Are Corn Futures Prices Getting “Jumpy”?

by

Anabelle Couleau, Teresa Serra, and Philip Garcia

Suggested citation format:

Are corn futures prices getting “Jumpy”?

Anabelle Couleau†, Teresa Serra, and Philip Garcia*


Copyright 2018 by Anabelle Couleau, Teresa Serra, and Philip Garcia. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

This material is based upon work that is supported by the National Institute of Food and Agriculture, U.S. Department of Agriculture, Hatch under accession number 1005769, and the Office of Futures and Options Research (OFOR) at UIUC.

*The authors are Ph.D. research assistant, and professors in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign.

† Contact: 326 Mumford Hall, 1301 W. Gregory Drive, Urbana, IL 61801. Phone: 217-333-1810. Email: couleau2@illinois.edu
Are corn futures prices getting “Jumpy”?

Corn futures markets have experienced increased intraday price jumps which have been blamed on public information shocks and the reduced trading latency brought by electronic trading. This paper contributes to shed light on this issue by assessing intraday jumps in the corn futures nearby transaction prices from 2008 to 2015. We use a nonparametric jump test and a variance analysis to estimate jump risk. Our results suggest that the real-time trading of major USDA reports has substantially increased the frequency and the magnitude of jump risk. In contrast, results suggest that the electronic platform along with reduced latency may have increased liquidity and prevented price spikes on non-USDA report days.

Key words: Corn futures, intraday, price jumps, jump risk, information shocks, nonparametric test.

Introduction

Intraday spikes in grain futures prices are a concern to hedgers as they cause difficulties in managing risk using futures contracts. Jumps are often blamed on public information shocks and the reduced trading latency brought by the adoption of state of the art trading technology by some traders. The Commodity Futures Trading Commission (CFTC) identified rather frequent “flash” events in the corn futures market between 2010 and 2015, occurring in hourly intervals. These extreme price movements raised concerns on the jump risk faced by market participants (CFTC 2015) and the relationship of this risk with automated trading (Meyer 2017; Onstad 2018), which reached nearly 39% of all futures trade volume in grains and oilseeds markets between 2012 and 2014 and 49% between 2014 and 2016 (Haynes and Roberts 2015, 2017).

Several jumps are identified around U.S. Department of Agriculture (USDA) announcements. Since May 21, 2012, all sensitive USDA reports are released during trading hours (at 7:30:00 am CT until December 2012 and at 11:00:00 am CT since January 2013). Several commercial traders have raised concerns that the new report release policy coupled with the recent technological changes in futures markets, may create an unfair playing field that essentially favors nonconventional trading firms that operate using technologies that can reduce trading speed to nanoseconds. Some traditional commodity investors have already announced the closure of their company due to their inability to react quickly and efficiently to increased price risk (Onstad 2018; Meyer 2018). Adjemian and Irwin (2018) show that real-time trading on USDA crop announcements leads to volatility spikes in agricultural futures prices that dissipate within a few minutes. In addition, Christensen et al. (2014) show that jump volatility risk is more relevant for conventional traders who take positions at a low speed, than for high-speed traders. Although evidence of jump risk in agricultural commodity markets has been provided, little is known about its magnitude, composition, timing and the type of traders (i.e., hedgers vs high speed traders) who bear this risk. We shed light on these issues in the corn futures market. The contributions of this paper are outlined in the following paragraph.

First, we identify the days and intraday time at which jumps occur and their economic magnitude. We also characterize market conditions in the presence of jumps using the bid-ask
spread and trading volume around jump times and identifying major crop report releases taking place in jump days. Second, this paper provides empirical evidence of the magnitude of intraday jump risk faced by traders operating at different temporal frequencies in agricultural futures markets. We call this the “sampling frequency of jumps”. Understanding the sampling frequency of jumps is important since automated trading in agricultural commodity markets has polarized trading latency, allowing nonconventional market participants to take and cancel positions at ultra-high speed, while hedgers continue to operate at a much slower pace. Third, we disentangle the portion of daily price variance due to jumps in the efficient prices from that due to market microstructure noise blurring price jumps, thus shedding light on jump risk composition and allowing for a better understanding of volatility and its dynamics.

To identify jump risk in corn futures prices, we use high frequency intraday data characterized by microstructure noise that induces autocorrelation in returns (Hansen and Lunde 2006). Huang and Tauchen (2005) show that noise biases jump-test results towards finding more jumps. This requires careful selection of research methods. We rely on the methods by Lee and Mykland (2008; 2012) and Christensen et al. (2014) who propose nonparametric approaches to detect intraday jumps, estimate jump risk and identify microstructure noise. We use nearby corn futures transaction prices, tick data time-stamped at the second and observed from January 2008 to December 2015. Main findings show increased jump risk and jump clustering with real time trading of USDA reports. The new report release policy has also changed intraday jump times, from a relatively even distribution throughout the day to a concentration of jumps around the report release time. Jump size has increased after May 21, 2012 for announcement days, but has declined for non-announcement days. We also show that traders operating at slow frequency face more jump risk than traders operating at higher frequency during announcement days. We find jump risk at one-second frequency sampling to be substantially distorted by noise, though noise related to jumps has tended to decrease over time.

The rest of the paper is organized in three sections. Section 2 offers a literature review. Section 3 describes the methodology. Section 4 presents the data structure and summarizes the empirical findings. The paper concludes in section 5.

