Valuing Public Information in Agricultural Commodity Markets:

WASDE Corn Reports

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Abstract

Monthly WASDE reports by USDA estimate current and future global supply-utilization balances for various commodities, including corn. Existing literature has shown that markets respond to WASDE releases (news effects) but has not quantified the value or distribution of benefits from those reports. We use Monte Carlo simulations of a quarterly model of the U.S. corn market to estimate the value of the WASDE forecast and its components. Our results show significant value to market participants from the WASDE reports, roughly $301 million or 0.55% of overall corn market value. The results also show significant value for each forecasted component of the reports: area ($145 million), yield ($188 million), production ($299 million), demand/stocks ($300 million) and exports ($320 million). The benefits of each component do not strictly sum when new information is added because substantial redistribution of benefits occurs, since specific information components help specific interest groups. The expected benefits or losses realized by consumers, producers or traders is often nearly as large as (and sometimes larger than) the net benefits to society from better information. In the base case benefits from WASDE information largely accrues to producers ($153 million) and consumers ($341 million). Traders lose $192 million, as they are presumed to buy at harvest, before valuable demand, stocks and export data is known. Farmers behave as traders when they choose to store, sell forward, or participate directly in futures markets. Thus, the net trader benefit or loss accrues partially to farmers as traders and partially to commercial agents. These results are sensitive to elasticity assumptions that capture both how agents behave in markets and how their welfare is measured.

Keywords: Market information, public information, World Agricultural Supply and Demand Estimates (WASDE), agricultural commodity markets

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Introduction

Information plays a vital role in ensuring the efficiency of market outcomes. With an inaccurate forecast, hence poor market information, quantities are misallocated over time and space due to inefficient price signals, resulting in social welfare losses. In agricultural commodity markets information is largely shaped by public information sources, which provide numerous historical statistics as well as projections on future supply, domestic use, trade, and storage. The monthly World Agricultural Supply and Demand Estimates (WASDE) issued by the World Agricultural Outlook Board (WAOB) of the United States Department of Agriculture (USDA) estimate current and future global supply-utilization balances for various commodities. Those forecasts are informed by area, yield and stocks surveys in the U.S. conducted by the National Agricultural Statistical Service (NASS) of USDA as well as by independent data from other public (and private) entities on trade and use. The Foreign Agricultural Service (FAS) of USDA through its network of overseas agricultural attaches collects information on foreign production and trade, informing WASDE export demand and foreign supply –use balance forecasts.

Market agents use information from WASDE (and other sources) to shape decision-making, as shown in recent literature (Lusk, 2013). That literature has found that WASDE reports influence market performance (news effects), but it does not attempt to quantify the value of that information (e.g. Adjemian,2012; Garcia et al., 1997; Isengildina-Massa et al., 2008). Much earlier work (Bradford and Kelejian 1977, 1978; Hayami and Peterson 1972) followed an approach similar to that found in early literature evaluating price stabilization policies to approximate the value of public information for agricultural markets. More recent work has also investigated “myths” that WASDE reports incorporate systematic biases, finding that those myths generally are not well founded, but that sampling error from the surveys on which the WASDE balances are based matters (Irwin, Sanders and Good, 2014). Irwin and Good (2015) also connsidered the role of emerging private forecasts, which they argue are not nationally representitive nor as complete as USDA efforts, but may complement WASDE outlook and NASS data. Nevertheless, controversy persists, leaving funding of WASDE and NASS efforts vulnerable in a budget limited environment. Given this recent empirical work, as well as increased scrutiny of WASDE in commodity markets and on government expenditures, a greater understanding of the value of this public information is both timely and warranted.

This paper develops an empirical model for quantifying the value of public information provided to agricultural markets, with specific application to WASDE reports on the US corn market. Our approach builds on advances in the price stabilization literature through the use of Monte-Carlo simulations to more accurately depict implications of detailed market forecast distributions and the impact of improving information over time. A dynamic quarterly model of the US corn market is fit to USDA's corn data from its feed grain database (USDA, ERS, 2015). In each quarter, beginning when area planted survey information first becomes available and continuing until full information is obtained (hence overlapping the prior and next crop years), predicted supply–use equilibrium takes into account history (prior quarters) and expectations on future supply-use balance. As the model progresses across time and new, improved forecasts are revealed, current and expected future equilibriums are continually estimated, while past period equilibrium outcomes become fixed. The process follows that of any dynamic market with updating information, where current decisions influence future supply and use balances through the irreversibility of previous outcomes.

The model is built along the lines of a standard commodity model, where supply-use balance establishes equilibrium conditions, and price is the endogenous variable determining components of that equilibrium. Uncertainty is captured as error realizations in the constants of linear supply and demand (component) functions. As information is updated over time, better forecasts are made, reducing the size of unobserved (unrealized) errors. Supply is uncertain through the uncertainty of both area and yield, while demand is uncertain through stocks, foreign and domestic use forecast errors. The supply-utilization balance of markets and of WASDE forecasts require estimation of forecast errors that are correlated. Moreover, stocks data rather than use are collected by USDA surveys and price determination is often informed by expected stocks-to-use ratios (Wright, 2011). We therefore utilize the theory of storage (Wright and Williams, 1982) to capture price dynamics both within and across crop years, which are linked by annual carry-out stocks.

The value of information is derived from the ability to forecast future events with greater accuracy, such that more efficient decisions can be made and current use will not exceed or fall below eventual supply as much as in less well-informed cases. Monte-Carlo simulations trace out the distributions of expected outcomes based on forecast errors found in historical WASDE data. Simulated forecast errors in the model include area, yield, exports, and stocks. While the expectation of the errors remains constant at

zero across time, the variance or likelihood of larger errors is declining as new quarterly forecasts become available, since information is continually improving. Predictions of expected distributions for prices, uses and welfare are compared to two counterfactual cases – behavior under a naïve forecast based on historical trends and under perfect information. Sensitivity analysis explores alternative behavioral parameter assumptions as well as decomposing the value of WASDE forecast components.

Results highlights

By adjusting the assumptions on forecast errors, value can be quantified based on the differences in expected social welfare across cases. Our results show significant value to market participants from the WASDE reports, roughly $301 million or 0.55% of corn market value (as measured by producer revenue). Since median welfare improvement was $340 million, the distribution of welfare outcomes is skewed, with information being more valuable when stocks are low and production shortfalls are likely. Additionally, our results show significant value for each component of the WASDE reports: area ($145 million), yield ($188 million), and production ($299 million). Improvement in overall welfare from better demand/stocks or export information is small after production information improves, but there is significant redistribution of benefits to producers and consumers.

Benefits from the WASDE information largely accrue to producers ($153 million) and consumers ($341 million). Traders lose $192 million, an amount equal to about 10% of the storage cost payments received. They are presumed to buy at harvest, before valuable demand, stocks and export data is known. Redistribution is large relative to net welfare gains. [1] Farmers who store, sell forward, or participate in futures markets realize part of the benefits/losses attributed here to traders. That is, farmers engage in some activities as producers, and some as traders. Other participants in commodities markets, in addition to farmers, also realize part of the trader profits or losses. An alternative model specification is included to identify by how much farmers as producers benefit from WASDE information, showing that adjusting supply (area and inputs at planting) to expected profits yields substantial value (as much as $137 million) to farmers.

[1] While the change in value due to new information for traders is negative, this is a deduction from storage charges. If firms can store below the market storage cost rate, their returns to trading are higher. The expected positive returns to traders from more efficient storage explains the rationale for participating in the market. Moreover, results suggest the uncertainty with only trend information available harms producers and consumers more so than traders.

The model utilized parameter values taken from literature rather than from our own econometric estimation. Therefore, sensitivity analyses were also performed to account for various assumptions on demand and supply parameters/elasticities. Given the nature of the model and ambiguities in previous literature on the magnitudes of these parameters, scenarios are presented which span the range of previously estimated elasticities. Information was shown to be $22 million more valuable in highly elastic cases relative to the base assumptions, and as much as $80 million less in the most inelastic cases, as the results are strongly dependent on supply parameter assumptions.

Roadmap

The next section provides background information on USDA data collection and forecasts. Next, we explore conceptual issues related to modeling and valuing public information. Our model specification is then described, followed by our Monte Carlo simulation strategy, and information on empirical implementation of our US corn market model. Results are provided next, including our estimates of the value attributable to the various components of WASDE forecasts as well as the sensitivity analysis on key model parameters. The concluding section summarizes our findings and their implications as well as limitations of our approach.

Background and Conceptual Issues

The World Agricultural Supply and Demand Estimates (WASDE) created by the United States Department of Agriculture's (USDA) World Agricultural Outlook Board (WAOB) are the most widely disseminated source of information on U.S. agricultural markets today (Adjemian 2012). In each monthly report estimates are made of past, current and future supply and demand quantities for various commodities important to US agricultural markets. WASDE estimates outcomes in detail for domestic supply and use as well as global outcomes influencing trade. This report is presented as a compilation from multiple sources within the USDA (and outside) describing the state of the market as well as providing a forecast (Vogel & Bange, 1999).

USDA's National Agricultural Statistical Service (NASS) is one key source. NASS surveys farmers and commercial agents to estimate area planted and harvested, yield, and stocks. FAS and its PS&D (Production, Supply and Demand) database provide information and outlook on foreign production, trade and other components of foreign and global supply utilization balances. NASS surveys, FAS data

and WAOB models generate estimates of historical data describing U.S. agricultural markets as well as outlook information on future expectations. Our methods focus on the outlook effort, as it is difficult to imagine a counterfactual scenario where there is no information, even on historical data, from USDA. While the historical data is also clearly valuable, our methods will not be able to estimate just how valuable it is. This means one issue we will not address is the controversy over estimating trend expectations (the basis for our naïve case and the WASDE starting point) before survey results become available (Irwin and Good, 2015).

Table 1 reports errors in expectations from various monthly WASDE reports, showing the extent to which information improves as time passes. It also shows the estimated forecast error from a naïve forecast. The naïve forecast error is based on annual linear trend forecasts, and is simply the difference between that trend forecast and actual outcomes. While additional information in the market is likely available beyond trend forecasting projections, particularly as the year proceeds, this method provides a baseline understanding to the role of USDA and WASDE information, and how the market would behave in the absence of any information. The updating of information provided by WASDE forecasts is shown in the reductions of the variance of forecast errors over the course of the year as new, improved forecasts are issued. It is seen in table 1 that early on WASDE forecasts exhibit errors similar to those of a naïve trend forecast, but information improves when survey data and observations on crop conditions here and abroad yield better market information.[2] These historical error distributions will be used to represent the case where USDA data informs markets as well as what errors might look like in a case corresponding with trend (naive) expectations. Table 1 shows that information on production is revealed relatively early in the crop year, while domestic use and foreign demand are slower to be resolved, as they are due to later events like foreign production and changes in exchange rates.

