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Price discovery and market reflexivity in agricultural futures contracts with different maturities

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Abstract: The purpose of this paper is to analyze market reflexivity in agricultural futures contracts with different maturities. To this end, we apply a four-dimensional Hawkes model to storable and non-storable agricultural commodities. We find market reflexivity for both storable and non-storable commodities. Reflexivity accounts for about 50 to 70 percent of the total trading activity. Differences between nearby and deferred contracts are less pronounced for non-storable than for storable commodities. We conclude that the co-existence of exogenous and endogenous price dynamics does not change qualitative characteristics of the price discovery process that have been observed earlier without consideration of market reflexivity.

Keywords: agricultural commodity futures; price discovery; market reflexivity; Hawkes process

JEL code: G14, C49

1. Introduction

Prices of commodity futures contracts with different maturities are linked through the forward curve. Understanding of the shape and the characteristics of the term structure is of utmost importance for storage decisions, hedging and roll-over strategies as well as calendar spread trading. Several strands of literature address this topic. The theoretical underpinning of the forward curve goes back to Working's (1949) theory of storage that establishes an equilibrium relation between nearby and distant futures contracts and explains storage under backwardation by the concept of convenience yield (Brennan 1958). In contrast, Keynes' theory of normal backwardation decomposes a futures price into an expected future spot price and an expected risk premium that risk averse hedgers grant to speculators (Fama and French 1987). The statistical modeling of the forward curve has benefitted from Nelson and Siegel's (1987) proposal to describe the term structure parsimoniously in terms of level, slope and curvature. A dynamic version of this model has been introduced by Diebold and Li (2006). Applications to commodity futures can be found in Karstanje, van der Wel and van Dijk (2017). An alternative method uses a set of state variables (factors), particularly spot price, convenience yield, and interest rate, to derive the forward curve under no-arbitrage conditions (Gibson and Schwartz 1990, Schwartz 1997). Applications of this approach to agricultural futures include Geman and Nguyen (2005) and Sorensen (2002), among others.

With the rise of modern market microstructure interest has shifted from the estimation of equilibrium relations towards the understanding price discovery, i.e. the question how new information is absorbed in asset prices and how this information is transferred along the forward curve. Since there is no explicit market microstructure theory designed to commodity futures with different maturities, most studies in this area are non-structural and try to identify empirical patterns in data. Mallory et al. (2015) use contemporaneous and time-lagged correlations of nearby and deferred futures contract for corn to investigate the speed at which liquidity providers revise their

beliefs in response to the occurrence of an information event. They find that correlation of price revisions disappears even for short time lags and conclude that new information to the market is immediately transmitted across all contract maturities. Hu et al. (2017) pursue a similar objective, but instead of simple correlations they apply co-integration techniques to explore price discovery among nearby and deferred futures contracts of corn and live cattle. They report a larger share of price discovery in nearer to maturity contracts. The dominance of nearer contracts, however, is less pronounced for live cattle than for corn, which is explained by differences in storability of these commodities. Recently, Volkenand et al. (2019) investigate the duration dependence among agricultural futures with different maturities, exploiting the fact that the time between market events (transactions or price changes) carries information (Easley and O'Hara 1992). They apply an autoregressive conditional duration (ACD) model to price durations for corn, wheat, live cattle, and lean hog. Their results confirm linkages between nearby and deferred futures contracts and suggest that information is quickly processed along the forward curve. However, they do not find varying degrees of duration dependence between storable and non-storable commodities.

The aforementioned studies rest on a traditional view of the price discovery mechanism according to which price revisions are driven by the arrival of exogenous information. This view has been challenged by the concept of market reflexivity (Soros 1987) which assumes that trading activity is also endogenously driven by positive feedback mechanisms. Sources of potential endogeneity encompass informational cascades leading to herding as well as speculation based on technical analysis (e.g. momentum trading) and algorithmic trading (Filimonov et al. 2014). Also hedging strategies combined with portfolio execution rules can lead to self-excitement of price moves (Kyle and Obizaheva 2012). While this co-existence of exogenous and endogenous price dynamics contradicts the efficient market hypothesis (Fama 1970), it can be helpful to understand puzzling phenomena on financial markets, such as "flash crashes" or excess volatility (Hardiman et al. 2013). The concept of market reflexivity has originally been introduced in a narrative, non-technical manner, but since then it experienced an underpinning by statistical methods that allow to disentangle exogenous and endogenous sources of market activities and thus measure the degree of market reflexivity. More specifically, self-exiting Hawkes processes have been proposed as a device to quantify reflexivity (e.g. Filimonov and Sornette 2012). Bacry et al. (2016), for example, find that fewer than 5% of the price changes in the DAX (German stock index) and BUND (German Bond) futures markets are driven by external sources. In the context of commodity futures markets Filimonov et al. (2014) find that reflexivity has increased since the mid-2000s to 70%. They trace this back to the increase of automated trading in the course of the transition to an electronic trading environment. In fact, automated trading generated about 40% of the total futures volume traded in the grain and oilseed markets between 2012 and 2014 (Haynes and Roberts 2015).

