Using USDA Forecasts to Estimate the Price Flexibility of Demand for Agricultural Commodities

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Abstract

We estimate the general equilibrium price flexibility of demand for corn and soybeans using monthly changes in expected supply as published by the USDA in the World Agricultural Supply and Demand Estimates (WASDE). Our estimates reflect the demand response to a one year supply shock and thus correspond to the inverse demand elasticity. At average inventory and without accounting for corn ethanol use we obtain a corn price flexibility estimate of −1.27 with a 95 percent confidence interval of (−1.62, −0.92) soybean price flexibility estimate of −1.05 with a 95 percent confidence interval of (−1.49, −0.61). We derive formally the conditions under which our estimates are consistent. These conditions include the absence of measurement error and smoothing bias in the WASDE projections. To address the possible failure of these conditions, we estimate the extent of measurement error and smoothing bias jointly with the price flexibility. We show that such imperfections in the WASDE projections exist but have a negligible effect on price flexibility estimates. We also show how demand flexibility varies by season, inventory, time horizon, and demand composition. In particular we find that, as corn ethanol production has grown to consume 33% of corn supply, the corn price flexibility has quadrupled to −4.80 and the soybean price flexibility has more than doubled to −2.76. Finally, we use our estimates to predict that a single year 4.5 million acre reduction in the Conservation Reserve Program would reduce corn prices by 24 percent at 2010-11 ethanol-use levels.

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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 the 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-quantity 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 formally 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 estimates consistently the short-run demand flexibility for an agricultural commodity. We then use such regressions to estimate the price flexibility of demand for corn and soybeans using data from 1980-2011. 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 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. Private forecasters consider USDA crop reports to be benchmarks for commodity forecasting, and numerous studies show that markets react to their release (Sumner and Mueller 1989; Garcia, et al. 1997; Good and Irwin 2006; Isengildina, Irwin and Good

2006b; Isengildina-Massa, et al. 2008; McKenzie 2008). These points suggest 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 USDA may smooth its supply change forecasts (Isengildina, Irwin and Good 2006a; McKenzie 2008). To address both of these issues and assess their effect on our estimates, we use Maximum Likelihood (ML) to estimate jointly the measurement error and smoothing parameters together with the price flexibility. We find that these issues have little if any effect on our flexibility estimates.

We focus on corn and soybeans because they are the dominant crops in terms of cash receipts to U.S. farmers (Westcott and Hoffman 1999; Strickland 2009). Both commodities are primarily used for animal feed (Ash and Dohlman 2008), together accounting for over 90% of feed for livestock (Baker and Lutman 2008). Corn and soybeans are predominantly grown in the Midwest, and farmers often rotate them over the same plot to increase yields (Edwards, Thurow and Eason 1988; Baker and Allen 2009). 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 2010/2011, 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. The next largest corn exporter, Argentina, produced 15% of traded corn. Brazilian soybeans comprised 34% of the world export market.

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 United States cotton to be -1.11. Incidentally, this estimate is similar to those we obtain for corn and soybeans using data from 1980-2010.

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: to the extent that supply shocks drive quantity variation, 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 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.

Some examples of price flexibility estimates from applied work include those for a system of U.S. aggregate food groups (Huang 1988), avocadoes (Carman and Green 1993), meat (Colman and Miah 2008), and fish (Jaffry, Pascoe and Robinson 1999). After Davis and Weiesnborn (1981) and Houck (1964), examples of estimated price flexibilities for corn and soybeans are rare. Gray et al. (1995) provides own-price flexibilities of -4 and -4.17 for corn and soybeans, respectively, although these are sourced to the Food and Agriculture Policy Research Institute (FAPRI).

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. Houck (1965) demonstrates that in a multi-commodity model with cross price effects, the price flexibility represents the lower absolute bound of the demand elasticity. Most commodity demand models found in the literature estimate demand elasticities directly, often using annual data. Most recently, Roberts and Schlenker(2010) estimate supply and demand elasticities for food commodities using instrumental variables and 42 years of annual data. They use deviations from trend yield as an instrument for supply shocks and estimate the global elasticity of demand for caloric energy to be -0.05.

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 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. Each year, he estimates the relationship between five USDA production forecasts and prices for harvest-time futures contracts, using first a nominal and then a livestock-price deflated series. Tomek applies a Wald (1940) estimator to address the measurement error in the government forecast. Because he estimates annual parameters using only five observations, Tomek argues against first differencing the data, preferring to analyze the levels rather than lose of a degree of freedom each year.

Chua and Tomek (1986) (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, they 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. Their sample spans 1989-2008. They 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.[1] 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 with which we observe supply projections.

In this article, we address directly each of Tomek's concerns and thereby differentiate our work from the existing literature. In the next section we show formally 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

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[1] Their reported estimates refer to a model that constrains the year fixed effects to be constant across some years. They state that this restricted specification is not rejected by an F-test.

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 2006a; McKenzie 2008) in the WASDE projections. We specify a time series model for the WASDE projections that incorporates these two imperfections, and we estimate it jointly with the flexibility parameter by maximum likelihood. 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 percent.

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 in March, which is the middle of the crop year. This price is realized after USDA releases the final estimates of Q_t but 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 by making two assumptions. These assumptions prove useful in expositing 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 March of crop year *t* that a WASDE forecast is released, and we denote the month *t*-τ WASDE forecast as $\bar{Q}_{t-\tau,t}$. For example, the August WASDE forecast for crop year *t* is $\bar{Q}_{7,t}$ because August comes 7 months before March. We observe WASDE forecasts corresponding to τ= 2, 4, 5, 6, 7, 8, 9, and 10. Under A2, $\bar{Q}_{t-\tau,t}$ equals expected supply as of *t*-τ, 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*-τ multiplied by the subsequent forecast revisions, i.e., 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 mean 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*-τ, the market expectation of the demand shifter is $\bar{u}_{t-\tau,t} = E_{t-\tau}[u_t]$. Similarly 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 March delivery $F_{t-\tau,t}$ equals the expected March cash price, e.g., Routledge, Seppi, and Spatt (2000),

$$F_{t-\tau,t} = E_{t-\tau}[P_t] = \alpha E_{t-\tau}\left[Q_t^{\theta} u_t\right]. \tag{1}$$

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, Fishe and Smith (2011) find no evidence that speculators earn risk premia in commodity futures markets by taking positions opposite commercial hedgers. They use data from 2000 to mid-2009 and their results reinforce those of Hartzmark (1987; 1991) 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 2). 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.

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

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

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

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

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

where $\beta_{\tau} = -\ln\left(E\left[\eta_{t-\tau}^{\theta}\right]\right)$ denotes a constant term that may depend on τ. In particular, WASDE revisions tend to be greater in August and September than in other months, so $E\left[\eta_{t-\tau}^{\theta}\right]$ may differ depending on the month. However, if the flexibility parameter θ equals 1, then $E\left[\eta_{t-\tau}^{\theta}\right] = E\left[\eta_{t-\tau}\right] = 1$ and $\beta_{\tau}=0$ in all months.

These derivations imply that, under A1 and A2, we can estimate the flexibility parameter θ 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*-τ 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 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 θ 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 to be 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 γ, 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

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

and the first difference is

$$\begin{aligned} \Delta \ln F_{t-\tau,t} &= \theta \Delta \ln \bar{Q}_{t-\tau,t} - \ln\left(E\left[\varphi_{t-\tau} \eta_{t-\tau}^{\theta} \right] \right) + \ln \varphi_{t-\tau} \\ &= \beta_t + \theta \Delta \ln \bar{Q}_{t-\tau,t} + \varepsilon_{t-\tau} \end{aligned} \tag{2}$$

where $\beta_\tau = -\ln\left(E\left[\varphi_{t-\tau} \eta_{t-\tau}^{\theta} \right] \right) + E\left[\ln \varphi_{t-\tau} \right]$ denotes a constant term that may depend on the month and $\varepsilon_{t-\tau} = \ln \varphi_{t-\tau} - E\left[\ln \varphi_{t-\tau} \right]$ 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 see this, consider

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

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 towards zero. In theory, the second term may also matter, and it can be signed in either direction. In our application, we argue that the second term is likely to be small.

