# USING USDA FORECASTS TO ESTIMATE THE PRICE FLEXIBILITY OF DEMAND FOR AGRICULTURAL COMMODITIES

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We estimate the general equilibrium price flexibility of demand for corn and soybeans using monthly changes in expected supply published by the USDA. Our estimates reflect the demand response to a one-year supply shock and thus correspond to the inverse demand elasticity. We derive the conditions under which our estimates are consistent, and we show how demand flexibility varies by season, inventory, time horizon, and demand composition. At average inventory and without accounting for corn-ethanol use, we obtain price flexibility estimates of −1.35 and −1.03 for corn and soybeans, respectively. Current corn-ethanol production levels are associated with much larger absolute flexibilities for both commodities.

*Key words*: commodity prices, corn, demand flexibility, futures prices, soybeans, USDA supply forecasts, WASDE.

*JEL Classification*: G13, Q11.

To identify the parameters in a commodity demand function, econometricians require supply-induced price variation. The annual harvest cycle implies that changes to supply occur annually, so conventional empirical methods often use data observed at annual intervals. Moreover, identification at an annual frequency is challenging because variation in annual prices and quantities reflects both supply and demand shocks. The use of instrumental variables to solve the identification problem necessarily reduces estimation precision, assuming valid instruments can be found. Thus, working only with annual data leads to imprecise parameter estimates and policy predictions with a high margin of error. In this article, we exploit monthly crop forecasts produced by the United States Department of Agriculture (USDA) to capture intra-year shocks to the expected supply of corn and soybeans. By measuring the response of prices to these shocks, we estimate the own-price demand flexibility for these two commodities, and we show how demand flexibility varies by season, inventory, time horizon, and demand composition.

Beginning in May of each year, the USDA releases the World Agricultural Supply and Demand Estimates (WASDE), which provide forecasts for several crops of annual U.S. production and inventory, among many other variables. The National Agricultural Statistics Service (NASS) and the Interagency Commodity Estimates Committees (ICEC) contribute to these projections by providing detailed farm surveys, weather forecasts, and expected market developments. The USDA releases a new WASDE report each month thereafter, although December reports do not revise the supply forecast. By the following January, the crop size is known with a high degree of certainty. First-differencing the monthly WASDE forecasts from May to January, not including December, provides seven observations per year of the change in expected annual supply with which to estimate the demand flexibility.

In this article, we show the conditions under which a regression of the month-to-month change in log futures prices on the month-to-month change in log WASDE supply forecast consistently estimates the short-run demand

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flexibility for an agricultural commodity.[1] We then use such regressions to estimate the price flexibility of demand for corn and soybeans using data from 1981–2010. In doing so, we control for a large set of potential demand shifters, although our framework ensures that the likely effect of demand shocks on our estimates is small.

We estimate general equilibrium demand parameters (Thurman and Wohlgenant 1989), which sometimes are referred to as total demand parameters (Buse 1958). Specifically, we estimate the price response to a change in the supply of a commodity without holding constant the prices or quantities of other commodities. In policy analysis, the general equilibrium flexibility is often the object of interest. When a commodity-specific policy is implemented, the prices of substitute and complementary commodities will be affected and thus should not be held constant when estimating demand parameters. See Thurman and Wohlgenant (1989) for further articulation of this point.

Two potential issues complicate our estimation approach. First, although futures prices for agricultural commodities represent the market's expectation about commodity supply and demand fundamentals, the WASDE forecast represents the government's prediction. Numerous studies show that markets react to the release of USDA crop reports (Adjemian 2012; Isengildina-Massa, et al. 2008; McKenzie 2008; Sumner and Mueller 1989), suggesting that market and government forecasts are closely aligned. Nonetheless, we allow for the possibility that their month-to-month changes may correlate less strongly. Second, recent research suggests that the USDA may smooth its supply change forecasts (Isengildina, Irwin and Good 2006). To address both of these issues, we use Maximum Likelihood to estimate jointly the measurement error and smoothing parameters together with price flexibility. We find that these issues have little if any effect on our flexibility estimates, so we present only our OLS estimates in this article.

We focus on corn and soybeans because they are the dominant crops in terms of cash receipts to U.S. farmers (Strickland 2009; Westcott and Hoffman 1999). As the world's largest producer and exporter of corn and soybeans, the United States grew 39% and 35% of the total world crop in 2010 and 2011, respectively, according to the USDA Foreign Agricultural Service (FAS). During that time, domestic producers accounted for 52% of corn exports, and 44% of soybean exports, globally.

## Background

Moore (1919) introduced to economics the term *flexibility of prices* (Houck 1966); he estimated the price effect of an attempt by the Southern States Cotton Acreage Reduction Convention to "organize the cotton farmers, merchants and bankers of the entire South in reducing cotton acreage during the coming year, so as to free them from the shearing operations of the interests, American and foreign, which have been holding down the price of cotton." Using annual data from 1889–1913, Moore estimated the annual price flexibility of demand for U.S. cotton to be −1.11. Incidentally, this estimate is similar to those we obtain for corn and soybeans using data from 1981–2010.

Moore's setting mirrors the one we study in the sense that quantity variation in his sample was dominated by supply shocks. In our framework, producers have little capacity to adjust output in response to price changes between monthly WASDE updates, which occur after the crop has been planted. Such highly inelastic supply implies that most of the quantity variation between WASDE updates emanates from supply shocks. It therefore is natural to treat quantity as the right-hand side variable in our regressions. Houck (1966) and Huang (1988) make a similar point in a more general context: if supply shocks drive quantity variation, then prices tend to bear the adjustment burden resulting from exogenous quantity shocks. Accordingly, price-dependent regressions estimate demand parameters more accurately than quantity-dependent regressions.

In the presence of strong and valid instruments, it does not matter which variable is placed on the left-hand side of a regression equation. In fact, Hahn and Hausman (2002) develop a specification test for the validity of instruments based on the difference between an instrumental variables estimate and the instrumental variables

[1] We measure the price change over the *month* since the last WASDE supply estimate rather than the price change on the *day* of the release because we aim to estimate the price effect of all supply information that reached the market during the month rather than the incremental information provided in the WASDE report.

estimate obtained after switching the right- and left-hand side variables. However, finding such instruments is difficult in practice, so it is sensible to place on the right-hand side the variable that is most plausibly exogenous. In our case, that variable is the expected quantity supplied.

In a single-commodity setting such as ours, the price flexibility of demand equals the inverse of the price elasticity of demand. We do not estimate cross-price effects, so we do not hold constant quantities or prices of other commodities. Most commodity demand models found in the literature estimate elasticities directly, often using annual data. For example, Roberts and Schlenker (2010) calculate supply and demand elasticities for food commodities using instrumental variables and 42 years of annual data; they use deviations from trend yield to instrument for supply, and estimate the global elasticity of demand for caloric energy to be −0.05. Examples of published price flexibilities for corn and soybeans are rare. Gray, Richardson, and McClaskey (1995) provide own-price flexibilities of −4 and −4.17 for corn and soybeans, respectively, although these are attributed to the Food and Agriculture Policy Research Institute (FAPRI).

Several researchers have estimated commodity demand parameters using government crop supply forecasts. Orazem and Falk (1989) isolate the unanticipated portion of USDA's August crop production report using a signal extraction model, and recover the soybean demand elasticity, which they estimate to be around −0.09. Motivated by the commodity price swings of the early 1970's, Gray (1974) uses futures prices and crop size forecasts to estimate the price elasticity of demand for two different years, to discover whether the shape of the demand curve is invariant to price level. Building on Gray's work, Tomek (1979) uses a similar model to measure the trend in demand parameters for corn from 1970–1978. For each year, Tomek estimates the relationship between five USDA production forecasts and prices for harvest-time futures contracts, first using a nominal and then a livestock-price deflated series.

Chua and Tomek (2010) estimate the price flexibility for corn using a regression of the price in cents per bushel on WASDE supply projections measured in millions of bushels. For prices, the authors use the December futures contract price on the day of the release of the WASDE report, and they use each of the July-November WASDE supply projections, giving them five observations per year, spanning the years 1989–2008. Chua and Tomek use month fixed effects to control for seasonality and year fixed effects to account for annual price level variation due to inflation and demand shifts.[2] Because price and quantity enter their models in levels rather than in log first differences, their flexibility estimates vary by observation. However, their estimates imply an own-price flexibility of demand for corn between −1.5 and −2 over the period studied.

While acknowledging the benefits of using intra-year projections to improve precision, Tomek (1979) lists four reasons why using government supply projections can lead to biased or inefficient demand parameter estimates. In the order he lists them, these concerns are: (i) demand shocks may be large and correlated with supply shocks, causing the estimator to confound supply and demand flexibilities; (ii) the intra-year variance of the USDA crop forecast may be small, leading to poor estimation precision; (iii) the WASDE projections may differ from the market forecast; and (iv) demand shocks may not be observable at the same frequency that we observe supply projections.

