The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0002-1466.htm

Simulating corn futures market reaction and prices under weekly yield forecasts

Francis Tsiboe
MTED-APM, USDA Economic Research Service, Kansas City, Missouri, USA
Jesse B. Tack
Department of Agricultural Economics, Kansas State University, Manhattan, Kansas, USA
Keith Coble and Ardian Harri
Department of Agricultural Economics, Mississippi State University, Starkville, Mississippi, USA, and
Joseph Cooper
Office of the Chief Economist, Washington, District of Columbia, USA

Received 3 April 2023
Revised 6 August 2023
Accepted 10 August 2023

Abstract

Purpose – The increased availability and adoption of precision agriculture technologies has left researchers to grapple with how to best utilize the associated high-frequency large-volume of data. Since the wealth of information from precision equipment can easily be aggregated in real-time, this poses an interesting question of how aggregates of high-frequency data may complement, or substitute for, publicly released periodic reports from government agencies.

Design/methodology/approach – This study utilized advances in event study and yield projection methodologies to test whether simulated weekly harvest-time yields potentially drive futures price that are significantly different from the status quo. The study employs a two-step methodology to ascertain how corn futures price reactions and price levels would have evolved if market participants had access to weekly forecasted yields. The marginal effects of new information on futures price returns are first established by exploiting the variation between news in publicly available information and price returns. Given this relationship, the study then estimates the counterfactual evolution of corn futures price attributable to new information associated with simulated weekly forecasted yields.

Findings – The results show that the market for corn exhibits only semi-strong form efficiency, as the "news" provided by the monthly Crop Production and World Agricultural Supply and Demand Estimates reports is incorporated into prices in at most two days after the release. As expected, an increase in corn yields relative to what was publicly known elicits a futures price decrease. The counterfactual analysis suggests that if weekly harvest-time yields were available to market participants, the daily corn futures price will potentially be relatively volatile during the harvest period, but the final price at the end of the harvest season will be lower.

Originality/value – The study uses simulation to show the potential evolution of corn futures price if market participants had access to weekly harvest-time yields. In doing so, the study provides insights centered around the ongoing debate regarding the economic value of USDA reports in the presence of growing information availability within the private sector.

Keywords Big data, Market information, Market efficiency, USDA reports

Paper type Research paper

The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or US Government determination or policy. This research was supported in part by the USDA, Economic Research Service, and the cooperative agreement 58–0111–19–007 with USDA, Office of Chief Economist.

0002-1466
DOI 10.1108/AFR-04-2023-0045

Introduction

Since the 1970s the United States Department of Agriculture (USDA) has published multiple report series that provide agricultural stakeholders with current and expected market conditions, thereby reducing informational uncertainties about prices and quantities. Perhaps the most known and accessed of these is the Monthly World Agricultural Supply and Demand Estimates (WASDE) report, but others include the Annual Acreage, Annual Prospective Plantings, Weekly Crop Progress and Condition, Monthly Grain Stocks and Monthly Crop Production reports. A common theme among them is that they rely on statistical survey approaches to collect production and usage data. As such, they do not provide publicly available information in real-time (daily or hourly) but rather on well-established release dates throughout the year [1]. Historically, much research has been devoted to estimating the economic value of the USDA reports (Gorham, 1978; Ying *et al.*, 2019; McKenzie and Darby, 2017; Schaefer *et al.*, 2004; Isengildina *et al.*, 2006; Sumner and Mueller, 1989); and more recently questions regarding their continued benefit has arisen in response to observed declines in USDA survey responses (Johansson *et al.*, 2017) and the growth within the private sector (e.g. (Woodard, 2016)) of relatively low-cost market information and analysis instruments. While much of the historical literature has employed some variant of event study methodology to show that amid private-sector information the USDA reports significantly impact markets and provide value, suggesting that the reports have economic significance, it remains an important question whether these benefits will continue to exist in the era of "big data" [2].

The transformation of farming operations including digitalization and automation (Digital agriculture [DA]), of which precision agriculture (PA) is a major element, has the potential to solve several agricultural challenges, including rising labor shortages, climate change and production costs, among others (McFadden *et al.*, 2023). Periodic reports based on survey of stakeholders in the precision agriculture technology supply (Erickson and Widmar 2015) and farm operations (Schimmelpfennig, 2016; Griffin *et al.*, 2017; Ofori *et al.*, 2020; McFadden *et al.*, 2023) all show that PA technologies have increased with the most adopted technologies between 1996 and 2019 being auto-steer and guidance systems, yield monitors, yield maps, soil maps and variable rate technologies (VRT). Yield monitors, which are of interest to this study, are in-cab devices that displays crop yields (e.g. bushels/acre) –and how those yields change over small areas [3]. When properly calibrated, the high-frequency data from yield monitors may be used to improve on-farm management (Griffin *et al.*, 2008; Coble *et al.*, 2018; Griffin *et al.*, 2018; Ofori *et al.*, 2020; Griffin and Traywick, 2021) [4]. A potential off-farm use of the associated high-frequency data – "big data" – generated from yield monitors is that they can be easily aggregated across producers in near real-time (Sykuta, 2016), which is an interesting contrast to the USDA report methodology which relies on periodic surveys to estimate various metrics of interest.

Previous studies have examined the possibility of generating production information – particularly yield – that is equally if not more accurate than those published in the USDA reports, by using satellite data on vegetation cover (Doraiswamy, 2004; Doraiswamy *et al.*, 2005; Kastens *et al.*, 2005; Mkhabela *et al.*, 2011), employing machine learning (Roznik *et al.*, 2023) or employing various sampling techniques on a large database of crop yields from producers (Tack *et al.*, 2019). One that is of interest to this study utilizes a unique dataset of end-of-season farm-level corn yields akin to that generated by precision technologies to simulate aggregated end-of-season yields. Tack *et al.* (2019) utilized various strategies that reflect conditions that private-sector aggregators are likely to face when estimating national end-of-season yields from precision technologies. Compared to USDA final end-of-season yields, Tack *et al.* (2019) showed that non-random sampling schemes are associated with biases that can be effectively removed by benchmarking procedures for removing systematic prediction error.

This study seeks to answer a simple but important question of whether high-frequency harvest-time yields available on a weekly basis can influence futures market prices (and reactions thereof) that are significantly different from the status quo. Here that status quo is taken to be monthly yield forecast from WASDE and Crop Production reports. More specifically, we utilize historic end-of-season farm-level corn yields that represent approximately 83% of US planted acres from 1999 to 2008 and Crop Progress and Condition (CPC) reports to simulate weekly yield projections as representative of those from live yield monitors. The idea is to utilize the farm-level yield data to represent the population of farm-level US corn yields, and the weekly variation in CPC information on the proportion of annual crop harvested to approximate how the yield population changes throughout the harvest season. Given the simulated weekly harvest-time yields, the study then employs a two-step methodology to measure how corn futures market reaction and prices would have evolved if market participants had access to weekly yield information. The first stage leverages event study methodology to estimate the marginal effects of new information on futures price returns. Given these estimates, the study then estimates the counterfactual evolution of corn futures price that is attributable to new information associated with weekly yield forecasts.

The empirical exercise generates several important insights. First, findings support the narrative that corn markets in the US exhibit only semi-strong form efficiency which implies that “news” accompanying the arrival of a report is quickly incorporated into prices. Second, the counterfactual analysis also shows that if weekly harvest-time yields were available to market participants, the daily corn futures price are likely to be more volatile during the harvest period and the final price at the end of the harvest season will be lower.

Data

This study utilized data from USDA’s Weekly Crop Progress and Condition (CPC), Monthly World Agricultural Supply and Demand Estimates (WASDE) and Monthly Crop Production (CP) from 1973 through 2022. The CPC provided information on the proportion of annual corn harvested under various conditions to simulate weekly corn yield data (described in the methods section). The WASDE and CP provided information on production expectations in the public domain. It is worth noting that CP and WASDE have a release day and content overlap rate of over 90% of the time, thus we include a categorical variable for their individual and joint release in our models.

While the data for USDA reports are retrieved from the various issues of each report, all previous studies used daily futures prices retrieved from the Chicago Board of Trade (CBOT) and then constructed a rolled-over nearby futures series from the retrieved data. The nearby contract is that with the closest settlement date; the “next out” contract is that which settles immediately after the nearby contract and the “far away” contract is that with the farthest settlement date. Following this nomenclature, the rolled-over nearby futures series are constructed by replacing the nearby contract price at the end of the month preceding expiration with the next out contract price. This replacement ensures that delivery periods of abnormal price observations are avoided (Ying *et al.*, 2019; Dorfman and Karali, 2015). Nearby futures are generally used because they are typically the most heavily traded and, hence, liquid contracts. Furthermore, theory indicates that nearby contracts for storable commodities like those in agricultural markets typically reflect the impact of both old and new crop information (Working, 1948). Isengildina-Massa *et al.* (2008) asserts that the use of nearby contract prices to ascertain the impact of USDA reports is reasonable since some of the reports contain information for both old and new crops. The open and close price for the composite contract series is shown in Figure 1a and b, respectively. The average rolled-over nearby contract price over the entire sample was ¢310.68/bushel and the average for 2022 (the last year in the data) was ¢691.25/bushel.