The presence of complementary private information sources in addition to WASDE offers an argument against strictly valuing WASDE forecasts based on outcomes relative to naïve trends. However, there is debate as to the extent to which those private forecasts improve on (or could substitute for) the USDA forecasts, and specifically on how complete and nationally representative they are (Irwin and Good, 2015). In the absence of USDA data and forecasts, relatively poor, limited private information would need to fill the gap. These private forecasts are often not free and nor publicly available, and typically rely heavily on USDA's historical databases.

[2] Historical errors, both naïve and in WASDE forecasts are estimated from data starting in 1993. Prior to 1993 USDA did not make production forecasts in May

There are also international sources for outlook information on some crops – from AMIS and the International Grains Council. These estimates are not independent of USDA data nor its outlook projections. They are competitive yet complementary to the USDA effort, and USDA is an active participant in AMIS. The FAO, who manages AMIS, and USDA share information, even if final data or projections may differ. Moreover, AMIS data are in principle a compilation of national outlook estimates by member governments, which may vary in quality. AMIS's track record is too new to see how accurate its' outlook is relative to WASDE.[3]

Our results will show that farmers benefit or lose from market information in their capacity as traders as well as producers. Additionally, the results suggest it is likely that farmers may benefit more from public information, since large commercial entities have greater capacity to generate data and market information if USDA data were not available. We shall assume the USDA forecasts are the best available public information, and our valuation estimate will be based on their forecasts.

Valuing Public Information

Information plays a vital role in ensuring the efficiency of agricultural commodity markets. The decisions to plant crop varieties, make investments, produce livestock, store or sell at harvest, and more are rooted in the information obtained through and about commodity markets. Accurate information and forecasts prevent misallocation of physical and financial resources over time, while imperfect (or incorrect) information can generate volatility in markets as agents respond quickly when presented with unexpected information. In addition to the overall gains from reduced volatility, greater information can shift welfare across market participants as select agents benefit/suffer under scenarios with misinformation.

In assessing value to public information, one must determine the decisions which are influenced by that information. The relationship of dynamic information on equilibria and welfare can be anecdotally explained through a scenario of bad information. An inaccurate forecast sets spot prices at inefficient

[3] While admittedly there are many information sources for the US corn market, both public and private, the difficulty of untangling the related and dependent sources makes it challenging to strictly assume WASDE is the sole source of information for determining market outcomes. Moreover, the naïve trend forecast cannot fully represent the information available to market participants without WASDE.

levels, generating an inefficient allocation of use, trade and stocks. As time progresses previous outcomes are fixed and the quantities now available are above or below efficient levels due to the inaccurate prior estimate. This distortionary effect of imperfect information on all future equilibria through a misallocation of initial consumption (use) sets all future outcomes on an inefficient path, influencing expected welfare. Accurate information, however, creates a smoothing of prices and consumption over the crop year, as quantities can be efficiently allocated and priced across time based on actual availability. Capturing the dynamics of the crop year and the timing of decisions is therefore important for effectively valuing information provided in WASDE reports.

Hayami and Peterson (1972) were among the first to propose a method for valuing information in an agricultural context. They analyzed the market in two separate forms: an inventory adjustment model and a production adjustment model. Defining these models through linear supply and demand functions, the authors were able to attribute changes in welfare in a two-period model due to more accurate early information. In their inventory adjustment model, production was determined exogenously, and information affected storage levels. In the production adjustment model, supply was endogenously determined by producers' expectations of market behavior. In either model the valuation of information can be attributed to improving on the inefficient levels of supply and demand caused by inaccurate information.

Bradford and Kelejian (1977) advanced this research through a model which linked prices with storage, as speculative stockholders determine efficient quantities stored to carry across time periods. Information influences stockholder behavior, which directly determines supply and demand throughout the year as well as carryover stocks before the next harvest. The storage literature provides the basis for understanding the linkage between storage costs, expected output prices, interest rates, and storage levels (Wright & Williams, 1982). Through this multi-period linkage of stocks, production, and prices their model more closely followed storage theory and market behavior.

The approaches in that early research utilized minimal discrete approximations to production uncertainty, as opposed to now more modern Monte Carlo simulation modeling. That approach was quite similar to the early approach taken to examine price stabilization policy (e.g. Waugh, 1944; Oi, 1961; Massell, 1969). Advances in examining stabilization policy resorted to Monte Carlo simulations to capture the distributions of uncertain model elements, since large number of repetitions and distributional assumptions could be used to better model uncertainty (e.g. Bigman and Reutlinger, 1979;

Wright, 2001; Gouel, 2013). While there has not been recent work valuing public agricultural commodity information, the Monte Carlo simulation approach is appropriate as a framework to advance the work on this topic.

Simulation Model

The research presented here estimates specific value to WASDE forecasts/reports through the use of dynamic multi-period Monte Carlo simulations of the US market for corn. Building off the inventory adjustment models that assessed information through limited discrete assumptions on information errors (Bradford & Kelejian, 1977; Hayami & Peterson, 1972), Monte Carlo simulations were produced to analyze the value of information based on forecast distributions under uncertainty. Asymptotically continuous forecast distributions can be derived for market outcomes that more accurately depict market behavior and consequences from better information. Relative to that early research, this approach also advances previous work by separating production uncertainty into correlated area and yield uncertainty, as well as through considering domestic use (hence feed use or stocks) and foreign demand uncertainty.

The model used here starts with a dynamic quarterly inventory adjustment model that analyzes the short run outcomes of the US corn market over the course of one crop year. Equilibrium conditions based on supply-use balance for each crop year fundamentally set the equations of the model. The price in the period corresponding to the quarter in which the forecast is issued is the corresponding endogenous variable. Expected quarterly future prices are then set based on storage theory, and supply and demand components each quarter may be calculated and then summed across quarters using linear functions embedded in the equilibrium conditions. Forecast errors are found in the constants of those functions. The long run model links these short run models again using storage theory along with the assumption that short run supply is based on expected prices found in the fourth quarter of the previous crop year. A ten-year sequence of one crop-year quarterly models is generated 3000 times, and distributions of current and expected prices, quantities, and welfare measures are observed.[4] The short

[4] Given the complexity of our uncertainty specification (forecast error realizations for area, yield, exports and feed demand by quarter), a large number of repetitions are required to consistently estimate expected outcome distributions. Additionally, 3,000 simulations were chosen based on the trade-off between computing speed and the convergence of the results. The simulation results appeared to converge toward a consistent solution with 1,000 simulations but we used more simulations to be cautious.

run model is similar to previous models that have set an unknown exogenous supply level. Farms also use information in choosing inputs (variety, fertilizer and chemical use, and area planted), so alternative assumptions on medium run supply response to expected prices are also captured in the way the sequence of short run models are linked. The focus of the short run component of the model is heavily on the role of information in shaping consumption (use) and inventory levels. In the longer run, supply for an upcoming crop year depends on expected harvest prices, with expectations formed at planting. The value of information can then be directly attributable to differences in various welfare measures under alternative information scenarios affecting production, use, storage and trade decisions. For example, a sensitivity analysis scenario with perfectly inelastic supply in the long run will help show that supply response allows farmers to realize significantly greater value from better market information.

The WASDE reports by the USDA are released monthly as projections of supply and use for the entire crop year. In order to create a multi-period single crop year model, information is required at less time-aggregated levels than yearly statistics. The least aggregated complete data on consumption and use for corn from the USDA is quarterly in its feed grain database (USDA, 2015). Previous research forced strong assumptions on similar statistics and disaggregated the quarterly data into a monthly model (Bradford & Kelejian, 1978). This method was not implemented here as it is expected that it would only increase complexity without improving the nature of the results, and is not supported by realistic data availability. Bradford & Kelejian (1978) do show a positive relationship between forecast frequency and value of information, implying the quarterly model used in this paper likely underestimates the true value of monthly WASDE reports.

The short run implementation of the model is a six-quarter model that links across three crop years: prior, current (year of focus), and following. By including the quarter before the crop year and assumptions on expectations about the next crop year, the model can evaluate the effect of stocks across crop years. Moreover, information is available before the beginning of the crop year, which is typically set when harvest begins. Information on the next crop year influences demand and stocks toward the end of a crop year, and information is not fully known until the next crop year has begun. The long run is captured by solving a sequence of these short run models, with solutions for one crop year becoming prior information for the next crop year simulated.

Each forecast catalogues a point in time that represents when new information is realized by market participants. As information is continually updated with each new forecast, the quarterly periods transition from expected outcomes to realized values and then to history over the course of the crop

year. Equilibriums for every quarter are determined by history, current events, and the expectations of future supply and demand, as well as the linkages across periods through expected prices and storage costs. With new information there are shifts in the expectations of supply and demand, as well as the realized values of prior quarter's use and trade levels, which generates new estimated equilibriums for the future periods. This process continues dynamically for each forecast period until all uncertainty on the current crop year is removed.

Though supply is fixed (once planting decisions are taken), it remains unknown to all market participants due to area and yield uncertainty until harvest.[5] Similar to market conditions, it is assumed here that farmers plant an unknown quantity of acres with uncertain yields. Expected area planted and yield will, however, depend on expected future prices at the time of planting. As time progresses, actual area becomes known to the market while yield remains uncertain. Updates to the expectations of crop yield are made throughout the season. When harvesting is finished, actual yield is realized and production is fully known. Uncertainty in demand, omitted in previous studies, is also considered in this model since each WASDE report makes projections on domestic use, exports and stocks.

The model specification is fully described below. Our simulation model is constructed around the supply-utilization (S-U) balance that serves as the basis for WASDE reports and USDA's Feedgrains and PS&D databases. Behavioral relationships for each component of S-U balance are then described, along with corresponding welfare measures for relevant agents – farmers, end users, and traders.

Supply-Utilization Equilibria

In each quarter, hence for the entire crop year, carry-in stocks plus production equals domestic demand, net exports and carry-out stocks:

(1) $S_{t-1} + Qs_t = Qd_t + E_t + S_t$ Quarterly S-U balance

(2) $S_0 + Qs_1 = \sum_{t=1}^{4} [Qd_t + E_t] + S_4$ Annual S-U balance

where S_t is stocks carried out from period (quarter) t, hence carried into quarter $t+1$, Qs_t is quantity supplied (harvested) in period t, Qd_t is domestic demand in period t, and E_t is exports during period t.

[5] We assume producers, consumers, end users and traders all have access to the same market information. This is least likely to be true for the naïve scenarios, where commercial agents may have better information if USDA information is no longer made public.

Production is harvested only in the first quarter of a crop year ($t = 1$). In each other quarter supply equals stocks carried in from the prior quarter (e.g. S_3 in quarter 4), so Qs_t = 0 for $t \neq 1$.