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 over-estimate 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. Animal feed use of wheat in the United States is small; 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[2] 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 as much from aggregate commodity demand rather than from correlated supply shocks or demand substitution.

Based on these arguments, we explore winter wheat prices as a control for aggregate demand, in addition to a set of macroeconomic variables. If a model that includes wheat as a control generates a larger flexibility estimate, then it may be that $\gamma>0$ and wheat is capturing the effect of aggregate demand shocks. However, if it produces a smaller flexibility estimate, then correlated supply shocks and demand substitution matter, in which case our flexibility estimate represents a partial flexibility with respect to wheat prices. It would be 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 partial equilibrium parameter estimate that constitutes a lower bound on the general equilibrium own price flexibility for corn and soybeans.

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 the right hand side of (2), arriving at (4).

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

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

Our control variables variables are listed in table 1, and 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 for commodities. These control variables make little difference to our estimates.

Relaxing Assumption A2: WASDE Forecast Equals Market Forecast

OLS regression applied to equation (4) generates consistent estimates of θ as long as the control variables X_t are adequate and the WASDE projection matches the projection of the futures market. However, even a small discrepancy between the WASDE and market projections can result in a large 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 USDA smooths WASDE projections to avoid making large revisions (Isengildina, Irwin and Good 2006a; McKenzie 2008). 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. We specify the month t-τ WASDE projection as such an average plus measurement error, i.e.,

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

where $v_{t-\tau}$ denotes the measurement error and ρ denotes the weight applied to the market expectation $\ln E_{t-\tau}[Q_t]$. If ρ=1, then there is no smoothing and the WASDE projection does not take into account previous projections. Taking differences of (5) yields

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

which we can write in infinite moving average form as

$$\Delta\ln\bar{Q}_{t-\tau,t} = \sum_{i=0}^{\infty}(1-\rho)^i(\rho\Delta\ln E_{t-\tau-i}[Q_t] + \Delta\ln v_{t-\tau-i}).$$

We assume that the measurement error $\ln v_{t-\tau}$ is white noise and uncorrelated with $\Delta\ln E_{t-\tau}[Q_t]$ at all leads and lags.

We want to measure the market price response to a supply induced change in expected quantity supplied, i.e., we would like to run the regression

$$\Delta\ln F_{t-\tau,t} = \beta' X_{t-\tau} + \theta\Delta\ln E_{t-\tau}[Q_t] + u_{t-\tau}$$

but we observe $\bar{Q}_{t-\tau,t}$ in lieu of $E_{t-\tau}[Q_t]$. Substituting in equation (5), we see that

$$\begin{aligned}\Delta\ln F_{t-\tau,t} &= \beta' X_{t-\tau} + \theta\Delta\ln E_{t-\tau}[Q_t] + u_{t-\tau}\\ &= \beta' X_{t-\tau} + \theta\rho^{-1}\Delta\ln\bar{Q}_{t-\tau,t} + u_{t-\tau} - \theta\rho^{-1}(1-\rho)\Delta\ln\bar{Q}_{t-\tau-1,t} - \theta\rho^{-1}\Delta\ln v_{t-\tau}\end{aligned}$$

To approximate the OLS bias suppose β=0, $E[\Delta\ln v_{t-\tau}] = 0$, $E\left[u_{t-\tau}\Delta\ln\bar{Q}_{t-\tau,t}\right] = 0$, $var[\Delta\ln v_{t-\tau}] = 2\sigma_v^2$, $var[u_{t-\tau}] = \sigma_u^2$, and $var\left[\Delta\ln E_{t-\tau}[Q_t]\right] = \sigma_Q^2$. These assumptions allow us to derive a simple analytic expression for the OLS bias in the presence of homoskedasticity and an infinite number of WASDE projections per crop year. In a set of simulations (available from the authors), we find that the bias is similar when we allow for heteroskedasticity and for only 8 WASDE projections per year, so the following analytic expression provides relevant insight.

The probability limit of the OLS estimator is

$$\theta_{OLS} = \frac{E\left[\Delta \ln F_{t-\tau,t} \Delta \ln \bar{Q}_{t-\tau,t}\right]}{E\left[\Delta \ln \bar{Q}_{t-\tau,t}\right]^2}$$

where

$$\begin{aligned} E\left[\Delta \ln F_{t-\tau,t} \Delta \ln \bar{Q}_{t-\tau,t}\right] &= \theta E\left[\Delta \ln E_{t-\tau}[Q_t] \Delta \ln \bar{Q}_{t-\tau,t}\right] \\ &= \theta E\left[\Delta \ln E_{t-\tau}[Q_t] \sum_{i=0}^{\infty} (1-\rho)^i \left(\rho \Delta \ln E_{t-\tau-i}[Q_t] + \Delta \ln v_{t-\tau-i}\right)\right] \\ &= \theta \rho \sigma_Q^2 \end{aligned}$$

and

$$\begin{aligned} E\left[\Delta \ln \bar{Q}_{t-\tau,t}\right]^2 &= \frac{\rho^2 \sigma_Q^2}{1-(1-\rho)^2} + \frac{2(1-\rho)\sigma_v^2}{1-(1-\rho)^2} \\ &= \frac{\rho^2 \sigma_Q^2 + 2\rho \sigma_v^2}{\rho(2-\rho)} \end{aligned}$$

Thus, the percent bias in OLS is

$$\%\text{bias} = \frac{\theta_{OLS} - \theta}{\theta} = \frac{\rho \sigma_Q^2 (2-\rho)}{\rho \sigma_Q^2 + 2\sigma_v^2} - 1 = \frac{\rho(2-\rho)}{\rho + 2\left(\sigma_v^2 / \sigma_Q^2\right)} - 1 .$$

In figure 1, we plot contours of the percent bias as a function of the smoothing parameter ρ and the relative variance of the measurement error σ_v^2 / σ_Q^2. Negative bias denotes an OLS bias towards zero. The figure shows that the bias tends to decrease as the smoothing parameter increases towards one, especially for relatively small measurement error. However, as long as there is even a small amount of measurement error, the magnitude of the effect of smoothing on the OLS bias is small. For example, when the relative variance of the measurement error equals 0.2, the bias is −17% for ρ=0.5 and −29% for ρ=1. With zero measurement error, the percent bias equals 1-ρ.

Measurement error can cause a large bias. Assuming no smoothing, the OLS bias goes from zero to 17 percent as the relative measurement error variance goes from zero to

0.1. To place these numbers in context, relative measurement error variance of 0.1 means that variance of the measurement error is 10 percent of the size of the variance of the revision in expected supply and therefore that the standard deviation of the measurement error is about 33 percent of the standard deviation of the supply revision. For measurement error variance equal to 0.5, the bias equals −50 percent when $\rho=1$, i.e., the OLS parameter is half the true value. To account for possible measurement error and smoothing bias in our application, we estimate equation (5) jointly with the flexibility equation.

Extensions of the Basic Framework

Interaction between Flexibility and Inventories

Not all corn and soybeans produced in a particular year get consumed in that year. Because these commodities are storable, holders of the commodity face a decision about whether to sell the commodity for consumption this year or to store it for possible sale at a higher price next 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 (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 our 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. 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. To account for seasonal variation in demand flexibilities, we define a dummy variable $LateSeason$, which classifies observations that occur during or after the typical corn and soybean harvest. In our sample, these include supply forecasts and futures prices from the months of October-January. By interacting $LateSeason$ 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 a 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 of the ethanol industry 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 case the mandate is binding in a future year acts to reduce the elasticity of demand for current ethanol use. To estimate the effect of the ethanol industry on corn and soybean demand flexibility, 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 that the spot price at t-τ is

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

where $c_{t-\tau,t}$ denotes a discount factor generated by the price of storing the commodity from month t-τ until the following March (t). The price of storage includes warehousing and financing costs as well as a convenience yield. Without 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 at full carry because the intertemporal price spread is determined only by warehousing and financing costs.