Given the average rolled-over nearby contract price, a measure of futures price returns can be specified as

$$r_i = 100 \times \ln\left(\frac{P_{i,d}}{P_{i,d-j}}\right) \tag{1}$$

where the subscript P_d is the settlement price of commodity i's nearby futures contract on day d. While j can take on any value greater than zero, it is naturally set to one. Typically, close-to-open, close-to-close or open-to-close methods are used in the determination of $P_{i,d}$ and $P_{i,d-1}$. For close-to-open, $P_{i,d-1}$ and $P_{i,d}$ are the closing and opening futures price for day $d-1$, and d, respectively, and for close-to-close, they both represent closing and opening futures price for the respective days. Open-to-close follow a similar nomenclature. If the markets are efficient, the impact of any new information should be reflected instantaneously in futures prices. Thus, for USDA reports released at the end or beginning of the day's trading session,

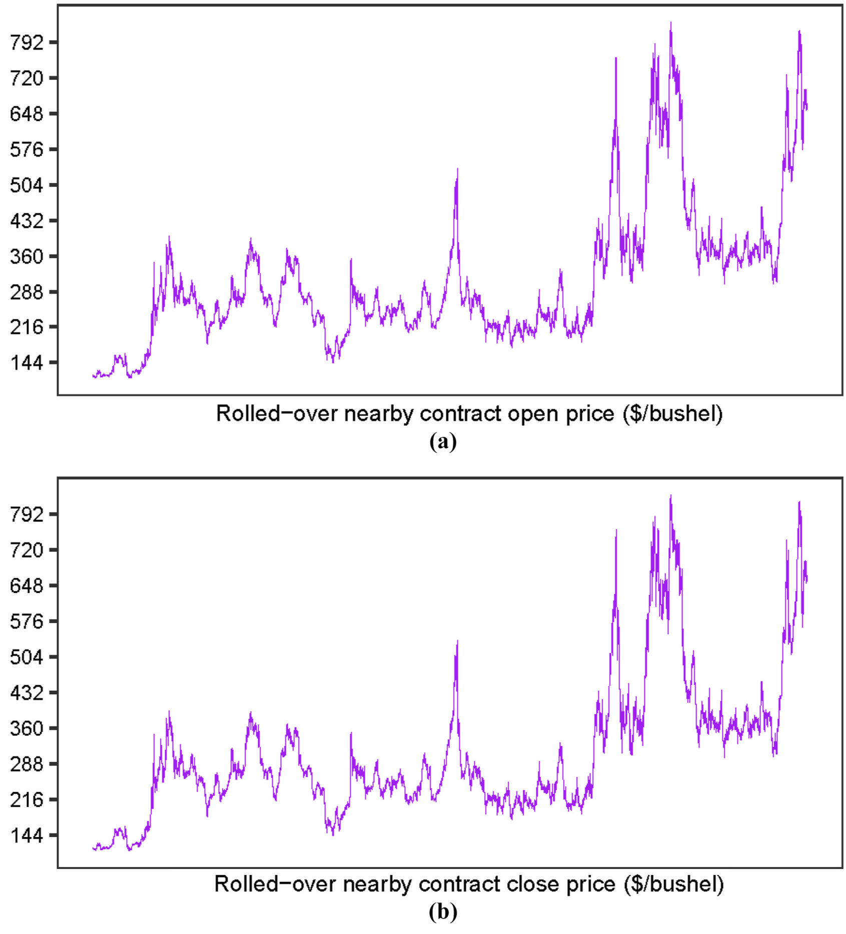
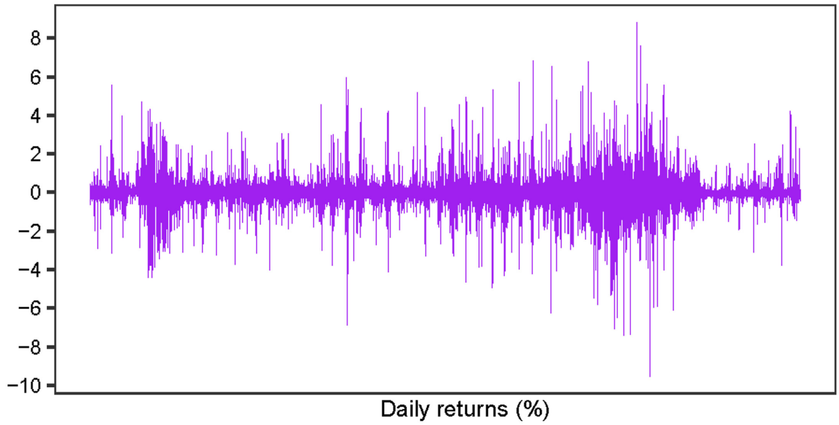


Figure 1.
Time series of the daily closing price and returns for corn futures, 1965–2022

(*continued*)



(c)

Figure 1

Note(s): The open and close price series in panels a and b were generated as the rolled-over nearby futures series constructed by replacing the nearby contract price at the end of the month preceding expiration with the next out contract price. The daily return series in panel c was generated using a method that accounts for changes in WASDE/Crop Production report release times: (1) before April 1994 the release time was 3:30 pm EST after the day's The open and close price series in panels A and B were generated as the rolled-over nearby futures series constructed by replacing the nearby contract price at the end of the month preceding expiration with the next out contract price. The daily return series in panel c was generated using a method that accounts for changes in WASDE/Crop Production report release times: (1) before April 1994 the release time was 3:30 pm EST after the day's
Source(s): Authors own creation

any new information should be incorporated into the price at the beginning of the following day's session. Thus, the close-to-open method will be appropriate. However, if reports are released during the trading session, the close-to-close method is appropriate.

For the periods analyzed in this study, the release times for the reports considered have changed three times, so we constructed the daily returns on futures price considering these changes. Before April 1994 WASDE/Crop Production was released at 3:30 pm EST after the day's closing session; thus, the event date is the next day, so we used a close to open futures price returns for that period. Between May 1994 to Dec 2012 WASDE/Crop Production was released at 8:30 am EST before the start of the day's opening session; thus, the event date is the same day, so we used open to close returns. From January 2013 to the current period WASDE/Crop Production is released at noon EST during the day's session; thus, the event date is the same day, so we used an open to close returns. The open to close returns price returns for the composite contract series is shown in Figure 1c.

In addition to the data above, the study used corn planted acres and production level (bu.) from the Risk Management Agency (RMA) Actual Production History (APH) database spanning from 1999 to 2008 as the basis to simulate weekly data akin to that of yield monitors. The total number of APH observations is about 1.5 million from 156,906 farms in 1,919 counties and 47 states. On average, farm size and yields were estimated at 82.15 hectares and 7,865 kg/ha, respectively.

Methods

This study employs a two-step methodology to ascertain how corn futures price reactions and price levels would have evolved if market participants had access to weekly forecasted yields. Particularly, the marginal effects of new information on futures price returns are first established by exploiting the variation between news in publicly available information and price returns. Given this relationship, the study then estimates the counterfactual evolution of corn futures price attributable to new information associated with weekly forecasted yields.

The event study methodology, introduced by Fama *et al.* (1969), is used in the accounting and finance disciplines as the standard methodology for testing the null hypothesis of market efficiency, and to examine the impact of some announcement or event on the wealth of a firm's security holders (Binder, 1998) [5]. In agricultural economics, researchers have used the event study methodology to ascertain the warning signs of looming food crises (World Food Programming (WFP) and Centre of Research and Studies on Economic Development (CERDI) 2012) and to analyze the impact of food contamination (Li *et al.*, 2010) or market situation (Gorham, 1978; Isengildina *et al.*, 2006; Ying *et al.*, 2019; Thomsen *et al.*, 2013) information release on commodity prices and quantities. Others have also used the method to analyze the relationships between online media -volume and sentiment- and futures prices of an agricultural commodity (Ortez *et al.*, 2023). In the context of this study, the main idea is that the conditional expectation of the final prices of contracts at maturity should be well represented by futures prices. Thus, spikes in the variability of futures return reflect changes in market participants' expectations of the maturity prices due to news in the USDA reports. Conditional on the contents of the news, and notably if the news is valuable to market participants, the changes in the futures return can either be positive or negative. Furthermore, if the market is efficient, the reaction to any news in the USDA reports should be instantaneous.