**Literature review**

A few studies discuss agricultural commodity price jump risk, in the context of futures and options prices modelling. They reach the conclusion that proper modeling of jumps can reduce pricing errors. Hilliard and Reis (1999) show that large price changes cause return non-normality in commodity markets and propose a jump-diffusion model to better capture futures prices behavior. Koekebakker and Lien (2004) estimate jumps size and intensity for wheat options prices, assuming futures prices follow a jump-diffusion process. They develop a futures option pricing model and find that accounting for jumps reduces pricing errors. Schmitz et al. (2014) model large price movements in U.S. corn, soybean and wheat spot prices using a Poisson jump-diffusion process with stochastic volatility. They find jump parameters to be significant and pricing errors lower than errors from a stochastic model without jumps. While these studies point toward the relevance of accounting for jumps in modelling daily agricultural prices, they don’t examine their intraday presence and behavior.
With increased trading speed, jumps occur and fade quickly. The literature studying the presence of jumps using intraday data often focuses on financial markets and is specially concerned about the relative contribution of jumps to total price variance (Huang and Tauchen 2005, Andersen, Bollerslev, and Diebold 2007, Andersen, Benzoni, and Lund 2002, Tauchen and Zhou 2011). Along these lines, Wu et al. (2015) examine jumps in agricultural futures markets using a model-free approach and 5-minute sampled returns. They identify jumps in corn futures transactions prices by taking the difference between the annualized standard deviation of realized variance and the bipower variation. Similar to Wu et al. (2015), most literature assessing intraday jumps, uses a 5-minute sampling frequency to eliminate microstructure noise, which can confound jump identification.

Christensen et al. (2014) suggest that jump occurrence is quite small (1% of the realized annualized realized variance) at the millisecond environment in equity indexes, foreign exchange rates and DJIA constituent markets, once the presence of market microstructure noise is filtered. They explain that the use of noise-filtered millisecond data reduces the likelihood of confounding volatility bursts with real jumps. They also show that price-jumps have a higher impact at lower sampling frequency (e.g. 5-minute or 15-minute) than at ultra-high frequency.

The factors influencing intraday jumps and the market characteristics during jumps have been investigated in financial markets. Several studies explore the impact of news on intraday price jumps (Boudt and Petitjean, 2014; Bjursell, Gentle and Wang, 2015; Chan and Gray, 2017; Jiang, Lo and Verdelhan, 2011). Boudt and Petitjean (2014) distinguish between jumps related to firm news and to macro-announcements, and explore how jumps are linked to market liquidity measures such as bid-ask spreads. Christensen et al. (2014) argue that liquidity measures appear to have more significant jumps than prices during extreme market events (e.g. flash crashes or earthquakes) at the millisecond lens. Both studies find that market liquidity measures worsen following a jump. Brogaard et al. (2018) investigate whether extreme price movements are caused by high frequency traders. By using two main methodological approaches, one that is indifferent and the other that controls for time-varying volatility, they conclude that high frequency traders do not cause extreme market price movements, but instead seem to act as liquidity suppliers during extreme price events.

**Methods**

With the arrival of high frequency trading and data, a variety of nonparametric tests have been developed to detect the jumps component in price variation. These methods have been applied to financial markets to better understand the sources of price risk (Barndorff-Nielsen and Shephard 2006; Aït-Sahalia and Jacod 2009; Lee and Mykland 2008). Nonparametric approaches are based on the comparison between the realized variance (RV), which captures the variance in prices generated by both the diffusive- and the jump-component, and an estimator of the integrated variance which is robust to the presence of jumps (e.g. bipower variation-BV initially proposed by Barndorff-Nielsen and Shephard 2004). Dumitriu and Urga (2012) use Monte Carlo simulation to compare alternative jump testing procedures and conclude that the approach by Lee and Mykland (2008) is the most effective, which nonetheless might be oversized under extreme volatile processes. Lee and Mykland's (2008) test is not robust to the presence of microstructure noise and thus must be applied to noise-filtered data (Lee and Mykland 2012).
Few studies have explicitly considered the effect of market microstructure noise on jump identification. Huang and Tauchen (2005) and Andersen et al. (2007) examine the effect of noise on jump detection assuming identically and independently distributed (i.i.d) noise, while Lee and Mykland (2012) and Christensen et al. (2014) adopt a more realistic scenario and consider non-i.i.d. noise, which is consistent with Hansen and Lunde (2006). Lee and Mykland's (2012) procedure allows assessment of the intensity of jumps for intraday time intervals, relative to the total daily price variation in the presence of noise. However, their procedure does not time-stamp jumps. Christensen et al. (2014) estimate the jump variance (JV) component of total price variation by relying on noise-filtered price RV and BV estimators and then identify the jump location using Lee and Mykland's (2008) test on 5-minute sampled returns and tick sampled returns filtered for microstructure noise. We follow their approach.

We first identify and time-stamp intraday jumps using Lee and Mykland's (2008) jump identification test applied on noise-filtered tick price data, which allows to disentangle jumps from volatility bursts (Christensen et al. 2014). We compare the presence of the jumps occurring during major USDA crop reports release days (Table 1) with jumps on non-announcement days and we characterize market liquidity around jump time. Second, we estimate the contribution of jump risk to total price risk by estimating the relevance of JV relative to RV using intraday returns and non-parametric methods. Intraday jumps may not affect all traders in the same fashion. For traders operating at high speed, a jump may be partially felt as an increasing trend. For slower traders, jumps may be felt in their entirety. This is reflected in the volatilities computed at different sampling frequencies. Consistently, we draw the JV signature plots at different sampling frequencies (e.g. one second, 5 minutes, or 15 minutes). These signature plots are also used to show the relevance of market microstructure noise during jump occurrence.