Convenience yield arises when firms are willing to store the commodity at an expected loss, perhaps because they value easy access to stocks (e.g., Kaldor 1939, Brennan 1958), 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 et al. (1997) dispute the existence of 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. Comparing prices at locations with no inventory to other locations with positive inventory necessarily makes it seem that firms are storing at a loss when they may not be. However, Carter and Revoredo-Giha (2007) and Franken et al. (2009) use firm-level data to show that firms do 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) $$\Delta \ln P_{t-\tau} = \beta' X_{t-\tau} + \theta \Delta \ln \bar{Q}_{t-\tau,t} + \ln c_{t-\tau,t} + u_{t-\tau}$$

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, 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 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. Therefore, we expect $E\left[\Delta \ln \bar{Q}_{t-\tau,t} \ln c_{t-\tau,t} \,|X_{t-\tau}\right] < 0$, and for OLS to produce larger negative flexibility estimates when spot prices are used in place of March 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 supply shock than prices for delivery in the current crop year. Over this longer horizon, we may also expect users to be able to adjust their plans more in response to a supply shock than for the current year. However, 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 medium-run flexibility of demand for corn and soybeans by substituting the crop year-ahead harvest-time futures price for $F_{t-\tau,t}$ in the regression in (4). We use the December contract for corn ($F_{t-\tau,t+9}$), and the November contract for soybeans ($F_{t-\tau,t+8}$) because the next-crop March contracts do not begin trading early enough to overlap with previous-crop WASDE reports. For example, in June of 2008, we use the December 2009 corn contract price rather than the March 2009 price to estimate the next-crop demand flexibility.

Similarly to (6), dynamic storage models imply $F_{t-\tau,t} = c_{t,t+9}F_{t-\tau,t+9}$, so that written in terms of the distant futures price, the equivalent of equation (4) is

$$(8) \qquad \Delta \ln F_{t-\tau,t+9} = \beta' X_{t-\tau} + \theta \Delta \ln \bar{Q}_{t-\tau,t} - \ln c_{t,t+9} + u_{t-\tau}$$

The negative sign on $\ln c_{t,t+9}$ suggests that, if $E\left[\Delta \ln \bar{Q}_{t-\tau,t} \ln c_{t,t+9} \,|X_{t-\tau}\right] < 0$, then OLS will produce less negative flexibility estimates when distant futures prices are used in place of futures prices. Thus, the change in flexibility estimates across various horizons reveals the extent to which the corn and soybean markets are less-than-full-carry storage markets.

Data

We gather futures market price data for Chicago Mercantile Exchange Group (CME) corn and soybean contracts expiring from May 1980 to January 2011 from eSignal FutureSource Workstation. The primary dependent variable in our analysis is the change in closing price from one WASDE announcement day to the next for the post-harvest March futures contract, because it exists for the entire crop year, is the first to deliver after the final WASDE report in January, and constitutes the middle of the crop year. In May 1994, 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.[3] As a result, we measure the commodity futures price associated with the announcement day by matching the report to the next available settlement price. In particular, for those reports published before the commencement of trading, we measure the closing commodity prices on the day of WASDE release. We use the following trading day's settlement price for those reports that were released after markets closed. We calculate the medium-run flexibility with the crop year-ahead December and November futures contract price for corn and soybeans, respectively, once again using the change in price between announcement days.

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

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, as well as Minneapolis malting barley, Gulf Coast sorghum, and Vancouver market canola cash prices are provided by the Commodity Research Bureau. Before 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.

WASDE is prepared in a lockup environment by an interagency team of U.S. government officials, administered by the World Agricultural Outlook Board (WAOB), whose analysts chair an Interagency Commodity Estimates Committee (ICEC) of experts for each commodity in the report. Every ICEC is composed of representatives from four USDA agencies: the Agricultural Marketing Service, the Economic Research Service, the Farm Services Agency, and the Foreign Agricultural Service. Weather analysis is provided by the Joint Agricultural Weather Facility, which is jointly managed by USDA and the National Oceanic and Atmospheric Administration. Each report includes assessments of domestic and foreign demand and supply of agricultural commodities, presented in a balance sheet format. Historical WASDE reports are archived by the Economics, Statistics, and Marketing Information System.

Each May, USDA publishes its initial annual corn and soybean crop forecasts for the upcoming crop in the WASDE report. Except in December, USDA revises these forecasts in all subsequent WASDE reports up to January. In May and June, production forecasts are based on NASS estimates of planted area published in the March 31st 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 30th Acreage report. From August through November, and again in January, WASDE reports project crop production based on NASS Crop Production figures[4]. The January report provides the final annual production revision.

Over the thirty-one year period from May 1980 through January 2011, the USDA published 248 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 given by first-differencing the within-crop-year production forecasts contained in the reports, yielding 217 observations in the final sample. We use a shorter sample to estimate the medium-run elasticity because, until the early 1990's for corn and soybeans, and the late 1990's for wheat (which we use as a control), the out-date futures contract began trading only 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, 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, M2 money supply, and the trade-weighted exchange index are archived by the St.

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

Louis Federal Reserve Bank. The Index of Real Economic Activity as calculated by Kilian (2009) is available at his personal 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 forecasted, rather than annual ethanol production figures, to account for the impact of ethanol on commodity price flexibilities. Specifically, we use annual USDA baseline projections for the share of corn use consumed by the ethanol industry.

Results and Discussion

Descriptive Statistics

Table 1 displays descriptive statistics for the levels of the variables in our model; table 2 shows the same in terms of percentage change. All futures and cash prices are presented in cents per bushel. Prices for both commodities display a wide range over the sample: contract and cash highs are four times as large as low values in table 1. WASDE supply forecasts run from 184 to 380 million metric tons (MMT) for corn, and 48 to 99 MMT for soybeans. Corn and soybean prices in table 2 are substantially more volatile than WASDE supply forecasts. Wheat prices experience similar levels of volatility as corn and soybeans. Table 2 shows that the log change in corn and soybean futures prices is insignificantly different from zero, indicating that no unconditional risk premium exists in our sample.

In figure 2, we plot the log price changes for the March futures contract against the revisions of log expected corn supply; figure 3 shows an identical chart for soybeans. Points in the figures represent the monthly USDA forecast revisions and the March contract futures price changes that occurred between announcement dates. The data demonstrate a negative relationship for both commodities—positive WASDE supply announcements are associated with decreased commodity prices. Moreover, colors in the figures suggest that the price-quantity relationship grows even more negative as the crop year progresses, especially for corn.

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. At the end of this section, we consolidate our flexibility estimates in figure 4.

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

We first use OLS to estimate how corn and soybean prices adjust to USDA supply forecasts, regressing log price changes on revisions in the log supply forecast. Table 3 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 4 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 each of table 3 and 4 implies that the price flexibility of demand is -1.34 for corn and -1.13 for soybeans. The associated 95 percent confidence intervals for these estimates are (-1.70,-0.97) for corn and (-1.59,-0.67) for soybeans. Thus, for either commodity, a 1 percent reduction in expected U.S. supply for a single crop year is associated with a price increase of a little greater than 1 percent. Inverting these estimates implies that the one-year elasticity of demand for U.S. corn is −0.75 and for soybeans it is −0.88. Multiplying these elasticities by 0.4, which is approximately the proportion of global supply sourced in the U.S., implies global demand elasticities of approximately −0.30 and −0.35 for corn and soybeans, respectively.

If assumption A1 fails, then these estimates may be biased, but the second column of tables 3 and 4 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 0.26 to 0.39 for corn and from 0.18 to 0.31 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 -1.04 and the soybean flexibility to -0.98. If the estimates in columns 1 and 2 were confounding supply and demand (i.e., if the supply curve were less than perfectly inelastic), then we would expect the flexibility estimates to increase rather than decrease 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 price 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 3 and 4, 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

$$\Delta \ln F_{t-\tau,t} = \beta_\tau + \beta_1 \left(S_{t-1} / U_{t-1} - \mu \right) + \theta_0 \Delta \ln \bar{Q}_{t-\tau,t} + \theta_1 \left(S_{t-1} / U_{t-1} - \mu \right) \cdot \Delta \ln \bar{Q}_{t-\tau,t} + u_{t-\tau}$$

We see that the corn flexibility estimate is –1.66 at average inventory levels. The flexibility increases in absolute value by 0.25 to –1.91 at the 2010-11 stocks-to-use level of 0.3 and to –2.16 at the 1996 stocks-to-use level of 0.2. For high inventory, the flexibility estimate becomes –1.16 at stocks-to-use of 0.6, such as in 1982-83 and –0.91 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 0.07.