Event study methodologies used in analyzing the announcement effects of USDA reports are of three strands. The first strand of event study methodologies, utilized by the early literature and as a preliminary test for the recent, relies on simple parametric (e.g. t-tests and F-tests) and nonparametric chi-square (e.g. Savage test, Kruskal–Wallis test and Van der Waerden test) tests of difference in measures of futures price variability following a report release and that of non-release days (see e.g. Sumner and Mueller (1989), Fortenbery and Sumner (1993), Sumner and Mueller (1989), Fortenbery and Sumner (1993), Mann and Dowen (1996) and Isengildina-Massa *et al.* (2008)). The second strand of event study methodologies used in analyzing the announcement effects of USDA reports utilizes time series regression frameworks (see e.g. Isengildina *et al.* (2006), Adjemian (2012), Karali (2012), Xie *et al.* (2016) and Ying *et al.* (2019)). These studies regressed measures of future price variability on a dummy for the release of several types of USDA reports and other control variables. Consequently, the second strand only provides a yes/no answer to whether the USDA reports influence the actions of market participants.

The third strand of methodologies also utilizes a regression framework. However, instead of release day indicators, they utilize a measure of the extent or size of the surprise in the reports. Unlike the second strand that utilizes all data points over their study period, the third strand uses only the data points around the announcement dates. The general framework for the third strand is represented as

$$r_{i,t} = \alpha + \gamma x^{e}_{i,t} + \beta x^{u}_{i,t} + \sum_{j}^{m} \delta_j x^{u}_{i,t-j} + \mu_{i,t}\,,$$

$$t = 0, \ldots, +k, i = 1, \ldots, I, \text{and}\, j < k \tag{2}$$

First, the time index is $t = 0, \ldots, +k$, where zero indicates the daytime trading session immediately following the release of an issue (i) of a given report (e.g. for this study CP and/or

WASDE). The release of one issue is taken as one event, hence the event index is i, and takes on values from 1 to I (I is the total number of issues from the inception of the given report to date). In this study we have a total of 367 events reflecting the monthly releases of CP and/or WASDE from 1973 to 2022. The variable $r_{i,t}$ has the same definition as before, and it could be calculated based on a close-to-open, close-to-close or open-to-close basis. The variable $x^e_{i,t}$, is a vector of expected information known to the market participant at the close of trading day $t-1$; $x^u_{i,t}$ is a vector of unanticipated information (the surprise), derived as $x^u_{i,t} = x^a_{i,t} - x^e_{i,t}$, where $x^a_{i,t}$ is a vector of announced information in report issue i. Previous studies have taken expected information as $x^a_{i,t-1}$ (a naïve assumption) (Lehecka, 2014; McKenzie and Darby, 2017; Gorham, 1978), the average of market analyst expectations (Frank *et al.*, 2008; Garcia *et al.*, 1997; Colling and Irwin, 1990) or the average of proprietary information (Schaefer *et al.*, 2004). Finally, $\mu_{i,t}$ is a stochastic term, and α, γ, β and δ_j are parameters to be estimated.

It follows from rational market expectations that $x^e_{i,t} = E[x^a_{i,t} \vert \Omega_{i.t-1}]$, where $\Omega_{i.t-1}$, is a vector of the information set at the close of trading day $t-1$, such that $x^u_{i,t}$ is uncorrelated with $\Omega_{i.t-1}$. Furthermore, it also follows from the efficient market hypothesis that $\gamma = 0$, because $\Omega_{i.t-1}$ will be reflected in prices at the close of trading day $t-1$. Additionally, $\delta_j \neq 0$ will violate the notion that the reaction to any news in the USDA reports should be instantaneous. Consequently, if markets are efficient, the relevant equation for the analysis reduces to

$$r_{i,t} = \alpha + x^u_{i,t}\beta + \mu_{i,t}\ , t = 0, \ldots, +k, \text{and}\ i = 1, \ldots, I, \tag{3}$$

Utilizing Equation (3), Gorham (1978) showed that private information, taken as the previous periods USDA forecast ($x^a_{i,t-1}$), correctly forecasted public-sector announcements ($x^a_{i,t}$) for soybeans, but not for corn and wheat. They found that, corn and, to a lesser extent, wheat reports had significant announcement effects on close-to-close price returns (r_i) from 1950 to 1977. Utilizing both Equations (4) and (5), and average of 15 market analyst expectations, Colling and Irwin (1990) showed that the hog futures market exhibited semi-strong form efficiency. They found that close-to-close price returns (r_i) from 1981 to 1988 (a) do not react to anticipated changes in reported information, (b) reacts rationally to unanticipated changes in reported information and (c) adjusts within a day to unanticipated information following release of reports. Using a similar framework as Colling and Irwin (1990), but taking $x^a_{i,t-1}$ as public-sector information and calculating price returns (r_i) on a close-to-open basis, Lehecka (2014) drew similar conclusions as for corn and soybean market efficiency and reaction to USDA Crop Progress and Condition reports from 1986 to 2012. McKenzie and Darby (2017) also utilized only Equation (3) and $x^a_{i,t-1}$ taken as private information, to show that USDA provides the futures market with important information, which is vital to the price discovery process.

Given our interest in the marginal effect of new information on futures returns, the preferred model is the methodology that falls under the regressions with a degree of surprise measure (Equations 2 and 3). The specific form of the preferred model is given by

$$\begin{aligned} r_{i,t} = \alpha + \beta x^u_{i,t} + \beta_T x^u_{i,t} T + \beta_L x^u_{i,t-1} + \beta_e \ln x^e_{i,t} + \sum_l \beta_{r,l} r_{i,t-l} + \beta_{RT} Report\_Type_{i,t} + \\ \beta_{OR} Other\_Reports_{i,t} + \beta_{MTH} Method_{i,t} + \beta_{Day} Day_{i,t} + \beta_{Month} Month_{i,t} + + \beta_{Regime} Regime_{i,t} \\ + \mu_{i,t} \end{aligned} \tag{4}$$

In this first stage of the analysis to estimate the marginal effect of new information on futures price returns, we set the market participant's expectation of the report ($x^e_{i,t}$) as the previous periods USDA forecast ($x^{a}_{i,t-1}$), and express the "surprise" ($x^{u}_{i,t}$) in percentage terms as $\left(\frac{x^{a}_{i,t} - x^{e}_{i,t}}{x^{e}_{i,t}}\right) \times 100\%$. To assess the decay in the market's reaction, the study included the measure of surprise for the current event ($x^{u}_{i,t}$) and its interaction with a categorical variable for the time index for the current event ($x^{u}_{i,t}T$). As customarily done in related works, we also control for; (1) one lag of surprise ($x^{u}_{i,t-1}$), (2) log of expected information ($\ln x^{e}_{i,t}$), (3) lags of futures price returns variability ($r_{i,t-l}$), (4) categorical variable for the type of report (CP, WASDE or both) ($Report\_Type_{i,t}$), a vector of dummies for the release of other reports (Crop Progress, Agricultural Prices, Grain Stocks and Feed Outlook) coinciding with the event ($Other\_Reports_{i,t}$), (5) method of futures price returns calculation (open to close vs close to open) ($Methode_{i,t}$), (6) a categorical variable for trading day of the week ($Day_{i,t}$), (7) a categorical variable for calendar months ($Month_{i,t}$) and (8) a categorical variable for structural breaks ($Regime_{i,t}$).

The study evaluates the following hypotheses. If one fails to jointly reject $\beta = 0$, $\delta_j = 0$ and $\gamma = 0$, then futures prices reflect public information and will not react to USDA reports since they do not provide "news" to the market. In this situation, the market exhibits strong form efficiency (Fama, 1970). On the other hand, the rejection of $\beta = 0$ can be taken as importance of USDA reports to the market. Furthermore, if $\beta \neq 0$ is coupled with $\delta_j = 0$ and $\gamma = 0$, then the underlying assumption is that markets exhibit only semi-strong form efficiency, as the "news" provided by the report is instantaneously incorporated into prices.

The parameters in β and β_T in Equation (4) represent the conditional marginal effect of new information on futures price returns for every instance of time after the arrival of the new information. If we consider a season specific future price index (P^{I}_{t}), taking on the value of 100 for the week before the first CP/WASDE crop year corn projection, we can dynamically extrapolate the conditional changes in the index given the reaction parameters (β and β_T) and the extent of the latest news. For the simulation that follows, we consider two types of news; news from actual USDA monthly projections (the status quo, i.e. $x^{a}_{i,t}$) and simulated news had the market had access to weekly harvest-time yield projection ($x^{w}_{i,t}$). In both cases, we set market participant's expectation of the yield forecast ($x^{e}_{i,t}$) as the previous periods USDA yield forecast ($x^{a}_{i,t-1}$). It is worth noting that before the first planted corn acres are harvested, the source of news for both cases will be from the actual USDA monthly projections.