In this article, we address each of Tomek's concerns and thereby differentiate our work from the existing literature. In the next section we show that, under two assumptions, ordinary least squares regression of the month-to-month change in log futures prices on the month-to-month change in log projected supply consistently estimates the short-run demand flexibility. The first of these assumptions is perfectly inelastic supply after the first WASDE report is released in May of each year, and zero correlation between supply and demand shocks. This condition assumes away Tomek's concerns (i) and (iv), because it implies that expected quantity supplied can only change due to a shift in the supply curve. Although the supply elasticity in our framework is likely close to zero, we nonetheless derive the potential bias in our estimates if this assumption is relaxed. To mitigate this bias in our application, we use a set of control variables to account for possible demand shifts.

Tomek's concern (iii) addresses measurement error and smoothing bias (Isengildina, Irwin and Good 2006) in the WASDE

[2] Chua and Tomek's (2010) reported estimates refer to a model that constrains the year fixed effects to be constant across some years. The authors state that this restricted specification is not rejected by an F-test.

projections. However, we find that measurement error and smoothing bias have little impact on our estimates. Tomek's concern (ii) is an empirical question of estimation efficiency; we show that using intra-year observations improves efficiency by about 20%.

## Modeling Framework

Let $P_t = \alpha Q_t^{\theta} u_t$ describe the inverse demand function of interest. This function has constant flexibility θ. The variable $Q_t$ is quantity supplied at the beginning of crop year $t$, $u_t$ is an aggregate demand shifter, and $P_t$ denotes a representative price during crop year $t$. For this representative price, we use the cash price at harvest. This price corresponds to December for corn and November for soybeans, and is realized just after USDA releases its penultimate estimate of $Q_t$, before the beginning of the growing season for the following crop. Our object of interest is the general-equilibrium demand function, which does not include relative prices of agricultural commodities as arguments. Thus, the demand shifter may depend on aggregate demand but not on relative prices of agricultural commodities.

We begin our estimations by making two assumptions that prove useful in expositing on our modeling framework, but we relax each of them before taking our method to the data. The assumptions are:

Assumption A1: After May, post-harvest supply is perfectly inelastic, and shocks to expected demand are independent of shocks to expected supply.

Assumption A2: WASDE forecast equals market forecast, and percentage increments to the WASDE are independent of the current forecast.

We define τ as the number of months before harvest of crop year $t$ that a WASDE forecast is released, and we denote the month $t-\tau$ WASDE forecast as $\bar{Q}_{t-\tau,t}$. For corn, the August WASDE forecast for crop year $t$ is $\bar{Q}_{4,t}$ because August comes 4 months before December. Likewise, we observe WASDE forecasts corresponding to $\tau = 1, 2, 3, 4, 5, 6,$ and 7. Under A2, $\bar{Q}_{t-\tau,t}$ equals expected supply as of $t-\tau$, i.e., $\bar{Q}_{t-\tau,t} = E_{t-\tau}[Q_t]$.

We write actual quantity supplied in crop year $t$ as its expectation at $t-\tau$, multiplied by the subsequent forecast revisions. That is, we write $Q_t = \bar{Q}_{t-\tau,t} \prod_{i=1}^{\tau} \eta_{t-\tau+i}$, where the forecast revision terms $\eta_{t-\tau+i}$ have a mean of one. By A2, the sequence of forecast revisions $\{\eta_{t-\tau+i}\}$ is independent. Moreover, this decomposition implies that we can define a recursive updating formula for the forecasts $\bar{Q}_{t-\tau,t} = \bar{Q}_{t-\tau-1,t}\eta_{t-\tau}$. As of time period $t-\tau$, the market expectation of the demand shifter is $\bar{u}_{t-\tau,t} = E_{t-\tau}[u_t]$. Similar to the supply shock, we specify $\bar{u}_{t-\tau,t} = \bar{u}_{t-\tau-1,t}\varphi_{t-\tau}$, where the forecast revision terms $\varphi_{t-\tau}$ are independent over time and, under A1, are uncorrelated with the supply shocks $\eta_{t-\tau}$.

During the growing season, the futures price for harvest delivery $F_{t-\tau,t}$ equals the expected harvest-time cash price (see e.g., Routledge, Seppi, and Spatt, 2000),

$$(1) \qquad F_{t-\tau,t} = E_{t-\tau}[P_t] = \alpha E_{t-\tau}[Q_t^{\Theta} u_t].$$

We do not incorporate a risk premium in equation (1). According to the normal backwardation theory (Keynes, 1930), expected spot prices exceed futures prices to compensate speculators for holding risky long positions and providing risk management services to hedgers. If a risk premium exists, then the futures price is a biased predictor of the forward spot price, speculators should earn the risk premium on average, and futures prices should measurably rise (or fall) over the life of the contract. Frank and Garcia (2009) test for biasedness of agricultural futures prices as predictors of spot prices, and, after allowing for structural breaks in the 1970s, find no evidence of a risk premium. Using data on positions held by individual traders from 2000 to mid-2009, Fishe and Smith (2011) find no evidence that speculators earn risk premia in commodity futures markets by taking positions contrary to commercial hedgers; their results reinforce those of Hartzmark (1991; 1987) from an earlier time period. Moreover, our data show no evidence that futures prices for corn and soybeans tend to rise or fall, on average (see table 1). Thus, we proceed without modeling a risk premium, although a constant risk premium would not change any of our results as it would be absorbed in the constant term of our regressions.

**Table 1. Descriptive Statistics for the Monthly Change in Commodity Price and Explanatory Variables, 1981–2010**

| | Mean | Std. Dev. | Low | High |
|---|---|---|---|---|
| ***Corn*** | | | | |
| Dec Futures Price | −1.16% | 8.42% | −32.19% | 23.41% |
| Distant Dec Futures Price | −0.14% | 4.83% | −26.22% | 10.73% |
| Cash Price | −1.25% | 10.54% | −38.86% | 27.66% |
| WASDE Supply Forecast | −0.17% | 3.02% | −17.66% | 9.20% |
| June 1 Stocks/Prev Year Use[a] | 0.42 | 0.17 | 0.20 | 0.96 |
| ***Soybeans*** | | | | |
| Nov Futures Price | −0.48% | 7.94% | −27.83% | 31.45% |
| Distant Nov Futures Price | −0.02% | 5.20% | −23.12% | 11.45% |
| Cash Price | −0.95% | 8.90% | −37.97% | 32.37% |
| WASDE Supply Forecast | −0.19% | 2.87% | −14.39% | 9.04% |
| June 1 Stocks/Prev Year Use[a] | 0.31 | 0.08 | 0.17 | 0.45 |
| ***Controls*** | | | | |
| Wheat: Dec Futures Price | −0.45% | 7.65% | −24.41% | 27.22% |
| Share of Corn Use for Ethanol[a] | 0.06 | 0.11 | 0 | 0.34 |
| Late Season Dummy[a] | 0.3 | 0.5 | 0 | 1 |
| Milk PPI | 1.12% | 3.62% | −13.59% | 11.54% |
| Livestock PPI | −1.06% | 3.73% | −10.81% | 14.75% |
| Poultry PPI | −0.02% | 7.63% | −22.38% | 22.62% |
| Real Economic Activity Index[b] | −1.31% | 109.43% | −1080.37% | 935.31% |
| Exchange Rate Index | −0.17% | 2.30% | −7.48% | 5.66% |
| M2 Money Supply in $B | 0.53% | 0.39% | −0.50% | 2.12% |
| Tbill Rate | −2.63% | 19.98% | −201.49% | 69.31% |
| Gasoline PPI | −1.00% | 7.67% | −40.24% | 16.41% |
| Farm Machinery PPI | 0.22% | 0.33% | −0.56% | 1.83% |
| Agricultural Chems. & Prods. PPI | 0.05% | 1.87% | −10.31% | 11.15% |
| Mixed Fertilizers PPI | 0.01% | 1.41% | −4.64% | 11.62% |
| Fertilizer Materials PPI | −0.15% | 3.02% | −18.29% | 14.62% |
| Nitrogenates PPI | −0.31% | 3.45% | −11.89% | 12.01% |
| Urea PPI | −0.20% | 6.21% | −22.21% | 46.61% |
| Phosphates PPI | −0.02% | 3.66% | −28.37% | 20.67% |
| Other Ag. Chems. PPI | 0.27% | 1.32% | −2.51% | 15.24% |

[a] Only the levels of these variables are used in the analysis.
[b] The level of Kilian's Index (2006) is recentered to make all observations positive.
Note: None of the changes in this table are significantly different from zero at normally accepted significance levels.