Despite the increasing interest in market reflexivity as an alternative to the prevalent tenet of market efficiency and rational expectations, there exists no empirical study applying this concept to the forward curve of commodities. Against this backdrop, our objective is to examine price discovery in nearby and deferred agricultural futures contracts while explicitly taking into account potential market reflexivity. We apply a four-dimensional Hawkes model to storable and non-storable agricultural commodities. The Hawkes model allows us to divide the intensity of the trading activity in a futures contract with a certain maturity into three parts: a reaction on external sources like new information, market reflexivity, and reactions on trading activity in contracts of different maturities. Using this approach, we review previous findings regarding price discovery in nearby and deferred futures contracts. In particular, we examine whether nearby contracts dominate deferred contracts in price discovery while accounting for potential market reflexivity (e.g. Gray and Rutledge 1971). We also explore whether price discovery and potential market reflexivity differ between storable and non-storable commodities. In line with Hu et al. (2017) we expect that dominance of nearby contracts in price discovery is more pronounced for storable commodities. Moreover, we conjecture that commodities with a high share of automated trading, such as grains and oilseeds, show a higher level of endogeneity. Since market microstructure theory emphasizes the importance of the direction of

the transactions in the price discovery process (c.f. Glosten et al. 1985), we differentiate between buyer- and seller-initiated transactions in our analyses.

The remainder of the paper is organized as follows: Section 2 explains the statistical methods used in the analyses. Section 3 presents the data set and the results of the empirical application and Section 4 concludes.

2. Methodology

The price discovery process has been mainly examined using two measures: The Hasbrouck information share (Hasbrouck 1995) and the Harris-McInish-Wood component share (Harris et al. 2002). Both measures are derived from a reduced form vector error correction model that is estimated based on equidistant time intervals. However, market microstructure theory shows that liquidity providers also incorporate the time between market events within the price setting process. Easley and O´Hara (1992), for instance, propose a sequential trade model in which market makers relate short durations between trades to the arrival of new information and adjust their prices accordingly. Since the timing of transactions and the frequency in which they occur have information value of their own, it has been realized that fixed-interval aggregation schemes lead to a loss of information (c.f. Bauwens 2007). Taking into account the irregular occurrence of transactions requires to consider the data as a point process. The simplest type of point process is the homogeneous Poisson process. Since the homogeneous Poisson process assumes independently distributed events, it is not suited to describe well-known structures such as correlations and clustering of transactions. The Autoregressive Conditional Duration (ACD) model (Engle and Russel 1998), in contrast, accounts for correlation structures in the data and can be used to model the time between transactions. However, in a multivariate framework, the asynchronous arrival of transactions renders the application of the ACD model difficult and dynamic intensity models are preferable. In autoregressive conditional intensity (ACI) models (Russell 1999), the intensity is directly modeled in terms of an autoregressive process. On the other hand, Hawkes processes (Hawkes 1971) describe the intensity in terms of an additive structure and can be regarded as clusters of Poisson processes. According to this view, all events belong to one of two classes – immigrants and descendants. The exogenous immigrants can trigger clusters of descendants, each of whom in turn can trigger own descendants. In this branching process, the so-called branching ratio is defined as the average number of daughter events per mother event. Hautsch (2004), Bowscher (2007), and Large (2007) confirm that Hawkes processes model the dynamics in financial point processes remarkably well. Since the linear structure of the Hawkes model allows to separate external influences on the process from internal feedback mechanisms, it is well suited to examine price discovery and potential market reflexivity. Technically speaking, Hawkes processes refer to a class of models for stochastic self-exciting and mutually exciting point processes (Hawkes 1971). These can be regarded as non-homogeneous Poisson processes whose intensity depends on both time t and the history of the process. The intensity function $\lambda_i(t)$ of a Hawkes process is defined as:

$$\lambda_i(t) = \mu_i + \sum_{j=1}^{D} \sum_{t_k^j < t} \phi_{ij}\left(t - t_k^j\right), \forall i, j \in [1 \dots D] \tag{1}$$

where D is the number of dimensions in the process. The non-negative parameter μ is the baseline intensity and commonly assumed to be constant. The baseline intensity describes the arrival rate of events triggered by external sources. In our analysis, we use μ to examine how futures contracts of different maturities react to new information. The non-negative kernel function, ϕ, describes the arrival rate of events that are triggered by previous events within the process. Various kernel functions can be found in the literature. The most widely used are power-law and exponential parameterizations of the kernel function. In our analysis, we follow Bacry et al. (2017) and choose the following exponential parametrization of the kernel functions:

$$\phi_{ij}(t) = \alpha_{ij}\beta_{ij} exp\left(-\beta_{ij}t\right)1_{t>0} \tag{2}$$

where α and $\beta > 0$. In this parametrization, α describes the degree of influence of past points on the intensity process and β determines the time decay of the influence of past points on the intensity process. From the chosen parametrization, it follows

$$\int_0^\infty \phi(t)dt = \alpha = \|\phi\|_1 \qquad (3)$$

where $\|\phi\|_1$ is a matrix of kernel norms. Each matrix element describes the total impact that events of the type defined by a column of the matrix has on events of the type defined by a row of the matrix. According to the population representation of a Hawkes process (Hawkes and Oakes 1974), the process is considered stable if $\|\phi\|_1 < 1$. For a stable Hawkes process, a kernel norm $\|\phi_{ii}\|_1$ stands for the average number of events of type i that is directly triggered by a past event of the same type i. In our analysis, we use $\|\phi_{ii}\|_1$ to measure market reflexivity in futures contracts with different maturities. On the other hand, a kernel norm $\|\phi_{ij}\|_1$ with $i \neq j$ stands for the average number of events of type i that is directly triggered by an event of a different type j. In our analysis, we use $\|\phi_{ij}\|_1$ to measure price discovery between futures contracts with different maturities. Furthermore, following Bacry et al. (2016), the ratio between the baseline intensity μ_i and the average intensity γ_i describes an exogeneity ratio, i.e., the ratio between the number of events that is triggered by external sources and the total number of events of type i:

$$R_i = \frac{\mu_i}{\gamma_i} \qquad (4)$$

where the average intensities can be derived by

$$\gamma = (I - \|\phi\|_1)^{-1}\mu \qquad (5)$$

with I as the identity matrix.