In simulating the weekly harvest-time yields, the study assumed that the seasonal productivity for each farm (f) is equal to their end of season (t) yield ($\overline{Y}_{ft}$). Secondly, for harvest week w, the study further assumes that, for each farm, the proportion of planted acres (A^{p}_{ft}) that are available for harvest is equal to that of the state (s) level statistic (θ_{stw}) published in the weekly CPC. Thus, farm i's harvested acres (A^{h}_{fstw}) and quantity (Q^{h}_{fstw}) for harvest week w are given by: $A^{h}_{fstw} = A^{p}_{ft} \times \theta_{stw}$ and $Q^{h}_{fstw} = A^{h}_{fstw} \times \overline{Y}_{ft}$. The variables A^{h}_{fstw} and Q^{h}_{fstw} are then taken as the weekly data from each farm during harvest. Given the live-streamed data, the study utilizes 11 different non-random aggregation methods similar to those in Tack *et al.* (2019) to estimate weekly harvest time yields. The methods used, which are extensively discussed in Tack *et al.* (2019) are: (1) all simple average, (2) all acreage weighted average, (3) I-state acreage weighted average and (4) C-belt acreage weighted average. The acreage weights are calculated as $\tau_{fstw} = \frac{A^{h}_{fstw}}{\sum_{f}^{N} A^{h}_{fstw}}$.

Based on initial work by Tack *et al.* (2019), non-random sampling schemes are associated with biases that can be effectively removed by benchmarking procedures for removing systematic prediction error. In this spirit, this study utilized two adjustments. The first is based on the long-run relationship

$$\bar{y}_t = \sigma_0 \widehat{y}_{tw} + \varepsilon_t \tag{5}$$

where $\bar{y}_t$ is the final yield for season t published by USDA several seasons later, and $\widehat{y}_{tw}$ is this study's weekly yield estimate. Thus, given the estimate of the long run correction term ($\widehat{\sigma}_0$), the benchmarked weekly yield estimate is given by $\widehat{y}^*_{tw} = \widehat{\sigma}_0 \widehat{y}_{tw}$. For the second benchmarking procedure, the study assumes the correction term is a function of harvest time information available during harvest week w. This was modeled as

$$\bar{y}_t = [\sigma_0 + \sigma_h(1 - \theta_{tw})]\widehat{y}_{tw} + \varepsilon_t \tag{6}$$

where θ_{tw} is the proportion of planted acres harvested and is calculated as $\theta_{tw} = \frac{\sum_i^N A^h_{istw}}{\sum_i^N A^p_{it}}$. Given the parameter estimates of Equation (6), the benchmarked weekly yield estimate is given by $\widehat{y}^{\#}_{tw} = [\widehat{\sigma}_0 + \widehat{\sigma}_h(1 - \theta_{tw})]\widehat{y}_{tw}$.

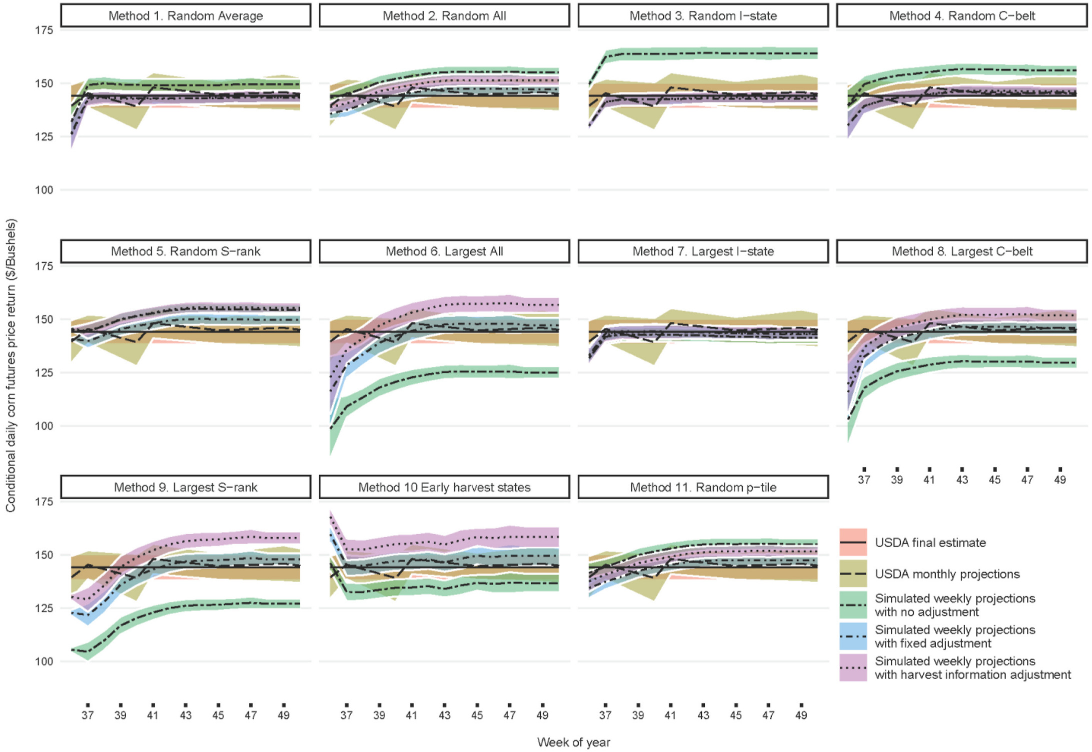
Although the CPC reports also include condition measures which may inform final yield levels, we do not include this information in our model. This decision is based on two factors. Firstly, condition estimates cease to be available during the relevant window when the harvest progress commences, which coincides with our projection window. As such, these estimates would not influence the temporal fluctuations within our projection window. Secondly, we postulate that condition estimates would contribute to regional variations in yields within a specific crop year. These variations are already implicitly captured in the farm-level end-of-season yields, and therefore, in the simulated weekly harvest-time yields.

The mean weekly harvest time yield projections for the various non-random aggregation methods together with the monthly yield projection from the CP and WASDE and the end of season final yields are shown in Figure 2. In most cases, the weekly harvest-time yields give a low forecast as the season starts that increases as more acreage is harvested. Without any adjustments, the weekly forecast is significantly different from equivalent forecast from USDA. However, after adjustments via benchmarking, the weekly forecast converges to the USDA forecast. Furthermore, Figure 2 indicates that simple benchmarking based on a single long-run correction term is robust to complex benchmarking that relies on harvest time information. The level of surprises associated with the weekly yield projections together with those from the USDA sources are shown in Figure 3. Here, it can be observed that, the level of market surprise for all cases is the same up until the week (34–36 weeks of the year) the first planted acres for corn come online for harvest. Over the course of the crop year, the mean level of surprise from actual USDA sources is 0.21 indicating that the yield information from public sources (i.e. USDA report) was 0.21% higher than expected. Along benchmarking lines, the weekly harvest time yield projections provided yield information that was 0.32% lower than expected when the forecast was not benchmarked. When benchmarked, the surprise was 0.17 and 1.79% higher when benchmarked with a simple long-run multiplier and harvest time information, respectively. If we consider only periods after the first planted acres of corn are harvested (34–51 weeks), the surprise was 0.31 and 2.75% when weekly yields are benchmarked with a simple long-run multiplier and harvest time information, respectively, while that of the USDA is 41%.

Results

Results from parametric and nonparametric tests based on the first strand of event study methodology (Table 1) suggest that returns variability for USDA report release days is significantly ($p < 0.05$) different from non-release days. Differences in variability across months also show that the reaction to reports could be influenced by the production cycles.