Taking equation (1) and invoking A1 and A2, the log futures price is:

$$\begin{aligned}\ln F_{t-\tau,t} &= \ln\alpha + \ln(E_{t-\tau}[Q_t^{\theta}u_t])\\ &= \ln\alpha + \ln\left(E_{t-\tau}\left[\bar{Q}^{\theta}_{t-\tau,t}\bar{u}_{t-\tau,t}\right.\right.\\ &\quad\left.\left.\times\prod_{i=1}^{\tau}\eta^{\theta}_{t-\tau+i}\varphi_{t-\tau+i}\right]\right)\\ &= \ln\alpha + \theta\ln\bar{Q}_{t-\tau,t} + \ln\bar{u}_{t-\tau,t}\\ &\quad + \ln\left(E_{t-\tau}\left[\prod_{i=1}^{\tau}\eta^{\theta}_{t-\tau+i}\varphi_{t-\tau+i}\right]\right)\\ &= \ln\alpha + \theta\ln\bar{Q}_{t-\tau,t} + \ln\bar{u}_{t-\tau,t}\\ &\quad + \sum_{i=1}^{\tau}\ln(E[\eta^{\theta}_{t-\tau+i}])\end{aligned}$$

where the last line follows from independence of $\eta_{t-\tau}$ and $\varphi_{t-\tau}$ over time, and the fact that $E[\varphi_{t-\tau+i}] = 1$. Differencing then yields

$$\begin{aligned}\Delta\ln F_{t-\tau,t} &= \ln F_{t-\tau,t} - \ln F_{t-\tau-1,t}\\ &= \theta\Delta\ln\bar{Q}_{t-\tau,t} + \ln\varphi_{t-\tau} - \ln(E[\eta^{\theta}_{t-\tau}])\\ &= \beta_{\tau} + \theta\Delta\ln\bar{Q}_{t-\tau,t} + \ln\varphi_{t-\tau}\end{aligned}$$

where $\beta_\tau = -\ln(E[\eta_{t-\tau}^{\theta}])$ denotes a constant term that may depend on $\tau$. In particular, WASDE revisions tend to be greater in August and September than in other months, so $E[\eta_{t-\tau}^{\theta}]$ may differ depending on the month.

These derivations imply that, under A1 and A2, we can estimate the flexibility parameter $\theta$ consistently by running a regression of $\Delta \ln F_{t-\tau,t}$ on $\Delta \ln \bar{Q}_{t-\tau,t}$ and month fixed effects. The error term in this regression is $\ln \varphi_{t-\tau}$, which is the month $t-\tau$ increment in the expected value of the demand shifter. By assumption, this error term is uncorrelated with the right-hand side variable in the regression, $\Delta \ln \bar{Q}_{t-\tau,t}$. Next, we proceed to relax A1 and A2, which requires adding control variables to this base regression and employing a maximum likelihood estimation technique.

### *Relaxing Assumption A1: Perfectly Inelastic Post-May Supply and Independent Supply and Demand Shocks*

This assumption implies that, after May, exogenous supply shocks provide the only source of changes in quantity supplied. The demand curve may shift, but inelastic supply means that such a shift will not affect the quantity supplied. If we relax this assumption to allow some supply response to price, then any shifts in the demand curve will change expected quantity supplied. It follows that $\Delta \ln \bar{Q}_{t-\tau,t}$ would be endogenous in a regression of $\Delta \ln F_{t-\tau,t}$ on $\Delta \ln \bar{Q}_{t-\tau,t}$ and the estimate of $\theta$ would be biased towards zero. Similarly, if we allow supply and demand shocks to be correlated, then our estimated price response to a supply shock will be contaminated by contemporaneous demand shocks that also affect prices.

In our application, the supply curve likely is close to perfectly inelastic. We analyze the monthly change in expected supply (production plus beginning inventories), starting in June, when the crop has been planted. A positive elasticity of supply could arise if farmers respond to price changes by altering the demand for inputs such as fertilizer, thereby changing yield and affecting supply. Similarly, farmers may respond to large negative price shocks by choosing not to harvest a crop. Thus, although the supply elasticity is likely small, we allow for the possibility of demand shifts and elastic supply.

To this end, we specify expected supply as following the recursion

$$\bar{Q}_{t-\tau,t} = \bar{Q}_{t-\tau-1,t}\left(\frac{F_{t-\tau,t}}{F_{t-\tau-1,t}}\right)^{\gamma}\eta_{t-\tau}$$

which we can re-write as $\Delta \ln \bar{Q}_{t-\tau,t} = \gamma\Delta \ln F_{t-\tau,t} + \ln \eta_{t-\tau}$. This equation states that, each month, the update in expected supply from $\bar{Q}_{t-\tau-1,t}$ to $\bar{Q}_{t-\tau,t}$ has two components. First, for positive $\gamma$, expected quantity supplied increases when the futures price increases. Second, as in the previous section $\eta_{t-\tau}$ captures the supply shock. With this specification, we can write actual quantity supplied as

$$Q_t = \left(\frac{P_t}{F_{t-\tau,t}}\right)^{\gamma}\bar{Q}_{t-\tau,t}\prod_{i=1}^{\tau}\eta_{t-\tau+i}.$$

Possible nonzero correlation between the supply and demand shocks implies that we cannot separate $\eta_{t-\tau}$ and $\varphi_{t-\tau}$ as we did in the previous section. Thus, the log futures price is

$$\ln F_{t-\tau,t} = \ln\alpha + \theta\ln\bar{Q}_{t-\tau,t} + \ln\bar{u}_{t-\tau,t} + \sum_{i=1}^{\tau}\ln(E[\phi_{t-\tau+i}\eta_{t-\tau+i}^{\theta}])$$

and the first difference is

$$(2)\qquad \Delta\ln F_{t-\tau,t} = \theta\Delta\ln\bar{Q}_{t-\tau,t} - \ln(E[\phi_{t-\tau}\eta_{t-\tau}^{\theta}]) + \ln\phi_{t-\tau} = \beta_t + \theta\Delta\ln\bar{Q}_{t-\tau,t} + \varepsilon_{t-\tau}$$

where $\beta_\tau = -\ln(E[\varphi_{t-\tau}\eta_{t-\tau}^{\theta}]) + E[\ln\varphi_{t-\tau}]$ denotes a constant term that may depend on the month and $\varepsilon_{t-\tau} = \ln\varphi_{t-\tau} - E[\ln\varphi_{t-\tau}]$ denotes an independent zero mean error term.

From equation (2), least squares regression of $\Delta \ln F_{t-\tau,t}$ on $\Delta \ln \bar{Q}_{t-\tau,t}$ and month fixed effects would yield a biased estimate of the flexibility because $\Delta \ln \bar{Q}_{t-\tau,t}$ is correlated with the error term. To illustrate this, consider

$$(3)\qquad E[\varepsilon_{t-\tau}\Delta\ln\bar{Q}_{t-\tau,t}] = \gamma E[\varepsilon_{t-\tau}\Delta\ln F_{t-\tau,t}] + E[\varepsilon_{t-\tau}\ln(\eta_{t-\tau})]$$

where we use the supply equation $\Delta \ln \bar{Q}_{t-\tau,t} = \gamma\Delta \ln F_{t-\tau,t} + \ln \eta_{t-\tau}$. This expression reveals that the bias of OLS applied to (2) is nonzero unless $\gamma = 0$ and the log supply and demand shocks are uncorrelated with each other. Intuition suggests that endogeneity of the right-hand side variable in demand estimation arises because the supply and demand curves are confounded. This intuition reflects the first term in (3) and causes OLS to be biased upwards (towards zero) because $\gamma E[\varepsilon_{t-\tau}\Delta \ln F_{t-\tau,t}] > 0$. In theory, the second term can be signed in either direction.

In our application, we argue that the second term in (3) is likely small because it is difficult to rationalize a high correlation between supply and demand shocks. For example, sorghum is a substitute for corn for animal feed use, which implies that an increase in sorghum prices would increase the demand for corn. Moreover, weather-induced reductions in corn supply tend to coincide with reductions in sorghum supply. Thus, in theory, a simple regression of corn prices on corn supply confounds the effect of the corn supply reduction and the increase in corn demand from the associated sorghum supply reduction. The regression would overestimate the flexibility of corn prices because it would attribute the effect of the combined corn and sorghum supply reduction entirely to corn. However, corn comprises about 95% of coarse grains used in animal feed, with sorghum, barley and oats comprising the remaining 5%. It follows that this source of bias must be small. The same argument applies for the relationship between soybeans and other oilseeds.

Wheat is also a potential substitute for corn in animal feed and in producing processed food for human consumption, although the market's capacity for such substitution may not be large. The use of wheat in animal feeds is small in the United States; it is of the same order of magnitude as that of sorghum. Moreover, wheat supply shocks are only weakly correlated with corn and soybean supply shocks, mostly because their growing seasons and regions only partially overlap. The winter wheat growing season runs from October-June, compared to May-October for corn and soybeans. From 1986–2010, the correlation between detrended[3] corn and winter-wheat yield in the United States was 0.10, and for soybeans and winter wheat, this correlation was −0.18. Neither of these correlations are statistically significant. Thus, any within-crop-year correlation between wheat prices and corn and soybean prices could emanate more from aggregate commodity demand than from correlated supply shocks or demand substitution.

Based on these arguments, we explore winter wheat prices as a control for aggregate demand. If a model that includes wheat as a control generates a larger flexibility estimate in absolute value, then it may be that $\gamma > 0$ and wheat is capturing the effect of aggregate demand shocks. However, if $\gamma > 0$ and including wheat produces a smaller absolute flexibility estimate, then correlated supply shocks and demand substitution matter, in which case this regression produces a partial flexibility with respect to wheat prices: the effect of a corn supply shock on corn prices, holding the price of a substitute good (wheat) constant. Thus, at worst, a model that includes wheat prices provides a partial equilibrium parameter estimate that constitutes a lower bound on the general equilibrium own-quantity flexibility for corn and soybeans.