This equilibrium condition must be respected for actual quantities produced and consumed, and will also be respected in assessing market expectations when using imperfect information to set the market price. Time subscripts (t) denote when transactions occur (t), and superscripts (f) indicate when forecasts are issued (f). Table 2 indicates when these periods are. With a forecast in each f period, expectations are determined for all current and future periods (all t ≥ f) such that the S-U equilibrium condition holds:

(3) $$S_{t-1}^f + Qs_t^f = Qd_t^f + E_t^f + S_t^f$$ Quarterly S-U expectations balance

where X_t^f is the expected value of variable X_t revealed in forecast period f. The future expectation of a variable is denoted by superscript f, where f indicates when that expectation is formed. How expectations are formed, and how the distribution of forecast errors is estimated for random variables are described when each variable in the model is subsequently defined. When each new forecast is issued, and as time passes, initial conditions, current market outcomes, and future expectations equilibrate according to this supply-use balance.

The crop year nominally begins with harvest ($t = 1$) but forecasts begin at planting time, the prior quarter ($t = 0$), since information is revealed by planting intentions surveys as well as observations of crop conditions before harvest. We denote forecast periods by f, where the first forecast ($f = 1$) is early in the quarter prior to harvest ($t = 0$). When there is no information other than history available, at $t = -1$ or before, $f = 0$ denotes a naïve trend forecast. Moreover, data is not fully revealed for use until after the crop year is over, at $t = 5$ ($f = 6$). Table 2 shows the calendar for the corn crop year using this nomenclature and shows when information is revealed by WASDE forecasts and NASS surveys.

We can write equilibrium conditions that apply when each forecast is issued that set the actual market outcome that quarter and initial conditions for later quarters:

(4) $f = 1$;

$$S_{-1} = Qd_0^1 + E_0^1 + S_0^1$$ Planting period

$$S_0^1 + Qs_1^1 - \sum_{t=1}^{4}[Qd_t^1 + E_t^1] = S_4^1$$ Crop year beginning at upcoming harvest

$$S_4^1 + Qs_5^1 - \sum_{t=5}^{8}[Qd_t^1 + E_t^1] = S_8^1$$ Next crop year

With the initial forecast ($f = 1$), expectations are determined by supply-utilization equilibrium conditions in the planting period for the crop year, and for the next crop year as in equation (4). Stock conditions and decisions link equilibrium outcomes across multiple years. With the initial stocks at time of planting (S_{-1}) pre-determined, the choice becomes how much to carry in to the new crop year (S_0^1) given expectations of supply and demand, as well as the carry-out stocks to the following two crop years (S_4^1 and S_8^1).

The model progresses dynamically with each subsequent forecast as follows:

$$(5) \quad f = 2,3,4,5; \qquad S_0 + Qs_1^f - \sum_{t=1}^{4}\left[Qd_t^f + E_t^f\right] = S_4^f \qquad \text{Current crop year}$$

$$S_4^f + Qs_5^f - \sum_{t=5}^{8}\left[Qd_t^f + E_t^f\right] = S_8^f \qquad \text{Next crop year}$$

With the carry-in stocks previously determined ($S_0 = S_0^1$), expectations for supply and demand are derived with each new forecast. As time passes and new information enters the market with each new forecast, new equilibrium expectations are set, and outcomes prior to each forecast period become realized. The final within-year forecast is:

$$(6) \quad f = 6; \qquad S_0 + Qs_1 - \sum_{t=1}^{4}\left[Qd_t + E_t\right] = S_4 \qquad \text{Prior (previously current) crop year known}$$

where all information is fully realized for the crop year, with final values fixed, and welfare outcomes may then be evaluated

This specification identifies effectively four agents in the model –producers (farmers) who derive income from production (Qs), consumers who will be later divided into feed users and industrial users (Qd), exporters who earn export revenue from overseas sales (E), and traders (farmers and commercial agents) who store and may realize gains or losses on stored grain (S). Farmers are both producers and traders, but they are not necessarily all traders. (Expected) behavior will depend on (expected) prices in each period (p_t^f). Each agent's welfare function will be specified once its behavior is modeled, and an overall welfare function can then be derived. Partial equilibrium measures (e.g. consumer and producer surplus) are used throughout.

Production risk

Production (Qs) is assumed equal to area[6] (A) times yield (Y) and is harvested in period 1, the first quarter of the new crop year:

$$(7) \quad Qs = Qs_t = A * Y \quad and \quad Qs_t = 0 \; \forall \; t \neq 1 \; or \; 5$$

Harvested production is uncertain until the second quarter of the crop year ($t = 2$), with area (A) planted uncertain prior to the beginning of the crop year ($in\ t = 0$) and yield uncertain until harvest is completed ($in\ t = 0\ and\ 1$). Information on expected area and yield have improved due to the WASDE forecasts, and gets better as time passes. Imperfect information results in forecast errors that are assumed to follow a normal ($N \sim (0, Var_{Qs})$) distribution, for area prior to the beginning of the crop year ($f = 1$) and until harvest is complete for yield, and so for production ($f = 1, 2$).

In order to capture supply response to future price expectations, we assume area planted and yield are determined by trend expectations and by expected harvest prices during planting. Once those planting decisions are taken supply is fixed, though uncertain until harvest. Specifications for representation of area, yield and so production are detailed below.

Area harvested

The model uses area harvested as the representation of area. A_0 is base data on area harvested, A^f is expected area harvested in forecast period f, and A is actual area harvested, so:

$$(8) \quad A = A_0 \left(1 + \beta_A * \frac{p_1^0 - \rho_1}{\rho_1}\right) + \varepsilon_A$$

where ε_A is the actual deviation from trend (naïve) area harvested, β_A is the short run supply elasticity with respect to area, and ρ_1 is the expected price for period 1 at planting in the base data. Land use (and input) decisions are assumed to be taken in period 0, well before harvest, and based on expected prices in that pre-harvest period. Prior to May and June WASDE reports:

$$(9) \qquad f = 0: \qquad A^0 = A_0 \left(1 + \beta_A * \frac{p_1^0 - \rho_1}{\rho_1}\right)$$

[6] Any differences between area planted and area harvested are ignored in the model for simplicity. While there is uncertainty on the differences in planted and harvested area, as well as the timing of when that information is revealed, it is assumed most of the uncertainty in forecasting production each year is in yield and the differences in area across years.

At $f = 1$, when the first relevant reports are issued, part of the error is revealed (ε_A^1), and at $f = 2$ area is known as the remainder of the error is revealed (ε_A^2).[7] Hence,

$$(10) \quad \varepsilon_A = \varepsilon_A^1 + \varepsilon_A^2$$
$$A^1 = A^0 + \varepsilon_A^1$$
$$A^2 = A^0 + \varepsilon_A^1 + \varepsilon_A^2 = A^0 + \varepsilon_A = A$$

Mean expectations of all errors are zero: $E(\varepsilon_A) = 0, E(\varepsilon_A^1) = 0, E(\varepsilon_A^2) = 0$. The variance of ε_A is the observed WASDE variance of harvested area around its trend or naïve expectation. The variance of ε_A^2 is the deviation of the June WASDE estimates from trend area harvested, which is less than the variance of ε_A since WASDE forecasts provide improved information. Since the naïve error and the WASDE forecast error are correlated we take that covariance into account. Expected prices driving supply (p_1^0) come from prior crop year forecasts, and must be updated as repetitions drive the model forward in time.

We can observe the historical error variances both for a naïve (trend) forecast ($Var(\varepsilon_A)$) and for the June WASDE report ($Var(\varepsilon_A^2)$) as well as estimating the error covariance matrix ($Cov(\varepsilon_A^1, \varepsilon_A^2)$). The Monte Carlo simulation model will generate realizations of area planted errors ε_A^1 and ε_A^2 using distributions estimated from historical data, and will also generate actual area harvested from $A = A^0 + \varepsilon_A^1 + \varepsilon_A^2$.

Yield

In May and June, since information on weather is limited, WASDE yield estimates are only somewhat better than naïve trend yield estimates.[8] When the crop year begins on September 1[9], much better information on yield is available, but yield remains uncertain. At the beginning of the next quarter ($t = 2$), once harvest is finished yield is essentially known, as reported in the November and December WASDE reports. Hence, the pattern by which information is revealed is similar to that for area, but delayed one quarter.

Y_0 is base data on yield, Y^0 *is* naïve (trend) expected yield (taking price expectations into account), hence when f = 0, Y^f is expected yield in forecast f and Y is actual yield.

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[7] (Expected) price responsiveness is fully captured in the initial forecast, A^0. Full information is assumed in periods when according to historical WASDE data forecast errors have nearly vanished (see Table 1). That occurs during period 2 for area, hence $A^2 = A$.

[8] Poor planting conditions (e.g. an overly wet spring) can influence expected and eventual yield.

[9] The convention in virtually all databases, including those of USDA and FAO, is to begin the crop year at harvest not planting. We follow that convention.

(11) $$Y = Y_0\left(1 + \beta_Y * \frac{p_1^0 - \rho_1}{\rho_1}\right) + \varepsilon_Y$$

where ε_Y is the actual deviation from trend yield, β_Y is the short run supply elasticity for yield response, and ρ_1 is the expected price for period 1 at planting in the base data. Prior to May, June WASDE reports:

(12) $$Y^0 = Y_0\left(1 + \beta_Y * \frac{p_1^0 - \rho_1}{\rho_1}\right)$$

At $f = 1$ and 2, when reports are issued, part of the error is revealed ($\varepsilon_Y^1, \varepsilon_Y^2$), and at $f = 3$ yield is known as the remainder of the error is revealed (ε_Y^3). Hence,

(13) $$\varepsilon_Y = \varepsilon_Y^1 + \varepsilon_Y^2 + \varepsilon_Y^3$$
$$Y^1 = Y^0 + \varepsilon_Y^1$$
$$Y^2 = Y^0 + \varepsilon_Y^1 + \varepsilon_Y^2$$
$$Y^3 = Y^0 + \varepsilon_Y^1 + \varepsilon_Y^2 + \varepsilon_Y^3 = Y^0 + \varepsilon_Y = Y$$

Mean expectations of all errors are zero: $E(\varepsilon_Y) = 0$, $E(\varepsilon_Y^1) = 0$, $E(\varepsilon_Y^2) = 0, E(\varepsilon_Y^3) = 0$. The variance of ε_Y is the actual variance of yield around its trend or naïve expectation. The variances of ε_Y^3 (and $\varepsilon_Y^2 + \varepsilon_Y^3$) are the deviations of the September (and June, respectively) WASDE estimates from trend yield, which are less than the variance of ε_Y since WASDE forecasts provide improved information. We can observe the historical error variances both for a naïve (trend) forecast ($Var(\varepsilon_Y)$) and for the WASDE reports ($Var(\varepsilon_Y^f)$), as well as estimating the error covariance matrix. The simulation model will generate yield errors: ε_Y^1, ε_Y^2 and ε_Y^3 using distributions estimated from this historical data, and will also generate actual yield from $Y = Y^0 + \varepsilon_Y^1 + \varepsilon_Y^2 + \varepsilon_Y^3$.