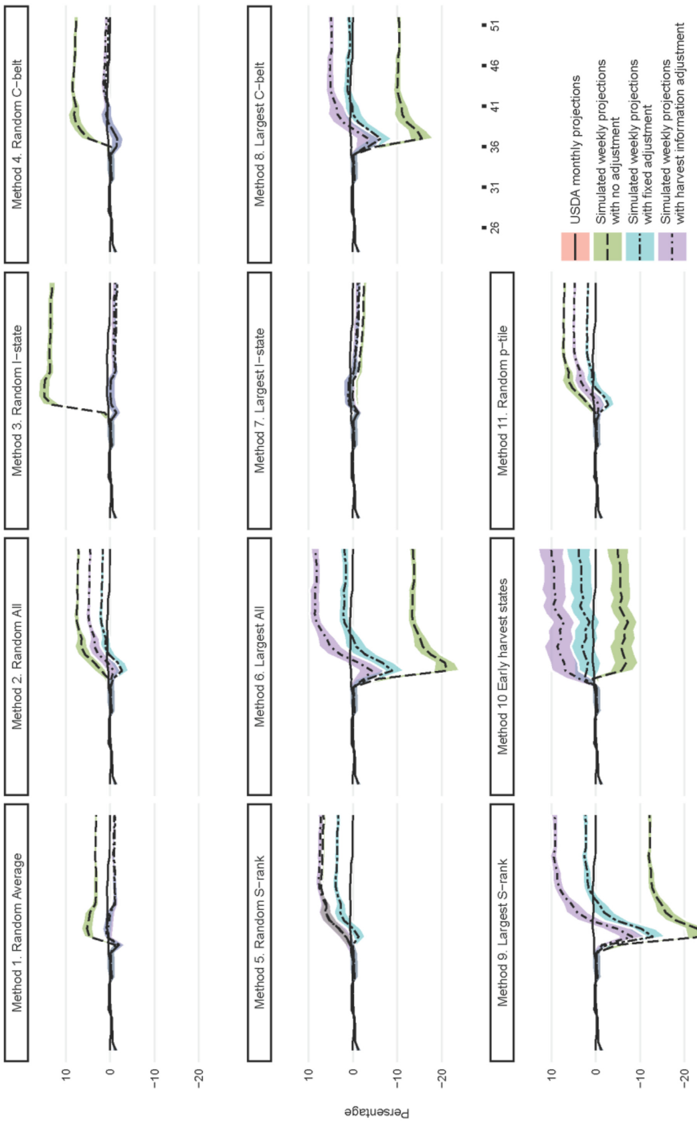
Under the EMH approach, Table 2 shows that the market for corn exhibits only semi-strong form efficiency, as the "news" provided by CP and WASDE reports is



Note(s): The USDA monthly projections and USDA final estimate are the monthly yield projection and final season yields retrieved from published Monthly World Agricultural Supply and Demand Estimates (WASDE) and Monthly Crop Production (CP) reports. The simulated weekly projections are based on end-of-season farm-level production and acreage information and weekly variation in USDA's Weekly Crop Progress and Condition (CPC). The panels are differentiated by the method used in aggregating the simulated data for the case of the simulated weekly projections

Source(s): Authors own creation

Figure 2.
Final and projected corn yields



Note(s): The level of market surprise is taken as the difference between the yield estimate anticipated by the market and the estimate published in the Monthly World Agricultural Supply and Demand Estimates (WASDE) or Monthly Crop Production (CP) reports. The anticipated yield estimate is taken as the estimate from the previous USDA monthly projections. The panels are differentiated by the method used in aggregating the simulated data for the case of the simulated weekly projections
Source(s): Authors own creation

Figure 3.
Level of market surprise about yield information

Table 1. Diagnostic test on daily corn futures price return's reaction to World agricultural supply and demand estimates (WASDE) and Crop production (CP) reports, 1973–2022

		Daily corn futures price returns (%) [variance]				Daily corn futures price returns variance homogeneity test			
	Event (count)[a]	Any day[b]	Four trading days preceding Report release Date	Report release day	Successive four trading days after report release date	*F*-test[c]	Levene[d]	Brown and Forsythe[d]	Kruskal–Wallis[d]
Pooled	205	2.41 [0.04]	2.31 [0.06]	3.79 [0.17]	2.30 [0.01]	0.61***	2.92***	2.78***	13.09
Report type									
WASDE	140	1.40 [0.04]	1.43 [0.05]	1.82 [0.10]	1.30 [0.03]	0.75**	1.56*	1.44	16.62
WASDE and CP	63	4.31 [0.08]	3.88 [0.12]	7.58 [0.42]	4.26 [0.00]	0.54***	2.73***	2.60***	7.08
Release month									
September	50	2.52 [−0.05]	2.09 [0.02]	4.04 [0.22]	2.71 [−0.17]	0.60***	1.44	1.32	10.39
October	59	2.49 [0.14]	2.43 [0.17]	5.62 [0.08]	2.11 [0.11]	0.41***	1.92**	1.66*	10.54
November	50	2.16 [−0.01]	2.17 [0.01]	2.79 [0.02]	2.08 [−0.04]	0.76	1.54*	1.43	4.92
December	46	2.42 [0.09]	2.53 [−0.02]	2.41 [0.39]	2.31 [0.15]	1.00	1.74**	1.29	17.36
Regime									
Pre 1986	58	0.36 [0.02]	0.34 [0.05]	0.93 [0.04]	0.29 [0.00]	0.34***	2.41***	2.37***	19.50
1986–1989	16	0.20 [−0.07]	0.17 [−0.07]	0.07 [−0.10]	0.25 [−0.06]	2.81**	1.18	0.93	7.74
1990–1995	22	0.77 [0.08]	0.44 [0.07]	0.76 [0.22]	1.08 [0.08]	1.01	1.92**	1.78**	14.43
1996–2001	24	2.38 [−0.03]	2.61 [0.29]	3.13 [−0.44]	1.88 [−0.29]	0.74	0.75	0.63	20.58
Post 2001	85	4.66 [0.09]	4.46 [0.01]	7.29 [0.47]	4.47 [0.11]	0.61***	2.08**	2.03**	15.48

Note(s): Single, double and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5% and 1% level. Numbers in parentheses are standard errors

[a] An event is the release of a CP and/or WASDE report

[b] Joint statistics for four trading days before the preceding release date, the report release day and successive four trading days after the report release date

[c] The variance homogeneity test is for release vs non-release days

[d] The variance homogeneity test is considered before and after release days

Source(s): Authors own creation

incorporated into prices in at most two days after the release. This conclusion corroborates that of Gorham (1978), where the study showed that corn and, to a lesser extent, wheat reports had significant announcement effects on close-to-close price returns from 1950 to 1977. Colling and Irwin (1990) also showed that the hog futures market exhibited semi-strong form efficiency. Particularly they showed that close-to-close price returns from 1981 to 1988 (a) do not react to anticipated changes in reported information, (b) react rationally to unanticipated changes in reported information and (c) adjust within a day to unanticipated information following the release of reports. Using a similar framework as Colling and Irwin (1990), Lehecka (2014) drew similar conclusions for corn and soybean market efficiency and reaction to USDA CPC reports from 1986 to 2012. McKenzie and Darby (2017) also showed that USDA provides the futures market with important information vital to the price discovery process.

Table 2. Corn futures price returns reaction to yield "news" announced in world agricultural supply and demand estimates (WASDE) and crop production reports, 1965–2022

Variable	Estimate	Variable	Estimate
News effect		*Trading day [base = Friday]*	
On release date	−0.050*** (0.018)	Monday	−0.016 (0.057)
1st day after release	0.030* (0.018)	Tuesday	0.097 (0.066)
2nd day after release	−0.020 (0.018)	Wednesday	0.088 (0.057)
3rd day after release	0.001 (0.018)	Thursday	0.010 (0.057)
4th day after release	0.004 (0.018)	*Trading month [base = January]*	
5th day after release	0.010 (0.018)	February	−0.170 (0.407)
6th day after release	0.008 (0.018)	March	0.094 (0.386)
7th day after release	−0.025 (0.018)	April	−0.139 (0.279)
8th day after release	0.004 (0.018)	May	−0.061 (0.111)
9th day after release	0.018 (0.018)	June	−0.232** (0.103)
10th day after release	−0.017 (0.018)	July	−0.205** (0.099)
11th day after release	−0.001 (0.018)	August	−0.127 (0.095)
12th day after release	−0.014 (0.018)	September	−0.129 (0.096)
13th day after release	−0.006 (0.018)	October	0.007 (0.098)
14th day after release	0.022 (0.018)	November	−0.115 (0.097)
15th day after release	−0.007 (0.018)	December	−0.012 (0.095)
16th day after release	−0.001 (0.018)	*Report type (base = WASDE)*	
17th day after release	−0.011 (0.018)	CP	−0.420* (0.250)
18th day after release	0.010 (0.018)	WASDE and CP	0.035 (0.067)
19th day after release	0.012 (0.018)	*Other USDA reports (dummy)*	
20th day after release	0.010 (0.018)	Crop Progress	−0.113 (0.077)
21st day after release	−0.004 (0.018)	Agricultural Prices	0.012 (0.088)
22nd day after release	0.007 (0.018)	Grain Stocks	−0.141 (0.175)
23rd day after release	0.018 (0.018)	Feed Outlook	0.071 (0.093)
Existing information		*Regime (base = before 1986)*	
Previous event's news	0.001 (0.004)	1986–1989	−0.115 (0.089)
Expected yield	0.318 (0.195)	1990–1995	−0.085 (0.090)
Previous return		1996–2001	−0.351** (0.142)
1 day before release	0.465*** (0.011)	After 2001	−0.289* (0.155)
2 days before release	−0.213*** (0.012)	*Return type [base = Close to open]*	
3 days before release	0.092*** (0.012)	Open to close	0.119 (0.117)
4 days before release	−0.043*** (0.012)	Intercept	−1.362 (0.893)
5 days before release	−0.004 (0.011)		
Sample size			8,752.000
R-squared			0.182
Model significance			33.285***
Log likelihood			−16958.968