**Jumps detection and location**

The log efficient transaction price which is free from microstructure noise and follows a martingale, is represented by \( P^*(t) \) and modeled as

\[
dP^*(t) = \mu(t)dt + \sigma(t)dW(t) + Y(t)dJ(t),
\]

where \( t \in [0,T] \) indexes time, \( W(t) \) is an \( F_t \)-adapted standard Brownian motion, with \( F_t \) being a right-continuous information filtration for market participants. \( \mu(t) \) is a drift and \( \sigma(t) \) is a stochastic volatility process, both \( F_t \)-adapted processes with an underlying Ito process with continuous sample paths. \( Y(t) \) is the predictable jump size, with a mean \( \mu_y(t) \) and a standard deviation \( \sigma_y(t) \). \( J(t) \) is assumed to follow a non-homogenous Poisson distribution (i.e., jumps arrival time is independently distributed but, for instance, they can arrive more frequently at a certain time of the day).

It is well known that market microstructure noise contaminates prices observed at high frequency. We use the pre-averaging method proposed by Lee and Mykland (2012) to clean observed prices from noise and obtain an estimate of the efficient market price (\( \hat{P} \)) on which we apply the jump detection test. The intuition behind pre-averaging techniques consists in averaging observed prices over non-overlapping windows to correct for the noise-induced autocorrelation (of order \( k \)) in returns.
The jump detection statistic is applied to each day and computed as the ratio of the last noise-filtered observed return in an intraday time window to the integrated volatility (IV) estimated by the jump-robust BV using the returns in that same window. Dividing by the IV helps controlling for time-varying volatility and avoids detecting spurious jumps during volatility bursts. The stochastic jump dynamics are then determined by shifting the time window to the right in a rolling window fashion.

Suppose a fixed time horizon (day trading session) $T$ with $N$ observations. The distance between two observations is denoted by $\Delta t_i = t_i - t_{i-1}$. In order to test for the presence of a jump in the realized return from $t_{i-1}$ to $t_i$, we examine the magnitude of this realized return and compare it against the returns’ realized volatility in the previous $W$ periods. The jump detection test statistic is denoted by $L(i)$ and is defined as:

$$L(i) = \frac{\hat{\beta}_{t_i} - \hat{\beta}_{t_{i-1}}}{\hat{\sigma}(t_i)}.$$  \hspace{1cm} (2)

The numerator $\hat{\beta}_{t_i} = \hat{\beta}_{t_{i-1}}$ corresponds to the noise-filtered returns and the denominator $\hat{\sigma}(t_i)$ is the instantaneous volatility estimated using the BV estimator as follows,

$$\hat{\sigma}(t_i) = \sqrt{\frac{1}{W^2 - 2} \sum_{j=-W+2}^{W-1} |\hat{r}_{t_j}| |\hat{r}_{t_{j-1}}|}.$$  \hspace{1cm} (3)

The optimal window size $W$ must be chosen so that the effect of jumps on the volatility measure disappears. Lehecka, Wang and Garcia (2014) show that USDA announcement effects, when announcements are released outside trading hours, are usually absorbed by the market in ten minutes. Joseph and Garcia (2018) identify longer periods (60 minutes) for the effects of USDA reports released during trading hours to fade. We define $W$ so that it covers on average one hour and a half$^1$.

Under the null of no jump, the test statistic $L(i)$ takes a small value and follows approximately a normal distribution. Lee and Mykland (2008) identify the null hypothesis’ rejection region by studying the asymptotic distribution of the maximum of the test statistic under the null of no jumps during the interval $(t_{i-1}, t_i]$. For this purpose, they assume that $L(i)$ sample maximum is Gumbel distributed. The null of no jump in $\hat{r}_{t_i}$ will be rejected if $|L(i)| > G^{-1}(1 - \alpha)S_N + C_N$, where $G^{-1}(1 - \alpha)$ is the $(1 - \alpha)$ quantile function of the standard Gumbel distribution and $C_N$ and $S_N$ are defined as,

$$C_n = \frac{(2 \log(N))^{1/2}}{c} - \frac{\log \pi + \log(\log N)}{2c (2 \log N)^{1/2}},$$

$$S_n = \frac{1}{c (2 \log N)^{1/2}},$$

where $c = \sqrt{\frac{2}{\sqrt{\pi}}}$. With the probability $\alpha$ of type I error, we reject the null hypothesis of no jump if $|L(i)| > \beta^* S_N + C_N$ with $\beta^*$ defined such that $\exp(-\exp\beta^*) = 0.99$ for 1% significance level, implying $\beta^* \approx 4.6001$. When Lee and Mykland (2008) test identifies a jump, we stamp it at $t_i$, corresponding to the last observation in $W$. We define the jump size in cents/bushel as the difference between the noise-filtered price (not in logarithm form) between $t_{i-1}$ and $t_i$, i.e. $\exp(\hat{p}(t_i)) - \exp(\hat{p}(t_{i-1}))$.

$^1$This corresponds to $W = 120$. In appendix B, we provide the distribution of jumps within the day for alternative values of $W (W = 125$ and $130)$ and find that the main results still hold for the different window sizes.
While Lee and Mykland's (2008) test allows to identify the number of jumps in a day, their timing, as well as their magnitude, it is not informative of who faces jump risk. As well known, while some market participants using state of the art technologies can take and cancel positions at ultra-high frequency, traditional hedgers operate at a much slower path. In this article we do not only want to identify jump risk, but we aim at shedding light on who faces this risk as well as how much do jumps add to price volatility. For this purpose, in the following subsection, we propose to derive the jump variance signature plots for the days in which jumps are identified.

