Are Corn Futures Prices Getting ‘Jumpy’?
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Abstract
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. In 2012, release of major crops reports by the U.S. Department of Agriculture (USDA) Agencies started to be traded in real-time. Such changes occurred during a period of emerging automated trading. This article assesses intraday jumps in the corn futures nearby transaction prices time-stamped at the nearest second from 2008 to 2015. We use a nonparametric jump test to detect the presence of intraday jumps and their intraday distribution. On days with significant jumps, we employ a variance analysis to estimate jump risk at different frequency sampling (1 second, 1 minute, for instance) to disentangle jump risk faced at various speed trading activities. This analysis compares intraday price jumps and daily jump risk on announcement and non-announcement report days. 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-announcement report days. In addition, we identify intraday patterns such as multiple jump clustering on announcement days and time-of-day effects. Finally, we find that jump risk increased more substantially for low frequency sampling scheme than for high frequency but noise related to jumps has tended to decrease over time.

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

JEL classification codes: C14, G13, G14, G18, Q13

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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).

Jumps have been identified around U.S. Department of Agriculture (USDA) announcements. Since May 21, 2012, 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). 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 (Meyer, 2018, Onstad, 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 three markets (corn, wheat, and soybean). 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 is emerging, 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 article makes several contributions. First, we identify the days and intraday time at which jumps occur and their economic magnitude. We 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. Our results complement the
findings by Adjemian and Irwin (2018) by showing that volatility jumps are the reason underlying volatility spikes during real-time trading of USDA announcements. Important implications for volatility forecasting are discussed. Second, this article 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 (2012, 2008) 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.
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 do not 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 primarily concerned about the relative contribution of jumps to total price variance (Huang and Tauchen, 2005, Andersen et al., 2007, 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 et al., 2015, Chan and Gray, 2017, Jiang et al., 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 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, A¨ıt-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)). Dumitru and Urga (2012) and conclude that the approach by Lee and Mykland (2008) is the most effective, which nonetheless might be oversized under extremely volatile processes. Lee and Mykland (2008)’s 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 (2012)’s
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 (2008)’s 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 (2008)’s jump iden-
tification test applied on noise-filtered tick price data, which allows us 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 contribu-
tion 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. To measure these differences, 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 a pre-averaging method proposed by Lee and Mykland (2012) to clean observed prices of 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:

$$L(i) = \frac{\hat{P}_{t_i} - \hat{P}_{t_{i-1}}}{\hat{\sigma}_{t_i}} \tag{2}$$

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

$$\hat{\sigma}_{t_i} = \sqrt{\frac{1}{W-2} \sum_{j=i-W+2}^{i-1} |\hat{r}_j| |\hat{r}_{j-1}|} \tag{3}$$

The optimal window size $W$ must be chosen so that the effect of jumps on the volatility measure disappears. Lehecka et al. (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.\footnote{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.}

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 $\hat{r}_t$ 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,

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

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

where $c = \sqrt{\frac{2}{\pi}}$. 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 $e^{-\beta^*} = 0.99$ for 1% significance level, implying $\beta^* \approx 4.6001$. When the 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. $e^{P_{t_i}} - e^{P_{t_{i-1}}}$.

*Jump variation component*

While Lee and Mykland (2008) test identifies the number of jumps in a day, their timing, and magnitude, it does little to inform directly who faces jump risk. For this purpose, we derive the jump variance signature plots for days in which jumps are identified. Since it is well known that some market participants using state of the art technologies can take and cancel positions at ultra-high frequency, but many traditional hedgers operate at a much slower path,
differences in jump variance at different sampling frequencies (i.e., speeds) provide insight into who faces this risk. On days when 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,

\[ RV_c = \frac{N}{N - K + 2K\psi_K} \sum_{i=0}^{N-K+1} \hat{r}_{t_i,K}^2 - \frac{\hat{\omega}^2}{\theta^2\psi_K} \]  

(4)

where \( N \) is the total number of intraday observations, \( \hat{r}_{t_i,K} \) is the noise-filtered return, \( \psi_K = \frac{1+2K^{-2}}{12} \), with \( K \) being determined as in Lee and Mykland (2012) and \( \hat{\omega} \) is estimated using \( \hat{\omega}_{AC} = -\frac{1}{N-1} \sum_{i=2}^{N} |\hat{r}_{t_i}| |\hat{r}_{t_{i-1}}| \) (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,

\[ BV_c = \frac{N}{N - 2K + 2K\psi_K} \sum_{i=0}^{N-K+1} |\hat{r}_{t_i,K}| |\hat{r}_{t_{i+K,K}}| - \frac{\hat{\omega}^2}{\theta^2\psi_K} \]  

(5)

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

\[ JV_c = RV_c - BV_c \xrightarrow{p} \sum_{i=1}^{N^J} J_i^2. \]  

(6)

The magnitude of \( JV_c \) expressed as a portion of total \( QV_c \) is given by equation (7),

\[ JV_{c,share} = (QV_c - BV_c)/QV_c. \]  

(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 speeds.