Various methods to estimate Hawkes processes have been proposed in the literature. Estimation procedures include Maximum Likelihood Estimation (Ogata 1998) and the resolution of a Wiener-Hopf system (Bacry et al. 2016). In our analysis, we follow Bacry et al. (2017) and estimate the Hawkes process with least-squares. To assess the goodness-of-fit of the estimated Hawkes model, we carry out a residual analysis according to Ogata (1989). Ogata's residual analysis of point process data is based on the random time change theorem by Meyer (1971). The random time change theorem states that a point process is transformed into a homogeneous Poisson process by its compensator $\Lambda(t)$. The compensator is determined by the Doob-Meyer decomposition of a point process and is described by the following monotonically increasing function:

$$\Lambda(t) = \int_0^t \lambda(t)dt. \qquad (6)$$

In accordance with Ogata (1989), we use the compensator with the conditional intensity $\hat{\lambda}$ of the estimated Hawkes model to transform the observed data and regard the resulting process as a residual process. In line with the random time change theorem, if the residual process behaves like a homogeneous Poisson process, then the conditional intensity $\hat{\lambda}$ of the estimated Hawkes model is a good approximation to the true intensity λ of the observed point process. To check whether the residual process behaves similar to a homogeneous Poisson process, we apply Kolmogorov-Smirnov and Ljung-Box tests. On the one hand, the Kolmogorov-Smirnov test examines the null hypothesis that the distribution of the residuals is a homogeneous Poisson distribution. On the other hand, the Ljung-Box test examines the null hypothesis that the residuals are independently distributed. If the null hypothesis of both the Kolmogorov-Smirnov test and the Ljung-Box test cannot be rejected at the 5% significance level, we conclude that the estimated Hawkes process is a good approximation of the observed point process.

3. Empirical application

3.1. Data

Empirical analyses of market reflexivity can be conducted for different time horizons. Long term analyses are useful if the development of endogeneity and its determinants over time are of interest. Long-term reflexivity is expected to be caused mainly by herding. In this paper, however, we focus on the analysis of short-term reflexivity. Short-term reflexivity is expected to be caused by algorithmic trading (Filimonov et al. 2014) that is supposed to distort the price discovery process in electronic commodity futures markets (cf. Tang and Xiong 2012; Bicchetti and Maystre 2013). Our empirical analysis is based on the Chicago Mercantile Exchange (CME) Group's Best-Bid-Best-Offer (BBO) futures data. We chose corn and live cattle because these commodities represent the most actively traded storable and non-storable agricultural futures contracts, respectively. For these commodities, futures contracts of the first two maturities are used, i.e., the nearest (front contract) and the next to nearest (back contract). We confine our analysis to the daytime trading session since it is much more active compared to the evening trading session. At the beginning of the daytime trading session, orders that have accumulated in the previous night are processed (cf. Gurgul et al. 2017), which can lead to a distorted picture of the price discovery process. Therefore, we exclude the first hour of the daytime trading session. Furthermore, to ensure stationarity of the parameters of the estimated Hawkes process, we follow Filimonov et al. (2014) and base our estimations on intervals of 10 minutes. Intervals of 10 minutes are considered to contain a sufficient number of events for reliable estimation. It can be assumed that in short intervals of 10 minutes, market reflexivity is not caused by behavioral mechanisms, such as herding, but instead is mainly caused by automated trading. The observation period covers all trading days in March 2016, which corresponds to 528 intervals of 10 minutes. BBO data contain top-of-book quotes, transactions, and corresponding time stamps with a resolution of one second. In line with the above-mentioned market microstructure models, we regard the trading activity as the starting point of the price formation process and base our analyses on transactions. However, many transactions share the same time stamp. Therefore, to take all transactions into account, we follow Wang et al. (2016) and simulate sub-second time stamps. In addition, BBO data do not include the direction of transactions. Therefore, to distinguish between buyer- and seller-initiated transactions, we apply the trade classification algorithm proposed by Lee and Ready (1991). To summarize, we analyze a four-dimensional point process whose dimensions are buyer- and seller-initiated transactions in a futures front and back contract for corn and for live cattle.