Jump variation component

On days for which the Lee and Mykland (2008) method identifies a significant jump, we estimate the daily proportion of $JV$ relative to the price quadratic variation ($QV$) (Christensen et al. 2014), which results in a relative magnitude of jump price risk. $QV$ captures both the diffusion- and jump-variation components of returns. An efficient estimator of $QV$ in the absence of microstructure noise is the well-known $RV$ (Andersen et al. 2001), which we compute using the noise-filtered price realized volatility estimate following Christensen et al. (2014) as,

$$RV^c = \frac{N}{N-K+2} \frac{1}{K\psi_K} \sum_{l=0}^{N-K+1} (\hat{r}_{t_l})^2 - \frac{\hat{\omega}^2}{\theta^2\psi_K}$$  \hspace{1cm} (4)

where $N$ is the total number of intraday observations, $\hat{r}_{t_l}$ is the noise-filtered return, $\psi_K = \frac{1}{12}$, with $K$ being determined as in Lee and Mykland (2012) and $\hat{\omega}$ is estimated using $\hat{\omega}_{AC} = -\frac{1}{N-1} \sum_{l=2}^{N} \mid \hat{r}_{t_l} \mid \mid \hat{r}_{t_{l-1}} \mid$ (Oomen 2006). The $RV^c$ is the sum of the $JV^c$ and a jump-robust estimator of the integrated variance. The latter is approximated by the $BV^c$ (Barndorff-Nielsen and Shephard 2004) which we also define on filtered prices as follows,

$$BV^c = \frac{N}{N-2K+2} \frac{1}{K\psi_K} \sum_{l=0}^{N-K+1} \hat{r}_{t_l-K} \mid \hat{r}_{t_{l-K+1}} \mid - \frac{\hat{\omega}^2}{\theta^2\psi_K}$$  \hspace{1cm} (5)

A consistent estimator of the $JV$ component in presence of noise is thus given by,

$$JV^c = RV^c - BV^c \rightarrow \sum_{i=1}^{N_j} J_i^c$$  \hspace{1cm} (6)

The magnitude of $JV^c$ expressed as a portion of total $QV^c$ is given by equation (7),

$$JV^c \text{ share} = \frac{QV^c - BV^c}{QV^c}$$ \hspace{1cm} (7)

Annualized $JV^c$ (expressed as a proportion of $QV^c$) signature plots can be developed to identify the importance of $JV^c$ at different sampling frequencies and thus provide a measure of the jump risk faced by traders taking positions at different speed. Through these signature plots, we further compare $JV^c$ to $JV$, based on observed, non-filtered prices, defined as $JV = RV - BV$, being $RV = \sum_{i=1}^{N} (r_{t_i})^2$ and $BV = \frac{N}{N-1} \frac{1}{2} \sum_{l=2}^{N} \mid r_{t_l} \mid \mid r_{t_{l-1}} \mid$. The difference between $JV^c$ and $JV$ shows the $JV$ portion that can be attributed to noise. As the sampling frequency declines, noise dissipates and $JV$ and $JV^c$ converge. The duration of noise variation is approximated by the sampling frequency for which the two measures converge.
Results

Data description

The data consist of CME Group’s BBO (Best-Bid-Offer) transaction prices, quotes and trade volumes for corn futures contracts, time-stamped to the nearest second and traded on the electronic platform. The sample period is from January 14, 2008 to December 4, 2015, resulting in 1956 trading days. The corn futures contracts are traded with five delivery months: March, May, July, September and December. We use the nearby series, defined as the nearest contract delivery month with the highest trading volume. We center our attention on transactions prices and the day trading hours, which concentrate most trading activity. We make an exception to this rule in the period from May 21, to December 31, 2012, when we consider a wider time window in order to observe market behavior during the report release time at 7:30:00 am CT.\(^2\) We purge the data to eliminate recording errors following Barndorff-Nielsen et al. (2009). When several trades have the same second time stamp, only the last observation within that time stamp is used. Days with limit-price moves (LPM) in which the prices stay locked for at least 30 minutes, have a reduced number of observations often inadequate for the empirical analysis and they are thus excluded.\(^3\)

Figure 1 depicts, in the top panel, the daily nearby corn contract closing transaction prices, and in the bottom panel, the annualized realized volatility of noise-filtered (Lee and Mykland 2012) transaction prices for the sample period. Episodes of high intraday volatility are observed during 2008-2010 and after 2013. Since 2013, the corn futures price volatility is characterized by salient daily spikes corresponding in most cases to the monthly or quarterly USDA agencies’ reports (Table 1). The change in market volatility dynamics since 2013 suggests that the release of USDA reports in real trading time has changed the intraday price behavior drastically.

We identify jumps in transactions prices and present our results for USDA announcement and non-announcement days separately. We select two crop reports identified to have a major impact on corn futures prices (Adjemian and Irwin 2018), the monthly WASDE and the quarterly Grain Stock (GS) report (see Table 1 for details). Since January 2013, both reports are released at 11:00:00 am CT. Following Adjemian and Irwin (2018), we refer to this period as the “real time” era as opposed to the halt era before 2012 and call it period 3. From June to December 2012, the reports were also released in real time, but earlier at 7:30:00 am CT when trading volume is usually lower. We consider this period (period 2) separately as we expect jump behavior to be different given different market liquidity conditions characterizing the market at 7:30 relative to 11:00. From January 2008 to May 2012, the report release time was 07:30:00 when markets were closed, which we call period 1. The average daily trade volume over our sample period is 95,954 contracts during announcement days and 80,877 during non-announcement days. In the following subsection, we identify the daily jump number, size and timing.

---

\(^2\) Trading hours considered are: before May 21, 2012, from 9:30 to 13:15; May 21-December 31, 2012: 7:00 to 14:00; January 2, - April 5, 2013, from 9:30 to 14:00; since April 8, 2013, from 8:30 to 13:15, and since July 6, 2015, from 8:30 to 13:20.