The fifth column of tables 3 and 4 allows flexibility to differ between early and late season. The estimated equation is

$$\Delta \ln F_{t-\tau,t} = \beta_\tau + \beta_1 LateSeason_{t-\tau} + \theta_0 \Delta \ln \bar{Q}_{t-\tau,t} + \theta_1 \left(LateSeason_{t-\tau} \cdot \Delta \ln \bar{Q}_{t-\tau,t} \right) + u_{t-\tau}$$

For corn, the early season flexibility estimate equals –1.23, and it increases to –1.23 –0.69 = –1.92 in the late season. However, the increment from early to late season is only statistically significant at the 14 percent level (*t*-statistic = 1.47). Flexibility also increases late in the season for soybeans, going from –0.97 early in the season to –1.49 late in the season. Similarly to corn, the increment in flexibility is not strongly significant with the *t*-statistic of 1.34 producing a *p*-value of 0.18.

In the sixth column of tables 3 and 4, we allow the price flexibility to vary by the USDA projected share of corn use consumed by ethanol, $\mathrm{E^b/U^b}$.[5] The regression equation is

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

We multiply ethanol use by 10 to make the coefficients most easily interpretable. In both tables, the coefficients β_1 and θ_1 represent the change in price flexibility resulting from a 10 percentage point 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 corn crop.

The ethanol effect is dramatic. For every 10% of projected corn use for ethanol, the corn flexibility increases by −1.04. In the 2009-10 and 2010-11 crop years, projected ethanol use was 33% of total corn use (see figure 5). At this level, the estimated flexibility equals −4.80 with a 95% confidence interval of (−6.21, −3.39). 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. In column 7, we add the late season 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

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[5] We set projected ethanol use to zero before 2002.

column 6 the differential effect of corn-ethanol use on the soybean flexibility (θ_1) is significant only at the 8% level (*t*-statistic 1.77).

In summary, taking estimates from columns 2, 4, and 6, we estimate the demand flexibilities for corn to be −1.27 on average, rising to −2.15 at low inventory levels and increasing to −4.80 at the ethanol production levels observed in the 2009-10 and 2010-11 crop years. For soybeans, we estimate the demand flexibilities to be −1.05 on average, rising slightly to −1.29 at low inventory levels and increasing to −2.76 at the corn-ethanol production levels observed in the 2009-10 and 2010-11 crop years. These results show that corn-ethanol has caused significant tightness in corn and soybean markets, which is manifested in prices that are very sensitive to small quantity changes.

Using Spot and Distant Futures Prices

Table 5 shows estimates from models that use cash prices and distant futures prices in place of the March futures price (see equations (7) and (8)). We also reproduce column 7 from tables 3 and 4 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-September WASDE reports, before considering the effect of ethanol. The corn price flexibility estimate calculated at the mean inventory and zero-ethanol levels is −1.64 using cash prices and −0.61 using distant futures prices, compared to −1.15 using March futures. Because the coefficient estimate decreases in absolute value as the horizon extends, these results are consistent with the presence of convenience yield as predicted by the discussion surrounding equations (6)-(8). Soybeans tell a similar story. The price flexibility estimate equals −0.95 for cash prices and −0.16 for distant futures, which is not statistically significant, compared to −0.76 for March futures. These results are also consistent with the presence of convenience yield.

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 slightly less than half that of corn, but it is not statistically significant for any horizon. Inventories significantly affect the cash price response for corn, but are not significant in any other case. For the most part, neither commodity shows a different response of cash prices to late season supply shocks compared to early season shocks.

Overall, the results in table 5 reinforce those in table 3 and 4 and add evidence of a significant convenience yield.

Accounting for Smoothing and Measurement Error

Figure 1 shows that the OLS estimator becomes more biased as measurement error increases, but the bias depends less strongly on the extent of smoothing by USDA of WASDE projections. To understand where on this spectrum our data lie, we estimate the parameters of the model in (4) jointly with the flexibility parameter. In so doing, we allow heteroskedasticity in the measurement error and the forecast revision by specifying a cubic function of the WASDE announcement month:

$$\sigma_{v\tau} = a_0 + a_1\tau + a_2(\tau - 6)^2 + a_2(\tau - 6)^3$$

$$\sigma_{Q\tau} = b_0 + b_1\tau + b_2(\tau - 6)^2 + b_3(\tau - 6)^3$$

where we center the higher order terms to reduce collinearity across terms. As in the regressions in tables 3-5, we have 8 WASDE reports per year, corresponding to $\tau = 2, 4, 5, 6, 7, 8, 9, 10$. The WASDE supply projection model is

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

where

$$\begin{bmatrix} \ln v_{t-\tau} \\ \Delta\ln E_{t-\tau}[Q_t] \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{v\tau}^2 & 0 \\ 0 & \sigma_{Q\tau}^2 \end{bmatrix}\right)$$

and $\Delta\ln E_{t-\tau}[Q_t] = \ln E_{t-\tau}[Q_t] - \ln E_{t-\tau+1}[Q_t]$ for τ = 4, 5, …, 9 and $\Delta\ln E_{t-\tau}[Q_t] = \ln E_{t-2}[Q_t] - \ln E_{t-4}[Q_t]$ for the January revision, which covers two months. To initialize the model each year, we specify $\ln\bar{Q}_{t-10,t} = \ln E_{t-10}[Q_t] + \ln v_{t-10}$.[6]

We write the flexibility model as

(10) $$\Delta \ln F_{t-\tau,t} = \beta' X_{t-\tau} + \theta\Delta \ln E_{t-\tau}\left[Q_t\right] + u_{t-\tau}$$

where $u_{t-\tau}$ is independent of $\ln v_{t-\tau}$ and $\Delta\ln E_{t-\tau}[Q_t]$ at all leads and lags. We specify $u_{t-\tau} \sim N\left(0,\sigma_{F\tau}^2\right)$ and $\sigma_{F\tau} = d_0 + d_1\tau + d_2(\tau-6)^2 + d_3(\tau-6)^3$. Note that we write (10) in terms of the true revision in expected supply rather than the value reported by USDA. This means that maximum likelihood estimation of (10) jointly with (9) produces consistent estimates of the flexibility in the presence of measurement error and smoothing.

Standard application of the Kalman filter and smoother (Hamilton 1994) produces the mean and variance of the true revision conditional on the sequence of observed forecasts. We denote these moments as

$$\xi_{t-\tau} \equiv E\left[\Delta \ln E_{t-\tau}\left[Q_t\right] \,\middle|\, \bar{Q}_{t-10,t}, \bar{Q}_{t-9,t}, \ldots \bar{Q}_{t-2,t}\right]$$
$$P_{t-\tau} \equiv \mathrm{var}\left[\Delta \ln E_{t-\tau}\left[Q_t\right] \,\middle|\, \bar{Q}_{t-10,t}, \bar{Q}_{t-9,t}, \ldots \bar{Q}_{t-2,t}\right]$$

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[6] We also estimated a model that adjusted for the fact that, by properties of the lognormal distribution, the mean of $\Delta\ln E_{t-\tau}[Q_t]$ should be $-0.5\sigma_{Q\tau}^2$ and the mean of $\ln v_{t-\tau}$ may also be nonzero. This adjustment made no difference to the model estimates, so we report results from the simpler model.

Thus, the conditional distribution of the futures price change is

$$(11) \qquad \Delta \ln F_{t-\tau,t} \left| \bar{Q}_{t-10,t}, \bar{Q}_{t-9,t}, \ldots \bar{Q}_{t-2,t} \right. \sim N\left(\beta' X_{t-\tau} + \theta \xi_{t-\tau}, \theta^2 P_{t-\tau} + \sigma_{F\tau}^2 \right)$$

Table 6 shows maximum likelihood estimates of the parameters in (9)-(11) for a model with no control variables. We obtain flexibility estimates of -1.38 for corn and -0.94 for soybeans. Compared to their OLS counterparts of -1.34 and -1.07, these estimates suggest very little induced bias from measurement error and smoothing. To improve the confidence interval estimates we use a bootstrap. We sample years as blocks to preserve the intra-year correlation structure. The resulting confidence intervals are skewed towards larger negative flexibility values.