To further control for demand shocks, we use a set of macroeconomic variables. Frankel (1986) articulates how monetary policy affects commodity prices by affecting both current demand and the demand for inventory (see also Rausser et al. 1986). Kilian (2009) shows that aggregate demand shocks generate much of the variation in crude oil prices, and his results extend to other commodities. Thus, our control variables include various producer price indexes, macroeconomic variables such as the 90-day T-bill rate, M2 money supply, and the trade-weighted exchange index, winter wheat prices, and Kilian's (2009) index of real economic activity, which represents global aggregate demand for commodities.

In sum, we expect the OLS bias to be small in our application. Nonetheless, we control for demand shocks by adding the control variables $X_{t-\tau}$ to (2),

$$(4) \qquad \Delta \ln F_{t-\tau,t} = \beta' X_{t-\tau} + \theta \Delta \ln \bar{Q}_{t-\tau,t} + \varepsilon_{t-\tau}.$$

However, adding the control variables makes little difference to our estimates.

*Relaxing Assumption A2: WASDE Forecast Equals Market Forecast*

The OLS regression applied to equation (4) generates consistent estimates of $\theta$ as long as the control variables $X_{t-\tau}$ are adequate and the WASDE supply projection matches the projection of the futures market. However, even a small discrepancy between the WASDE and market projections can result in a large

[3] For these calculations, we detrended using a linear trend. We combine soft and hard winter wheat, for which the USDA began reporting yields in 1986.

measurement error bias in (4) because each variable is a percentage change (Rose, 2006). For example, suppose the market and government forecasts differ by up to 1%. If the change in the market forecast is 2%, the change in the government forecast will range between 1–3%, so the measurement error is 50% of the change in the market forecast. Moreover, there is evidence that WASDE projections are smoothed (Isengildina, Irwin and Good, 2006). Together, measurement error and smoothing bias the flexibility estimates from the regression in (4).

Smoothed predictions would produce projections that are a weighted average of the market projection and last month's projection. To allow for both measurement error and smoothing, we specify the month $t-\tau$ WASDE projection as

$$\ln \bar{Q}_{t-\tau,t} = \rho \ln E_{t-\tau}[Q_t] + (1-\rho)\ln \bar{Q}_{t-\tau-1,t} + \ln \upsilon_{t-\tau} \tag{5}$$

where $\upsilon_{t-\tau}$ denotes the measurement error and $\rho$ denotes the weight applied to the market expectation $\ln E_{t-\tau}[Q_t]$. If $\rho = 1$, then there is no smoothing and the WASDE projection does not take into account previous projections. To account for possible measurement error and smoothing bias in our application, we estimated equation (5) jointly with the flexibility equation (4). Allowing for these biases produced very similar flexibility estimates, so we report only our OLS results in this article.

## Extensions of the Basic Framework

### *Interaction between Flexibility and Inventories*

Not all corn and soybeans produced in a particular year are consumed in that year. Because these commodities are storable, holders of the commodity face a decision about whether to sell the commodity for consumption or to store it for possible sale at a higher price the following year (Williams and Wright 1991). Thus, the demand for corn and soybeans can be decomposed into the demand for current use and the demand for inventories. As Wright (2011) shows, the demand for inventories is more elastic than the demand for immediate use. Thus, we also estimate models in which we interact the supply forecast with stocks as a proportion of use. We use stocks as of June 1 each year because this value is determined before the first WASDE revision in June, and is therefore exogenous to prices. Similarly, we measure stocks relative to use in the prior crop year.

### *Seasonal Variation in Flexibility*

Price flexibility may change based on seasonal factors for three reasons. First, firms that use corn and soybeans as inputs tend to plan annual consumption based on expected crop size. Because it is expensive to change these plans, price adjustments may be smaller for similar supply shocks during summer months, when plans are not yet finalized. Once their plans are in place, and firms are less able to adapt to quantity surprises, price adjustments are likely to be higher through the fall and winter, leading to a larger commodity demand flexibility. Second, markets may respond differently across seasons because the USDA uses different methods across seasons to generate supply projections. Third, futures prices may grow more flexible to a similar supply shock as the contract nears expiry due to the Samuelson effect (1965). To account for seasonal variation in demand flexibilities, we define a dummy variable *non-NASS*, which classifies observations that occur before the first NASS crop production forecasts in August. In our sample, these include supply revisions and futures prices from the months of June and July. By interacting *non-NASS* with $\Delta \ln \bar{Q}_{t-\tau,t}$, we test the hypothesis that commodity prices become more flexible as the season progresses.

### *Interaction between Flexibility and Ethanol Production*

More than one-third of the 2010–11 United States corn crop will be converted to ethanol for fuel use. Under federal mandates, corn ethanol production has tripled since 2005, causing dramatic changes in United States grain markets. The effect the ethanol industry has on price flexibilities depends on whether the mandate is binding. If the mandate is binding, then demand for corn for ethanol use is perfectly inelastic. If the mandate is not binding and spare ethanol production capacity exists, then demand for corn for ethanol use may be elastic. However, as pointed out by Anderson and Coble (2010), and consistent with the rational storage model (e.g. Routledge, Seppi and Spatt, 2000), the incentive to store in the case the mandate is binding in a future year acts to reduce the elasticity of demand for current ethanol use. To estimate changes in corn and soybean demand flexibility as ethanol production has grown, we also estimate models in which we interact the supply forecast with the WASDE projection of use of corn for ethanol production as a proportion of projected total use.

### *Using Spot Prices in Place of Futures Prices*

Dynamic storage models (e.g. Williams and Wright 1991) imply a period $t-\tau$ spot price

$$(6) \qquad P_{t-\tau} = c_{t-\tau,t} E_{t-\tau}[P_t] = c_{t-\tau,t} F_{t-\tau,t}$$

where $c_{t-\tau,t}$ denotes a discount factor generated by the price of storing the commodity from month $t-\tau$ until the following harvest ($t$). The price of storage includes warehousing and financing costs as well as a convenience yield. Without a convenience yield, $c_{t-\tau,t}$ would be less than one, but in the presence of convenience yield it may exceed one. When the convenience yield equals zero, we refer to the market as being at full carry because the intertemporal price spread is determined only by warehousing and financing costs.

A convenience yield arises when firms are willing to store the commodity at an expected loss, perhaps because they value easy access to stocks (Brennan 1958; Kaldor 1939), or because of high fixed costs of acquiring or disposing of a batch of inventory (Bobenrieth, Bobenrieth and Wright 2004), or as a loss-leading strategy to draw in customers who pay for merchandizing services (Paul 1970). Williams and Wright (1989) and Brennan, Williams, and Wright (1997) dispute the existence of a convenience yield. Using a model that allows commodities to be stored differentially across space, they show that transportation costs can cause inventory at inconvenient locations to be unable to be shipped out in a timely manner, leading to an aggregate-level illusion of losses on storage. However, Carter and Revoredo-Giha (2007) and Franken, Garcia, and Irwin (2009) use firm-level data to show that firms do sometimes hold inventory at an apparent expected loss.

Equation (6) implies that the equivalent of equation (4) written in terms of the spot price is

$$(7) \qquad \Delta \ln P_{t-\tau} = \beta' X_{t-\tau} + \theta \Delta \ln \bar{Q}_{t-\tau,t} + \ln c_{t-\tau,t} + u_{t-\tau}.$$

If the futures market were always at full carry, then the cost of carry would be essentially constant, and the term $\ln c_{t-\tau,t}$ would be absorbed into the constant term. To the extent that $\ln c_{t-\tau,t}$ varies negatively with $\Delta \ln \bar{Q}_{t-\tau,t}$ and is not controlled for in $X_{t-\tau}$, the cost of carry is subsumed in the regression error $\varepsilon_{t-\tau} = \ln c_{t-\tau,t} + u_{t-\tau}$ and may produce omitted variable bias. In theoretical models with a convenience yield (Brennan, 1958), the discount factor $c_{t-\tau,t}$ depends positively on price. When supply shocks increase prices and decrease inventory, firms become more willing to store at less than full carry (Routledge, Seppi and Spatt 2000). Thus, $c_{t-\tau,t}$ may be negatively correlated with $\Delta \ln \bar{Q}_{t-\tau,t}$; a drop in the supply forecast lowers expected inventory, increases prices and raises convenience yield. These arguments imply $E[\Delta \ln \bar{Q}_{t-\tau,t} \ln c_{t-\tau,t} | X_{t-\tau}] < 0$ and therefore increased negative flexibility estimates when using spot prices in place of futures prices.