3.2. Descriptive statistics

Table 1 contains descriptive statistics for the corn and live cattle data, which is based on 528 intervals of 10 minutes over the one month observation period. The total number of buyer- and seller-initiated transactions is considerably higher in the front contract than in the back contract for corn. In contrast, the total number of transactions is similar in the front and back contract for live cattle. The number of seller-initiated transactions is higher than the number of buyer-initiated transactions in both the front and back contract for corn. In contrast, the number of seller-initiated transactions is lower than the number of buyer-initiated transactions in both the front and back contract for live cattle. The coefficients of variation show that the number of transactions varies more widely over the intervals for live cattle than for corn. The trading volume is much higher for corn than for live cattle. Moreover, the trading volume is significantly higher in the front contract than in the back contract for corn. In contrast, the trading volume is similar in both the front and back contract for live cattle. Furthermore, the imbalance between buy- and sell volume is larger for corn than for live cattle. A high coefficient of variation indicates that the trading volume varies considerably over the intervals. The coefficient of variation is higher for corn than for live cattle.

Table 1. Descriptive statistics

Variable	Commodity	Corn				Live cattle			
	Contract	Front		Back		Front		Back	
	Type	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Number of Transactions	Total	102,778	105,822	30,607	31,762	35,801	35,474	36,426	35,025
	Min.	14	34	1	4	1	1	1	1
	Mean	194.655	200.420	58.078	60.155	70.061	69.285	71.424	68.811
	Max.	2,127	2,519	946	889	426	373	532	584
	St. dev.	177.603	191.665	67.799	66.629	52.744	50.727	52.819	54.116
	Coeff. var.	1.096	1.046	0.857	0.903	1.328	1.366	1.352	1.272
Volume (number of contracts)	Min.	149	110	4	12	2	2	2	2
	Mean	1,991	2,083	402	434	248	249	237	232
	Max.	22,131	29,561	5,926	7,546	2,532	1,512	1,962	2,416
	St. dev.	2,009	2,467	516	596	225	210	209	214
	Coeff. var.	1.009	1.185	1.284	1.372	0.905	0.842	0.882	0.922
Mid-quotes (corn: cents/bushel) (cattle: cents/pound)	Min.	348		352		131		123	
	Mean	364		369		137		127	
	Max.	373		377		142		131	
	St. dev	5.683		5.594		2.553		2.131	
	Coeff. var.	0.016		0.015		0.019		0.017	

To avoid bid-ask bounce effects, our descriptive statistics are based on mid-quotes rather than transaction prices. The mid-quotes are higher in the back contract than in the front contract for corn. This points to a normal forward curve during the observation period. In contrast, mid-quotes are higher in the front contract than in the back contract for live cattle. This points to an inverted forward curve during the observation period. The standard deviation of the mid-quotes is higher for corn than for live cattle. However, low coefficients of variation for both corn and live cattle indicate that prices exhibit little volatility during the observation period.

3.3. Results

Table 2 shows the estimated baseline intensities μ, the derived average intensities γ, and exogeneity ratios R for corn and live cattle. All figures for μ, γ, and R are mean values over 528 intervals of 10 minutes.

Table 2. Estimated baseline intensities, average intensities, and exogeneity ratios

Commodity	Corn				Live cattle			
Contract	Front		Back		Front		Back	
Transaction	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Baseline intensity	0.194	0.193	0.061	0.062	0.077	0.078	0.083	0.081
Average intensity	0.327	0.337	0.097	0.101	0.119	0.117	0.121	0.117
Exogeneity ratio	0.636	0.629	0.663	0.670	0.701	0.699	0.714	0.733

The baseline intensity μ is by far the highest for the front contract of corn. This means that in absolute terms, the number of transactions that is triggered by external sources is highest for the front contract of corn. In addition, μ is of similar size for buyer- and seller-initiated transactions in a contract of a certain maturity for both corn and live cattle. It is striking that μ is noticeably larger in the front contract than in the back contract for corn. In contrast, μ is of similar size in the front contract and back contract for live cattle. This suggests that price discovery takes place in the front contract for corn, but not for live cattle. These estimation results for the baseline intensity μ are

therefore in line with Working (1949) and Gray and Rutledge (1971). Compared to the baseline intensity, the derived average intensity γ is higher for all examined contracts. Similar to the baseline intensity, γ is considerably larger in the front contract than in the back contract for corn. In contrast, γ is of similar size in the front and back contract for live cattle. The derived exogeneity ratio R is higher for live cattle than for corn. About 70% of all observed transactions in the live cattle futures are triggered by external sources. On the other hand, about 65% of all observed transactions in the corn futures contracts are triggered by external sources, such as new information. The results also find that R is of similar size for buyer- and seller-initiated transactions in a corn or live cattle contract of a certain maturity. Moreover, R is slightly higher in the back contract than in the front contract for both corn and live cattle. Apparently, the derived exogeneity ratio is considerably higher for the examined agricultural futures contracts than for the DAX and BUND futures contracts examined by Bacry et al. (2016). Moreover, the derived exogeneity ratios are higher than the corresponding figures in Filimonov et al. (2014).