Note(s): Single, double and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5% and 1% level. Numbers in parentheses are standard errors
Source(s): Authors own creation

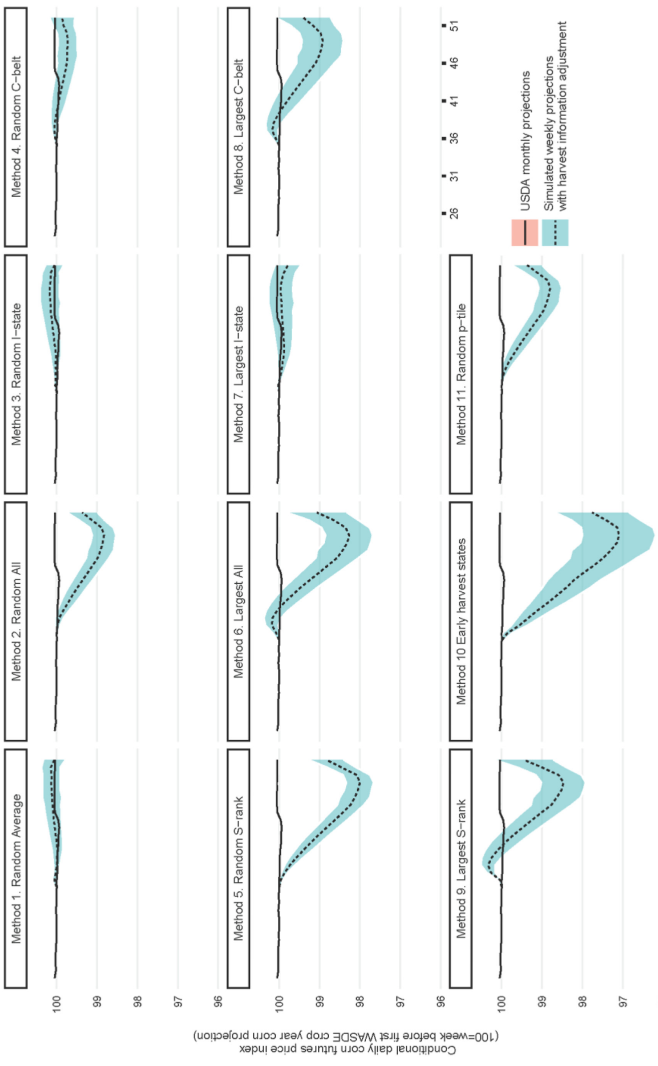
As expected, a 1% increase in corn yield (a supply-side factor) relative to what was publicly known, elicits a futures price returns decrease of 0.050% on the day of report release. Given that the mean price was ¢691.25/bushel in 2022, a 1% unanticipated increase in yield would elicit a ¢0.35/bushel decrease in futures price. In this case, market participants expected a low yield but the yield from a certified public source (USDA) was higher which translates to an increase in supply compared to what they anticipated, so they update their willingness to pay (price) downwards.

Next, we consider a future price index (P_t^I), taking on the value of 100 for the week before the first CP/WASDE crop year corn projection, and how it changes due to different sources of news. Figure 4 shows the conditional evolution of the index solely driven by market participants reaction to news from actual USDA yield projections and that from the simulated weekly projections benchmarked with a harvest time information, throughout the crop year. The overall difference in the level of the index and their Coefficient Of variation (CV) across the two sources of news are also shown on Figure 5. Across all aggregation methods, it can be observed that generally, if weekly harvest-time yields were available to market participants, the daily corn futures price will potentially be relatively volatile during the harvest period, but the final price at the end of the harvest season will be lower relative to the case when the only news available to market participants were the actual USDA yield projections.

Since the marginal effects are constant, and Figure 3 shows that the direction of the news across the two are generally the same, the potential forces driving these differences are the relative difference in the magnitude and frequency of the news sources. Initial yield forecast at the beginning of the season are mostly lower across all sources, which leads to positive surprise values as the season progresses. For the case of the status quo scenario, the initial reaction and subsequent decay happens monthly. On the contrary for the case of the week, once the first acres come online for harvest, the window for market participants to update their expectation reduces to one week. In this window they react to any changes in their expectation. Given that, yield forecast is typically less optimistic at the beginning of the crop year, the general trend is that market participants expectations lead to a positive surprise value. As shown above, the magnitude of this surprise is larger for the case of the weekly forecast, so it leads to relatively larger downward adjustment to market participants willingness to pay, even though the process is relatively volatile. Overall, across all the different aggregation methods employed, if weekly harvest-time yields were available to market participants, the daily corn futures price will potentially be 8.64% more volatile during the harvest period, and the final price at the end of the harvest season will be 0.33 lower.

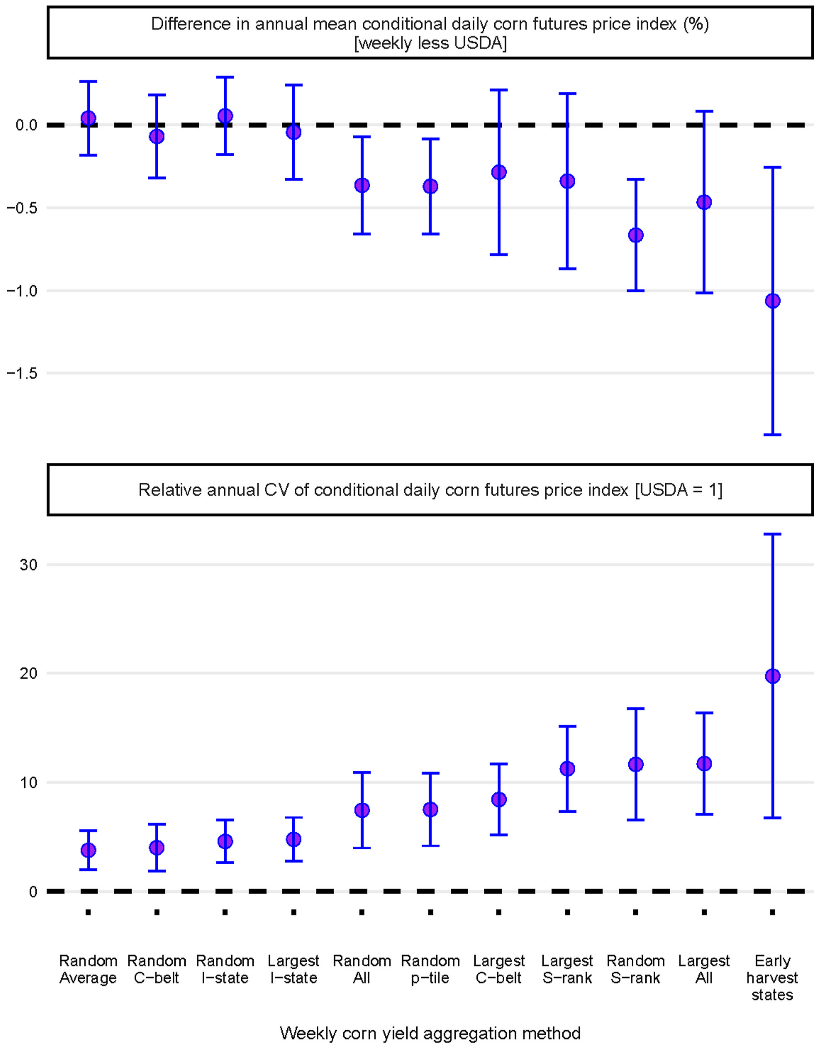
Conclusion

The insights from this study are interesting as the advent of precision agriculture technologies, and its associated revolution of "Big Ag-Data" has left researchers to grapple with how to best use the wealth of information available. Since this information can be aggregated to a higher level in real-time, it is interesting whether equivalent but periodic information from public sources will remain relevant. To this end, this study utilized advances in event study and yield projection methodologies to test whether weekly harvest time yield forecasts will potentially yield futures prices that are significantly different from the status quo of monthly harvest time yield forecasts from public sources. The results from an event study framework support the narrative that corn markets in the US exhibit only semi-strong form efficiency. This implies that "news" accompanying the arrival of a report is incorporated into prices immediately. Using estimates from the event study framework, we also conducted a counterfactual simulation analysis to show that if weekly harvest-time



Note(s): Each panel shows the conditional evolution of corn price returns attributable to the arrival of new information on the market from two sources. The conditional evolution labeled USDA monthly projections is based on news from USDA's Monthly World Agricultural Supply and Demand Estimates (WASDE) and Monthly Crop Production (CP) reports. The conditional evolution labeled Simulated weekly projections with harvest information adjustment is based on simulated news from sources with a relatively high frequency than WASDE and CP. The high-frequency news is simulated based on end-of-season farm-level production and acreage information and weekly variation in USDA's Weekly Crop Progress and Condition (CPC). The panels are differentiated by the method used in aggregating the simulated data for the case of the simulated weekly projections
Source(s): Authors own creation

Figure 4.
Conditional returns to corn futures price attributable to new yield information



Note(s): The figure shows the mean and CV difference in the conditional evolution of corn futures price attributable to the arrival of new information on the market from two sources. The base evolution is based on news from USDA's Monthly World Agricultural Supply and Demand Estimates (WASDE) and Monthly Crop Production (CP) reports. The alternate evolution is based on simulated news from sources with a relatively high frequency than WASDE and CP. The high-frequency news is simulated based on end-of-season farm-level production and acreage information and weekly variation in USDA's Weekly Crop Progress and Condition (CPC). Each estimate on the figure is differentiated by the method used in aggregating the simulated data for the case of the alternate evolution

Source(s): Authors own creation

Figure 5.
Potential differences in corn futures price attributable weekly yield projection

yields were available to market participants, the vdaily corn futures price will potentially be relatively volatile during the harvest period, but the final price at the end of the harvest season will be lower.