### *Medium-Run Flexibility*

Our regression models identify the flexibility of demand using variation in expected supply for a single year. In response to a drop in supply that raises prices one year, we would expect planted acreage in the following year to increase. Through this supply response, we may expect prices for delivery in the following crop year to respond less to a current year's supply shock than would prices for delivery in the current crop year. Users may also to be able to adjust their plans more in response to a supply shock over this longer horizon than for the current year. To the extent that corn and soybeans are full carry storage markets, such expected longer-run adjustments should be reflected in current prices through the medium of storage.

We estimate the medium-run flexibility of demand for corn and soybeans by substituting the distant, year-ahead harvest-time futures price $F_{t-\tau,t+12}$ for $F_{t-\tau,t}$ in the regression in (4). As before, we use the December contract for corn and the November contract for soybeans. For example, in June of 2008, we use the December 2009 corn contract price rather than the December 2008 price to estimate the medium-run demand flexibility.

Similar to (6), dynamic storage models imply $F_{t-\tau,t} = c_{t,t+12} F_{t-\tau,t+12}$, so that written in terms of the distant futures price, the equivalent of equation (4) is

$$(8)\qquad \Delta \ln F_{t-\tau,t+12} = \beta' X_{t-\tau} + \theta \Delta \ln \bar{Q}_{t-\tau,t} - \ln c_{t,t+12} + u_{t-\tau}.$$

The negative sign on $\ln c_{t,t+12}$ suggests that, if $E[\Delta \ln \bar{Q}_{t-\tau,t} \ln c_{t,t+12} | X_{t-\tau}] < 0$, then OLS will produce less negative flexibility estimates when distant futures prices are used in place of current-year futures prices. Thus, the difference in flexibility estimates across various horizons may indicate the extent to which the corn and soybean markets are less-than-full-carry storage markets.

## Data

We gather futures market price data for the Chicago Mercantile Exchange Group (CME) corn and soybean contracts expiring from May 1981 to November 2010 from eSignal Future-Source Workstation. The primary dependent variable in our analysis is the change in closing price between WASDE announcement days, which occur around twenty trading days apart, for the harvest-time futures contract; that is, the December expiration for corn, and November expiration for soybeans. To estimate the demand flexibility at different horizons, we also use the change in cash and distant, year-ahead harvest-contract futures prices between WASDE announcements. In May 1994, the USDA moved the publication time for the WASDE report from after the close of trading to before the opening of trading on domestic futures markets.[4] As a result, we match the report to the next available commodity futures settlement price. In particular, for those reports published before the commencement of trading, we use the closing commodity price on the day of WASDE release, but use the following trading day's settlement price for those reports that were released after markets closed.

The USDA maintains publicly available, daily cash prices from 1992 to the present for No 2. Yellow corn and No. 1 soybeans in the Central Illinois market, and soft red winter wheat in the St. Louis market at the Livestock & Grain Market News web portal. Previous daily cash prices for these commodities are obtained from the Commodity Research Bureau. For dates prior to March 28, 1982, corn prices are collected from the Chicago market, as are soft red winter wheat prices prior to April 29, 1982. We use changes in these prices between WASDE announcement days to generate the price flexibility with respect to spot prices.

Historical WASDE reports are archived by the Economics, Statistics, and Marketing Information System. Each May, the USDA publishes its initial annual corn and soybean crop forecasts for the upcoming crop in the WASDE report. Except in December, the USDA revises these forecasts in all subsequent months up to January, although the methods used to generate the projections differ from month-to-month. In May and June, production forecasts are based on NASS estimates of planted area published in the March 31*st* Prospective Plantings report, as well as models that project harvest and yield based on historical trends, adjusted for planting progress. For July, planted and harvested acreage are drawn from the June 30*th* Acreage report. From August through November, and again in January, WASDE reports projected crop production based on NASS Crop Production figures.[5] Production estimates are finalized in the January report.

Over the thirty-year period from May 1981 through January 2010, the USDA published 240 WASDE reports that included new production forecasts for corn and soybeans; these reports comprise our sample of government supply forecasts. We calculate supply as the sum of beginning stocks and production published in the WASDE. The percentage change in the crop forecast is calculated by first-differencing the within-crop-year monthly production forecasts. Because we use harvest-time contracts, we remove January reports that are published after the contract expires, yielding 180 observations in the final sample. We use a shorter sample to estimate the medium-run elasticity because, until the early-1990s for corn and soybeans, and the late-1990s for wheat (which we use as a control), distant futures contracts began trading after the first few WASDE reports.

We obtain data for our study controls from several sources. Producer Price Indices (PPI) data are maintained by the United States Bureau of Labor Statistics (BLS). We use the PPI for milk, livestock, poultry, gasoline,

[4] The USDA also released the December 1994 WASDE after markets closed; all subsequent reports have been published at 8:30am EST.

[5] Until the mid-1980s, NASS also made crop production forecasts in July.

farm machinery, agricultural chemicals and products, mixed fertilizers, fertilizer materials, nitrogenates, urea, phosphates, and other agricultural chemicals. Macroeconomic data for the 90-day T-bill rate, the M2 money supply, and the trade-weighted exchange index are archived by the St. Louis Federal Reserve Bank. The Index of Real Economic Activity as calculated by Kilian (2009) is available on his website. For each commodity crop year, the stocks-to-use ratio is calculated as the current year June 1st stocks estimate published in the NASS Grain Stocks report, divided by the prior year's final annual use estimate in the WASDE. We use June 1 stocks rather than crop-year ending stocks (September 1) to avoid using an inventory variable that is endogenous to prices. For the same reason, we use USDA forecasts for share of corn use consumed by the ethanol industry, rather than annual ethanol production figures.

## Results and Discussion

### *Descriptive Statistics*

Table 1 displays descriptive statistics for the variables in our model, reported in log change at the monthly frequency. All futures and cash prices are presented in cents per bushel. Corn and soybean prices display a wide range over the sample, and are substantially more volatile than WASDE supply forecasts. Corn and soybean price changes have a standard deviation three times larger than their supply forecasts. Wheat prices are as volatile as corn and soybeans. The change in corn and soybean futures prices is insignificantly different from zero, indicating that no unconditional risk premium exists in our sample. Next, we present several tables of estimates of the price flexibility of demand for corn and soybeans using the methods described in the previous sections.

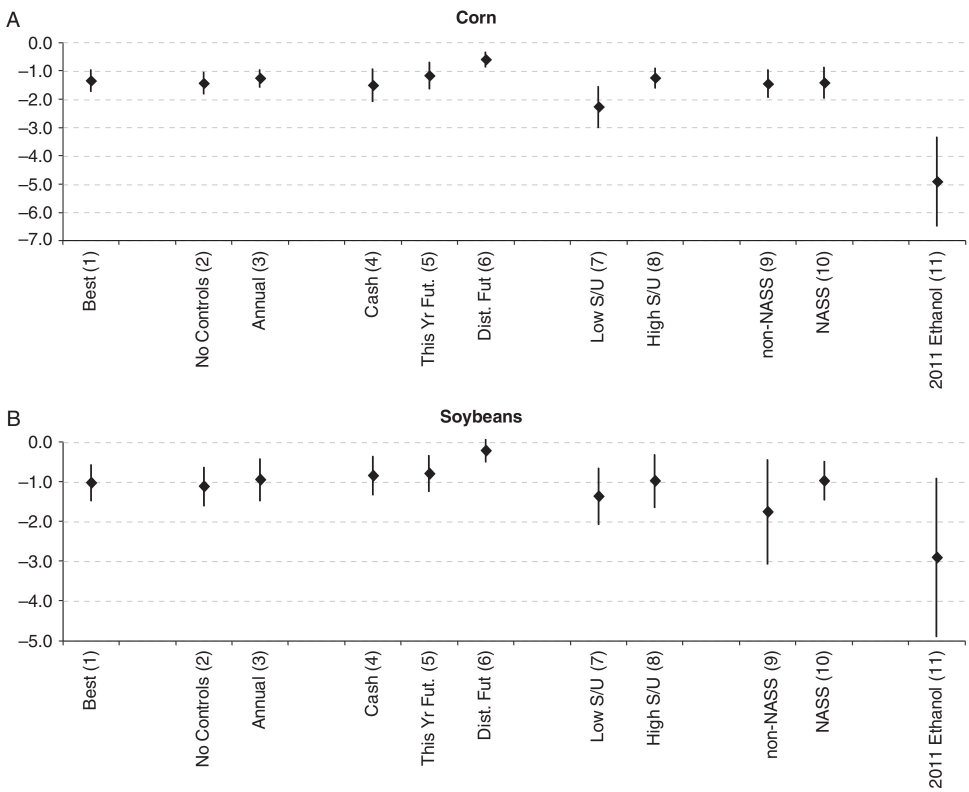


**Figure 1. Summary of Estimated Demand Flexibilities**

*Note*: The estimates are: (1) all controls except wheat, no interactions, column 2 of tables 2 and 3; (2) no controls or interactions, column 1 of tables 2 and 3; (3) using only one observation per year – the change in projection from May to November, no controls or interactions; (4) cash prices, all controls except wheat, all interactions, columns 1 and 4 of table 4; (5) Nearest-to-expire "harvest" contract (Corn-Dec; Soy-Nov) futures prices, all controls except wheat, all interactions, columns 2 and 5 of table 4; (6) Next-crop "harvest" contract futures prices, all controls except wheat, all interactions, columns 3 and 6 of table 4; (7) S/U = 0.2 for corn, S/U = 0.1 for soybeans; no controls, column 4 of tables 2 and 3; (8) S/U = 0.6 for corn, S/U = 0.5 for soybeans; no controls, column 4 of tables 2 and 3; (9) no controls, column 5 of tables 2 and 3; (10) no controls, column 5 of tables 2 and 3; (11) no controls, column 6 of tables 2 and 3.