Figure 1 presents the estimated matrices of kernel norms $\|\phi\|_1$ for corn and live cattle. All figures are mean values over 528 intervals of 10 minutes. Each kernel norm describes the total impact that transactions of a certain contract type have on transactions of the same or on other contracts. Figure 1 has to be interpreted column-wise. A darker background color of a kernel norm illustrates a larger impact than a lighter color. On the one hand, a kernel norm $\|\phi_{ii}\|_1$ on the diagonals of the matrices describes the impact that transactions of a certain type have on transactions of the same type. On the other hand, a kernel norm $\|\phi_{ij}\|_1$ on the off-diagonals of the matrices describes the impact that transactions of a certain type have on transactions of a different type. In general, the kernel norm values are higher for corn than for live cattle. According to the population representation of the Hawkes process, each buyer-initiated (seller-initiated) transaction directly triggers 0.3102 buyer-initiated transactions (0.3147 seller-initiated) on average in the front contract for corn. The respective values for live cattle are slightly smaller. Apparently, the kernel norm values on the diagonals of the matrix are considerably higher compared to those on the off-diagonals for both, corn and live cattle. This indicates that a substantial part of the observed transactions is endogenously driven for both commodities. In addition, the kernel norm values on the diagonals of the matrix are higher in the front contract than in the back contract for corn. In contrast, the kernel norm values on the diagonals are of similar size in the front and back contract for live cattle. As expected, the estimation results for the matrices of kernel norms $\|\phi\|_1$ show that differences between front and back contracts are less pronounced for live cattle than for corn.

Figure 1. Estimated matrices of kernel norms

Corn		Front		Back			Live cattle		Front		Back	
		Buy	Sell	Buy	Sell				Buy	Sell	Buy	Sell
Front	Buy	0,3102	0,0315	0,0128	0,0100		Front	Buy	0,2132	0,0170	0,0488	0,0184
	Sell	0,0284	0,3147	0,0094	0,0138			Sell	0,0197	0,2490	0,0136	0,0236
Back	Buy	0,0531	0,0375	0,2434	0,0252		Back	Buy	0,0675	0,0181	0,2046	0,0169
	Sell	0,0363	0,0596	0,0186	0,2301			Sell	0,0186	0,0269	0,0165	0,2137

The kernel norms on the off-diagonals show that in the case of corn the impact of front contracts on back contracts is larger than vice versa. This relationship, however, is not prevalent for live cattle. Thus, our results are in line with Hu et al. (2017), who show that nearby futures contracts dominate

deferred futures contracts in price discovery for storable commodities, but not for non-storable commodities. No differences can be identified between buyer- and seller-initiated transactions.

Table 3 contains the results of the residual analyses of the estimated Hawkes processes for corn and for live cattle. For more than about 80% of the 10-minute intervals, the Kolmogorov-Smirnov test does not reject the null hypothesis that the distribution of the residuals is homogeneous Poisson at the 5% significance level for corn and live cattle. Except for the front contract of corn, for more than approximately 90% of the 10-minute intervals the Ljung-Box test does not reject the null hypothesis that the residuals are independently distributed at the 5% significance level. We can therefore conclude that the estimated Hawkes process with the chosen parameterization of the kernel function is a good approximation of the observed point process.

Table 3. Residual analyses

Commodity	Corn				Live cattle			
Contract	Front		Back		Front		Back	
Transaction	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Kolmogorov-Smirnov	0.84	0.84	0.88	0.89	0.91	0.87	0.91	0.88
Ljung-Box	0.64	0.67	0.94	0.92	0.92	0.91	0.91	0.91

To provide a graphical illustration of the estimation results, In general, the average intensity shows a relatively constant progression for both corn and live cattle; however, in 错误!书签自引用无效。 it is noticeable that γ increases considerably towards the end of the observation period for corn on March 31, 2016. On this day at 11:00 am, the USDA informed the public that corn production was greater than previously estimated (USDA 2016). This demonstrates that besides volatility and trading volume, the intensity of trading activity also increases significantly following a USDA report.

Figure 2 displays the evolution of the average intensity γ over the whole observation period for both corn and live cattle. The figure is based on daily mean values of the average intensity. In general, the evolution of γ for the front contract is similar to the evolution of γ for the back contract for both corn and live cattle. In particular, γ is higher for the front contract than for the back contract throughout the whole observation period for corn. In contrast, for live cattle, γ is higher for the front contract than for the back contract in the first half of the observation period only. In addition, the evolution of the average intensity of buyer-initiated transactions is similar to the evolution of the average intensity of seller-initiated transactions in a contract of a certain maturity for both corn and live cattle.