Expected Production

Expected Production is expected area (harvested) times expected yield:

(14) $$Qs^f = A^f * Y^f$$

Hence at:

(15) $$f = 0 \qquad Qs^0 = A^0 * Y^0$$
$$f = 1 \qquad Qs^1 = (A^0 + \varepsilon_A^1) * (Y^0 + \varepsilon_Y^1)$$
$$f = 2 \qquad Qs^2 = (A^0 + \varepsilon_A^1 + \varepsilon_A^2) * (Y^0 + \varepsilon_Y^1 + \varepsilon_A^2) = A * (Y^0 + \varepsilon_Y^1 + \varepsilon_A^2)$$
$$f = 3,4,5,6 \qquad Qs^f = (A^0 + \varepsilon_A^1 + \varepsilon_A^2) * (Y^0 + \varepsilon_Y^1 + \varepsilon_A^2 + \varepsilon_A^3) = A * Y = Qs$$

Observation of historical data suggest that early yield forecast errors are correlated with area forecast errors, so a full variance-covariance matrix for the production related error terms ($\varepsilon_A^1, \varepsilon_A^2, \varepsilon_Y^1, \varepsilon_Y^2, \varepsilon_Y^3$) was

generated from historical data and a Cholesky transformation is used to generate error realizations for the Monte Carlo simulation scenarios that duplicate that historical pattern.

Farmers derive welfare from production and from their storage/marketing activities. We shall equate producer surplus in this model with the income due to production and cannot differentiate any benefits from storage and marketing that may accrue to farmers, traders or other intermediaries. Since this is a short run model, and production is treated as perfectly inelastic over that timeframe, producer surplus is approximated effectively as revenue accruing to production at the price during the harvest period:

$$(16) \quad \pi_{Qs} = p_1 * Qs \quad and \quad \Delta\pi_{Qs} = p_1 * Qs - p_1^0 * Qs_1^0$$

where π_{Qs} is producer surplus (farm income) evaluated at harvest prices.

Any actual farm income and gains due to storage are lumped with trader income/costs to be derived later. Benefits accruing to farmers as a consequence of their trading activities, such as storage, forward selling, or participation in futures markets, are also captured in trader profits not producer revenue. This methodology cannot disentangle who among various commodity market participants realizes the benefits or losses accruing to traders.

In the scenarios when supply is not assumed to be endogenous β_Y and β_A are set equal to zero, so supply is perfectly inelastic in the medium to long run. When price responsiveness and endogenous supply are considered, the dynamics of supply adjustment across crop years will generate different market outcomes and so different welfare outcomes due to that adjustment. Nevertheless, producer welfare remains measured as revenue because in the short run supply is perfectly inelastic.

Utilization

Demand components in WASDE supply-utilization balances include various domestic uses, exports and annual carry-out stocks. The WASDE forecast provides estimates of exports and stocks, conducting quarterly stocks surveys and collecting some weekly (from FAS/USDA) and some monthly trade data (from ITC/Commerce). Domestic use (feed use) is treated as a residual, insuring supply-use balance holds. As shown above, this means forecast errors for stocks and use are not independent, so we specify one of these, calculating the other from this equilibrium condition. In principle, from a modeling perspective, it makes more sense to specify the error as an error in the domestic use (demand) functions, but this error will show up in WASDE reports as an error in expected stocks, and that is what NASS surveys measure. The S-U balance relationship can be used with historical data to specify/compute a use error component from the observed stocks errors.

With an improved forecast (when a new WASDE report is issued):

$$(17) \quad S_{t-1}^0 + \varepsilon_{S,t-1}^f + Qs_1^0 + \varepsilon_{Qs}^f = Qd_t^0 + \varepsilon_{Qd,t}^f + E_t^0 + \varepsilon_{E,t}^f + S_t^0 + \varepsilon_{S,t}^f$$

Quarterly S-U expectations error balance

$$(18) \quad \varepsilon_{S,t-1}^f + \varepsilon_{Qs}^f - \varepsilon_{Qd,t}^f - \varepsilon_{E,t}^f = \varepsilon_{S,t}^f$$

Annual S-U expectations error balance

$$(19) \quad \varepsilon_{S,0}^f + \varepsilon_{Qs}^f - \sum_{t=1}^{4}\left[\varepsilon_{Qd,t}^f - \varepsilon_{E,t}^f\right] = \varepsilon_{S,4}^f$$

where X_t^0 is a naïve (trend) expectation for variable X_t, and $\varepsilon_{X,t}^f$ is the (revealed) errors in expectations for X_t as expectations improve over a naive forecast in forecast period f. Over time, as new WASDE forecasts are issued, $X_t^0 + \sum_f \varepsilon_{X,t}^f$ approaches actual X_t. Therefore, initially $\varepsilon_{X,t} = \sum_f \varepsilon_{X,t}^f$ is the deviation of actual X_t from a naïve forecast of X_t^0.

Domestic use and export functions depend on the short run price (the price in the quarter when use or exports occur), although in actuality these errors may follow improving production information and use may be moved across quarters. We shall assume price effects capture the consequences of production expectations on use and ignore across quarter 'arbitrage', as rationale expectations are assumed, but need to build domestic and export demand functions that include error terms reflecting imperfect information.

Domestic Use

Domestic demand (Qd) is broken into components in the WASDE report – Food, seed and industrial use (FSI), and Feed Use. Further disaggregation (e.g. into seed use, ethanol use, etc.) is possible from USDA's quarterly feed grain database, but these broader categories will be used here since prior estimates of demand elasticities can be found from the literature for those components and at this level of aggregation. Hence:

$$(20) \quad Qd_t = QFSI_t + QFEED_t$$

Each demand component is modeled as a linear function of price that is benchmarked to base data on quarterly demand with a slope relative to price that gives the assumed elasticity at that initial point.

$$(21) \quad QFSI_t = QFSI_t^0\left(1 - \beta_{QFSI} * \frac{p_t - \rho_t}{\rho_t}\right) + \varepsilon_{QFSI,t}$$

$$QFEED_t = QFEED_t^0 \left(1 - \beta_{QFEED} * \frac{p_t - \rho_t}{\rho_t}\right) + \varepsilon_{QFEED,t}$$

where $QFSI_t^0$ and $QFEED_t^0$ denote base data (trend expectation) in quarter t for domestic demand components FSI and Feed Use, respectively. Similarly, β_{QFSI} and β_{QFEED} are the demand price elasticities and $\varepsilon_{QFSI,t}$ and $\varepsilon_{QFEED,t}$ are the errors (uncertainty) for each domestic demand component.

As noted above, WASDE reports and data collection treat domestic use as a residual, explicitly measuring stocks and production instead. This means we cannot observe the historical patterns of the error terms of quarterly component demand equations. We can compute from supply-utilization balance a measure of the annual domestic use error in each forecast. Therefore, we build into the model that error in a manner similar to treatment of the errors in production estimation. Hence,

$$(22) \quad \varepsilon_{Qd} = \sum_{t=1}^{4} [Qd_t - Qd_t^0]$$

is the difference between domestic use at p_0 and trend use. ε_{Qd}^f is the part of ε_{Qd} revealed by forecast f, so:

$$(23) \quad \varepsilon_{Qd} = \sum_{f=2}^{6} [\varepsilon_{Qd}^f]$$

We need to assume quarterly values for $\varepsilon_{QFSI,t}$ and $\varepsilon_{QFEED,t}$ since they represent some unobserved consumption that generates utility, and so are part of the constants of the demand functions used to measure that. We must make some strong assumptions to do so. We shall assume that this error is entirely due to feed use (not FSI), since feed use is the largest and most uncertain component of domestic use, hence $\varepsilon_{QFSI,t} = 0$. We shall further assume that the error in feed use is proportionally weighted across quarters according to historical use patterns.

Consumer surplus relative to the base outcome is calculated each quarter from these functions as the sum of surplus from actual feed use and FSI use in that quarter. Since demand functions are linear, surplus measures are simply the triangles defined by price, quantity used and the intercept of the demand function:

$$(24) \quad \pi_{QFSI} = \sum_{t=1}^{4} (pmax_{FSI,t} - p_t)(QFSI_t)/2$$

$$\pi_{QFEED} = \sum_{t=1}^{4} (pmax_{FEED,t} - p_t)(QFSI_t)/2$$

where $pmax_{FSI,t}$ and $pmax_{FEED,t}$ are the intercepts of the linear demand function in each quarter found from the demand equations above (by setting $QFSI_t = 0$ & $QFEED_t = 0$), and including the appropriate $\varepsilon_{QFSI,t}$ and $\varepsilon_{QFEED,t}$ as part of that constant.

Exports

Exports are modeled and information on exports is revealed in a manner similar to domestic use, except that WASDE reports explicitly estimate/observe export data over short time horizons. Exports are uncertain because of production uncertainty, hence availability, as reflected in the expected price, and because foreign demand depends also on uncertain foreign production. USDA estimates production worldwide, but information is not as timely as for the US, in part because production in some key competitor countries occurs in the southern hemisphere, giving rise to a six month lag relative to the US crop year schedule. Hence, we need price dependent export demand functions that exhibit the errors slowly revealed by WASDE reports:

$$(25) \quad E_t = E_t^0 \left(1 - \beta_E * \frac{p_t - \rho_t}{\rho_t}\right) + \varepsilon_{E,t}$$

where E_t^0 denotes base export data (trend expectations) in quarter t, β_E is the export demand price elasticity, and $\varepsilon_{E,t}$ is the error (uncertainty) in export demand each quarter.

As for domestic use, we shall assume errors revealed about exports are shared proportionally across quarters according to historic quarterly export patterns. As for domestic use, export demand functions need to be adjusted as information about past exports is revealed.

Exports are described by a demand function representing the behavior of foreigners, so export surplus (π_{Export}) can be computed in a manner similar to end user surplus (see equation 24). Since this accrues to foreigners, it is not included in overall welfare, intended to capture benefits to U.S. domestic interest groups. Nevertheless, it provides evidence on the net spillover effects of WASDE information to trade partners and competitors, although the distribution of benefits is likely to matter, as it does for domestic agents. Also, a global social welfare estimate would add the exporter welfare to our current overall welfare measure.

Stocks and Prices

Uncertainty in annual carry-out stocks is based on uncertainty in the other components of supply-utilization balance and may be derived from them (or observed, as in practice). The theory of storage (Williams and Wright, 1982; Wright, 2011) is used to model short term pricing and to establish annual price levels as a function of expected stocks.

From our equilibrium condition (supply-utilization balance) expected annual carry-out stocks are:

$$(26) \quad S_4^f = S_0^f + Qs_1^f - \sum_{t=1}^{4}\left[QFSI_t^f + QFEED_t^f + E_t^f\right]$$

$$S_8^f = S_4^f + Qs_5^f - \sum_{t=5}^{8}\left[QFSI_t^f + QFEED_t^f + E_t^f\right]$$

Hence, stocks link crop years because the annual carry out from one year becomes the carry-in for the next year. Similarly, stocks link quarters because carry-out from one quarter equals carry-in to the next quarter. We assume that expected stocks also respect these linkages.