Through these signature plots, we can also 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 \( BV = \frac{N}{N-1} \frac{\pi}{2} \sum_{i=2}^{N} |r_{t_i}| |r_{t_{i-1}}| \).
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.

**Empirical design and results**

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 represent most trading activity. We make an exception to this rule in the period May 21, to December 31, 2012, using a wider time window to observe market behavior when the report release time was 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.

\(^2\)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 on announcement days (13 during 2008-2012, and 1 in 2013).
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 since 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.

Jump identification test

Here, 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 hours 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 sampling 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.\footnote{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 Lee and Mykland (2008)’s test results by increasing the window size to $W=125$ and 130. The results, presented in appendix B, are similar to the ones using $W=120$.}
We find 495 days with at least one jump, which represents 25.3% of the total trading days (figure 2), with behavior differing by announcement days. On non-announcement days, the average number of jumps occurring declines from 0.32 jumps in period 1, to 0.24 in period 2, and 0.26 in period 3. Also, on non-announcement days, the percentage of jumps occurring declines from 95% in period 1 to 71% in period 2 and to 65% in period 3. A decreased presence of jumps suggest that automated trading is not likely to have increased jump risk, at least outside public information release event times. In contrast, on announcement days, jumps occur 100% of the time in period 3 and 83% of those days have jumps clustered 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. They further find a low jumps rate (9%) associated to inventory announcements. Our percentage is closer to Lahaye et al. (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 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/bushel in period 1, 1.7 (-1.6) cents/bushel period 2, and 1.1 (-1.2) cents/bushel 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 displayed against trading days to expiration across nearby contracts. Using Bai and Perron (2003)’s structural breaks test, we find that one structural break occurs at 36 days prior to expiration. Jumps in efficient prices are significantly more prevalent in the last 36 trading days before maturity. 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 a key 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 jumps on 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 left, middle and right panels present the two variables for period 1, period 2 and period 3, respectively. Liquidity measures in these panels are compared against the same liquidity measures on no-jump days. The filled bullet points correspond to the cases when the null hypothesis of the two-way Wilcoxon

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5Note that the counterfactual liquidity variables are measured using the maximum price change on days when no significant jump is detected.
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 become 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 on announcement days, and tend to decline over time, with spreads reaching about 0.5 cents/bushel in periods 1 and 2, but not exceeding 0.4 cents/bushel in period 3. The volume around jumps on non-announcement days has tended to decline as well from a maximum of about 1,000 contracts/minute to near 800 contracts/minute. On announcement days, 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 cents/bushels in period 2, and 0.8 cents/bushels in period 3. Hence, bid-ask 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 on non-announcement days has not changed substantially over the period studied, volume on announcement days has sharply 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 has resulted in a substantial increase in transactions costs, particularly 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 with at least one statistically significant jump using the Lee and Mykland (2008)’s 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 $RV$ ($AJV^\text{share}$) signature volatility plots for announcement
and non-announcement days in the three periods are presented in Figures 6-8, respectively.\footnote{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.}

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 in 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 $AJV^{c,\text{share}}$ 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 on announcement days, which may be due to the increased market liquidity during this time that may reduce market frictions that cause noise. Indeed, in the second and third periods, the noise associated with 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 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 et al. (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, 2017, Adjemian et al., 2017, Bunek and Janzen, 2015).

To shed light on the evolution of jump risk over time, a monthly average $AJV^{\text{share}}$ is estimated when at least one statistically significant jump occurs (Figure 9). 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 $AJV^{\text{share}} = (ARV - ABV)/ARV$, 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 AVJ 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 complained that the new USDA report release policy and the recent technological changes in futures markets, essentially favor high speed traders. In this article, 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 on USDA report release days that appear to be driven by the changes in the release policy in 2012 and 2013. We find real time trading of USDA reports 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) periods 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 larger jumps have also been accompanied by higher transactions costs, with bid-ask 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, particularly 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.