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Figure 2. Evolution of average intensities (y-axis) for corn and live cattle, March 2016
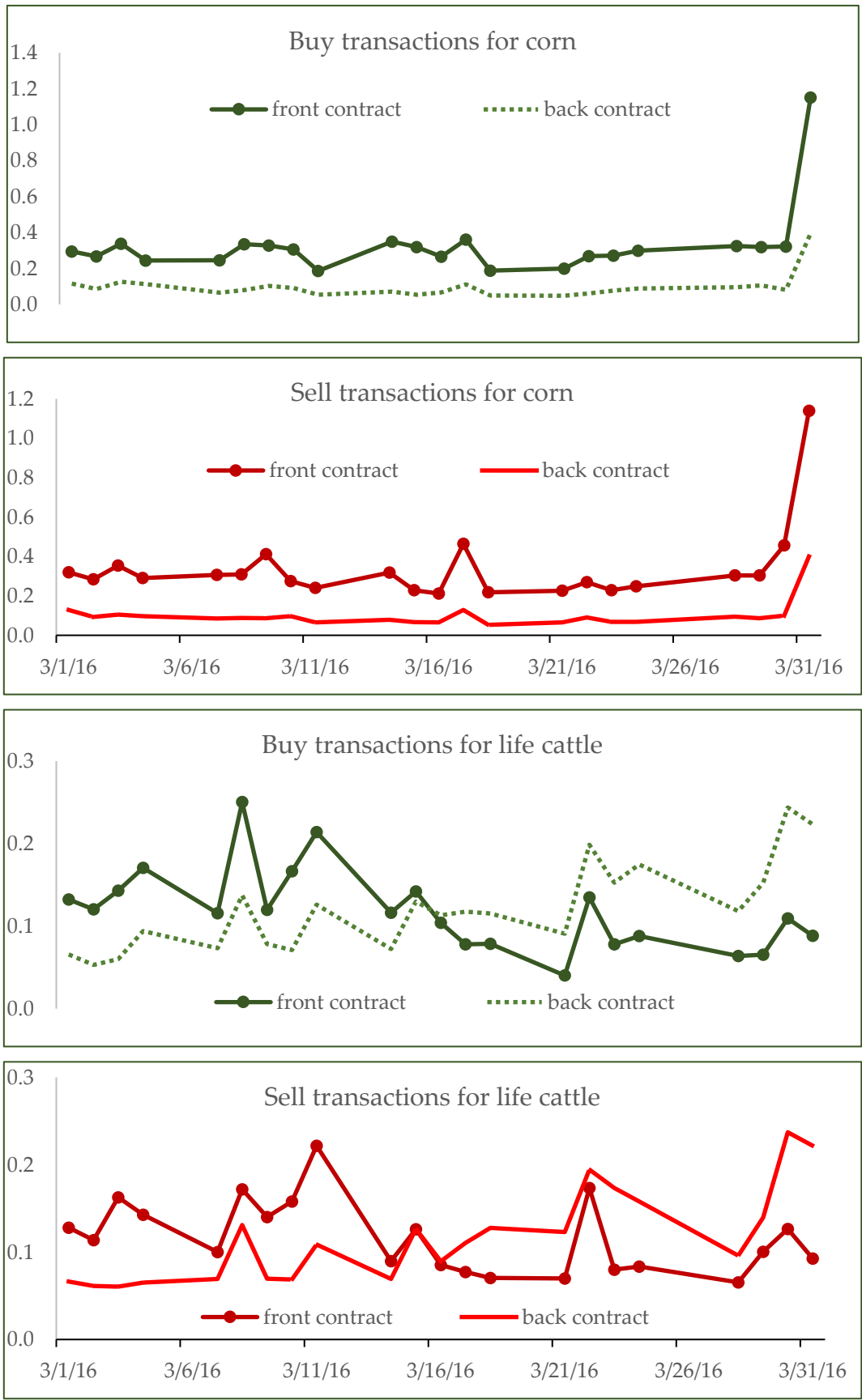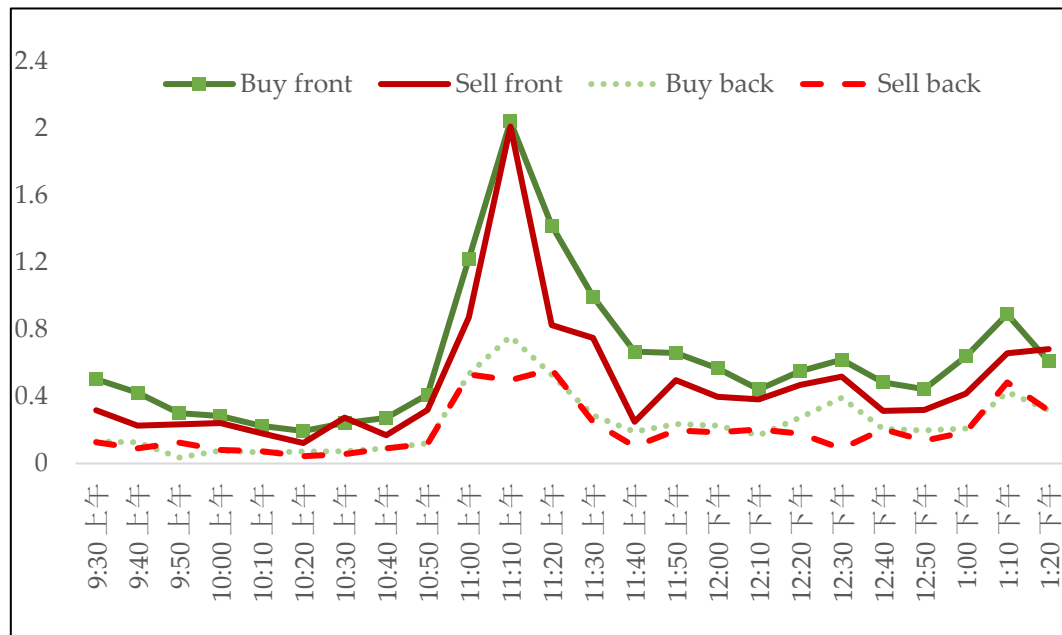
Figure 3 depicts the evolution of the baseline intensity μ on the day of the release of the USDA report for corn. The figure is based on 24 intervals of 10 minutes. The baseline intensity μ increases considerably at the time of the publication of the USDA report for transactions in both the front and back contract. Moreover, the evolution of μ for seller-initiated transactions is similar to the evolution of μ for buyer-initiated transactions at the time of the publication of the USDA report for the front contract. In contrast, for the back contract, the evolution of μ for seller-initiated transactions differs from the evolution of μ for buyer-initiated transactions at the time of the publication of the USDA report.