Pricing within a crop year presumes, according to the theory of storage, that the expected price in one quarter must equal the price in the prior quarter plus storage costs whenever stocks are held from one quarter to the next. Hence:

$$(27) \quad For\ t = 2,3,4,6,7,8;\ \ p_t^f = p_{t-1}^f + \alpha$$

where α is the cost to store one quarter. Across crop years expected prices can disconnect from this relationship, for example if a low production (shortfall) year is followed by an expected high (surplus) production year. In principle, stocks would be completely drawn down (to zero) in the short year, and the price in the short year would exceed the price in the abundant year by more than storage costs. This relationship can easily occur if stocks are low relative to the uncertainty in production each year. This would be represented by a complementary slackness condition relating annual carry-out stocks to the expected prices before and after harvest:

$$(28) \quad p_5^f \leq p_4^f + \alpha; \qquad S_4^f \geq 0 \quad and \quad \left(p_5^f - p_4^f - \alpha\right)S_4^f = 0$$

In practice stocks never are zero, as there is a pipeline level of stocks that must be maintained. The minimum stocks level is also not well known, nor is the "convenience yield"[10] associated with holding stocks when this pricing relationship suggests they should be sold. We approximate the L shaped stocks demand function represented above by a function that asymptotically approaches either the short run pricing linkage (when stock and supply are abundant) or the minimum stocks level (when supply is low):

$$(29) \quad S_4^f = Smin + \varphi/\left(p_4^f + \alpha - p_5^f\right)$$

where $Smin$ is the exogenously assumed minimum stocks level; and φ is a constant fitting this pricing relationship to observed market data. The model presumes agents are looking ahead to the next crop year, so to close the model we need a function explaining carry-out stocks from the next crop year ($t = 8$). We presume it is based on a long run expectation of some minimum price that prevails when stocks are abundant (p^*).

$$(30) \quad S_8^f = Smin + \varphi/\left(p_8^f + \alpha - p^*\right)$$

Figure 1 depicts this stocks demand relationship for this latter condition with p^* set at \$3.00 per bushel and $Smin$ at 600 million bushels, which we believe are reasonable assumptions for the U.S. corn market.

Welfare

The costs of stockholding reduce producer revenue relative to export revenue plus expenditures on domestic use. Traders may also realize gains or losses on the stocks they hold, when expectations and so prices change. We can compute the net costs to traders by comparing these revenue streams:

$$(31) \quad TC = \sum_{t=1}^{4} [p_t\{QFSI_t + QFEED_t + E_t\}] - p_1 * Qs$$

By computing actual storage costs we can also determine net trader profit (or loss):

$$(32) \quad \pi_T = TC - \sum_{t=1}^{4} \alpha * S_t$$

Overall welfare for any simulated scenario is the sum of producer surplus, consumer surplus and net trader profit:

[10] Convenience yield is the (positive) difference between the expected future price and the current price plus storage costs. It applies for the quarters that cross crop years, and when stocks fall near minimum (pipeline) levels. It was first introduced by Keynes (1930) and its relevance to the theory of storage is explained by Wright (2001).

$$(33) \quad W = \pi_{Qs} + \pi_{Qd} + \pi_T$$

Foreigner welfare (π_{Export}) is calculated separately, and can be added to W to gauge global welfare.

Monte Carlo Simulation Strategy

Monte Carlo simulations generate estimates of the distributions of various equilibrium outcome measures (prices, quantities and welfare) based on assumptions concerning uncertain exogenous factors. In this case area planted/harvested, yield, therefore production; domestic feed use; and exports were all considered stochastic. The error terms in the above model specification define when information is revealed about each of these terms. Assumptions and historical data are used to describe when information is revealed by WASDE reports and what a naïve forecast might look like. Table 1 summarized that historical information. The error terms are assumed to be normally distributed, and correlated. A random number generator establishes for each iteration a realization of each error term such that the distribution of the error terms over a large number of iterations follows the observed distribution, including its covariance.

The model used here has a short term module that is repeated over time in order to capture a sequence of years. Hence, the number of iterations is the number of years in that sequence (10 years are projected here) times the number of repetitions of that sequence. Since there are several correlated error terms, and based on experimentation with the model, it became clear that a large number of iterations is needed to accurately reproduce the assumed distributions of the error terms. Therefore, 3000 repetitions of the 10 year sequence are solved, resulting in 30,000 iterations for each scenario examined. Experimentation with varying numbers of repetitions indicated results are consistent at this large number of iterations, hence crop years simulated.

The model incorporates short run elements and long run elements. The short run version of the model begins with the quarter before harvest when planting occurs, finding expected equilibrium during the next crop year and setting initial conditions (most importantly, carry-in stocks levels). Then that quarter becomes history and the first quarter of the crop year is simulated, determining actions taken during that quarter based on history and expected future outcomes. This is repeated by moving forward through each of the four quarters in the crop year, as prior quarters become history and future expectations are over fewer quarters in the crop years. The solution of the fourth quarter is the same as the solution of the prior quarter for this crop year, but applicable to the next crop year. A final outcome

is established based on revealed uncertainty once the crop year has completed and all decisions have been taken. That final outcome describes quantities and prices each quarter, and is used to calculate welfare measures. The model then moves forward to the next crop year, assuming that quarter 4 is now the history establishing initial conditions for that next crop year.

In principle, one might choose to iterate over 1000 years (or more), repeating this sequence that many times. In order to avoid persistence effects that might occur as large stocks build in some simulations, we chose to instead repeat sequences of ten year projections. That builds in sufficient variability in initial and terminal conditions so that they are not overly important in averaging model outcomes across the entire sample of simulations. The goal is for the predictions of the model to accurately trace out the distributions of market outcomes under presumed existing uncertainty, and under varying assumptions on information availability. Our selection of base case matters to the relevance of the results, so we have chosen it to approximate recent "normal years".

Three basic cases incorporating different assumptions on the timing and extent of market information are considered, and the 30,000 iterations are repeated for each case. In each case the same assumptions on underlying uncertainty are assumed, and the same realizations of error components are used. Differences across scenarios are in when information about that uncertainty is revealed. A perfect information case presumes that the variations in the stochastic terms are fully known immediately (f=0). The WASDE case assumes that the distributions of error terms as described in the specification above follow deviations from trend predications as in the historical WASDE forecasts since 1994. In the naïve case, it is presumed that information becomes available one quarter later than in the WASDE case, when market outcomes have already occurred and when there has been sufficient time to observe what those outcomes were. Variations on the base cases are used to conduct sensitivity analysis on key parameters – price responsiveness of uses and supply. Additional sensitivity analysis cases are also used to assess the value of each component of the WASDE forecasts.

Empirical Model Implementation

The short run model is benchmarked to data on US corn market after the 2007-08 food crisis from the USDA's Feedgrains database. The intent is to represent an average over recent normal years for benchmarking. Therefore, our base data is for variables averaged over the 2010/11, 2011/12 and

2013/14 crop years.[11] The 2012/13 crop year was omitted in benchmarking the model due to the extremely low yields in that year, though included when deriving the empirical forecast error distributions. The feed grain database includes information at the level of aggregation in the model specification on a quarterly basis. Table 3 present the base data assumed in this model.

To ensure a dynamically stable model, the expected outcome in the next crop year is based on the same assumed base outcome for the current crop year. That is, if the stochastic elements of the model remain fixed at their base levels, the same base outcome will be repeated year after year. Trends are therefore suppressed. Carry-in and carry-out stocks levels were adjusted slightly from observed averages so that they are the same in each base year. The assumed level is above minimum stocks, but is not so large as to drive prices near minimum assumed price levels. The minimum assumed stocks and price levels, at 600 million bushels and $3.00 per bushel, are judgment calls based on recent market behavior.

As noted above, stochastic terms in the model include production as captured by area and yield, and use as captured by feed use and export demand. Table 1 reported deviations from a naïve trend forecast for each of these elements and standard deviations, in both percentage terms relative to base market outcomes and in the units of measure for each term. The model's random number generator and Cholesky transformation generate correlated percentage error realizations that are transformed to the appropriate units of each error using the mean values of variables in the base case. The WASDE forecast for the first month of each quarter is used to establish errors. Hence, September is the month of the first report once a new crop year begins. June reports inform both the final quarter of a crop year and expectation on the next crop year. December and March reports inform quarters 2 and 3 of a crop year. As noted earlier, we are likely underestimating the value of WASDE reports since they are actually provided monthly, and some information is available ahead of the schedule we assume. Table 1 indicates how important this might be by showing forecast errors in additional months beyond those built into the model.

The model implementation is completed by specifying parameters for the various behavioral equations included in our model specification. These are elasticities of demand for feed use, food use and exports as well as supply elasticities for area planted and yield adjustments. As corn is a major agricultural commodity in the US, a great deal of research has been undertaken to estimate these elasticities.

[11] We use this recent data to establish base levels for variables but distributions for errors are estimated from data going back to 1993. Those estimations are for errors in percentage terms, so that they can be applied to this more current base year approximation.

Moreover, several simulation models used to evaluate policy alternatives have assumed elasticities based on that literature and on author judgment. Table 4 presents the results of various studies estimating or assuming these supply and demand elasticities. The studies showed markedly different responsiveness of demand or supply to changes in prices. This empirical literature showed the elasticity of demand for exports ranged from -0.3 to -1.727; feed and residual use elasticities ranged from -0.11 to -0.9; and FSI elasticities ranged from -0.064 to -0.33. In our base case the demand elasticities used to calculate the slopes of demand functions are FSI (-0.2), Feed (-0.4), and exports (-1.0). Supply elasticities ranged from 0 to 0.4 for area and 0 to 0.2 for yield. Given the ambiguity of the results from previous literature, and evident difficulties in estimating them, we have benchmarked our model to a set of assumed elasticities rather than directly using econometrically estimated models. The elasticities chosen for the base case are in the middle of this wide range of previously estimated values.

The slope of the demand curve is important both because it describes how agents behave and is also a key factor in the computation of welfare measures. Similarly, there is controversy on what are appropriate supply elasticities[12], and these are key to determining effects on producer revenue. To account for the potential differences in the value of information due to elasticity assumptions, the model was simulated over an additional three sensitivity analysis scenarios. Alternative scenario 1 represents a case with the more elastic supply and demand parameters found in Table 4 for each category. Scenario 2 is less elastic than the original WASDE model, based on the lower range of elasticities found in table 4. Scenario 3 makes supply perfectly inelastic in the long run, largely to assess how the effects due to supply parameter changes matter. These assumptions were used to re-estimate the distributions of the outcomes of the three information cases- naïve, perfect and WASDE.

Decomposition of the value of various WASDE components is assessed by assuming only the error term associated with a specific component is revealed according to the WASDE schedule. Since it makes little sense to assume better domestic use or export forecasts in the absence of a better production forecast, in those cases we conducted simulations assuming that the production forecast, and either the domestic demand or export forecast, improved according the WASDE schedule. This allows us to approximately estimate the added value from area, yield, production, export and demand/stocks forecasts separately.

