\psi_{\tau t}\right] \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}.
\end{aligned}$$

The parameters θ_1 and θ_2 are

$$
\begin{aligned}
\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} &= \begin{bmatrix} E\left[\psi_{t-1}^2\right] & E\left[\psi_{t-1}\psi_t\right] \\ E\left[\psi_{t-1}\psi_t\right] & E\left[\psi_t^2\right] \end{bmatrix}^{-1} \begin{bmatrix} E\left[\tilde{p}_{\tau t}\psi_{t-1}\right] \\ E\left[\tilde{p}_{\tau t}\psi_t\right] \end{bmatrix} \\
&= \begin{bmatrix} \sigma_\psi^2 & E\left[\psi_{t-1}\psi_{\tau t}\right] \\ E\left[\psi_{t-1}\psi_{\tau t}\right] & \sigma_\psi^2 \end{bmatrix}^{-1} \begin{bmatrix} E\left[\tilde{p}_{\tau t}\psi_{t-1}\right] \\ \pi\sigma_{\tau p}^2 \end{bmatrix}, \\
&= \frac{1}{\sigma_\psi^4 - E\left[\psi_{t-1}\psi_{\tau t}\right]^2} \begin{bmatrix} \sigma_\psi^2 E\left[\tilde{p}_{\tau t}\psi_{t-1}\right] - \pi\sigma_{\tau p}^2 E\left[\psi_{t-1}\psi_{\tau t}\right] \\ \pi\sigma_{\tau p}^2\sigma_\psi^2 - E\left[\tilde{p}_{\tau t}\psi_{t-1}\right] E\left[\psi_{t-1}\psi_{\tau t}\right] \end{bmatrix} \\
&= \frac{1}{\sigma_\psi^4 - \rho_1^2\sigma_\psi^4} \begin{bmatrix} \pi_1\sigma_\psi^2\sigma_{\tau p}^2 - \pi\rho_1\sigma_{\tau p}^2\sigma_\psi^2 \\ \pi\sigma_{\tau p}^2\sigma_\psi^2 - \pi_1\rho_1\sigma_{\tau p}^2\sigma_\psi^2 \end{bmatrix}.
\end{aligned}
$$

where we define $\pi_1 \equiv E\left[\tilde{p}_{\tau t}\psi_{t-1}\right]\sigma_{\tau p}^{-2}$ to be the coefficient from a regression of ψ_{t-1} on $\tilde{p}_{\tau t}$ and $\rho_1 \equiv E\left[\psi_{t-1}\psi_t\right]\sigma_\psi^{-2} = E\left[\psi_{t-1}\psi_{\tau t}\right]\sigma_\psi^{-2}$ to be the first order autocorrelation coefficient for ψ_t.

Thus, we have

$$
\begin{aligned}
E\left[\varepsilon_{\tau t}\psi_{\tau t}\right] &= \pi\sigma_{\tau p}^2 - \frac{\rho_1\sigma_\psi^2\left(\pi_1\sigma_\psi^2\sigma_{\tau p}^2 - \pi\rho_1\sigma_{\tau p}^2\sigma_\psi^2\right) - \left(\sigma_\psi^2 - \sigma_\eta^2\right)\left(\pi\sigma_{\tau p}^2\sigma_\psi^2 - \pi_1\rho_1\sigma_{\tau p}^2\sigma_\psi^2\right)}{\sigma_\psi^4 - \rho_1^2\sigma_\psi^4} \\
&= \sigma_{\tau p}^2\left(\pi - \frac{\rho_1\sigma_\psi^2\left(\pi_1 - \pi\rho_1\right) - \left(\sigma_\psi^2 - \sigma_\eta^2\right)\left(\pi - \pi_1\rho_1\right)}{\sigma_\psi^2 - \rho_1\sigma_\psi^2}\right) \\
&= \sigma_{\tau p}^2\sigma_\psi^{-2}\left(\pi\rho_1\sigma_\psi^2 + \sigma_\eta^2\left(\pi - \pi_1\rho_1\right)\left(1 - \rho_1\right)^{-1}\right)
\end{aligned}
$$

Putting the pieces together implies

$$
\begin{aligned}
\phi_{31} &= \frac{\pi\sigma_\eta^2 - \sigma_{\tau p}^{-2}\sigma_\psi^2 E\left[\varepsilon_{\tau t}\psi_{\tau t}\right]}{\sigma_\psi^2 - \sigma_{\tau p}^2\pi^2 - \sigma_{\tau p}^{-2}\sigma_\psi^2\sigma_\varepsilon^2} \\
&= \frac{\pi\sigma_\eta^2 - \pi\rho_1\sigma_\psi^2 - \sigma_\eta^2\left(\pi - \pi_1\rho_1\right)\left(1 - \rho_1\right)^{-1}}{\sigma_\psi^2 - \sigma_{\tau p}^2\pi^2 - \sigma_{\tau p}^{-2}\sigma_\psi^2\sigma_\varepsilon^2}
\end{aligned}
$$