\(^3\) A total of 32 LPM are excluded, among which 14 were located announcement days (13 during 2008-2012, and 1 in 2013).
Jump identification test

In this subsection, we present the results of the nonparametric test by Lee and Mykland (2008) used to identify jumps and their timing of occurrence. We filter observed prices for noise using the pre-averaging technique proposed by Lee and Mykland (2012), which essentially implies removing the price autocorrelation originated by noise (see appendix A for further details). To conduct the test in (2), we choose $W = 120$ noise-filtered sampled observations, which is approximately equivalent to one and a half clock hour and is expected to be robust to jumps that are likely to be comprised between the first 10-60 minutes after the announcement (Lehecka et al. 2014, Joseph and Garcia 2018). To avoid losing observations at the beginning of the trading day due to the rolling window technique, the first rolling window to conduct the test starts at 03:00:00 am. The low trading overnight and/or the morning halt before May 21st, 2012 requires going back to 03:00:00 am in order to have enough observations.\(^4\)

We find 495 days with at least one jump, which represents 25.3% of the total trading days (Figure 2). The average number of jumps occurring on non-announcement days declines from 0.32 jumps in period 1, to 0.24 in period 2, and 0.26 in period 3. Also, the percentage of jumps occurring on non-announcement days declines from 95% in period 1 to 71% in period 2 and to 65% in period 3. A decreased presence of jumps on non-announcement days is suggestive that automated trading is not likely to have increased jump risk, at least outside public information release event times. By turning to announcement days, jumps occur 100% of the time in period 3 and 83% of those days have a jump cluster within 2 minutes after the announcement time (i.e. at least two jumps are detected within 2 minutes), which leads to an average of 2.30 jumps per announcement day. This contrasts with 0.35 jumps per announcement day in period 1, and 1.75 jumps in period 2, which suggests that after the USDA releases reports when the market is open, jumps in efficient prices tend to occur more often and to cluster. Maheu and McCurdy (2004) have suggested that price jumps cluster during new information and reflect the structure of the information arrival process. Using 5-minute sampled returns, Bjursell et al. (2015) find energy price jumps to affect between 4% and 7% of the total trading days in their sample at 1% significance level. They further find a low jumps rate (9%) associated to inventory announcements. Our percentage is closer to Lahaye, Laurent and Neely (2011) who find 25% of the trading days with at least one jump in the foreign exchange market. They also find that jumps in foreign exchange markets, financial index futures and 30-year U.S. treasury bonds futures markets tend to cluster around public announcements time.

Figure 3 shows the percentage of detected jumps per intraday time intervals in the three periods. In period 1, jumps occurred slightly more often during the first and the last intervals of the day trading session, with a relatively even distribution throughout the day. The incorporation of information, both private and public, at the market opening, as well as the lack of liquidity at the end of the trading session are likely to create more frequent price jumps. In period 2, jumps occurred most often (40%) in the first interval of the day, at 07:30:00 am CT, coinciding with the USDA report releases time during this period. Finally, in the third period, almost half of the

\(^4\) Consequently, a detected jump at the beginning of the day will depend on the prevailing fundamental volatility before the day session starts. We assess the robustness of the Lee and Mykland's (2008) test results by increasing the window size to $W = 125$ and 130. The results, presented in appendix B, are similar to the ones using $W = 120$. 

intraday jumps (45%) are detected from 10:30:00 am to 11:29:59 am, which is consistent with the clustering of jumps during USDA report release time discussed above (Figure 2). The second intraday interval with more presence of jumps is at the end of the day (20%). In other words, changes in USDA reports release times shift the timing and the structure of the absorption of fundamental information by the futures market, increasing the proportion of price-jumps occurring around the release time. For announcement days, average positive (negative) jump size has increased from 1.6 (-2.8) cents per bushel in period 1, to 4.6 (-6) cents per bushel in period 2, and to 4.1 (-3.8) cents per bushel in period 3, representing 0.8% (0.6%), 1.1% (1.3%), and 1.4% (1.3%) of the average price of the corresponding day. Non-announcement days register efficient price jumps of smaller size, which represent between 0.3% and 0.4% of the average daily price. The average size of positive (negative) jumps goes from 1.8 (-1.7 ) cents/bu in period 1, 1.7 (-1.6) cents/bu period 2, and 1.1 (-1.2) cents/bu in period 3, respectively. While jump size during announcement days has increased with the change in USDA announcement release policy, it has declined for non-announcement days. This finding suggests that while real time trading of USDA announcements has caused more volatility spikes, technological changes affecting agricultural commodity markets may have increased liquidity provision at high frequency and reduced spikes outside announcement sessions.

In Figure 4, the total number of jumps is depicted by days to roll-over date across nearby contracts. Using Bai and Perron's (2003) structural breaks test, we find that one structural break occurs at 36 days before roll-over. Jumps in efficient prices are significantly more prevalent from 36 trading days until the roll-over date of the nearby series. This is compatible with the Samuelson hypothesis that the most relevant information is revealed close to contract maturity (Samuelson 1965). Incorporation of this information into the market may be the reason underlying increased jumps. Also, a progressive decline of liquidity as the contract approaches maturity may be another underlying factor causing price jumps.