[12] Traditionally it has been assumed that area is price responsive with a small elasticity but yield is not. Miao, Khanna and Huang (2015) recently argued that previous estimates are too small, and that yield is also price responsive. Our base case reflects the traditional assumption while one sensitivity analysis scenario assumes more elastic area and yield response.

Results

Table 5 presents results from three scenarios representing alternative assumptions on information availability and timing. Then results for overall (net) expected welfare and welfare measures for specific agents are reported for each assumption – Naïve expectations, Perfect information and WASDE expectations. To facilitate comparisons, differences in these average (or expected) outcomes across scenarios are calculated. These scenarios are all generated using the base elasticity assumptions.

In this base case overall welfare has increased on average by $301 million from the Naïve expectations scenario to the WASDE expectations scenario. It increased further, by another $284 million, in the Perfect information scenario, $585 million higher than in the Naive scenario. This improvement due to WASDE reports is 0.55% of corn market value as measured by producer revenue. Hence, there is significant value to WASDE reports, though it is a small fraction of overall market value

The overall welfare gains are distributed unequally across agents. Like the gains from trade, there are winners and losers but also net gains. Moreover, the redistributions of benefits are large relative to the net gains. Consumers (end users) gain the most, at $341 million, due to a $240 million or 0.49% reduction in expenditure on corn. Producers gain additional revenue amounting to on average $153 million, or 0.28% of their revenue. Traders' profit declines $192 million, or 8.7% of base trader costs. It is important to remember the assumptions in setting these measures (that producers sell at harvest), and to remember that farmers who hold stocks are counted as traders. The trader welfare measure represents benefits accruing to not only farmers but also commercial agents, and it is not possible with this methodology to separate benefits or costs between those sub-agents.

Export revenue has increased $172 million or 2.3%, resulting in an increase in foreigner surplus of $19 million as price increases offset effects of quantity increases. This is a spillover benefit, not counted in overall welfare that was constructed to capture outcomes for domestic agents only.

The fact that WASDE has moved more than half of the way to the value of the perfect information outcome suggests further returns to better information could be difficult to achieve given the inherent uncertainty in forecasting agricultural production and trade, and the expected increasing marginal costs of acquiring better information. Information from the perfect information case suggest only small additional gains to consumers, and bigger gains to producers, to some extent at the expense of traders.

Producer revenue is $465 million higher in the perfect information case, while trade losses are $213 million higher.

Table 6 reports results comparing scenarios that introduce only components of the WASDE forecast in order to assess the incremental contributions of each component. In the export and demand/stocks cases, however, the scenario presumes WASDE production information is also known. The area forecast, for example, increases overall welfare by $145 million. This is the gain in expected welfare when only the area forecast improvements due to WASDE information are included, and is relative to naïve expectations. For yield, these gains amount to $188 million. Producer revenue gains are larger, however, in the yield case, at $152 million, relative to the area case, where producer gains are only $32 million. Similarly sized changes in the other direction are found for trader profit, while the increases in consumer surplus are similar in size to the overall gains, when all information becomes available. The gains from production forecasts – the combination of better area and better yield forecasts -- are not quite additive, at $299 million, with gains to each agent being similar to that found for yield information improvement. Overall gains from the export demand forecast (hence from better information on foreign production and trade) are $320 million. Since the production information is assumed to be known in this scenario, marginal net gains are small, at about $21 million. The distribution of gains is different, however, producer gains and traders losses are smaller by $86 million, while consumer surplus is largely unchanged. Marginal gains from the feed demand forecast, hence from better stocks information, are also small, with producer gains in this case increasing by $38 million, while trader losses are larger by $31 million. Each of these components is contributing to the distribution of welfare gains from the information contained in WASDE reports, with the production information accounting for the biggest portion of overall or net gains.

Table 7 presents sensitivity analysis from scenarios that varied the demand and supply elasticities around the assumptions of the base case. The first column reports outcomes for the base case, the final column of table 5. Elasticities assumed are shown at the bottom of this table, and are at the "reasonable" extremes of results from our literature search (see Table 4). Overall welfare gains or their distribution are of a similar magnitude, except when perfectly inelastic supply is coupled with lower demand elasticities. In that case overall welfare gains are only $221 million, and the smallest producer gains, at $94 million, are found. More elastic demand also means lower consumer surplus gains. Trader losses are greatest, at $604 million, and consumer surplus gains the largest, when demand is assumed to be more inelastic. In the case of producers, however, greater elasticity, hence greater adjustment in the

face of market signals, results in greater gains from better information. Both the overall gains and their distribution across agents are clearly sensitive to these elasticity assumptions. This sensitivity is due both to the market behaviors these elasticities represent and to the calculation method to arrive at welfare measures.

Exporter surplus, hence the spillover gains realized by foreigners, behave like demand and are larger when export demand is more inelastic. Since exports are a fraction of domestic use (16% in the base case), the magnitude of these spillovers is smaller in size than are consumer surplus gains. In the inelastic demand case foreigner gains rise to $56 million. But when that is coupled with inelastic supply, spillover gains disappear.

Results presented above have shown that the incremental contributions of WASDE components are not additive, and that expected welfare and its distribution across agents are sensitive to supply and demand elasticity assumptions. This is because the model, and notably stocks demand, is not linear. Prices spike when there are production shortfalls and low carry-in stocks under inelastic demand, but are much less variable when there are surpluses that end up in carry-over stocks. Stocks persistence means there are more cases of large supply resulting in low prices and revenue than of shortfalls and disproportionally higher prices and producer revenue. This behavior results in skewed distributions for both overall welfare and the welfare of each agent. The median overall net welfare gain due to WADSE information (compared to a corresponding naïve outcome) is $340 million, $39 million larger than the mean net gain. Means are generally higher than median values in each scenario for producer revenue and trader profit, and they are usually lower for consumer surplus. The skewness in overall welfare is greater in the WASDE case than in the naive information case. For example, median overall welfare is $49 million lower than mean welfare in the naïve scenario, and $103 million lower in the WASDE scenario. Median producer revenue is $223 million lower in the naïve scenario, but only $2 million lower in the WASDE scenario, however. Median consumer surplus revenue is $370 million higher in the naïve scenario, and $269 million higher in the WASDE scenario. Figure 2 presents histograms showing this skewness for both overall welfare and for the welfare of each agent type in our base case under WASDE expectations. The skewness is seen as more pronounced for consumer surplus and trader profit relative to producer revenue. Differences in means, medians, and skewness across information assumptions and across agents result in skewness in the other direction for net gains to WASDE information.

Conclusions

WASDE reports published monthly by USDA provide public information on both past and likely future outcomes in global agricultural commodity markets. Recent literature has shown that these reports are essentially unbiased and that markets respond to the news in those reports (Irwin, Sanders and Good, 2014; Lusk, 2013). This paper attempts to estimate the value of that news to market participants utilizing a methodology that has advanced in investigating price stabilization policy but has not been updated to address the value of public market information. Monte Carlo simulations of a quarterly model of the U.S. corn market generate estimates of the magnitude and distribution of economic benefits due to WASDE reports for that market. Separate experiments determine the distribution of this value to farmers as producers, traders (including farmers), and consumers (end users). They also estimate the value of each component of forecasts included in WASDE reports – area and yield, hence production; exports; and demand/stocks. Sensitivity analysis explored the wide range of estimated elasticities describing supply and demand behavior in the corn market.

The expected value of WASDE outlook information on the U.S. corn market is estimated to equal $301 million, or 0.55% of corn market value as measured by production revenue. Since the model is non-linear outcomes distributions are skewed. So that median net gains are $340 million. While these are only a small fraction of market value, it surely exceeds the marginal costs of generating this information, and as we will see below, this is likely an underestimate of the value of these reports. The analysis also generates an estimate of net foreigner surplus, or spillovers of better WASDE information onto global markets. Foreigner surplus was estimated at $19 million, which sums benefits or losses to trading partners as well as competitors.

One reason why market response is so strong to these reports is that the benefit to certain agents is often larger than overall (net) welfare gains, and there are losers as well as winners. Like the gains from trade, the redistribution of benefits between agents is often at least as great as the net gains. This methodology identifies impacts on producers (revenue valued at harvest prices), traders, and consumers. Farmers behave as both producers and traders. End users may also behave as traders along with commercial agents like grain elevator operators and the multi-national grain exporters, who are only traders. In our base case results, consumers are the biggest winners from better information, and producers also gain while trader profits are smaller. These outcomes are sensitive to assumptions on elasticities that are used to measure both market behavior and welfare.

Alternative assumptions on supply elasticities revealed differences in model predictions. Similarly, alternative assumptions on demand elasticities also alter the estimates of both the overall welfare impact of WASDE reports and the distribution of those impacts. Overall welfare impacts of WASDE information in the entire set of scenarios ranged from $221 to $348 million. Trader losses ranged from $192 to $604 million. The more inelastic an agent is, the greater its gains from better information. Trader profits are smallest when demand elasticities are the smallest, and foreigner surplus spillover is almost three times as great when more inelastic export demand is assumed. Moreover, non-linearity of the model, due largely to stockholding behavior, leads to skewed distributions of overall benefits and the extent of redistribution. Any market model is dependent on the quality of behavioral information it incorporates, and this exercise highlights the need to continue to reevaluate the magnitude of price responsiveness in agricultural markets.

One limiting assumption of this methodology is the availability of market information if the public information provided by USDA were no longer available – the assumptions of the "naïve" scenario. While there is now "competing" private information on agricultural markets, most of that is complementary to and reliant on USDA data and outlook reports. It is difficult to predict when market information would become available, or how accurate it would be, in the absence of USDA data. If public information disappears, it is likely that some sub-sets of agents (e.g. large commercial traders) would suffer less than the decline in information available to farmers (as either producers or traders). Hence, one role of the WASDE reports is to level the playing field.

There are several other limitations to this methodology, most of which would result in underestimation of the value attributable to USDA data and to WASDE reports. First, generation of the outlook reports is an integral part of the process of collecting historical data. Without that historical data, gauging market trends as well as understanding adjustments to various shocks (e.g. weather) would be more difficult. Even our naïve scenario must assume historical data is available, and abstracts from the difficult task of identifying trends, and when they might change. Secondly, WASDE reports are issued monthly, as are numerous other reports, while this model assumes information improves on a quarterly basis. Data limitations and the requirement to keep the model manageable necessitated this approach. A more time disaggregated model would likely find higher value to the more timely information available in those more frequent reports. Thirdly, in spite of its seeming complexity, this is a rather simple model that may well exclude mechanisms (such as futures trading and inter-quarter arbitrage) that would allow traders to take advantage of frequent, timely information.

