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% 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 the consideration of market reflexivity.

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 modelling 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 et al. (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 the modern market microstructure, interest has shifted from the estimation of equilibrium relations towards the understanding of price discovery, i.e., the question of 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 for 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 contracts 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 the 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 the 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. The authors report linkages between nearby and deferred futures contracts. They conclude that information is quickly processed along the forward curve.

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). Furthermore, hedging strategies combined with portfolio execution rules can lead to self-excitement of price moves (Kyle and Obizhaev 2019). 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 one 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 less 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 in 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 (cf. Glosten and Milgrom 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 dataset 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, Easley and O'Hara (1992) show that liquidity providers also consider the time between market events within the price setting process. Since the timing of transactions and the frequency in which they occur have information value of their own, fixed-interval aggregation schemes lead to a loss of information (cf. Bauwens and Hautsch 2007). Taking into account the irregular occurrence of transactions requires one 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 ACD model (Engle and Russell 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), Bowsher (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 one 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:

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

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

$$\int_0^\infty \phi(t)dt = \alpha = \|\phi\|_1 \tag{3}$$

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. 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:

$$R_i = \frac{\mu_i}{\gamma_i} \tag{4}$$

where the average intensities can be derived by

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

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:

$$\Lambda(t) = \int_0^t \lambda(t)dt. \tag{6}$$

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). For our analysis we utilize the Chicago Mercantile Exchange (CME) Group's best-bid–best-offer (BBO) futures data. We focus on corn, wheat, live cattle and lean hog. These commodities represent the most actively traded storable and non-storable agricultural futures contracts, respectively. The analysis is based on futures contracts of the first two maturities, i.e., the nearest (front contract) and the next to nearest (back contract).[1] We confine our analysis to the daytime trading session because the trading activity is much higher 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 and Syrek 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 min. Intervals of 10 min are considered to contain a sufficient number of events for reliable estimation. It can be assumed that in short intervals of 10 min, 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 min. March has been chosen as the observation period, because we want to exclude a rollover of contracts and the effect of a new harvest. On the other hand, we are interested in the effect of a release of three public reports on the short-term reflexivity: a World Agricultural Supply and Demand Estimates (WASDE) report on world agricultural supply and demand estimations, the United States Department of Agriculture (USDA) report on prospective plantings, and a National Agricultural Statistics Service (NASS) report on grain stocks. 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, wheat, live cattle and lean hog.

3.2. Descriptive Statistics

Table 1 contains descriptive statistics for the considered commodities. The total number of buyer- and seller-initiated transactions is considerably higher in the front contract than in the back contract for corn and wheat. In contrast, the total number of transactions is similar in the front and back contract

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[1] An inclusion of further contracts with longer maturities would be desirable to obtain a clearer picture of price discovery along the entire term structure curve. However, this comes at the cost of increasing the dimension of the Hawkes model. Moreover, the number of transactions becomes rather small for futures contracts with longer maturity, which renders the estimation unreliable.

for live cattle and lean hog. 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 storable than for non-storable commodities.

Table 1. Descriptive statistics.

Variable	Commodity	Corn				Wheat			
	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	80,038	77,586	22,873	23,273
	Min.	14	34	1	4	12	11	1	1
	Mean	194.655	200.420	58.078	60.155	145.524	141.065	41.815	42.469
	Max.	2127	2519	946	889	1237	1392	349	277
	Std Dev	177.603	191.665	67.799	66.629	129.876	127.539	37.675	36.888
	CV	1.096	1.046	0.857	0.903	1.120	1.106	1.110	1.151
Volume (number of contracts)	Min.	149	110	4	12	50	84	8	4
	Mean	1991	2083	402	434	781	763	180	175
	Max.	22,131	29,561	5926	7546	6771	6,206	2127	1468
	Std Dev	2009	2467	516	596	775	714	197	174
	CV	1.009	1.185	1.284	1.372	0.993	0.937	1.099	0.995
Mid-quotes (cents per bushel)	Min.	348		352		446		453	
	Mean	364		369		466		472	
	Max.	373		377		479		486	
	Std Dev	5.683		5.594		8.199		8.341	
	CV	0.016		0.015		0.018		0.018	