The estimates in table 6 imply that measurement error is much larger for corn than soybeans. The standard deviation of the measurement error for corn is between 1.6 and 2.2 percent for June through August, after which it drops 1 percent or less. For comparison, the standard deviation of the change in expected supply is 5.1, 5.6, and 4.8 percent in July, August, and September and much smaller in other months. In contrast, the estimated standard deviation of the measurement error for soybeans is less than 0.4 percent in all months. Corn also shows greater evidence of smoothing, with a smoothing parameter of 0.50 compared to 0.70 for soybeans.

As another check on the magnitude of the measurement error and smoothing bias, we estimate the models in table 3 and 4 using a single observation per year. Specifically, we use the update in the WASDE supply forecast from May to January. 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 −1.28 for corn and −1.00 for soybeans. Their counterparts that use the intermediate months are −1.34 and −1.13. The similarity of these estimates provides further evidence that measurement error and smoothing do not generate significant bias in our estimates. Comparing the standard errors from these two estimates, we find a 20 percent reduction from using the intra-year data. This reduction provides one measure of the efficiency gains from using intra-year data.

Results Summary

Figure 4 summarizes our estimation results, consolidating the estimates from tables 3-6 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 −1.27 with a 95 percent confidence interval of (−1.62, −0.92). See column 2 of table 3.

(ii) Our best soybean price flexibility estimate at average inventory levels and without accounting for corn ethanol use is −1.05 with a 95 percent confidence interval of (−1.49, −0.61). See column 2 of table 4.

(iii) Using monthly rather than annual data narrows our confidence intervals by about 20 percent.

(iv) Measurement error and smoothing of WASDE projections generate little if any bias in flexibility estimates.

(v) Nearby prices are more responsive to expected supply shocks than prices for delivery long into the future.

(vi) At recent ethanol levels such as those forecast for in 2010-2011, our best the corn price flexibility estimate is −4.80 with a 95 percent confidence interval of (−6.21, −3.39). The corresponding soybean flexibility is −2.76 with a 95% confidence interval of (−4.52, −1.00). Conditional on projected ethanol use, corn and soybean price flexibilities are insensitive to inventory levels and season. See column 6 of tables 3 and 4.

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 formally 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 has about 31 million acres enrolled, and corn is 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 percent increase in supply. On average over the 1980-2011 sample period, our corn price flexibility estimate is −1.27. This flexibility implies a 6.4 percent price reduction from opening the CRP for a year. However, at 2010-11 ethanol use levels, our flexibility estimate of −4.80 predicts a corn price reduction of 24 percent from this policy. This is a substantial effect that reflects the tightness of the corn market in 2011.

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Table 1: Descriptive Statistics for Commodity Price and Explanatory Variables in the Levels: 1980-2011

	Mean	Std. Dev.	Low	High
Corn				
Corn: Mar Futures Price	286	89	159	727
Corn: Dec Futures Price	288	84	176	679
Corn: Cash Price	263	88	127	639
Corn: WASDE Supply Forecast	275	47	184	380
Corn: June 1 Stocks/Prev Year Use[a]	0.43	0.17	0.20	0.96
Soybeans				
Soy: Mar Futures Price	685	197	436	1618
Soy: Dec Futures Price	668	182	454	1516
Soy: Cash Price	664	198	400	1589
Soy: WASDE Supply Forecast	73	13	48	99
Soy: June 1 Stocks/Prev Year Use[a]	0.32	0.09	0.17	0.45
Controls				
Wheat: Mar Futures Price	403	133	249	909
Wheat: Dec Futures Price	418	143	250	918
Wheat: Cash Price	361	109	200	839
Share of Corn Use for Ethanol[a]	0.06	0.11	0	0.34
Late Season Dummy[a]	0.4	0.5	0	1
Milk PPI	104	16	83	164
Livestock PPI	103	13	75	145
Poultry PPI	139	31	87	224
Real Economic Activity Index[b]	53	23	0	112
Exchange Rate Index	95	15	71	140
M2 Money Supply in $B	4349	2030	1527	8841
Tbill Rate in %	5.16	3.22	0.10	15.50
Gasoline PPI	107	61	46	344
Farm Machinery PPI	134	29	80	193
Agricultural Chems. & Prods. PPI	131	44	88	342
Mixed Fertilizers PPI	121	37	90	295
Fertilizer Materials PPI	128	67	81	485
Nitrogenates PPI	135	67	72	420
Urea PPI	106	42	58	336
Phosphates PPI	123	71	80	543
Other Ag. Chems. PPI	133	26	81	186

[a] Only the levels of these variables are used in the analysis

[b] Kilian's (2006) Index is recentered to make all observations positive

Table 2: Descriptive Statistics for the Monthly Change in Commodity Price and Explanatory Variables: 1980-2011

	Mean	Std. Dev.	Low	High
Corn				
Corn: Mar Futures Price	-0.74%	7.65%	-31.30%	22.76%
Corn: Dec Futures Price	-0.01%	5.08%	-26.22%	17.36%
Corn: Cash Price	-0.44%	10.08%	-38.86%	27.66%
Corn: WASDE Supply Forecast	-0.17%	2.82%	-17.66%	9.20%
Soybeans				
Soy: Mar Futures Price	-0.32%	7.41%	-27.15%	29.91%
Soy: Dec Futures Price	0.25%	5.44%	-23.12%	22.98%
Soy: Cash Price	-0.39%	8.60%	-37.97%	32.37%
Soy: WASDE Supply Forecast	0.03%	3.33%	-14.39%	17.09%
Controls				
Wheat: Mar Futures Price	-0.31%	7.22%	-23.96%	24.31%
Wheat: Dec Futures Price	0.31%	5.65%	-21.31%	17.65%
Wheat: Cash Price	0.94%	9.46%	-32.78%	29.39%
Milk PPI	0.52%	4.35%	-25.16%	11.54%
Livestock PPI	-0.60%	4.36%	-18.88%	14.75%
Poultry PPI	-0.41%	8.07%	-22.38%	31.05%
Real Economic Activity Index	-1.16%	106.31%	-1149.68%	1004.62%
Exchange Rate Index	-0.15%	2.39%	-7.48%	5.66%
M2 Money Supply in $B	0.62%	0.53%	-0.50%	3.79%
Tbill Rate	-0.02%	0.21%	-2.01%	0.69%
Gasoline PPI	-1.26%	7.81%	-40.24%	16.41%
Farm Machinery PPI	0.26%	0.40%	-0.68%	2.39%
Agricultural Chems. & Prods. PPI	0.18%	2.55%	-22.11%	11.15%
Mixed Fertilizers PPI	0.04%	2.42%	-26.35%	11.62%
Fertilizer Materials PPI	0.15%	4.05%	-31.59%	15.50%
Nitrogenates PPI	0.15%	4.51%	-21.39%	27.85%
Urea PPI	-0.04%	7.15%	-43.29%	46.61%
Phosphates PPI	0.13%	4.64%	-38.23%	20.67%
Other Ag. Chems. PPI	0.28%	1.36%	-4.81%	15.24%

Note: Significance levels are indicated by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: OLS Corn Demand Models Using March Futures: 1980-2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient Estimates							
Supply	-1.34***	-1.27***	-1.04***	-1.66***	-1.23***	-1.04***	-1.15***
	(0.19)	(0.18)	(0.15)	(0.20)	(0.19)	(0.15)	(0.19)
Stocks / Use - 0.4				-0.0024			-0.0048
				(0.029)			(0.028)
(Stocks / Use - 0.4) x Supply				2.46**			0.85
				(0.95)			(1.00)
Late Season					0.020		0.039**
					(0.013)		(0.017)
Late Season x Supply					-0.69		-0.27
					(0.47)		(0.39)
10 x Ethanol Share of Use[a]						0.0089	0.011***
						(0.0058)	(0.0043)
10 x Ethanol Share[a] x Supply						-1.14***	-0.91***
						(0.23)	(0.27)
Wheat Price[b]			0.53***				
			(0.05)				
Constant	0.011	-0.042***	-0.034***	0.013	-0.0082	0.0017	-0.034**
	(0.0095)	(0.015)	(0.01)	(0.0098)	(0.0079)	(0.0086)	(0.015)
Controls[c]	No	Yes	Yes	No	No	No	Yes
Conditional Price Flexibility Implied by Coefficient Estimates							
Setting				S/U=0.2	Early Seas.	Eth=20%	
Flexibility				-2.15***	-1.23***	-3.32***	
				(0.34)	(0.19)	(0.43)	
Setting				S/U=0.6	Late Seas.	Eth=33%	
Flexibility				-1.17***	-1.92***	-4.80***	
				(0.16)	(0.43)	(0.72)	
R^2	26%	39%	60%	29%	27%	36%	47%
Observations[d]	217	217	184	217	217	217	217

[a] Drawn from USDA baseline projections in February for the next harvest. Represents a 10 percentage point increase.