We consolidate our flexibility estimates in figure 1.

### Estimating the Price Flexibility of Demand for Corn and Soybeans with OLS

Using OLS, we estimate how corn and soybean prices adjust to USDA supply forecasts, regressing log price changes on revisions in the log supply forecast. Table 2 presents a series of models for corn that include different sets of control variables and that allow for the flexibility to vary by season, inventory, and demand composition. Table 3 presents the same models for soybeans. All standard errors are robust to first-order autocorrelation and heteroskedasticity. Both tables show that our specification explains a substantial portion of the variability in commodity price changes.

Under assumptions A1 and A2, the first column in tables 2 and 3 implies that the price flexibility of demand is −1.44 for corn and −1.12 for soybeans. The associated 95% confidence intervals for these estimates are (−1.83,–1.05) for corn and (−1.61,–0.63) for soybeans. Thus, for either commodity, a 1% reduction in expected U.S. supply for a single crop year is associated with a price increase of slightly greater than 1%. Inverting these estimates implies that the one-year elasticity of demand for U.S. corn is −0.70, and for soybeans it is −0.90. Multiplying these elasticities by 0.4, which is approximately the proportion of global supply sourced in the United States, implies global demand elasticities of −0.28 and −0.36 for corn and soybeans, respectively.

If assumption A1 fails, then these estimates may be biased, but the second column of tables 2 and 3 shows little evidence of such bias. In column 2, we add all of our control variables except wheat prices. With the addition of these controls, the $R^2$ increases from 0.29 to 0.44 for corn and from 0.19 to 0.35 for soybeans, indicating that these variables absorb a significant amount of the variation in prices. Accordingly, the standard errors on our flexibility estimates also drop slightly. However, the flexibility estimates remain virtually unchanged.

Adding wheat prices as a control in column 3 reduces the corn flexibility estimate to −1.16 and the soybean flexibility to −0.99. If the estimates in columns 1 and 2 were confounding supply and demand (i.e., if the supply curve was less than perfectly inelastic), then we would expect the flexibility estimates to increase rather than decrease in absolute terms when we add demand controls. Thus, wheat prices operate through the second channel for possible bias, namely correlation between supply and demand shocks. As such, they provide a lower bound on the general equilibrium own-quantity flexibility for corn and soybeans. Because this estimate is so similar to that in column 2, we proceed without controlling for wheat prices in the remainder of the article.

In column 4 of tables 2 and 3, we interact the supply projection with the ratio of stocks on June 1 to use in the previous crop year. We subtract the mean from the stocks-to-use variables (rounded to one decimal place) to aid interpretation of the coefficients. Specifically, stocks-to-use enters the model as (S/U-0.4) for corn and (S/U-0.3) for soybeans. This normalization permits the coefficient on supply to be the estimated flexibility at the mean S/U level. The regression equation is thus

$$\begin{aligned}\Delta \ln F_{t-\tau,t} &\\ &= \beta_\tau + \beta_1 (S_{t-1}/U_{t-1} - \mu) \\ &\quad + \theta_0 \Delta \ln \bar{Q}_{t-\tau,t} + \theta_1 (S_{t-1}/U_{t-1} - \mu) \\ &\quad \cdot \Delta \ln \bar{Q}_{t-\tau,t} + u_{t-\tau}.\end{aligned}$$

The corn flexibility estimate is −1.76 at average inventory levels. The flexibility increases in absolute value by 0.26 to −2.02 at the 2010–11 stocks-to-use level of 0.3, and to −2.27 at the 1996 stocks-to-use level of 0.2. For high inventory, the flexibility estimate becomes −1.25 at stocks-to-use of 0.6, such as in 1982–83, and −1.0 at stocks-to-use of 0.7, such as in 1986–87. Soybean flexibility is insensitive to inventories. A decrease in stocks-to-use of 0.1 reduces the flexibility by a statistically insignificant amount of 0.2.

The fifth column of tables 2 and 3 allows flexibility to vary seasonally. The estimated equation is

$$\begin{aligned}\Delta \ln F_{t-\tau,t} &\\ &= \beta_\tau + \beta_1 \mathit{non\text{-}NASS}_{t-\tau} \\ &\quad + \theta_0 \Delta \ln \bar{Q}_{t-\tau,t} + \theta_1 (\mathit{non\text{-}NASS}_{t-\tau} \\ &\quad \cdot \Delta \ln \bar{Q}_{t-\tau,t}) + u_{t-\tau}.\end{aligned}$$

For corn, the flexibility estimate for USDA revisions released before August equals −1.46, and it decreases to −1.46 – (−0.04) = −1.42 as the harvest nears. However, the incremental change in price flexibility is insignificant ($t$-statistic = 0.12). Flexibility also decreases as

**Table 2. OLS Corn Demand Models Using Harvest Contract Futures, 1981–2010**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Coefficient Estimates* | | | | | | | |
| Supply | −1.44*** | −1.35*** | −1.16*** | −1.76*** | −1.42*** | −1.14*** | −1.17*** |
| | (0.20) | (0.20) | (0.16) | (0.21) | (0.28) | (0.17) | (0.24) |
| Stocks / Use - 0.4 | | | | 0.0032 | | | −0.0090 |
| | | | | (0.030) | | | (0.029) |
| (Stocks / Use - 0.4) × Supply | | | | 2.55** | | | 0.88 |
| | | | | (1.00) | | | (1.20) |
| Non-NASS Reports | | | | | −0.055*** | | −0.0036 |
| | | | | | (0.019) | | (0.024) |
| Non-NASS Reports × Supply | | | | | −0.043 | | −0.23 |
| | | | | | (0.37) | | (0.40) |
| 10 × Ethanol Share of Use[a] | | | | | | 0.0074 | 0.013** |
| | | | | | | (0.0067) | (0.0051) |
| 10 × Ethanol Share[a] × Supply | | | | | | −1.13*** | −1.04*** |
| | | | | | | (0.25) | (0.29) |
| Wheat Price[b] | | | 0.53*** | | | | |
| | | | (0.065) | | | | |
| Constant | 0.014 | −0.048*** | −0.053*** | 0.016 | 0.014 | 0.0054 | −0.045*** |
| | (0.011) | (0.017) | (0.013) | (0.011) | (0.011) | (0.0093) | (0.017) |
| Controls[c] | No | Yes | Yes | No | No | No | Yes |
| *Conditional Price Flexibility Implied by Coefficient Estimates* | | | | | | | |
| Setting | | | | S/U = 0.2 | Non-NASS | Eth = 20% | |
| Flexibility | | | | −2.27*** | −1.46*** | −3.39*** | |
| | | | | (0.37) | (0.25) | (0.48) | |
| Setting | | | | S/U = 0.6 | NASS | Eth = 33% | |
| Flexibility | | | | −1.25*** | −1.42*** | −4.91*** | |
| | | | | (0.18) | (0.28) | (0.81) | |
| $R^2$ | 29% | 44% | 64% | 32% | 29% | 38% | 53% |
| Observations | 180 | 180 | 180 | 180 | 180 | 180 | 180 |

[a] Drawn from USDA baseline projections in February for the next harvest. Represents a 10 percentage point increase.
[b] Current Year December contract futures prices.
[c] All regressions include monthly dummies.
*Note*: All variables except dummies enter as monthly changes. Newey-West std. errors are shown in parentheses.
Significance levels are indicated by asterisks: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**Table 3. OLS Soybean Demand Models Using Harvest Contract Futures, 1981–2010**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Coefficient Estimates* | | | | | | | |
| Supply | −1.12*** | −1.03*** | −0.99*** | −1.18*** | −0.98*** | −0.90*** | −0.80*** |
| | (0.25) | (0.23) | (0.21) | (0.22) | (0.25) | (0.25) | (0.23) |
| Stocks / Use - 0.3 | | | | −0.026 | | | 0.045 |
| | | | | (0.067) | | | (0.067) |
| (Stocks / Use - 0.3) × Supply | | | | 1.95 | | | 0.87 |
| | | | | (2.74) | | | (3.09) |
| Non-NASS Reports | | | | | −0.041** | | 0.0098 |
| | | | | | (0.017) | | (0.024) |
| Non-NASS Reports × Supply | | | | | −0.78 | | −0.90 |
| | | | | | (0.66) | | (0.59) |
| 10 × Ethanol Share of Corn Use[a] | | | | | | 0.0060 | 0.0090 |
| | | | | | | (0.0066) | (0.0059) |
| 10 × Ethanol Share[a] × Corn Supply | | | | | | −0.61* | −0.25 |
| | | | | | | (0.34) | (0.30) |
| Wheat Price[b] | | | 0.44*** | | | | |
| | | | (0.067) | | | | |
| Constant | 0.023** | −0.034* | −0.038** | 0.024** | 0.023** | 0.020* | −0.040** |
| | (0.011) | (0.019) | (0.016) | (0.010) | (0.011) | (0.011) | (0.020) |
| Controls[c] | No | Yes | Yes | No | No | Yes | Yes |
| *Conditional Price Flexibility Implied by Coefficient Estimates* | | | | | | | |
| Setting | | | | S/U = 0.1 | Non-NASS | Eth = 20% | |
| Flexibility | | | | −1.57** | −1.76** | −2.12** | |
| | | | | (0.60) | (0.67) | (0.58) | |
| Setting | | | | S/U = 0.5 | NASS | Eth = 33% | |
| Flexibility | | | | −0.79 | −0.98*** | −2.95** | |
| | | | | (0.58) | (0.25) | (1.02) | |
| $R^2$ | 19% | 35% | 51% | 20% | 20% | 23% | 39% |
| Observations | 180 | 180 | 180 | 180 | 180 | 180 | 180 |