Our results complement the findings by Adjemian and Irwin (2018) that real time trading of USDA announcements leads to volatility spikes. We show that the reason underlying these spikes are volatility jumps. This has important implications for volatility forecasting during announcements. While Merton (1980) and Nelson (1992) suggested that high-frequency returns observed during a fixed time interval allow a good estimation of volatility, their assumption of a continuous sample path diffusion is usually violated in practice. In response, several articles have proposed the use of realized volatility measures that circumvent the data problems, while still retaining most of the intraday information relevant for measuring, modeling and forecasting volatility. Andersen et al. (2003) showed that simple realized volatility models outperform GARCH and realized stochastic volatility models in out-of-sample volatility forecasting. Later, Andersen et al. (2007) separated the jumps from the continuous sample path variation of returns and showed that almost all the predictability in return volatility comes from the no-jump component. In short, jumps are difficult to predict and while volatility forecasting is important to pricing, resource allocation and risk management, USDA report release policy makes volatility almost impossible to predict on announcement days. Hence, while real-time trading of USDA reports allows a quick price discovery process, this comes at a cost of heightened and unpredictable volatility.
References


Meyer, G. (2018). Last commodities hedge funds go off beaten track. Available at: https://www.ft.com/content/fbe5a554-36b3-11e8-8eee-e06bde01c544.


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), January 15, 2008 - December 4, 2015

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

Notes: The vertical dashed line corresponds to May 21st, 2012, and to the first trading day of January 2013.
Figure 3: Timing of significant intraday jumps out of total number of jumps in each period with $W=120$, January 15, 2008 - December 4, 2015
Figure 4: Total number of significant jumps and days to expiration across nearby contracts, January 15, 2008 - December 4, 2015

Notes: The significant jumps are identified using Lee and Mykland (2008)'s test presented in text. The vertical grey line identifies the significant structural break detected with Bai and Perron (2003) test at 36 days.
Figure 5: Minute-by-minute maximum bid-ask spread and trading volume using a window of 10-minute before and after the jump (dashed grey line) on announcement and non-announcement days, January 15, 2008 - December 4, 2015

Notes: The periods are the same time periods as in Figures 2 and 3. Here, the first two panels on each line represent period 1, the second panels on each line represent period 2, and the last two panels on each line period 3. Tests are performed to assess differences compared to non-jump day measures. The filled dark bullet points 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, January 15, 2008 - May 18, 2012

Notes: ‘+’ curves are constructed using $AJV^{share}$ while ‘o’ curves use equation $AJV_{c,share}$. Announcement days are defined as in table 1. $AJV^{share} = \frac{ARV - ABV}{ARV}$, where $ARV$ is the annualized realized volatility $\sqrt{252 \cdot RV}$ and $ABV$ is the annualized bipower variation $\sqrt{252 \cdot BV}$. $AJV_{c,share} = \frac{ARV_{c} - ABV_{c}}{ARV_{c}}$, where $ARV_{c}$ is the noise-corrected annualized realized volatility $\sqrt{252 \cdot RV_{c}}$ and $ABV_{c}$ is the noise-corrected annualized bipower variation $\sqrt{252 \cdot BV_{c}}$. 
Figure 7: Annualized transaction prices jump variation share signature plot for announcement and non-announcement days, January 15, 2008 - May 18, 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 $\sqrt{252} \times BV$. $AJV^{c,\text{share}} = \frac{ARV^{c} - ABV^{c}}{ARV^{c}}$, 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 $\sqrt{252} \times BV^{c}$. 
### Period 3 (announcement days)

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### Period 3 (non-announcement days)

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Figure 8: Annualized transaction prices jump variation share signature plot for announcement and non-announcement days, January 15, 2008 - May 18, 2012

Notes: ‘+’ curves are constructed using $AJV^{share}$ while ‘o’ curves use equation $AJV^{c,share}$. Announcement days are defined as in table 1. $AJV^{share} = \frac{ARV - ABV}{ARV}$, where $ARV$ is the annualized realized volatility $\sqrt{252 * RV}$ and $ABV$ is the annualized bipower variation $\sqrt{252 * BV}$. $AJV^{c,share} = \frac{ARV^{c} - ABV^{c}}{ARV^{c}}$, where $ARV^{c}$ is the noise-corrected annualized realized volatility $\sqrt{252 * RV^{c}}$ and $ABV^{c}$ is the noise-corrected annualized bipower variation $\sqrt{252 * BV^{c}}$. 

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Figure 9: Annualized jump variation share by month, January 2008 - 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, January 2008 - November 2015

<table>
<thead>
<tr>
<th>Year</th>
<th>WASDE reports dates</th>
<th>Grain Stock reports dates</th>
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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. 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, of removing autocorrelations in returns by subsampling every $k$ observations, where $k - 1$ is the autocorrelation order. 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 10: Timing of significant intraday jumps out of total number of jumps in each period with \( W=125 \), January 15, 2008 - December 4, 2015](image)

Notes: With \( W=125 \), a total of 485 days have at least one jump, 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 11: Timing of significant intraday jumps out of total number of jumps in each period with $W=130$, January 15, 2008 - December 4, 2015

Notes: 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).