[b] March contract futures prices

[c] All regressions include monthly dummies

[d] The sample size differs based on the availability of prices for Barley and Sorghum

Note: Newey-West std. errors are shown in parentheses. Significance levels are indicated by asterisks: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: OLS Soybean Demand Models Using March Futures: 1980-2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient Estimates							
Supply	-1.13***	-1.05***	-0.98***	-1.16***	-0.97***	-0.94***	-0.76***
	(0.23)	(0.22)	(0.19)	(0.22)	(0.28)	(0.24)	(0.26)
Stocks / Use - 0.3				-0.013			0.077
				(0.057)			(0.060)
(Stocks / Use - 0.3) x Supply				0.67			-1.72
				(2.46)			(2.92)
Late Season					0.016		0.049**
					(0.014)		(0.020)
Late Season x Supply					-0.52		-0.36
					(0.39)		(0.34)
10 x Ethanol Share of Corn Use[a]						0.0089	0.014**
						(0.0059)	(0.0053)
10 x Ethanol Share[a] x Corn Supply						-0.55*	-0.36
						(0.31)	(0.28)
Wheat Price[b]			0.46***				
			(0.058)				
Constant	0.015	-0.0076	-0.0015	0.015	0.00026	0.0097	-0.033*
	(0.0095)	(0.015)	(0.012)	(0.0095)	(0.0096)	(0.0094)	(0.017)
Controls[c]	No	Yes	Yes	No	No	Yes	Yes
Conditional Price Flexibility Implied by Coefficient Estimates							
Setting				S/U=0.1	Early Seas.	Eth=20%	
Flexibility				-1.29***	-0.97***	-2.04***	
				(0.54)	(0.28)	(0.52)	
Setting				S/U=0.5	Late Seas.	Eth=33%	
Flexibility				-1.02***	-1.49***	-2.76***	
				(0.51)	(0.29)	(0.90)	
R^2	18%	31%	49%	18%	19%	22%	35%
Observations[d]	217	217	186	217	217	217	217

[a] Drawn from USDA baseline projections in February for the next harvest. Represents a 10 percentage point increase.

[b] March contract futures prices

[c] All regressions include monthly dummies

[d] The sample size differs based on the availability of prices for Canola

Note: Newey-West std. errors are shown in parentheses. Significance levels are indicated by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: OLS Demand Models Using Different Dependent Variables: 1980-2010

	Corn			Soybeans		
	Cash (1)	Mar Fut (2)	Dec Fut (3)	Cash (4)	Mar Fut (5)	Nov Fut (6)
Supply	-1.64***	-1.15***	-0.61***	-0.95***	-0.76***	-0.16
	(0.25)	(0.19)	(0.14)	(0.33)	(0.26)	(0.12)
Stocks / Use - m[a]	0.014	-0.0048	-0.028	0.19***	0.077	0.052
	(0.041)	(0.028)	(0.021)	(0.064)	(0.060)	(0.046)
(Stocks / Use - m[a]) x Supply	2.06*	0.85	0.73	-2.14	-1.72	1.29
	(1.17)	(1.00)	(0.51)	(3.07)	(2.92)	(1.23)
Late Season	0.076**	0.043**	0.036**	0.046**	0.049**	0.043***
	(0.021)	(0.018)	(0.014)	(0.019)	(0.020)	(0.014)
Late Season x Supply	-0.04	-0.27	-0.07	-0.59*	-0.36	-0.11
	(0.50)	(0.39)	(0.25)	(0.34)	(0.34)	(0.24)
Ethanol Share of Corn Use[b]	0.017***	0.011***	0.008**	0.016*	0.014**	0.011***
	(0.005)	(0.0043)	(0.003)	(0.005)	(0.005)	(0.004)
Ethanol Share[b] x Supply	-0.88***	-0.91***	-0.56***	-0.37	-0.36	-0.21
	(0.32)	(0.27)	(0.15)	(0.31)	(0.28)	(0.15)
Controls[c]	Yes	Yes	Yes	Yes	Yes	Yes
R^2	48%	47%	61%	41%	35%	44%
Observations[d]	217	217	184	217	217	184

[a] m=0.4 for corn; m=0.3 for soybeans

[b] Drawn from USDA baseline projections in February for the next harvest

[c] All regressions include monthly dummies

[d] The sample size differs based on the availability of prices for Wheat, Barley, Sorghum, and Canola

Note: Newey-West std. errors are shown in parentheses. Significance levels are indicated by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6: Joint Maximum Likelihood Estimation of Smoothing, Measurement Error and Flexibility Parameters

	Corn		Soybeans	
Parameter Estimates				
Supply	-1.38	(0.30)	-0.94	(0.20)
ρ	0.51	(0.06)	0.70	(0.06)
a_0	0.0594	(0.0125)	-0.0048	(0.0076)
a_1	-0.0112	(0.0022)	0.0002	(0.0009)
a_2	0.0007	(0.0003)	0.0003	(0.0002)
a_3	0.0007	(0.0001)	0.0000	(0.0001)
b_0	0.0277	(0.0191)	-0.0111	(0.0133)
b_1	-0.0126	(0.0045)	-0.0066	(0.0025)
b_2	0.0033	(0.0014)	0.0050	(0.0007)
b_3	0.0011	(0.0005)	0.0006	(0.0002)
d_0	0.0661	(0.0147)	0.0105	(0.0227)
d_1	-0.0020	(0.0019)	0.0098	(0.0040)
d_2	-0.0002	(0.0010)	-0.0015	(0.0011)
d_3	0.0000	(0.0000)	-0.0009	(0.0004)

Seasonal Standard Deviations Implied by Model

Month	τ	Noise $\sigma_{v\tau}$	Signal $\sigma_{Q\tau}$	Price $\sigma_{F\tau}$	Noise $\sigma_{v\tau}$	Signal $\sigma_{Q\tau}$	Price $\sigma_{F\tau}$
May	10	0.005			0.001		
June	9	0.016	0.025	0.046	0.001	0.008	0.061
July	8	0.022	0.051	0.049	0.002	0.039	0.076
August	7	0.018	0.056	0.052	0.003	0.052	0.076
September	6	0.008	0.048	0.054	0.004	0.051	0.069
October	5	0.003	0.033	0.056	0.004	0.040	0.059
November	4	0.011	0.018	0.057	0.003	0.023	0.051
January	2	0.000	0.017	0.058	0.001	0.015	0.065

Bootstrap Intervals for Flexibility

	Corn	Soybeans
95% Confidence Interval	–2.04, –0.84	–1.41, –0.67

Note: Robust standard errors in parentheses. Bootstrap conducted by sampling years as blocks to preserve intra-year correlation structure. 1000 bootstrap replications conducted. Monthly dummies included.