Figure 3. Evolution of the baseline intensity (y-axis) for corn on March 31, 2016

The evolution of the baseline intensity for corn on March 31, 2016 suggests that new information is quickly incorporated into market prices through trading activity. Moreover, it is becoming clearer that new information does not only affect nearby futures contracts, but also affects deferred futures contracts.

Compared to the whole observation period, the kernel norm values $\|\phi_{ii}\|_1$ on the diagonal of the matrix are considerably higher for corn on March 31, 2016. This indicates an increase in market reflexivity on the publication day of the USDA report. Moreover, compared to the whole observation period, the kernel norm values $\|\phi_{ij}\|_1$ on the off-diagonal of the matrix are higher for the back contract for corn on March 31, 2016. This indicates an increase in the impact that transactions in the back contract have on transactions in both the front and back contract on the publication day of the USDA report.

Figure 4 presents the estimated matrix of kernel norms $\|\phi\|_1$ for corn on March 31, 2016. The figures are mean values over 24 intervals of 10 minutes.

Compared to the whole observation period, the kernel norm values $\|\phi_{ii}\|_1$ on the diagonal of the matrix are considerably higher for corn on March 31, 2016. This indicates an increase in market reflexivity on the publication day of the USDA report. Moreover, compared to the whole observation period, the kernel norm values $\|\phi_{ij}\|_1$ on the off-diagonal of the matrix are higher for the back contract for corn on March 31, 2016. This indicates an increase in the impact that transactions in the back contract have on transactions in both the front and back contract on the publication day of the USDA report.

Figure 4. Estimated matrix of kernel norms for corn on March 31, 2016

Corn		Front		Back	
(March 31, 2016)		Buy	Sell	Buy	Sell
Front	Buy	0,3770	0,0290	0,0170	0,0130
	Sell	0,0360	0,4380	0,0120	0,0290
Back	Buy	0,0370	0,0420	0,2660	0,0260
	Sell	0,0120	0,1090	0,0200	0,2990

To gain an overall picture of the price formation process in agricultural futures contracts with different maturities, Figure 5 illustrates the composition of the estimated intensity of the trading activity in both the front and back contract for corn and live cattle. The figure is based on mean values of 528 intervals of 10 minutes. It shows the relative contribution of the estimated baseline intensity μ_i and the kernel norms $\|\phi_{ii}\|_1$ and $\|\phi_{ij}\|_1$ to the total intensity $\hat{\lambda}_i$.

Figure 5. Composition of the estimated intensity for corn and live cattle
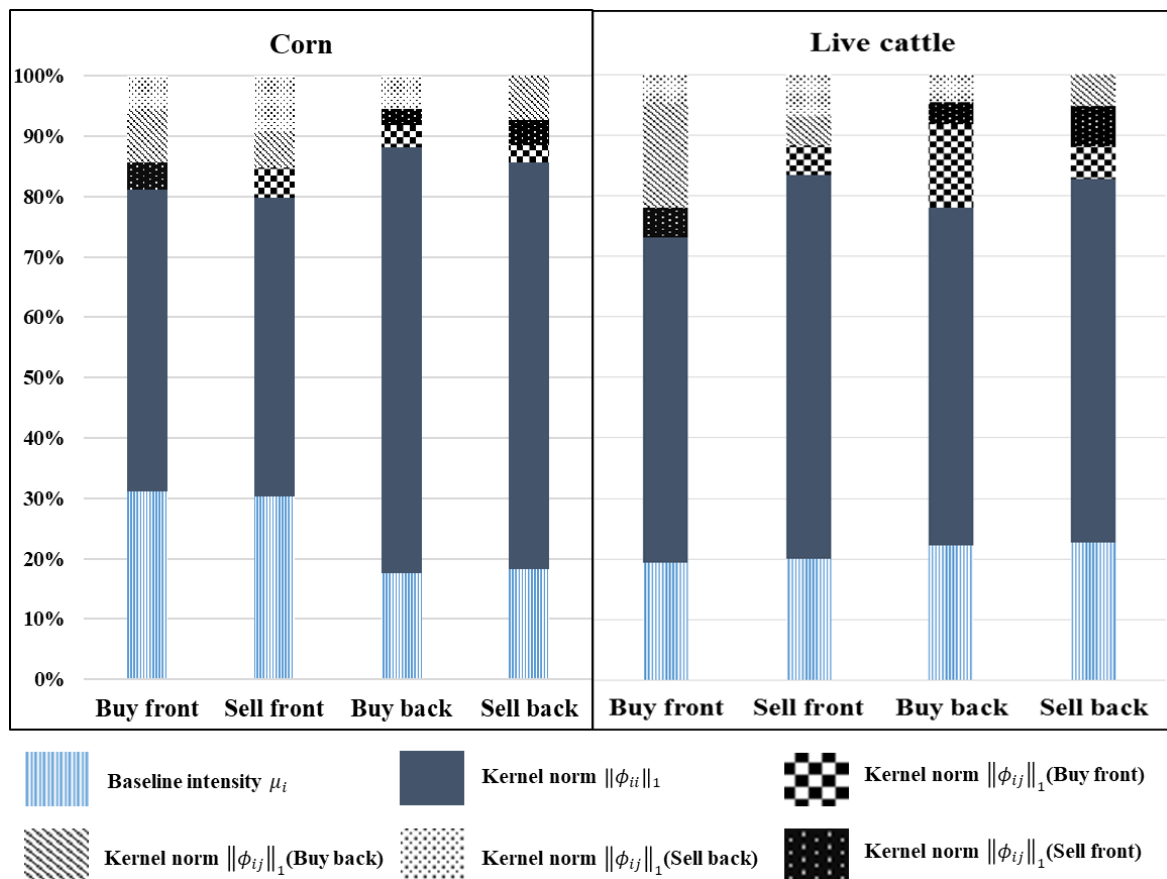
The relative contribution of the baseline intensity μ_i to the total intensity $\hat{\lambda}_i$ is largest for the front contract of corn. It amounts to approximately 30%. This means that external sources, such as