Some nuance worth noting is that day-to-day volatility can be higher with high-frequency yields, as we see in this study, but one would also expect fewer big jumps in prices than when information is more infrequent as in the latter case there is more pent-up demand for info. Particularly, day-to-day volatility in futures prices could be greater if there is some actor that takes precision agriculture yield data and aggregates it into a digestible format and that the data is reflective of most of the current year's production. However, perhaps there would be fewer larger jumps in prices if market participants come to depend less on periodic NASS and private sector yield updates, which likely have larger changes than one would see in the day-to-day precision agriculture yield updates.

In conclusion, our study, though innovative and significant, presents several limitations that warrant acknowledgment. We omitted condition measures from the Crop Progress and Condition (CPC) report due to their timing and perceived contribution to farm-level regional yield variations. However, this might restrict the breadth of our yield projections. The assumption that all state farms follow identical harvest progress as per the CPC could potentially overlook farm-to-farm variations due to factors like crop variety, management practices and microclimatic differences. Our model's objective of capturing real-time crop yield impacts might already be influenced by the undisclosed implementations of advanced information gathering techniques, like satellite imagery and yield weather models, by informed traders. This could potentially distort our sample and affect our study's interpretations and generalizations due to the non-public information contamination. Additionally, our methodology of treating each year in isolation and using the average outcomes as representative might not aptly reflect the specific dynamics of individual years, especially those with significant yield surprises. For example, in years with negative yield surprises, our model predicts a decrease in final prices due to an increase in market volatility, which contradicts the likely increase in prices due to a decreased supply. Our failure to condition our analysis on whether a year had a positive or negative yield surprise, and reliance on an unconditional average, underlines another methodological limitation. Nevertheless, our model serves as a vital leap towards predicting crop yields using real-time data and potentially influencing market behavior. It lays a foundation for future advancements, encouraging subsequent research to refine the methodology, incorporate nuanced conditioning factors and address these dynamics and limitations.

Notes

1. Among the USDA reports, CPC is the only report available on a relatively high-frequency basis with a new issue coming out every week for selected relevant crop.
2. Big Data is defined by several characteristics beyond size, particularly, the volume, velocity, variety and veracity of the data (Coble *et al.*, 2016; 2018; Griffin *et al.*, 2018).
3. Yield monitors have three components; a grain flow sensor to establish grain yield measurement; a moisture sensor to capture grain moisture content to aid storage/drying of the harvest and a differential global positioning system (DGPS) receiver to record and geo-reference the harvest (yield) (McFadden *et al.*, 2023).
4. Recent data shows that; (1) 61.6% [80.5%] of corn [winter wheat] planted acres in 2016 [2017] used yield monitors to determine the crop moisture content; and (2) 68.6, 94.4 and 95.6% of soybean (2018), cotton (2019) and sorghum (2019) planted acres were managed with yield monitors to help determine chemical input use (McFadden *et al.*, 2023).
5. See Corrado (2011) and Binder (1998) for an extensive review of the event study methodology since Fama *et al.* (1969).

References

Adjemian, M.K. (2012), "Quantifying the WASDE announcement effect", *American Journal of Agricultural Economics*, Vol. 94 No. 1, pp. 238-256, available at: https://academic.oup.com/ajae/article-lookup/doi/10.1093/ajae/aar131

Binder, J. (1998), "The event study methodology since 1969", *Review of Quantitative Finance and Accounting*, Vol. 11 No. 2, pp. 111-137, available at: http://link.springer.com/article/10.1023/A%3A1008295500105%5Cnhttp://link.springer.com/article/10.1023/A:1008295500105#%5Cnhttp://link.springer.com/content/pdf/10.1023%2FA%3A1008295500105.pdf

Coble, K., Griffin, T., Ahearn, M., Ferrell, S., McFadden, J., Sonka, S. and Fulton, J. (2016), "Advancing U.S. Agricultural competitiveness with big data and agricultural economic market information, analysis, and research", available at: https://fabe.osu.edu/sites/fabe/files/imce/images/10-7-2016BigData_v1.pdf

Coble, K.H., Mishra, A.K., Ferrell, S. and Griffin, T. (2018), "Big data in agriculture: a challenge for the future", *Applied Economic Perspectives and Policy*, Vol. 40 No. 1, pp. 79-96, doi: 10.1093/aepp/ppx056.

Colling, P.L. and Irwin, S.H. (1990), "The reaction of live hog futures prices to USDA 'hogs and pigs reports.'", *American Journal of Agricultural Economics*, Vol. 72 No. 1, p. 84, available at: https://academic.oup.com/ajae/article-lookup/doi/10.2307/1243147

Corrado, C.J. (2011), "Event studies: a methodology review", *Accounting and Finance*, Vol. 51 No. 1, pp. 207-234.

Doraiswamy, P. (2004), "Crop condition and yield simulations using Landsat and MODIS", *Remote Sensing of Environment*, Vol. 92 No. 4, pp. 548-559, available at: https://linkinghub.elsevier.com/retrieve/pii/S0034425704001853

Doraiswamy, P.C., Sinclair, T.R., Hollinger, S., Akhmedov, B., Stern, A. and Prueger, J. (2005), "Application of MODIS derived parameters for regional crop yield assessment", *Remote Sensing of Environment*, Vol. 97 No. 2, pp. 192-202, available at: https://linkinghub.elsevier.com/retrieve/pii/S0034425705001355

Dorfman, J.H. and Karali, B. (2015), "A nonparametric search for information effects from USDA reports", *Journal of Agricultural and Resource Economics*, Vol. 40 No. 1, pp. 124-143.

Erickson, B. and Widmar, D.A. (2015), *2015 Precision Agricultural Services : Dealership Survey Results, Draft*, Purdue University, available at: https://agribusiness.purdue.edu/wp-content/uploads/2019/08/2015-crop-life-purdue-precision-dealer-survey.pdf

Fama, E.F. (1970), "Efficient capital markets: a review of theory and empirical work", *The Journal of Finance*, Vol. 25 No. 2, p. 383, available at: https://www.jstor.org/stable/2325486?origin=crossref

Fama, E.F., Fisher, L., Jensen, M.C. and Roll, R. (1969), "The adjustment of stock prices to new information", *International Economic Review*, 10:1, available at: http://content.ebscohost.com/ContentServer.asp?T=P&P=AN&K=5711094&S=R&D=bth&EbscoContent=dGJyMNHr7ESeqa84y9fwOLCmr0uepq5Ss6u4Sa+WxWXS&ContentCustomer=dGJyMOzpsEqyqbdOuePfgeyx44Dt6fIA%5Cnhttp://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=5711094&si

Fortenbery, T.R. and Sumner, D.A. (1993), "The effects of USDA reports in futures and options markets", *Journal of Futures Markets*, Vol. 13 No. 2, pp. 157-173, available at: http://doi.wiley.com/10.1002/fut.3990130204

Frank, J., Garcia, P. and Irwin, S.H. (2008), "To what surprises do hog futures markets respond?", *Journal of Agricultural and Applied Economics*, Vol. 40 No. 1, pp. 73-87, available at: https://www.cambridge.org/core/product/identifier/S107407080002798X/type/journal_article

Garcia, P., Irwin, S.H., Leuthold, R.M. and Yang, L. (1997), "The value of public information in commodity futures markets", *Journal of Economic Behavior and Organization*, Vol. 32 No. 4, pp. 559-570, available at: https://linkinghub.elsevier.com/retrieve/pii/S0167268197000139

Gorham, M. (1978), "Public and private sector information in agricultural commodities", *Economic Review-Federal Reserve Bank of San Francisco*, pp. 30-38.