In Figure 5, we present the behavior of two market variables, bid-ask spread and trading volume, in the minutes preceding and following the jump in announcement and non-announcement days. More specifically, we examine the maximum bid-ask spread and total volume within 1 minute bins for a 10-minute window before and after the jump. The four right, middle and left panels depict the two variables for period 1, period 2 and period 3, respectively. Liquidity measures in these panels are compared against the same liquidity measures in no-jump days arbitrarily chosen that serve as the counterfactual. The filled bullet points correspond to the cases when the null hypothesis of the two-way Wilcoxon test (also called Mann-Whitney test) of no significant difference in mean between two series is rejected at 1% significance level. In general, spreads and volumes follow an n-shape around jumps, with the peak occurring right after the jump. Relative to no-jump days, spreads and volumes start to be significantly higher a few minutes before jump occurrence and do not return back to normal levels within the ten-minute interval considered. On non-announcement days, spreads do not widen as much as in announcement days, and tend to decline over time: while spreads reach about 0.5 cents/bushel in periods 1 and 2, they do not go beyond 0.4 cents/bushel in the third period. The volume around jumps in non-announcement days has tended to decline as well, from a maximum of about 1,000 contracts/minute, to around 800 contracts/minute.

---

Note that the counterfactual liquidity variables are measured using the maximum price change on days when no jump is detected, or in other words, per-minute bid-ask spread and trading volume levels for non-significant jumps.
Now we turn to the panels for announcement days represented by red curves. Suppression of the morning trading halt has widened spreads around jumps, from a maximum of about 0.6 cents/bushel in period 1, 1.2 bushels in period 2 and 0.8 bushels in period 3. Hence, spreads associated to jumps on announcement days are substantially above spreads during jumps on non-announcement days. Volume has also increased from a maximum of 2,000-2,500 contracts/minute in periods 1 and 2, to more than 6,000 in period 3.

In short, price volatility jumps are usually accompanied by a jump in trading volume that is higher for announcement than non-announcement days. While volume in non-announcement days has not changed substantially over the period studied, volume in announcement days has drastically increased since 2013. As for the spread, while most jumps cause spreads to widen slightly above 2 ticks, real time trading of USDA reports causes spreads above 3 ticks in period 3 and almost 5 ticks in period 2. Hence, real time trading of USDA reports causes substantial transactions costs, specially when reports are released during illiquid periods (period 2).

**Jump variance**

The estimator of the $JV$ component of the total price $RV$ is defined as the difference between $RV$ and $BV$ and calculated for days in which we identify at least one statistically significant jump using the Lee and Mykland's (2008) test. To assess intraday jump risk faced by different traders operating at different speed, we measure $JV$ at different sampling frequencies. The annualized $JV$ as a proportion of annualized $RV$ ($AJV^{share}$) signature volatility plots for announcement and non-announcement days in the three periods are presented in Figure 6, Figure 7, and Figure 8, respectively. When price series are not filtered for microstructure noise and sampled at every tick, $AJV$ accounts for nearly 15% of the total price volatility per day on average throughout the period of study. The noise-filtered $AJV$ ($AJV^c$) at the same frequency represents less than 5% of the total efficient price volatility in first two periods, which implies noise volatility share is twice as big as the efficient price jump risk share, and around 7% in the third period (post-2013), which implies that noise volatility share during the post-2013 period is as relevant as the efficient price jump risk share.

While noise volatility during jump occurrence has recently declined, its duration has increased on non-announcement days. The two measures ($AJV$ and $AJV^c$ share) converge faster in the first period (1-minute frequency sampling) than in the post-2013 period (2-minute frequency sampling). These results shed light on the duration of the market microstructure noise volatility occurring during jumps and show that duration has doubled recently. Conversely, the gap closes faster in announcement days, which may be due to the increased market liquidity during this time that may reduce market frictions causing noise. Indeed, in the second and third periods, the noise associated to jumps is virtually zero after 30 and 10 seconds, respectively, on announcement days, compared to 1 to 2 minutes on non-announcement days. This has implications for price discovery, defined as the speed with which futures price changes reflect the efficient price changes. During

---

6 In Figure 6, Figure 7, and Figure 8, $ARV$ and $ABV$ are constructed using tick transaction price data time-stamped at different sampling frequencies. On announcement days, tick data are on average spaced every 2.5 seconds, and on non-announcement days, they are spaced every 3.2 seconds. The measures $ARV^c$ and $ABV^c$ are constructed using the noise filtering technique on the tick transaction data as specified in the appendix.
announcement days, price discovery occurs relatively faster than during non-announcement days. This may reflect increased presence of high frequency liquidity providers during these days. This interpretation is in line with Brogaard, Hendershott, and Riordan (2014) who find that during stressful periods, high frequency traders tend to supply liquidity and trade in opposite direction to pricing errors.

\( AJV^{\text{share}} \) progressively declines as the sampling frequency diminishes, until stabilizing around values between 5% and 7%, the only exception being the announcement days post-2013, for which \( AJV^{\text{share}} \) stabilizes at around 12%. This indicates that high jump risk is persistent throughout the day, which is compatible with the results of Joseph and Garcia (2018), who show a relatively long duration of intraday report effects. The results are also compatible with increased jump risk due to real-time trading of announcements, which is in line with previous literature (Janzen and Adjemian 2016; Adjemian et al. 2017; Bunek and Janzen 2015).

As noted above, the \( AJV^{\text{share}} \) is estimated for each day with at least one statistically significant jump and a monthly average is presented in Figure 9. This sheds light on the evolution of jump risk over time. We compare jump risk at tick sampling frequency (\( AJV^{c,\text{share}} \)) with the 5- and 15-minute sampling frequencies (\( AJV^{\text{share}} \)). The \( AJV^{\text{share}} \) is estimated as

\[
AJV^{\text{share}} = \frac{ARV - ABV}{ARV},
\]

where \( ARV \) is the annualized realized volatility (\( \sqrt{252 \times RV} \)) and \( ABV \) is the annualized bipower variation (\( \sqrt{252 \times BV} \)). The \( AJV^{c,\text{share}} \) is computed similarly using noised-filtered returns.