new information, account for approximately 30% of the total intensity of both buyer-initiated and seller-initiated transactions for the front contract of corn. Moreover, the relative contribution of μ_i is noticeably larger in the front contract than in the back contract for corn. In contrast, the relative contribution of μ_i is of similar size in the front and back contract for live cattle. Therefore, in line with Working (1949) and Gray and Rutledge (1971), the composition of the estimated intensity suggests that nearby futures contracts dominate deferred futures contracts in price discovery for storable commodities, but not for non-storable commodities.

Compared to the relative contribution of μ_i, the relative contribution of the kernel norms $\|\phi_{ii}\|_1$ to the total intensity is considerably larger. More specifically, the relative contribution of $\|\phi_{ii}\|_1$ to the total intensity is largest for the back contract of corn. It amounts to roughly 70%, which means that market reflexivity accounts for about 70% of the total intensity of both buyer-initiated and seller-initiated transactions for the back contract of corn. Moreover, the relative contribution of $\|\phi_{ii}\|_1$ is clearly larger in the back contract than in the front contract for corn. In contrast, the relative contribution of $\|\phi_{ii}\|_1$ is of similar size in the front and back contract for live cattle.

As expected, the composition of the estimated intensity shows that differences between front and back contracts in the degree of market reflexivity are less pronounced for live cattle than for corn. Compared to the relative contribution of $\|\phi_{ii}\|_1$, the relative contribution of the kernel norms $\|\phi_{ij}\|_1$ to the total intensity is considerably smaller. More specifically, the relative contribution of $\|\phi_{ij}\|_1$ to the total intensity is higher for live cattle than for corn. It is shown that buyer-initiated transactions in the back contract account for almost 20% of the total intensity of buyer-initiated transactions in the front contract for live cattle. On the other hand, buyer-initiated transactions in the back contract account for approximately 10% of the total intensity of buyer-initiated transactions in the front contract for corn. Therefore, in line with Kendall (1981), the composition of the estimated intensity suggests that interdependencies of current and subsequent supply might link futures contracts of different maturities for non-storable commodities.

4. Conclusions

This paper is the first to examine price discovery in nearby and deferred agricultural commodities futures contracts while explicitly considering potential market reflexivity. For this purpose, we apply a four-dimensional Hawkes model with an exponential parametrization of the kernel functions to storable and non-storable agricultural commodities. We find market reflexivity for both storable and non-storable commodities. Reflexivity accounts for about 50 to 70% of the total trading activity irrespective of whether transactions have been buyer- or seller-initiated. Storable commodities show a higher level of reflexivity than non-storable commodities and differences between nearby and deferred contracts are less pronounced for non-storable commodities than for storable ones.

What are the implications of these findings for the price discovery process in agricultural commodity futures? The presence of market reflexivity seems to contradict the efficient market hypothesis and Filimonov et al. (2014) argue that reflexivity is likely to result in a less efficient price discovery process. Though our analysis does not allow an evaluation of the presence of reflexivity we can at least compare our results with previous empirical findings on price discovery in agricultural commodity futures markets and screen them for irregularities. Regarding the relation between nearby and deferred futures contracts our results are in line with Mallory et al. (2015) who find that new information to the market is immediately transmitted across all contract maturities. Moreover, we can replicate the finding of Hu et al. (2017) that nearby contracts are dominant in price discovery for storable commodities, but not for non-storable commodities. Finally, we observe an increased baseline intensity at the time of a USDA publication suggesting that external information is quickly incorporated into market prices through trading activity despite the presence of market reflexivity. From these findings we conclude that the co-existence of exogenous and endogenous price dynamics does not change qualitative characteristics of the price discovery process that have been observed earlier without consideration of market reflexivity.

Some aspects could be incorporated in further empirical analyses to obtain a clearer picture about price discovery in agricultural commodity futures in the presence of market reflexivity. The empirical basis could be broadened by including additional commodities. Moreover, price discovery and market reflexivity should be examined over a longer observation period covering, for example, markets in normal backwardation and in contango. From a methodological point of view, the Hawkes model can be extended and amended in several ways. Covariates such as order imbalances between buyer- and seller-initiated transactions can be included into the intensity function. Other parameterizations of the kernel function such as power-law parameterizations or other estimation methods such as non-parametric estimation techniques can be applied to check the robustness of the results. Finally, methods allowing the assessment of the direct impact of market reflexivity on the price formation process need to be explored.

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