Tables

Table 1: Estimates of World Caloric Supply with Alternative Models

	ω_t as Yield Shock			ψ_t as Yield Shock		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Panel A. Two Stage Least Squares						
Supply Elast.	0.107***	0.104***	0.088***	0.108***	0.103***	0.088***
	(0.024)	(0.025)	(0.019)	(0.024)	(0.025)	(0.020)
Shock	1.202***	1.240***	1.222***	1.315***	1.356***	1.335***
	(0.131)	(0.117)	(0.094)	(0.145)	(0.128)	(0.105)
Panel B. OLS Including ψ_t as Yield Shock						
Supply Elast.	0.110***	0.089***	0.088***	0.112***	0.090***	0.089***
	(0.013)	(0.014)	(0.012)	(0.013)	(0.014)	(0.012)
Shock	1.216***	1.194***	1.223***	1.334***	1.313***	1.338***
	(0.111)	(0.106)	(0.087)	(0.121)	(0.114)	(0.096)
Panel C. OLS Omitting Yield Shock						
Supply Elast.	0.049**	0.023	0.022	0.049**	0.023	0.022
	(0.023)	(0.026)	(0.026)	(0.023)	(0.026)	(0.026)
p-value for Hausman test (H_0=exogeneity)	0.873	0.490	0.995	0.881	0.530	0.995
p-value for test of omitted variable bias (H_0=no bias)	0.007	0.007	0.009	0.006	0.006	0.008
Observations	46	46	46	46	46	46
Spline Knots	3	4	5	3	4	5

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

Table 2: Decomposition of Supply Estimates

	a_t **as LHS Variable**			y_t **as LHS Variable**			ψ_t **as LHS Variable**		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Panel A. Two Stage Least Squares									
Supply Elast.	0.086***	0.082***	0.072***	0.021**	0.021*	0.017	0	0	0
	(0.021)	(0.021)	(0.018)	(0.011)	(0.011)	(0.011)			
Shock	0.263**	0.288***	0.274***	0.052	0.068	0.061	1	1	1
	(0.122)	(0.109)	(0.093)	(0.064)	(0.06)	(0.057)			
Panel B. OLS Including ψ_t as Yield Shock									
Supply Elast.	0.081***	0.064***	0.063***	0.031***	0.026***	0.026***	0	0	0
	(0.011)	(0.012)	(0.010)	(0.006)	(0.007)	(0.006)			
Shock	0.242**	0.227**	0.246***	0.092*	0.086	0.092*	1	1	1
	(0.102)	(0.095)	(0.084)	(0.052)	(0.053)	(0.051)			
Panel C. OLS Omitting Yield Shock									
Supply Elast.	0.070***	0.053***	0.051***	0.026***	0.022***	0.021***	-0.048***	-0.051***	-0.050***
	(0.010)	(0.011)	(0.010)	(0.005)	(0.006)	(0.006)	(0.015)	(0.018)	(0.017)
Panel B - Panel A	-0.005	-0.018	-0.008	0.010	0.005	0.009	0	0	0
Panel C - Panel B	-0.011	-0.012	-0.012	-0.004	-0.004	-0.005	-0.048	-0.051	-0.050
p-value for Hausman test (H_0=exogeneity)	0.778	0.315	0.588	0.326	0.625	0.342	N/A	N/A	N/A
p-value for test of omitted variable bias (H_0=no bias)	0.086	0.095	0.055	0.106	0.138	0.102	0.003	0.006	0.006
Observations	46	46	46	46	46	46	46	46	46
Spline Knots	3	4	5	3	4	5	3	4	5

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

Table 3: Estimates of World Caloric Supply as the Production Weighted Average of Country-Specific Estimates of Growing Area Response to Price

	(1)	(2)	(3)
Panel A. Two Stage Least Squares			
Supply Elast.	0.096***	0.093***	0.087***
	(0.028)	(0.032)	(0.026)
Shock	0.283*	0.311*	0.300**
	(0.171)	(0.173)	(0.141)
Panel B. OLS Including ψ_t as Yield Shock			
Supply Elast.	0.102***	0.088***	0.088***
	(0.012)	(0.014)	(0.013)
Shock	0.307***	0.293***	0.305***
	(0.097)	(0.096)	(0.095)
Panel C. OLS Omitting Yield Shock			
Supply Elast.	0.087***	0.073***	0.073***
	(0.015)	(0.017)	(0.017)
Observations	46	46	46
Spline Knots	3	4	5