Figure 1: Percent Bias of OLS with Measurement Error and Smoothing

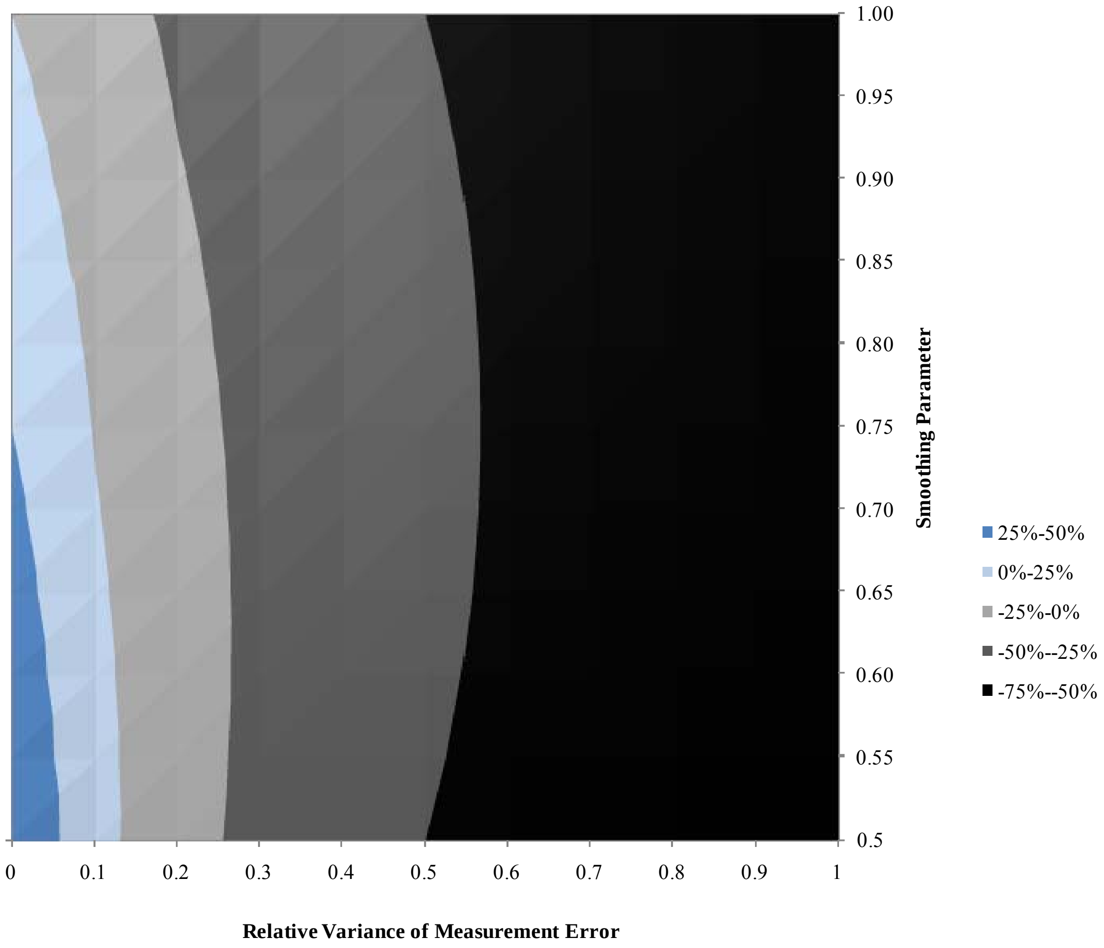


Figure 2

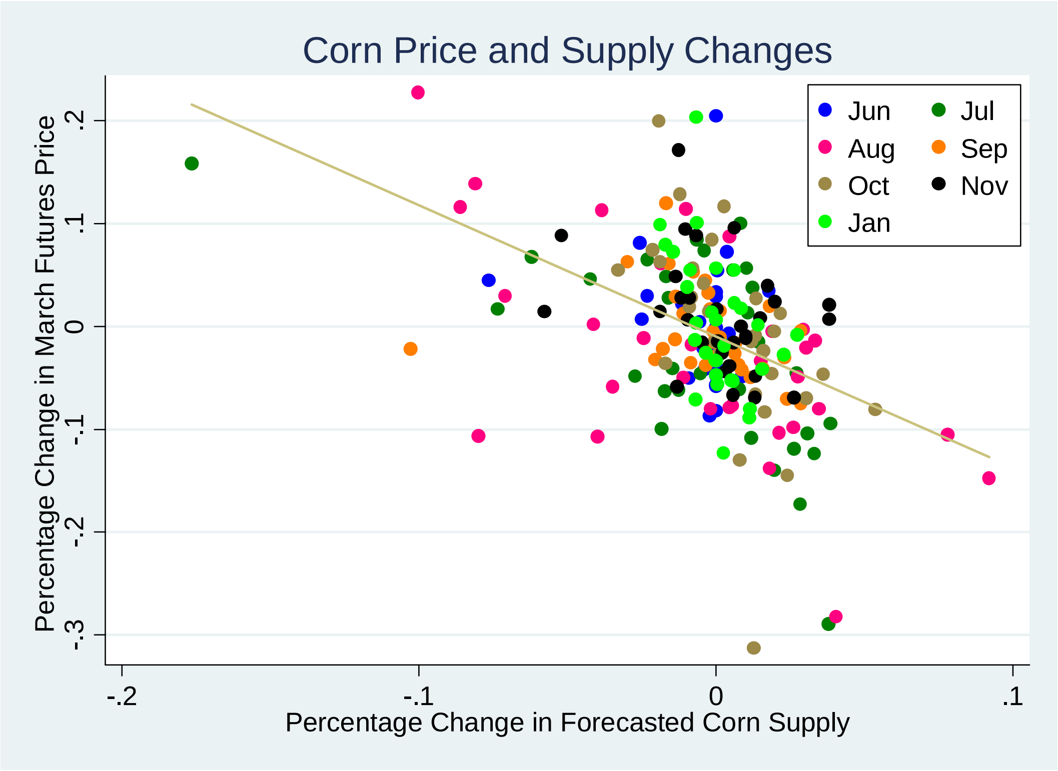

Corn Price and Supply Changes
Percentage Change in March Futures Price
.2
.1
0
-.1
-.2
-.3
-.2
-.1
0
.1
Percentage Change in Forecasted Corn Supply
Jun
Jul
Aug
Sep
Oct
Nov
Jan