Griffin, T.W. and Traywick, L. (2021), "The role of variable rate technology in fertilizer usage", *Journal of Applied Farm Economics*, Vol. 3 No. 2, available at: https://docs.lib.purdue.edu/jafe/vol3/iss2/6

Griffin, T.W., Dobbins, C.L., Vyn, T.J., Florax, R.J.G.M. and Lowenberg-Deboer, J.M. (2008), "Spatial analysis of yield monitor data: case studies of on-farm trials and farm management decision making", *Precision Agriculture*, Vol. 9 No. 5, pp. 269-283.

Griffin, T.W., Miller, N.J., Bergtold, J., Shanoyan, A., Sharda, A. and Ciampitti, I.A. (2017), "Farm's sequence of adoption of information-intensive precision agricultural technology", *Applied Engineering in Agriculture*, Vol. 33 No. 4, pp. 521-527.

Griffin, T.W., Shockley, J.M. and Mark, T.B. (2018), "Economics of precision farming", *Precision Agriculture Basics*, pp. 221-230.

Isengildina, O., Irwin, S.H. and Good, D.L. (2006), "The value of USDA situation and outlook information in hog and cattle markets", *Journal of Agricultural and Resource Economics*, Vol. 31 No. 2, pp. 262-282.

Isengildina-Massa, O., Irwin, S.H., Good, D.L. and Gomez, J.K. (2008), "The impact of situation and outlook information in corn and soybean futures markets: evidence from WASDE reports", *Journal of Agricultural and Applied Economics*, Vol. 40 No. 1, pp. 89-103, available at: https://www.cambridge.org/core/product/identifier/S1074070800027991/type/journal_article

Johansson, R., Effland, A. and Coble, K. (2017), "Falling response rates to USDA crop surveys: why it matters", *Farmdoc Daily*, Vol. 7 No. 9.

Karali, B. (2012), "Do USDA announcements affect comovements across commodity futures returns?", *Journal of Agricultural and Resource Economics*, Vol. 37 No. 1, pp. 77-97.

Kastens, J., Kastens, T., Kastens, D., Price, K., Martinko, E. and Lee, R. (2005), "Image masking for crop yield forecasting using AVHRR NDVI time series imagery", *Remote Sensing of Environment*, Vol. 99 No. 3, pp. 341-356, available at: https://linkinghub.elsevier.com/retrieve/pii/S0034425705003056

Lehecka, G.V. (2014), "The Value of USDA crop progress and condition information: reactions of corn and soybean futures markets", *Journal of Agricultural and Resource Economics*, Vol. 39 No. 1, pp. 88-105.

Li, Y., Wailes, J.E., McKenzie, A. and Thomsen, M. (2010), "LL601 contamination and its impact on U.S. Rice prices", *Journal of Agricultural and Applied Economics*, Vol. 42 No. 1, pp. 31-38, available at: http://journals.cambridge.org/abstract_S1074070800003278 (accessed 21 October 2015).

Mann, T.L. and Dowen, R.J. (1996), "Are hog and pig reports informative?", *Journal of Futures Markets*, Vol. 16 No. 3, pp. 273-287, available at: http://doi.wiley.com/10.1002/%28SICI%291096-9934%28199605%2916%3A3%3C273%3A%3AAID-FUT2%3E3.0.CO%3B2-G

McFadden, J., Njuki, E. and Griffin, T. (2023), "Precision agriculture in the digital era: recent adoption on U.S. Farms", USDA-ERS Economic Information Bulletin No. EIB-248, available at: https://www.ers.usda.gov/webdocs/publications/105894/eib-248.pdf?v=1083

McKenzie, A.M. and Darby, J.L. (2017), "Information content of USDA rice reports and price reactions of rice futures", *Agribusiness*, Vol. 33 No. 4, pp. 552-568, available at: http://doi.wiley.com/10.1002/agr.21489

Mkhabela, M.S., Bullock, P., Raj, S., Wang, S. and Yang, Y. (2011), "Crop yield forecasting on the canadian prairies using MODIS NDVI data", *Agricultural and Forest Meteorology*, Vol. 151 No. 3, pp. 385-393, doi: 10.1016/j.agrformet.2010.11.012.

Ofori, E., Griffin, T. and Yeager, E. (2020), "Duration analyses of precision agriculture technology adoption: what's influencing farmers' time-to-adoption decisions?", *Agricultural Finance Review*, Vol. 80 No. 5, pp. 647-664, doi: 10.1108/AFR-11-2019-0121.

Ortez, M., Widmar, N.O., Mallory, M.L., Wolf, C.A. and Bir, C. (2023), "Online media in dairy markets: a US dairy futures market study", *Agricultural Finance Review*, Vol. 83 No. 1, pp. 168-185, available at: https://www.emerald.com/insight/content/doi/10.1108/AFR-03-2022-0034/full/html

Roznik, M., Mishra, A.K. and Boyd, M.S. (2023), "Using a machine learning approach and big data to augment WASDE forecasts: empirical evidence from US corn yield", *Journal of Forecasting*, available at: https://onlinelibrary.wiley.com/doi/10.1002/for.2956

Schaefer, M.P., Myers, R.J. and Koontz, S.R. (2004), "Rational expectations and market efficiency in the U.S. live cattle futures market: the role of proprietary information", *Journal of Futures Markets*, Vol. 24 No. 5, pp. 429-451, available at: http://doi.wiley.com/10.1002/fut.10124

Schimmelpfennig, D. (2016), "Farm profits and adoption of precision agriculture", Economic Research Report.

Sumner, D.A. and Mueller, R.A.E. (1989), "Are harvest forecasts news? USDA announcements and futures market reactions", *American Journal of Agricultural Economics*, Vol. 71 No. 1, p. 1, available at: https://academic.oup.com/ajae/article-lookup/doi/10.2307/1241769

Sykuta, M.E. (2016), "Big data in agriculture: property rights, privacy and competition in Ag data services", *International Food and Agribusiness Management Review Special Issue*, Vol. 19 A, pp. 58-74.

Thomsen, M., McKenzie, A.M. and Power, G.J. (2013), "Was there a peso problem in cattle options?", *Agricultural Finance Review*, Vol. 73 No. 3, pp. 526-538, available at: https://www.emerald.com/insight/content/doi/10.1108/AFR-09-2012-0048/full/html

Tack, J., Coble, K.H., Johansson, R., Harri, A. and Barnett, B.J. (2019), "The potential implications of 'big Ag data' for USDA forecasts", *Applied Economic Perspectives and Policy*, available at: https://academic.oup.com/aepp/advance-article/doi/10.1093/aepp/ppy028/5272601

Woodard, J. (2016), "Big data and Ag-Analytics", *Agricultural Finance Review*, Vol. 76 No. 1, pp. 15-26, available at: https://www.emerald.com/insight/content/doi/10.1108/AFR-03-2016-0018/full/html

Working, H. (1948), "Theory of the inverse carrying charge in futures markets", *Journal of Farm Economics*, Vol. 30 No. 1, p. 1, available at: https://academic.oup.com/ajae/article-lookup/doi/10.2307/1232678

World Food Programming (WFP), and Centre of Research and Studies on Economic Development (CERDI) (2012), "The ALert for price spike (ALPS)", available at: http://foodprices.vam.wfp.org/alps.aspx (accessed 10 October 2016).

Xie, R., Isengildina-Massa, O., Dwyer, G.P. and Sharp, J.L. (2016), "The impact of public and semi-public information on cotton futures market", *Applied Economics*, Vol. 48 No. 36, pp. 3416-3431, available at: http://www.tandfonline.com/doi/full/10.1080/00036846.2016.1139677

Ying, J., Chen, Y. and Dorfman, J.H. (2019), "Flexible tests for USDA report announcement effects in futures markets", *American Journal of Agricultural Economics*, Vol. 101 No. 4, pp. 1228-1246, available at: https://academic.oup.com/ajae/article/101/4/1228/5485173

About the authors

Francis Tsiboe is a Research Agricultural Economist in Economic Research Service at United States Department of Agriculture. Francis Tsiboe is the corresponding author and can be contacted at: ftsiboe@hotmail.com

Jesse B. Tack is a professor of agricultural economics in the Department of Agricultural Economics at Kansas State University.

Keith Coble is the vice president of MSU Division of Agriculture, Forestry and Veterinary Medicine and a professor of agricultural economics in the Department of Agricultural Economics at Mississippi State University.

Ardian Harri is the interim department head and a professor of agricultural economics in the Department of Agricultural Economics at Mississippi State University.

Joseph Cooper is the senior policy advisor to the Chief Economist, at the Office of the Chief Economist at United States Department of Agriculture.