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

Table 4: Estimates of Growing Area Response to Price in the United States

	(1)	(2)	(3)
Panel A. Two Stage Least Squares			
Supply Elast.	0.300***	0.293***	0.285***
	(0.067)	(0.071)	(0.069)
Shock	0.853**	0.914**	0.892**
	(0.398)	(0.368)	(0.368)
Panel B. OLS Including ψ_t as Yield Shock			
Supply Elast.	0.320***	0.291***	0.295***
	(0.036)	(0.041)	(0.041)
Shock	0.938***	0.909***	0.927***
	(0.334)	(0.331)	(0.336)
Panel C. OLS Omitting Yield Shock			
Supply Elast.	0.275***	0.245***	0.249***
	(0.034)	(0.040)	(0.040)
p-value for Hausman test (H_0=exogeneity)	0.744	0.980	0.877
p-value for test of omitted variable bias (H_0=no bias)	0.038	0.047	0.055
Observations	46	46	46
Spline Knots	3	4	5

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

Figures

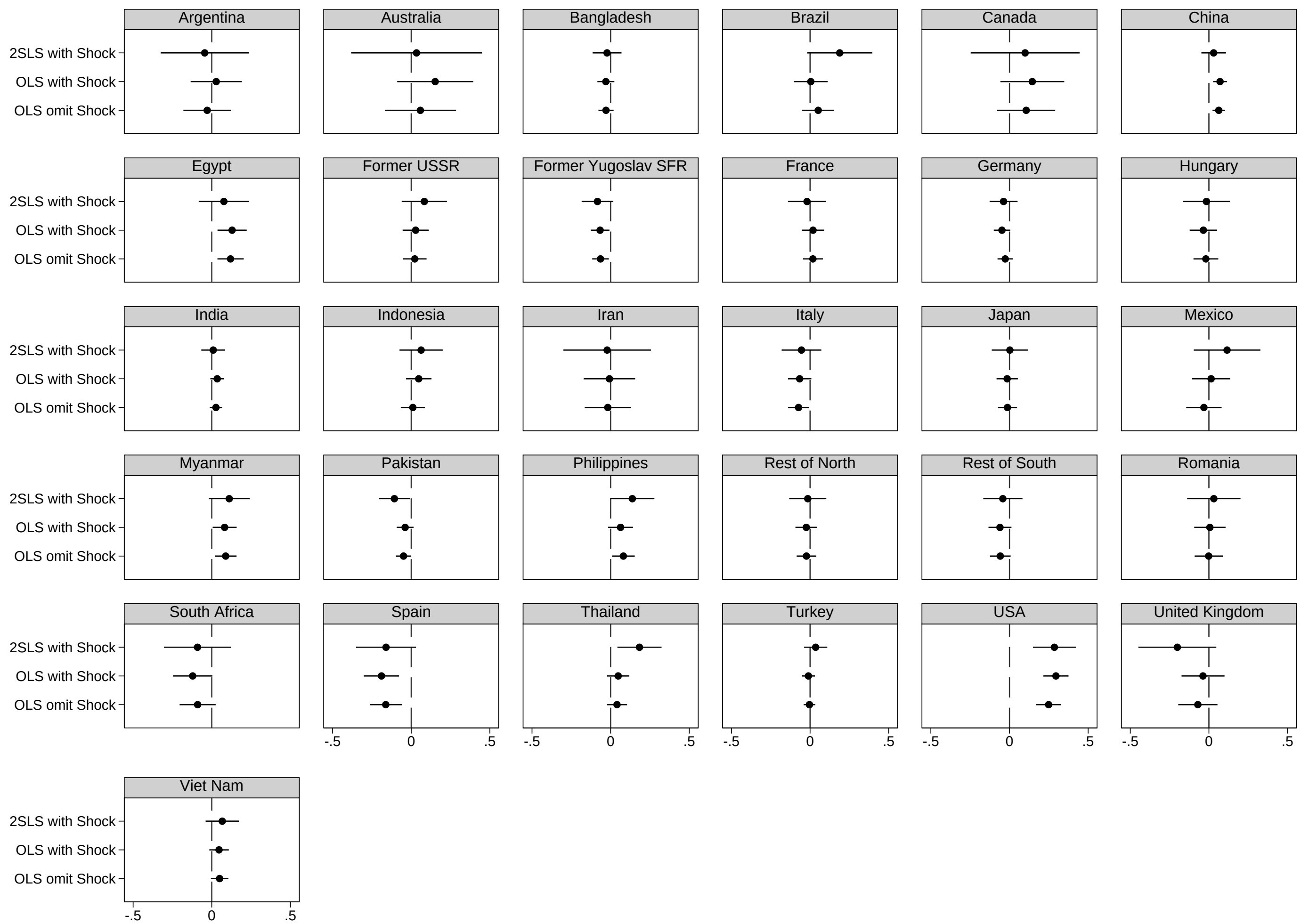

Figure 1: Country-Specific Estimates of Growing Area Response to Price