[a] Drawn from USDA baseline projections in February for the next harvest. Represents a 10 percentage point increase.
[b] Current year December contract futures prices.
[c] All regressions include monthly dummies.
*Note*: All variables except dummies enter as monthly changes. Newey-West std. errors are shown in parentheses.
Significance levels are indicated by asterisks: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

the season progresses for soybeans, going from −1.76 to −0.97; this increment is insignificant, with the *t*-statistic of 1.2 producing a *p*-value of 0.24.

In the sixth column of tables 2 and 3, we allow the price flexibility to vary by the USDA projected share of corn use consumed by ethanol, $E^b/U^b$.[6] The regression equation is

$$\Delta \ln F_{t-\tau,t} = \beta_\tau + \beta_1(10E^b/U^b) + \theta_0 \Delta \ln \bar{Q}_{t-\tau,t} + \theta_1(10E^b/U^b) \cdot \Delta \ln \bar{Q}_{t-\tau,t} + u_{t-\tau}.$$

We multiply ethanol use by 10 to make the coefficients more easily interpretable. In both tables, the coefficients $\beta_1$ and $\theta_1$ represent the change in price flexibility resulting from a 10% increase in the expected corn share devoted to ethanol production. The corn price has become more flexible as ethanol has consumed a larger portion of the U.S. corn crop.

The ethanol effect is dramatic. For every 10% of projected corn use for ethanol, the corn flexibility has increased by −1.13. In the 2009–10 and 2010–11 crop years, projected ethanol use was 33% of total corn use. At this level, the estimated flexibility equals −4.91, with a 95% confidence interval of (−6.50, −3.32). Corn inventory levels have declined as ethanol use has increased in the past five years, so the estimates in column 6 could confound the effect of low inventory with that of ethanol demand.[7] In column 7, we add the seasonal and inventory interaction terms, as well as the demand controls to the model. The estimated corn flexibility changes only slightly from that in column 6, and neither the late-season or inventory interactions terms are significant. We estimate soybean prices to be about half as sensitive to corn ethanol use, although in column 6 the differential effect of corn-ethanol use on soybean flexibility ($\theta_1$) is significant only at the 7% level (*t*-statistic 1.81).

As another check on the magnitude of the measurement error and smoothing bias, we estimate the models in tables 2 and 3 using a single observation per year. Specifically, we use the update in the WASDE supply forecast from May to November. Measurement error and smoothing affect the month-to-month updates of expected supply, so eliminating the intermediate updates would change the estimated flexibility if these issues were generating bias. For the model with no controls, we obtain estimates of −1.26 for corn and −0.95 for soybeans; their counterparts that use the intermediate months are −1.44 and −1.12. The statistical similarity of these estimates shown in figure 1 provides further evidence that measurement error and smoothing do not generate significant bias in our estimates.

In summary, taking estimates from columns 2, 4, and 6, we estimate the demand flexibilities for corn to be −1.35 on average, rising to −2.27 at low inventory levels and increasing to −4.91 at the ethanol production levels observed in the 2009–10 and 2010–11 crop years. For soybeans, we estimate the demand flexibilities to be −1.03 on average, rising slightly to −1.37 at low inventory levels and increasing to −2.91 at the corn-ethanol production levels observed in the 2009–10 and 2010–11 crop years. These results show that significant tightness has developed in the corn and soybean markets, concurrent with the rise in corn-ethanol production, which is manifested in prices that are very sensitive to small quantity changes.

### *Using Spot and Distant Futures Prices*

Table 4 shows estimates from models that use cash prices and distant futures prices in place of the harvest contract futures price (see equations (7) and (8)). We also reproduce column 7 from tables 2 and 3 for comparison. The coefficient on supply in these models equals the price flexibility evaluated at the mean of stocks-to-use and covering the June-July WASDE reports, before considering the effect of ethanol. The corn price flexibility estimate calculated at the mean inventory and zero-ethanol levels is −1.51 using cash prices and −0.60 using distant futures prices, compared to −1.17 using harvest-time futures. Because the coefficient estimate decreases in absolute value as the horizon extends, these results suggest the presence of convenience yield as predicted by the discussion surrounding equations (6)–(8). However, the difference between the cash and harvest futures estimates is small and statistically insignificant, so it is difficult to draw strong conclusions about the existence of convenience yield based on corn price responses. Soybean results tell a similar story. The price flexibility estimate equals −0.85 for cash prices, −0.80 for the harvest futures contract, and −0.22 for distant futures;

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[6] We set projected ethanol use to zero prior to 2002.

[7] Like Chua and Tomek, we also tested for a structural break in the demand for our commodities beginning in 2006. We found a significant break, which is consistent with the results of tables 2 and 3 because ethanol production expanded dramatically after 2006.

**Table 4. OLS Demand Models For Various Supply Horizons, 1981–2010**

| | Corn | | | Soybeans | | |
|---|---|---|---|---|---|---|
| | Cash (1) | Dec Fut (2) | Distant Fut[a] (3) | Cash (4) | Nov Fut (5) | Distant Fut[a] (6) |
| Supply | −1.51*** | −1.17*** | −0.60*** | −0.85*** | −0.80*** | −0.22 |
| | (0.29) | (0.24) | (0.14) | (0.25) | (0.23) | (0.15) |
| Stocks/Use-m[b] | 0.014 | −0.0090 | −0.057*** | 0.18** | 0.045 | −0.012 |
| | (0.049) | (0.029) | (0.023) | (0.075) | (0.067) | (0.045) |
| (Stocks/Use-m[b]) × Supply | 2.25* | 0.88 | 0.55 | 0.44 | 0.87 | 1.20 |
| | (1.32) | (1.20) | (0.48) | (3.37) | (3.09) | (1.10) |
| Non-NASS Reports | 0.020 | −0.0036 | −0.013 | 0.052** | 0.0098 | −0.011 |
| | (0.027) | (0.024) | (0.012) | (0.024) | (0.024) | (0.012) |
| Non-NASS Reports × Supply | −0.37 | −0.23 | −0.15 | −0.61 | −0.90 | −0.70*** |
| | (0.46) | (0.40) | (0.20) | (0.52) | (0.59) | (0.25) |
| Ethanol Share of Corn Use[c] | 0.020*** | 0.013** | 0.0084*** | 0.013** | 0.0090 | 0.0069* |
| | (0.0068) | (0.0051) | (0.0031) | (0.0062) | (0.0059) | (0.0039) |
| Ethanol Share[c] × Supply | −0.95** | −1.04*** | −0.61*** | −0.26 | −0.25 | −0.19 |
| | (0.37) | (0.29) | (0.19) | (0.34) | (0.30) | (0.16) |
| Controls[d] | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 52% | 53% | 60% | 43% | 39% | 49% |
| Observations[e] | 180 | 180 | 116 | 180 | 180 | 116 |

[a]These contracts are for one-year ahead December (Corn) or November (Soy) delivery.
[b]m = 0.4 for corn; m = 0.3 for soybeans.
[c]Drawn from USDA baseline projections in February for the next harvest. These coefficients represent a 10 percentage point increase in the ethanol share.
[d]All regressions include monthly dummies.
[e]Distant, year-ahead futures contracts were not traded in May of the current year until 1992.
*Note*: All variables except dummies enter as monthly changes. Newey-West std. errors are shown in parentheses. Significance levels are indicated by asterisks: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

the latter is not statistically significant. Like the corn results, the confidence intervals for these estimates overlap enough that, although they decline with the delivery horizon, they are not sufficient to reveal a convenience yield in the soybean market.

The ethanol-directed share of the corn crop affects corn flexibility at all horizons significantly and with similar magnitudes. For soybeans the ethanol effect is not statistically significant at any horizon. Inventories significantly affect the cash price response for corn at the 10% level, but are not significant in any other case. Neither commodity shows a different response of cash prices or current year futures to seasonal variation in supply revisions, although distant soybean futures appear more sensitive to earlier shocks. Overall, the results in table 4 reinforce those in tables 2 and 3.