The \( AJV^{c,\text{share}} \) at tick sampling frequency (green bars in Figure 9) increases after January 2013 from an average of 4.3% (pre-2013) to 7.3% (post-2013). To test whether the \( AJV^{c,\text{share}} \) and \( AJV^{\text{share}} \) significantly changed post-2013 compared to pre-2013 period, we use the Wilcoxon rank-sum test to test the null hypothesis that the distribution of two independent samples is equal. We find that the \( AJV \) shares at 1 tick and 5-minute frequency distributions are significantly different in the post-2013 period compared to the pre-2013, while no significant change is found for \( AJV \) share at 15-minute frequency sampling. The increase in the \( AJV^{c,\text{share}} \) at tick sampling leads to a reduction in the distance between \( AJV^{c,\text{share}} \) at tick sampling and the \( AJV \) share computed at 5-minute, and 15-minute frequency, from 0.8% pre-2013 to -0.5% post-2013, and from 2% pre-2013 to -0.3% post-2013, respectively. As a result, and compatible with volatility signature plot results, post-2013 jump risk is less related to noise and more to efficient price jumps. Our results are also compatible with Christensen et al. (2014) findings who show the average jump volatility risk increases as trading frequency declines. Traditional traders who trade at slower frequency face increased jump volatility risk, with the 15-minute \( AJV \) share reaching nearly 15% in June 2014.

**Conclusions**

Corn futures markets have experienced increased intraday price jumps which have been blamed on public information shocks and the reduced trading latency brought by electronic trading. The presence of relevant price jumps creates an unfavorable scenario for commercial traders who have already complained that the new USDA report release policy and the recent technological changes in futures markets, essentially favor high speed traders. In this paper, we shed light on the prevalence of price jumps in the US corn futures market. Using high frequency data observed from
2008 to 2015 and nonparametric methods, this article identifies price jumps, their magnitude and timing. We also examine market conditions around price jumps, the microstructure noise affecting price jumps and the type of traders who bear jump risk.

We apply the nonparametric jump test developed by Lee and Mykland (2008) and we find that jumps are relatively frequent, affecting a quarter of the total number of days in our sample. Recent years have seen an increased presence of jumps during USDA report release days that are driven by the changes in the release policy in 2012 and 2013. We find real time trading of USDA reports to generate 1.75 and 2.30 price jumps per announcement day in the second (May 21, to December 31, 2012) and third (since January 2013) period respectively, which contrasts with 0.35 jumps per announcement day in the first period (January 14, 2008 to December 4, 2015), when reports were released outside trading hours. The size of the jumps has also changed. Positive (negative) jump size has increased from 1.6 (-2.8) cents per bushel in the first period, to 4.6 (-6) cents per bushel in the second period, and to 4.1 (-3.8) cents per bushel for positive (negative) jumps after 2013, respectively. These bigger jumps have also been accompanied by higher transactions costs, with spreads beyond 3 ticks in the most recent period, as well as by heightened volume reaching around 6,000 contracts per minute after 2013. Non-announcement days, in contrast, are experiencing less jumps of a smaller size. Decreased presence of jumps on non-announcement days is suggestive that automated trading is not likely to have increased jump risk, at least outside public information release event times.

As for the type of traders bearing jump risk, those operating at slow frequency face relatively more efficient price jump risk than traders at higher frequency during announcement days. No substantial differences are appreciated on non-announcement days. We find jump risk at one-second frequency sampling to be substantially distorted by noise, though noise related to jumps has tended to decrease over time. This finding suggests that public information is absorbed more efficiently post-2013 than pre-2013, which may be due to electronic trading bringing in more traders and increasing market liquidity. In a hedging context, the new report policy has increased execution risk, specially around announcement times, which can limit hedging activities and affect the sustainability of commercial traders. In contrast, results suggest that the electronic platform along with reduced latency may have increased liquidity and prevented price spikes on non-announcement days.
References


Meyer, G. 2018. “Last commodities hedge funds go off beaten track.” *Financial Times*. Available at: https://www.ft.com/content/fbe5a554-36b3-11e8-8eee-e06bde01c544 [Accessed April 24, 2018].


Figures

Figure 1. Daily nearby corn futures transaction prices (closing price) in logarithm form (top panel) and annualized realized volatility of noise-filtered transaction prices (bottom panel), from January 15, 2008 to December 4, 2015.

Notes: noise-filtered transaction prices are obtained using Lee and Mykland’s (2012) approach (see appendix A).
Figure 2. Number of daily jumps detected using Lee and Mykland’s (2008) jump test on noise-filtered prices for announcement and non-announcement days, from January 15, 2008 to December 4, 2015.

Notes: The vertical dashed lines correspond to May 21st, 2012, and to the first trading day of January 2013.
Figure 3. Percentage of intraday significant jumps out of total number of jumps within each of the three periods with $W = 120$, from January 15, 2008 to December 4, 2015.
Figure 4. Total number of jumps from Lee and Mykland’s (2008) test per days to roll-over date across nearby contracts, from 2008 to 2015.

Notes: the vertical grey line denotes the significant structural break detected with Bai and Perron’s (2003) test at 36 days.
Figure 5. Minute by minute maximum bid-ask spread and trading volume in a window of 10-minutes before and after the jump (dashed grey line) on announcement and non-announcement days from January 15, 2008 to May 18, 2012 (four top panels), from May 21, 2012 to December 31, 2012 (four middle panels), and from January 2, 2013 to December 4, 2015 (four bottom panels).

Notes: The filled dark bullets refer to the null of the two-way Wilcoxon test of no significant difference in mean between the two series being rejected at 1% significance level.
Figure 6. Annualized transaction prices jump variation share signature plot for announcement and non-announcement days, from January 15, 2008 to May 18, 2012.