The value of information is limited by the decisions that are enabled and improved by better information. While in some cases it is hard to identify actions that can be taken given better information, for WASDE reports that is not the case. These results suggest that significant value, especially to specific agents, can be attributed to both USDA data and to its outlook reports. It should be no surprise that markets respond when these reports are issued, because agents with much at stake can take better informed decisions.

References

Adjemian, M. K. (2012). Quantifying the WASDE Announcement Effect. *American Journal of Agricultural Economics, 94*(1), 238-256. doi: 10.1093/ajae/aar131

Adjemian, M. K., & Smith, A. (2012). Using USDA Forecasts to Estimate the Price Flexibility of Demand for Agricultural Commodities. *American Journal of Agricultural Economics, 94*(4), 978-995. doi: 10.1093/ajae/aas032

Babcock, B. A. (2008). Distributional Implications of U.S. Ethanol Policy. [Article]. *Review of Agricultural Economics, 30*(3), 533-542. doi: 10.1111/j.1467-9353.2008.00428.x

Baur, R. F., & Orazem, P. F. (1994). The Rationality and Price Effects of U.S. Department of Agriculture Forecasts of Oranges. *The Journal of Finance, 49*(2), 681-695. doi: 10.1111/j.1540-6261.1994.tb05157.x

Bigman, D. and S. Reutlinger (1979). Food Price Stabilization: National Buffer Stocks and Trade Policies. *American Journal of Agricultural Economics*, 61(4): 657-667.

Boussios, David, and Andrew Barkley. 2014. "Producer Expectations and the Extensive Margin in Grain Supply Response." *Agricultural and Resource Economics Review* no. 43 (3):335-356.

Bradford, D. F., & Kelejian, H. H. (1977). The Value of Information for Crop Forecasting in a Market System: Some Theoretical Issues. *The Review of Economic Studies, 44*(3), 519-531. doi: 10.2307/2296905

Bradford, D. F., & Kelejian, H. H. (1978). The Value of Information for Crop Forecasting with Bayesian Speculators: Theory and Empirical Results. *The Bell Journal of Economics, 9*(1), 123-144. doi: 10.2307/3003616

Bredahl, M. E., Meyers, W. H., & Collins, K. J. (1979). The Elasticity of Foreign Demand for U.S. Agricultural Products: The Importance of the Price Transmission Elasticity. *American Journal of Agricultural Economics, 61*(1), 58-63. doi: 10.2307/1239500

Chambers, R. G., & Just, R. E. (1981). Effects of Exchange Rate Changes on U.S. Agriculture: A Dynamic Analysis. *American Journal of Agricultural Economics, 63*(1), 32-46. doi: 10.2307/1239809

Chavas, Jean-Paul, and Matthew T. Holt. 1990. "Acreage Decisions under Risk: The Case of Corn and Soybeans." *American Journal of Agricultural Economics* no. 72 (3):529-538. doi: 10.2307/1243021.

Choi, Jung-sup, and Peter G Helmberger. 1993. "How sensitive are crop yields to price changes and farm programs?" *Journal of Agricultural and Applied Economics* no. 25 (01):237-244.

Fortenbery, T. R., & Park, H. (2008). The effect of ethanol production on the US national corn price: University of Wisconsin, Agricultural and Applied Economics.

Garcia, P., Irwin, S. H., Leuthold, R. M., & Yang, L. (1997). The value of public information in commodity futures markets. *Journal of Economic Behavior & Organization, 32*(4), 559-570. doi: 10.1016/s0167-2681(97)00013-9

Gardiner, W., & Dixit, P. M. (1987). Price elasticity of export demand: concepts and estimates. *Foreign agricultural economic report*.

Gouel, C. (2013). Optimal food price stabilisation policy. *European Economic Review*, 57, 118–134.

Haniotis, T., Baffes, J., & Ames, G. C. (1988). The demand and supply of US agricultural exports: the case of wheat, corn, and soybeans. *Southern Journal of Agricultural Economics, 20*(2), 45-55.

Hayami, Y., & Peterson, W. (1972). Social Returns to Public Information Services: Statistical Reporting of U.S. Farm Commodities. *The American Economic Review, 62*(1/2), 119-130. doi: 10.2307/1821478

Hendricks, Nathan P., Aaron Smith, and Daniel A. Sumner. 2014. "Crop Supply Dynamics and the Illusion of Partial Adjustment." *American Journal of Agricultural Economics*. doi: 10.1093/ajae/aau024.

Irwin, S., and D. Good (2015). "Forming Expectations for the 2015 U.S. Average Corn Yield: What Does History Teach Us?" farmdoc daily (5):36, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, February 26, 2015.

Irwin, S. H., Sanders, D. R., & Good, D. L. (2014). Evaluation of Selected USDA WAOB and NASS Forecasts and Estimates in Corn and Soybeans *Marketing and Outlook Research Report 2014-01*. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Isengildina, O., Irwin, S. H., & Good, D. L. (2006). Are Revisions to USDA Crop Production Forecasts Smoothed? *American Journal of Agricultural Economics, 88*(4), 1091-1104. doi: 10.1111/j.1467-8276.2006.00918.x

Isengildina-Massa, O., Irwin, S. H., Good, D. L., & Gomez, J. K. (2008). The Impact of Situation and Outlook Information in Corn and Soybean Futures Markets: Evidence from WASDE Reports. *Agribusiness, 24*(4), 18.

Just, R. E., & Weninger, Q. (1999). Are Crop Yields Normally Distributed? *American Journal of Agricultural Economics, 81*(2), 287-304. doi: 10.2307/1244582

Kastens, T. L., Schroeder, T. C., & Ron, P. (1998). Evaluation of Extension and USDA Price and Production Forecasts. *Journal of Agricultural and Resource Economics, 23*(1), 244-261. doi: 10.2307/40986979

Keynes J.M. (1930). A Treatise on Money: The Applied Theory of Money, Londres, Macmillan, vol. 2.

Lusk, J.L. "From Farm Income to Food Consumption: Valuing USDA Data Products."The Council on Food, Agricultural & Resource Economics (C-FARE), Washington, D.C., 2013. (http://www.cfare.org/UserFiles/file/events/c-fare-data-review-full-report.pdf)

Lin, William, and Robert Dismukes. 2007. "Supply response under risk: Implications for counter-cyclical payments' production impact." *Applied Economic Perspectives and Policy* no. 29 (1):64-86.

MacDonald, S. (2005). *A Comparison of USDA's Agricultural Export Forecasts with ARIMA-based Forecasts.* Paper presented at the 2005 Federal Forecasters Conference, Washington D.C.

Massell, B.F. (1969). Price Stabilization and Welfare. *The Quarterly Journal of Economics*, 83(2): 284-298.

McNew, K. P., & Espinosa, J. A. (1994). The informational content of USDA crop reports: Impacts on uncertainty and expectations in grain futures markets. *Journal of Futures Markets, 14*(4), 475-492. doi: 10.1002/fut.3990140408

Miao, Ruiqing, Madhu Khanna, and Haixiao Huang. 2015. "Responsiveness of Crop Yield and Acreage to Prices and Climate." *American Journal of Agricultural Economics*:aav025.

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica, 29*(3), 315-335. doi: 10.2307/1909635

Oi, W.Y. (19610. The Desirability of Price Instability Under Perfect Competition. *Econometrica,* 29(1): 58-64.

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

Orazem, Peter F, and John A Miranowski. 1994. "A dynamic model of acreage allocation with general and crop-specific soil capital." *American Journal of Agricultural Economics* no. 76 (3):385-395.

Reimer, J. J., Zheng, X., & Gehlhar, M. J. (2012). Export Demand Elasticity Estimation for Major U.S. Crops. *Journal of Agricultural and Applied Economics, 44*(4), 501-515.

Roberts, Michael J, and Wolfram Schlenker. 2013. Identifying supply and demand elasticities of agricultural commodities: implications for the US ethanol mandate. In *NBER Working Papers*: National Bureau of Economic Research.

Taylor, R. D., Mattson, J., Andino, J., & Koo, W. (2006). *Ethanol's impact on the US Corn Industry*: Center for Agricultural Policy and Trade Studies, Department of Agribusiness and Applied Economics, North Dakota State University.

USDA, E. R. S. (2015). *Feed Grains Database*.

Vogel, F. A., & Bange, G. A. (1999). Understanding USDA Crop Forecasts. *Miscellaneous Publication No. 1554, US Department of Agriculture, National Agricultural Statistics Service, and Office of the Chief Economist, World Agricultural Outlook Board*.

Waugh, F.V. (1944). Does the Consumer Benefit from Price Instability? *The Quarterly Journal of Economics,* 58(4): 602-614.

Womack, A. W. (1976). The US Demand for Corn, Sorghum, Oats and Barley: An Econometric Analysis: University of Minnesota, Department of Applied Economics.

Wright, B. D. (2011). The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy, 33*(1), 32-58. doi: 10.1093/aepp/ppq033

Wright, B.D. (2001). Storage and Price Stabilization. *The Handbook of Agricultural Economics*, Volume 1B. Bruce L. Gardner and Gordon C. Rausser, eds. Elsevier Science B.V., Amsterdam.

Wright, B. D., & Williams, J. C. (1982). The Economic Role of Commodity Storage. *The Economic Journal, 92*(367), 596-614. doi: 10.2307/2232552

Table 1. Area, Yield, Production, Stocks and Export Uncertainties

		Area	Yield	Production		Exports		Stocks	
		CV*	CV*	CV*	StDev	CV*	StDev	CV*	StDev
Trend adjusted variation									
	Naïve error+	5.4%	8.2%	10.0%	1291	25.3%	444	51.9%	629
Errors in WASDE reports prior to harvest									
	May	2.5%	8.3%	9.3%	1201	24.8%	437	59.6%	663
	June	2.4%	8.4%	9.2%	1187	24.9%	438	58.5%	651
	August	0.9%	4.8%	4.3%	549	19.8%	350	37.6%	418
Errors in WASDE reports during crop year									
	September	0.9%	4.0%	3.5%	454	19.1%	338	35.5%	395
	November		0.8%	0.8%	102	15.1%	267	29.9%	333
	December					13.4%	236	25.4%	282
	March					7.9%	140	24.6%	274
	June					4.3%	76	12.0%	134
	August					1.6%	28	8.7%	105
Errors in WASDE reports after crop year									
	September							9.4%	115

+ Standard deviation of the error term from a naïve (trend) forecast, and relative to the base variable value (CV).

* Standard deviation of the forecast error in that month's report, and relative to the base variable value.

WASDE forecast errors are from monthly reports between 1993 and 2014.

Base variable values are an average over the 2010/11, 2011/12 and 2013/14 crop years.