### *Results Summary*

Figure 1 summarizes our estimation results, consolidating the estimates from tables 2–4, and adding some additional robustness checks. Our findings are as follows:

(i) Our best corn price flexibility estimate at average inventory levels and without accounting for corn ethanol use is −1.35, with a 95% confidence interval of (−1.74, −0.96). See column 2 of table 2.
(ii) Our best soybean price flexibility estimate at average inventory levels and without accounting for corn ethanol use is −1.03, with a 95% confidence interval of (−1.48, −0.58). See column 2 of table 3.
(iii) Measurement error and smoothing of WASDE projections generate little if any bias in flexibility estimates.
(iv) Nearby prices are more responsive to expected supply shocks than prices for delivery long into the future. See table 4.
(v) At recent ethanol levels such as those forecasted for 2010–2011, our best corn price flexibility estimate is −4.91, with a 95% confidence interval of (−6.50, −3.32). The corresponding soybean flexibility is −2.91, with a 95% confidence interval of (−4.91, −0.91). Conditional on projected ethanol use, corn and soybean price flexibilities are insensitive to inventory levels and season. See column 7 of tables 2 and 3.

## Conclusion and Implications

We present a method to estimate the demand flexibility for agricultural commodities that offers a much larger sample size than conventional models. We show how researchers can use publicly-available USDA forecasts to estimate demand parameters, and we estimate the short-run demand flexibility for corn and soybeans. Beyond providing more observations and thereby improving upon the statistical power of previous estimates, our technique permits the study of demand characteristics over the course of the crop year, furnishing a seasonal demand response to supply shocks. Larger data sets allow practitioners to analyze the data in new ways, and also make it possible to conduct policy analysis after the passage of a relatively short amount of time. For example, we estimate a substantial increase in corn and soybean price flexibility resulting from the recent boom in corn-ethanol production.

Our flexibility estimates are useful for policy analysis. As an example, we consider the effect of a hypothetical policy to open some land from the conservations reserve program (CRP) for corn production. In 2010–11, the CRP had about 31 million acres enrolled, and corn was planted on about 90 million acres. If 4.5 million acres were opened up for a single year, and if those acres represented average corn land, then we would expect a 5% increase in supply. On average over the 1981–2011 sample period, our corn price flexibility estimate is −1.35. This flexibility implies a 6.8% price reduction from opening the CRP for a year. However, at 2010–11 ethanol use levels, our flexibility estimate of −4.91 predicts a corn price reduction of 25% from this policy. This is a substantial effect that reflects the tightness of the corn market in 2011.

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## References

Adjemian, M.K. 2012. Quantifying the WASDE Announcement Effect. *American Journal of Agricultural Economics* 94(1):238–256.

Anderson, J.D., and K.H. Coble. 2010. Impact of Renewable Fuels Standard Ethanol Mandates on the Corn Market. *Agribusiness* 26(1):49–63.

Bobenrieth, E.S.A., J.R.A. Bobenrieth, and B.D. Wright. 2004. A Model of Supply of Storage. *Economic Development and Cultural Change* 52:605–616.

Brennan, D., J. Williams, and B.D. Wright. 1997. Convenience Yield Without the Convenience: A Spatio-Temporal Interpretation of Storage Under Backwardation. *The Economic Journal* 107:1009–1022.

Brennan, M.J. 1958. The Supply of Storage. *American Economic Review* 48:50–72.

Buse, R. 1958. Total Elasticities - A Predictive Device. *Journal of Farm Economics* 40:881–891.

Carter, C., and C.L. Revoredo-Giha. 2007. The Working Curve and Commodity Storage Under Backwardation. *American Journal of Agricultural Economics* 89(4):864–872.

Chua, H.W.P., and W.G. Tomek. 2010. "On the Relationship of Expected Supply and Demand to Futures Prices." Paper presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, date.

Fishe, R.P.H., and A.D. Smith. 2011. "Identifying Informed Traders in Futures Markets." Working Paper, Department, University of California, Davis.

Frank, J., and P. Garcia. 2009. Time-Varying Risk Premium: Further Evidence in Agricultural Futures Markets. *Applied Economics* 41:715–725.

Frankel, J.A. 1986. Expectations and commodity price dynamics: The overshooting model. *American Journal of Agricultural Economics* 68(2)344–348.

Franken, J.R.V., P. Garcia, and S.H. Irwin. 2009. Is Storage at a Loss Merely an Illusion of Spatial Aggregation? *Journal of Agribusiness* 27(1/2):65–84.

Gray, A.W., J.W. Richardson, and J. McClaskey. 1995. Farm-Level Impacts of Revenue Assurance. *Review of Agricultural Economics* 17(2):171–183.

Gray, R.W. 1974. "Grain Reserve Issues." Paper presented at USDA Agricultural Outlook Conference. Washington, DC, December 9–12.

Hahn, J., and J. Housman. 2002. A New Specification Test for the Validity of Instrumental Variables. *Econometrica* 70(1):163–189.

Hartzmark, M.L. 1991. Luck Versus Forecast Ability: Determinant of Trader Performance in Futures Markets. *Journal of Business* 64(1):49–74.

Hartzmark, M.L. 1987. Returns to Individual Traders of Futures: Aggregate Results. *Journal of Political Economy* 95(6):1292–1306.

Houck, J.P. 1966. A Look at Flexibilities and Elasticities. *Journal of Farm Economics* 48(2):225–232.

Huang, K.S. 1988. An Inverse Demand System for U.S. Composite Foods. *American Journal of Agricultural Economics* 70(4):902–909.

Isengildina-Massa, O., S.H. Irwin, D.L. Good, and J.K. Gomez. 2008. The Impact of Situation and Outlook Information in Corn and Soybean Futures Markets: Evidence from WASDE Reports. *Journal of Agricultural and Applied Economics* 40(1):89–103.

Isengildina, O., S.H. Irwin, and D.L. Good. 2006. Are Revisions to USDA Crop Production Forecasts Smoothed. *American Journal of Agricultural Economics* 88(4):1091–1104.

Kaldor, N. 1939. Speculation and Economic Stability. *The Review of Economic Studies* 7(1):1–27.

Keynes, J.M. 1930. *A Treatise on Money*. New York: Harcourt, Brace.

Kilian, L. 2009. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review* 99:1053–1069.

McKenzie, A.M. 2008. Pre-Harvest Price Expectations for Corn: The Information Content of USDA Reports and New Crop Futures. *American Journal of Agricultural Economics* 90(2):351–366.

Moore, H.L. 1919. Empirical Laws of Demand and Supply and the Flexibility of Prices. *Political Science Quarterly* 34(4):546–567.

Orazem, P., and B. Falk. 1989. Measuring Market Responses to Error-Ridden Government Announcements. *Quarterly Review of Economics and Business* 29(2):41–55.

Paul, A.B. 1970. The Pricing of Binspace: A Contribution to the Theory of Storage. *American Journal of Agricultural Economics* 52(1):1–12.

Rausser, G.C., J.A. Chalfant, H.A. Love, and K.G. Stamoulis. 1986. Macroeconomic linkages, taxes, and subsidies in the U.S. agricultural sector. *American Journal of Agricultural Economics* 68(2)page numbers.

Roberts, M.J., and W. Schlenker. 2010. "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate." Working Paper No. 15921. National Bureau of Economic Research, Washington, DC.

Rose, H. 2006. Do Gains in Test Scores Explain Labor Market Outcomes? *Economics of Education Review* 25(4):430–446.

Routledge, B.R., D.J. Seppi, and C.S. Spatt. 2000. Equilibrium Forward Curves for Commodities. *Journal of Finance* 55: 1297–1338.

Samuelson, P.A. 1965. Proof that Properly Anticipated Futures Prices Fluctuate Randomly. *Industrial Management Review* 6(2):41–49.

Strickland, R. 2009. "Farm Income and Costs: 2009 Farm Sector Income Forecast". Washington, DC, USDA Economic Research Service Briefing Room.

Sumner, D.A., and R.A.E. Mueller. 1989. Are Harvest Forecasts News? USDA Announcements and Futures Market Reactions. *American Journal of Agricultural Economics* 71(1):1–8.

Thurman, W.N., and M.K. Wohlgenant. 1989. Consistent Estimation of General Equilibrium Welfare Effects. *American Journal of Agricultural Economics* 71(4):1041–1045.

Tomek, W.G. 1979. Estimating Demand Relations Using Futures Prices. *Agricultural Economics Research* 31(4):30–39.

Westcott, P.C., and L.A. Hoffman. 1999. "Price Determination for Corn and Wheat: The Role of Market Factors and Government Programs." USDA, Economic Research Service, Washington, DC.

Williams, J.C., and B. Wright. 1989. A Theory of Negative Prices for Storage. *Journal of Futures Markets* 9:1–13.

Williams, J.C., and B.D. Wright. 1991. *Storage and Commodity Markets*. Cambridge: Cambridge University Press.

Wright, B.D. 2011. The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy* 33(1):32–58.