Variable	Commodity	Live Cattle				Lean Hog			
	Contract	Front		Back		Front		Back	
	Type	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Number of Transactions	Total	35,801	35,474	36,426	35,025	25,077	26,892	25,160	23,845
	Min.	1	1	1	1	1	1	1	1
	Mean	70.061	69.285	71.424	68.811	49.364	52.833	49.237	46.755
	Max.	426	373	532	584	371	371	261	328
	Std Dev	52.744	50.727	52.819	54.116	44.705	43.991	36.408	34.376
	CV	1.328	1.366	1.352	1.272	1.104	1.201	1.352	1.360
Volume (number of contracts)	Min.	2	2	2	2	0	0	0	0
	Mean	248	249	237	232	171	179	152	142
	Max.	2532	1512	1962	2416	1586	1661	106	1343
	Std Dev	225	210	209	214	181	179	135	128
	CV	0.905	0.842	0.882	0.922	1.058	1.003	0.883	0.898
Mid-quotes (cents per pound)	Min.	131		123		68		80	
	Mean	137		127		70		82	
	Max.	142		131		73		84	
	Std Dev	2.553		2.131		0.937		1.040	
	CV	0.019		0.017		0.013		0.013	

The trading volume is much higher for storable than for non-storable commodities. Moreover, the trading volume is significantly higher in the front contract than in the back contract for corn and for wheat. In contrast, the trading volume is similar in both the front and back contract for live cattle and lean hog. Furthermore, the imbalance between the buy-and-sell volume is larger for corn and wheat than for live cattle and lean hog. A high coefficient of variation indicates that the trading volume varies considerably over the intervals. The coefficient of variation is highest for corn.

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, wheat, and lean hog. 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 storable than for non-storable commodities. However, low coefficients of variation for all commodities 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. All figures for μ, γ, and R are mean values over 528 intervals of 10 min. As a robustness check, we conducted additional calculations with a different time interval length (30 min) for corn and lean hog (see Tables A1 and A2, Figure A1 in the Appendix A). The qualitative findings are similar and, thus, we focus on the discussion of the results of the 10-min intervals in what follows.

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

Contract	Front		Back		Front		Back	
Transaction	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
Commodity	Corn				Wheat			
Baseline intensity	0.194	0.193	0.061	0.062	0.15	0.149	0.046	0.048
Average intensity	0.327	0.337	0.097	0.101	0.25	0.241	0.071	0.072
Exogeneity ratio	0.636	0.629	0.663	0.67	0.654	0.657	0.704	0.726
Commodity	Live cattle				Lean Hog			
Baseline intensity	0.077	0.078	0.083	0.081	0.058	0.063	0.061	0.059
Average intensity	0.119	0.117	0.121	0.117	0.085	0.09	0.085	0.08
Exogeneity ratio	0.701	0.699	0.714	0.733	0.743	0.741	0.76	0.772
Commodity	Corn				Wheat			
Baseline intensity	0.194	0.193	0.061	0.062	0.150	0.149	0.046	0.048
Average intensity	0.327	0.337	0.097	0.101	0.250	0.241	0.071	0.072
Exogeneity ratio	0.636	0.629	0.663	0.670	0.654	0.657	0.704	0.726
Commodity	Live cattle				Lean Hog			
Baseline intensity	0.077	0.078	0.083	0.081	0.058	0.063	0.061	0.059
Average intensity	0.119	0.117	0.121	0.117	0.085	0.090	0.085	0.080
Exogeneity ratio	0.701	0.699	0.714	0.733	0.743	0.741	0.760	0.772