Figure 3

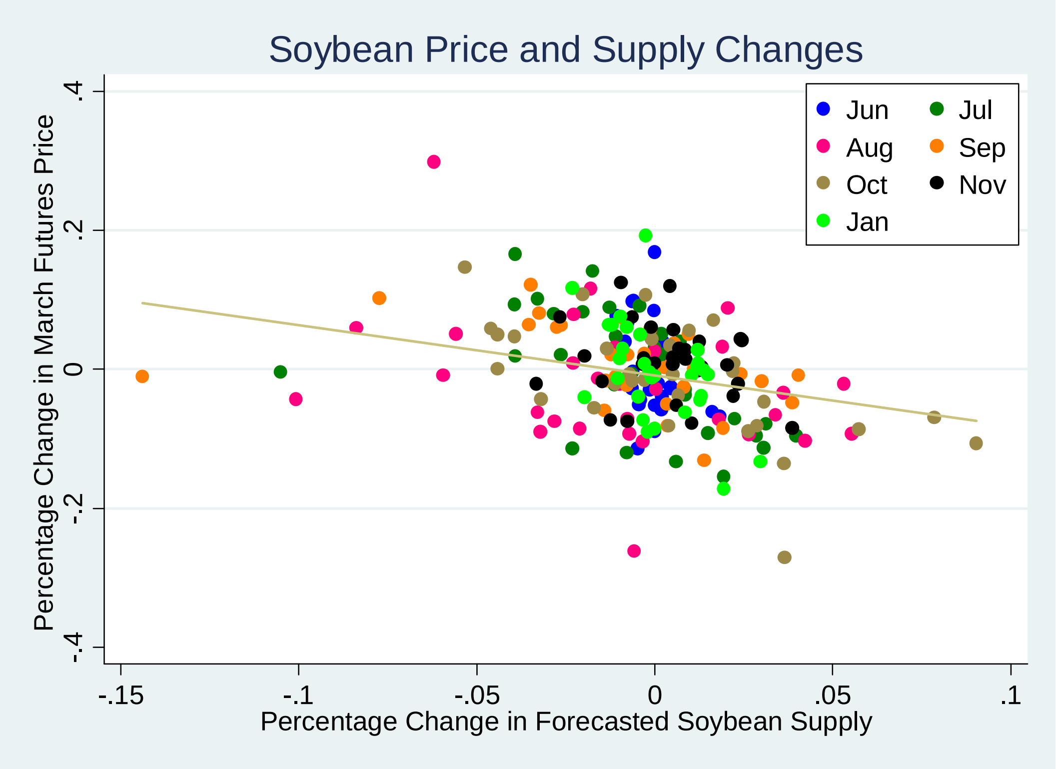
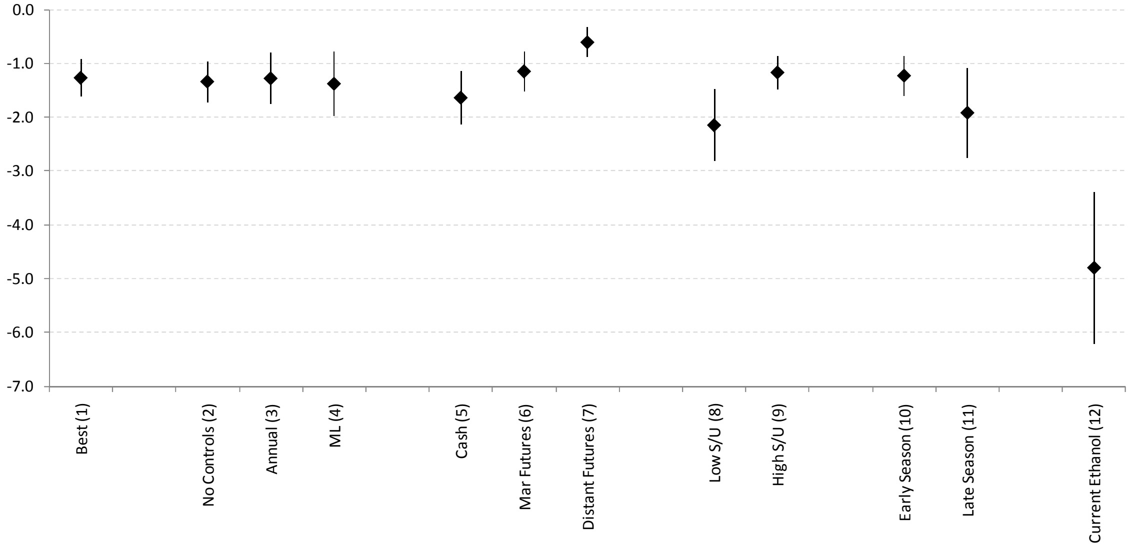
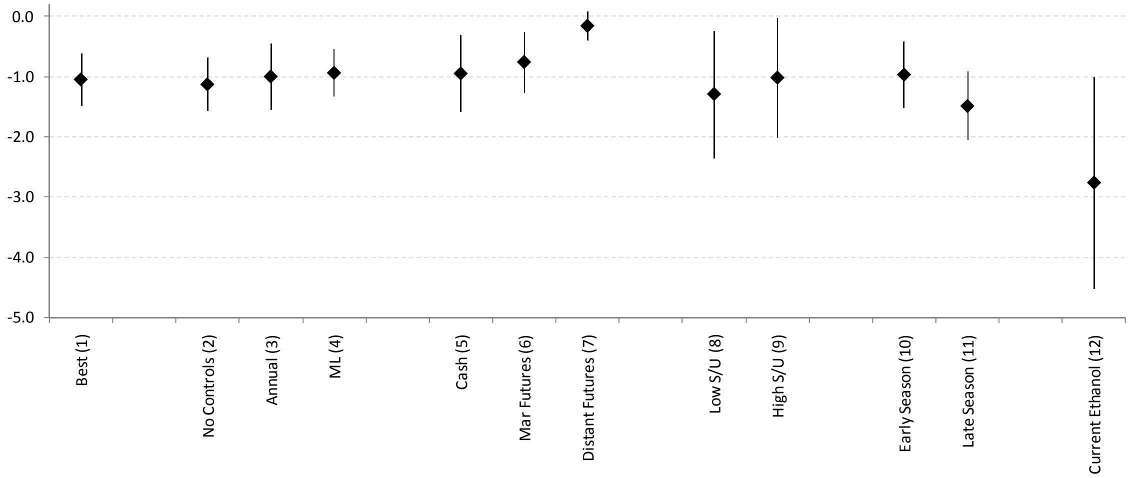

Soybean Price and Supply Changes
Percentage Change in March Futures Price
.4
.2
0
-.2
-.4
-.15
-.1
-.05
0
.05
.1
Percentage Change in Forecasted Soybean Supply
● Jun
● Jul
● Aug
● Sep
● Oct
● Nov
● Jan

Figure 4: Summary of Estimated Demand Flexibilities

Panel A: Corn



Panel B: Soybeans



Note: The estimates are: (1) all controls except wheat, no interactions, column 2 of tables 3 and 4; (2) no controls or interactions, column 1 of tables 3 and 4; (3) using only one observation per year – the change in projection from May to January, no controls or interactions; (4) joint maximum likelihood estimation of measurement error, smoothing, and flexibility, no controls or interactions, table 6; (5) cash prices, all controls except wheat, all interactions, columns 1 and 4 of table 5; (6) March futures prices, all controls except wheat, all interactions, columns 1 and 4 of table 5; (7) New crop futures prices, all controls except wheat, all interactions, columns 1 and 4 of table 5; (8) S/U=0.2 for corn, S/U=0.1 for soybeans; no controls, column 4 of tables 3 and 4; (9) S/U=0.6 for corn, S/U=0.5 for soybeans; no controls, column 4 of tables 3 and 4; (10) no controls, column 5 of tables 3 and 4; (11) no controls, column 5 of tables 3 and 4; (10) no controls, column 6 of tables 3 and 4.

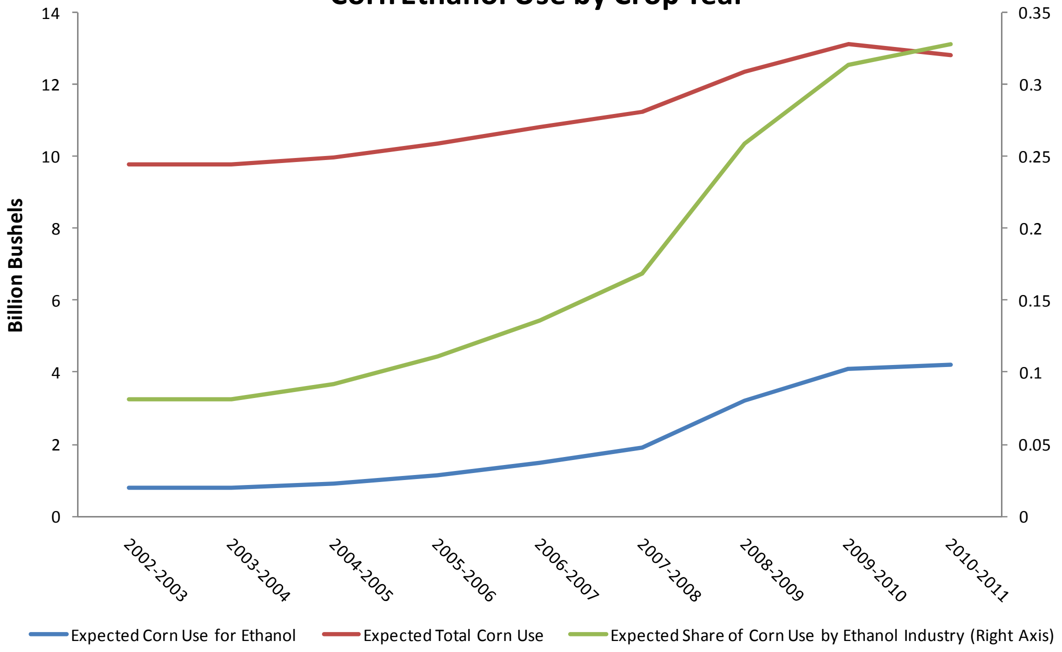


Figure 5: USDA Baseline Projections for Corn Ethanol Use by Crop Year