Notes: ‘+’ curves are constructed using $AJV_{share}^{s hare}$ while ‘o’ curves use equation $AJV_{share}^{c, share}$. Announcement days are defined as in table 1. $AJV_{share}^{s hare} = \frac{ARV - ABV}{ARV}$, where $ARV$ is the annualized realized volatility ($\sqrt{252 \times RV}$) and $ABV$ is the annualized bipower variation ($\sqrt{252 \times BV}$). $AJV_{share}^{c, share} = \frac{ARV^{c} - ABV^{c}}{ABV^{c}}$, where $ARV^{c}$ is the noise-corrected annualized realized volatility ($\sqrt{252 \times RV^{c}}$) and $ABV^{c}$ is the noise-corrected annualized bipower variation ($\sqrt{252 \times BV^{c}}$).
Figure 7. Annualized transaction prices jump variation share signature plot for announcement and non-announcement days, from May 21, 2012 to December 31, 2012.

Notes: ‘+’ curves are constructed using $AJV_{\text{share}}$ while ‘o’ curves use equation $AJV_{c, \text{share}}$. Announcement days are defined as in table 1. $AJV_{\text{share}} = \frac{ARV - ABV}{ARV}$, where $ARV$ is the annualized realized volatility ($\sqrt{252 \times RV}$) and $ABV$ is the annualized bipower variation ($\sqrt{252 \times BV}$). $AJV_{c, \text{share}} = \frac{ARV - ABV}{ARV_c}$, where $ARV_c$ is the noise-corrected annualized realized volatility ($\sqrt{252 \times RV_c}$) and $ABV_c$ is the noise-corrected annualized bipower variation ($\sqrt{252 \times BV_c}$).
Figure 8. Annualized transaction prices jump variation share signature plot for announcement and non-announcement days, from January 2, 2013 to December 4, 2015.

Notes: ‘+’ curves are constructed using $AJV^{\text{share}}$ while ‘o’ curves use equation $AJV^{c. \text{share}}$. Announcement days are defined as in table 1. $AJV^{\text{share}} = \frac{ARV - ABV}{ARV}$, where $ARV$ is the annualized realized volatility ($\sqrt{252} \times RV$) and $ABV$ is the annualized bipower variation ($\sqrt{252} \times BV$). $AJV^{c. \text{share}} = \frac{ARV^{c} - ABV^{c}}{ARV^{c}}$, where $ARV^{c}$ is the noise-corrected annualized realized volatility ($\sqrt{252} \times RV^{c}$) and $ABV^{c}$ is the noise-corrected annualized bipower variation ($\sqrt{252} \times BV^{c}$).
Figure 9. Annualized jump variation share by month from January 2008 to November 2015.

Notes: The green bars refer to the monthly average of the daily annualized jump variation proportion using noise-filtered transaction prices (1-second frequency) \( (AJV_{c.\ share} = \frac{ARV_{c} - ABV_{c}}{ARV_{c}}) \). At 5-minute and 15-minute, daily annualized jump variation proportion is computed using observed transaction prices \( (AJV_{\ share} = \frac{ARV - ABV}{ARV}) \).
Table 1. Summary of 117 USDA report announcement days during the sample from January 2008 to December 2015.

<table>
<thead>
<tr>
<th>Year</th>
<th>World Agricultural Supply and Demand Estimates (WASDE) report</th>
<th>Grain Stock reports</th>
</tr>
</thead>
</table>

*Notes:* The WASDE report is monthly, while the Grain stock report is quarterly. Both are released at 11:00:00 am central time. In bold are days when both reports are released at the same time. The crop production reports are released at the same time as WASDE report so the effects of such USDA reports should be interpreted as an aggregate effect (Adjemian and Irwin 2018).

Appendices

A. Lee and Mykland’s (2012) filtering approach.

The latent price process is unobservable due to the presence of microstructure noise. Several methods have been developed to filter microstructure noise. In this paper, we employ the pre-averaging approach by Lee and Mykland (2012), a technique also applied in recent research for jumps detection (e.g. Brogaard et al. 2018). This method consists, first, on subsampling every $k$ observations, where $k-1$ is the autocorrelation order, to remove autocorrelations in returns. Second, subsampled prices are averaged over a block of non-overlapping windows (denoted by $M$, the smoothing parameter - see equation 4 in Lee and Mykland 2012). In our study, daily autocorrelation functions identify a serial correlation order of four lags on average. As a result, in order to filter price series for noise, we subsample prices every five ticks and we then smooth the subsampled prices over the smoothing parameter $M$ that has an average value of two over the sample. Note that smoothing noisy prices results in testing jumps on a frequency sampling that is closer to 30 seconds or 1 minute than 1 second.

B. Robustness analysis of the jump test results with a longer window size: $W = 125$ and 130.

Figure B1. Percentage of intraday significant jumps out of total number of jumps within each of the three periods with $W = 125$, from January 15, 2008 to December 4, 2015.

With $W = 125$, a total of 485 days have at least one jumps, and a total of 653 jumps are detected (On announcement days, the average number of jumps per day is 0.29 in period 1, 1.5 in period
2, and 2.33 in period 3; while on non-announcement days, the average number of jumps per day is 0.32, 0.25, and 0.25 in periods 1, 2, and 3, respectively).

Figure B2. Percentage of intraday significant jumps out of total number of jumps within each of the three periods with $W = 130$, from January 15, 2008 to December 4, 2015.

With $W = 130$, a total 479 days have at least one jumps, and a total of 650 jumps are detected (On announcement days, the average number of jumps per day is 0.33 in period 1, 1.4 in period 2, and 2.33 in period 3; while on non-announcement days, the average number of jumps per day is 0.31, 0.25, and 0.25 in periods 1, 2, and 3, respectively).