Table 2. Corn Market Information and Uncertainty Calendar

t	Quarterly Periods	Uncertainty (Naïve case)	f	WASDE Release Months	Information Improvements for current crop year only
	Prior crop year (Y = 0)				
t = -1, Y = 0, Q = 3	March-May Q3	Supply (Area, Yield) Exports Domestic Use Stocks (t=-1,0,4)	0		Initial conditions from historical data - uncertain initial stocks and use data Naïve expectations
t = 0, Y = 0, Q = 4	June- August Q4	Supply (Area, Yield) Exports Domestic Use Stocks (t=-1,0,4)	1	May, June, July (Area planted survey) (Stocks survey in June)	Area Stocks (t=-1,0)
	Current crop year (Y = 1)				
t=1, Y = 1, Q = 1	September- November Q1	Supply (Area, Yield) Exports Domestic Use Stocks (t=4)	2	August, September, October (Yield surveys) (Stocks survey in September)	Area now known Yield Stocks (t=0 now known) Exports (Foreign production)
t=2, Y = 1, Q = 2	December- February Q2	Exports Stocks (t=4) Domestic Use	3	November, December, January (Stocks survey in December)	Area known Yield now known Stocks (t= 0 now known) Exports (Foreign production)
t=3, Y = 1, Q = 3	March-May Q3	Exports Stocks (t=4) Domestic Use	4	February, March, April (Stocks survey in March)	Area known Yield known Stocks (t= 0 known) Exports (Foreign production)
t= 4, Y = 1, Q = 4	June- August Q4	Exports Stocks (t=4) Domestic Use Future supply & use	5	*May, June, July* *(For next crop year)*	Area known Yield known Stocks (t= 0 known) Exports (Foreign production)
	Next crop year (Y = 2)				
t= 5, Y = 2, Q = 1	September- November Q1	Future supply & use	6	*August, September, October* *(For next crop year)* *(Stocks survey in September)*	Stocks (t= 4 now known) Exports now known Domestic use resolved

Figure 1. Prices across Crop years versus Minimum Stocks

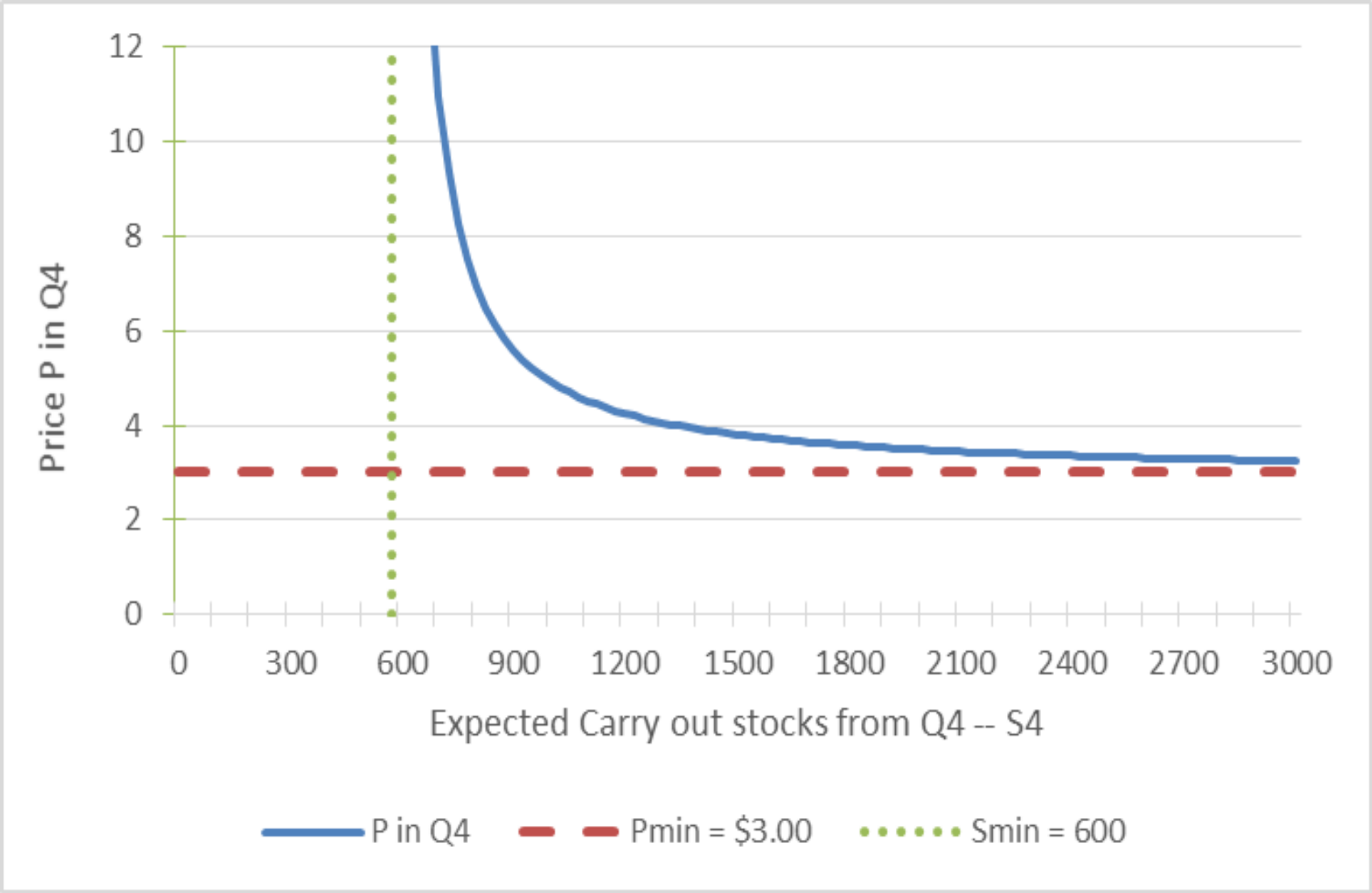

Table 3. Base Data: Perfect Information Outcome

	Prior crop year		Current crop year				Annual	Next crop year				Annual
	Q3	Q4	Q1	Q2	Q3	Q4	Total	Q1	Q2	Q3	Q4	Total
	t = -1	0	1	2	3	4		1	2	3	4	
Price ($/bushel)		4.52	4.25	4.34	6.19	4.43		4.25	4.34	6.19	4.43	
Area (million acres)			84.3				84.3	84.3				84.3
Yield (bushels/acre)			154.2				154.2	154.2				154.2
Production*			12990				12990	12990				12990
Domestic use - FSI		1618	1581	1606	1644	1618	6449	1581	1606	1644	1618	6449
Domestic use - Feed		398	2047	1521	812	398	4778	2047	1521	812	398	4778
Exports		431	403	413	516	431	1763	403	413	516	431	1763
Stocks (carry-out)	3547	1100				1100					1100	

* Quantities are in million bushels

[+] Base data are an average of outcomes for the 2010/11,11/2 and 13/14 crop years (omitting the extradorinarily low production year 2012/13)

Table 4. Own-Price Supply and Demand Elasticities from the Literature

Demand- Exports	**Elasticity Values**
Babcock (2008)#	-1.2
Bredahl, Meyers, and Collins (1979)	-1.31
Chambers and Just (1981)	Range -0.47 to-0.63
Fortenbery and Park (2008)	Range -.26 to-.32
Gardiner and Dixit (1987)^	Range -0.3 to -0.6
Hanoitis, Baffes, and Ames (1988)*	-1.727
Reimer, Zheng, and Gehlhar (2012)	Range -1.11 to -1.64
Demand- Feed and Residuals	
Babcock (2008)#	-0.4
Fortenbery and Park (2008)	Range -.3 to -.4
Taylor, Mattson, Andino, Koo (2006)	-0.11
Womack (1976)	Range -.4 to -.9
Demand- Food, Seed, and Industrial	
Babcock (2008)#	-0.1
Fortenbery and Park (2008)	Range -0.075 to -.064
	-0.33
Taylor, Mattson, Andino, Koo (2006)**	-0.22
Womack (1976)	Range -.08 to -.14
Supply- Area	
Boussios and Barkley (2014)	0.26
Chavas and Holt (1990)	0.15
Hendricks, Smith, and Sumner (2014)	0.4
Lin and Desmukes (2007)	Range 0.17 to 0.35
Miao, Khanna, and Huang (2015)	0.45
Orazem and Miranowski (1994)	0.1
Roberts and Schenkler (2013)	Range 0.086 to 0.114
Supply- Yield	
Boussios and Barkley (2014)	0.18
Choi and Helmberger (1993)	0.27
Miao, Khanna, and Huang (2015)	0.26

*Notes: * Export demand elasticity is a relative price elasticity, measuring the response of US exports to changes of the US export price to the trade weighted export price of US competitors. #- All of Babcock (2008) numbers were estimated to fit model, as opposed to derived. ^- Their review of papers found elasticities to fall in that range. **- The elasticities represent "Ethanol Demand" and "other Industrial Use".*

Table 5. WASDE Valuations – Welfare across Agents and Information Cases ($ millions)

	Naïve Expectations	**Perfect Information**	**WASDE Expectations**	*Perfect Improvement over Naïve*	*WASDE Improvement over Naïve*
Overall Welfare	$150,726	$151,311	$151,027	$585	$301
Producer Revenue	54,322	54,941	54,475	618	153
Consumer Surplus	96,229	96,600	96,570	371	341
Trader Profit	175	(230)	(17)	(405)	(192)
Export Revenue	7,268	7,619	7,440	351	172
Consumer expenditure	49,256	49,072	49,016	(185)	(240)
Export Welfare	4,448	4,345	4,467	(102)	19
Storage Costs	2,027	1,980	1,999	(47)	(28)

Table 6. WASDE Valuations Improvement over Naïve outcome- Forecast Components ($ millions)

	Area	Yield	Production	Export Demand	Feed Demand/ Stocks
Overall Welfare	$145	$188	$299	$320	$300
Producer Revenue	32	152	186	100	224
Consumer Surplus	125	199	338	355	333
Trader Profit	(12)	(163)	(226)	(135)	(257)
Export Revenue	56	88	124	173	131
Consumer expenditure	(48)	(110)	(183)	(234)	(183)
Storage Costs	(12)	(11)	(19)	(25)	(24)
Exporter Surplus	10	40	60	(1)	76

Table 7. WASDE Valuations—Sensitivity Analysis on Elasticities (Improvement over Naïve in $ millions)

	Base	Elastic Supply & Elastic Demand	Elastic Supply & Inelastic Demand	Inelastic Supply and Inelastic Demand
Overall Welfare	301	323	348	221
Producer Revenue	153	279	231	94
Consumer Surplus	341	265	721	369
Trader Profit	(192)	(220)	(604)	(242)
Export Revenue	172	179	179	182
Consumer expenditure	(240)	(143)	(577)	(358)
Export Welfare	19	24	56	(17)
Storage Costs	(28)	(22)	(25)	(28)
Elasticities Assumed				
Export demand	-1.0	-1.5	-0.5	-0.5
Feed demand	-0.4	-0.5	-0.3	-0.3
FSI demand	-0.2	-0.3	-0.1	-0.1
Area Planted	0.2	0.4	0.1	0
Yield	0	0.2	0	0

Figure 2. Simulation Histograms of the Valuations for the Base Case with WASDE Information Available