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 all commodities. It is striking that μ is noticeably larger in the front contract than in the back contract for corn and wheat. In contrast, μ is of similar size in the front contract and back contract for live cattle and lean hog. This suggests that price discovery takes place in the front contract for storable commodities, but not for non-storable commodities. 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 and wheat. In contrast, γ is of similar size in the front and back contract for live cattle and lean hog. The derived exogeneity ratio R is higher for non-storable than for storable commodities. About 75% (65%) of all observed transactions in the lean hog (corn) futures are triggered by external sources. The results also find that R is of similar size for buyer- and seller-initiated transactions in a commodity futures contract of a certain maturity. Moreover, R is slightly higher in the back contract than in the front contract for all commodities. 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 $\|\phi\|_1$. 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. 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. 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 storable than for non-storable commodities. 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 other commodities 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 all commodities. This indicates that a substantial part of the observed transactions is endogenously driven and points to the presence of market reflexivity for all 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 and wheat. In contrast, the kernel norm values on the diagonals are of similar size in the front and back contract for live cattle and lean hog. 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 non-storable than for storable commodities.

Corn		Front		Back	
		Buy	Sell	Buy	Sell
Front	Buy	0.3102	0.0315	0.0128	0.0100
	Sell	0.0284	0.3147	0.0094	0.0138
Back	Buy	0.0531	0.0375	0.2434	0.0252
	Sell	0.0363	0.0596	0.0186	0.2301

Wheat		Front		Back	
		Buy	Sell	Buy	Sell
Front	Buy	0.2868	0.0288	0.0152	0.0106
	Sell	0.0344	0.2828	0.0091	0.0136
Back	Buy	0.0570	0.0389	0.1946	0.0206
	Sell	0.0421	0.0634	0.0228	0.1787

Live cattle		Front		Back	
		Buy	Sell	Buy	Sell
Front	Buy	0.2132	0.0170	0.0488	0.0184
	Sell	0.0197	0.2490	0.0136	0.0236
Back	Buy	0.0675	0.0181	0.2046	0.0169
	Sell	0.0186	0.0269	0.0165	0.2137

Lean hog		Front		Back	
		Buy	Sell	Buy	Sell
Front	Buy	0.1925	0.0179	0.0377	0.0172
	Sell	0.0163	0.2012	0.0191	0.0272
Back	Buy	0.0359	0.0188	0.1718	0.0199
	Sell	0.0161	0.0405	0.0156	0.1611

Figure 1. Estimated matrices of kernel norms.

The kernel norms on the off-diagonals show that in the cases of corn and wheat, the impact of front contracts on back contracts is larger than vice versa. This relationship, however, is not

prevalent for live cattle and lean hog. 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 more than about 80% of the 10-min 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 the considered commodities. Except for the front contracts of corn and wheat, for more than approximately 90% of the 10-min 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.

Contract	Front		Back		Front		Back	
Transaction	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
Commodity	Corn				Wheat			
Kolmogorov–Smirnov	0.84	0.84	0.88	0.89	0.87	0.83	0.89	0.89
Ljung–Box	0.64	0.67	0.94	0.92	0.78	0.80	0.94	0.94
Commodity	Live cattle				Lean Hog			
Kolmogorov–Smirnov	0.91	0.87	0.91	0.88	0.93	0.93	0.91	0.90
Ljung–Box	0.92	0.91	0.91	0.91	0.94	0.93	0.93	0.93

Figure 2 displays the evolution of the average intensity γ over the whole observation period. 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 all commodities. In particular, γ is higher for the front contract than for the back contract throughout the whole observation period for corn and wheat. In contrast, for live cattle and lean hog, 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 all commodities.

In general, the average intensity shows a relatively constant progression for all commodities; however, γ increases around certain days where public information became available. For instance, the average intensity increases for all commodities on 9 March 2016 when the USDA released its monthly WASDE report (USDA 2016b). Furthermore, γ increases for live cattle on 22 March 2016 following a USDA cattle on feed report (USDA 2016c). Most notably, γ increases considerably towards the end of the observation period for corn and wheat on 31 March 2016. On this day (11:00 a.m.), the USDA reported an unexpected increase in the corn acreage (USDA 2016a). On the same day, the USDA published its quarterly grain stocks reports (USDA 2016d). This may explain why the increase in average intensities is rather pronounced at that time. Overall, Figure 2 documents that the publication of USDA reports affects not only volatility and trading volume, but also the intensity of trading activity.
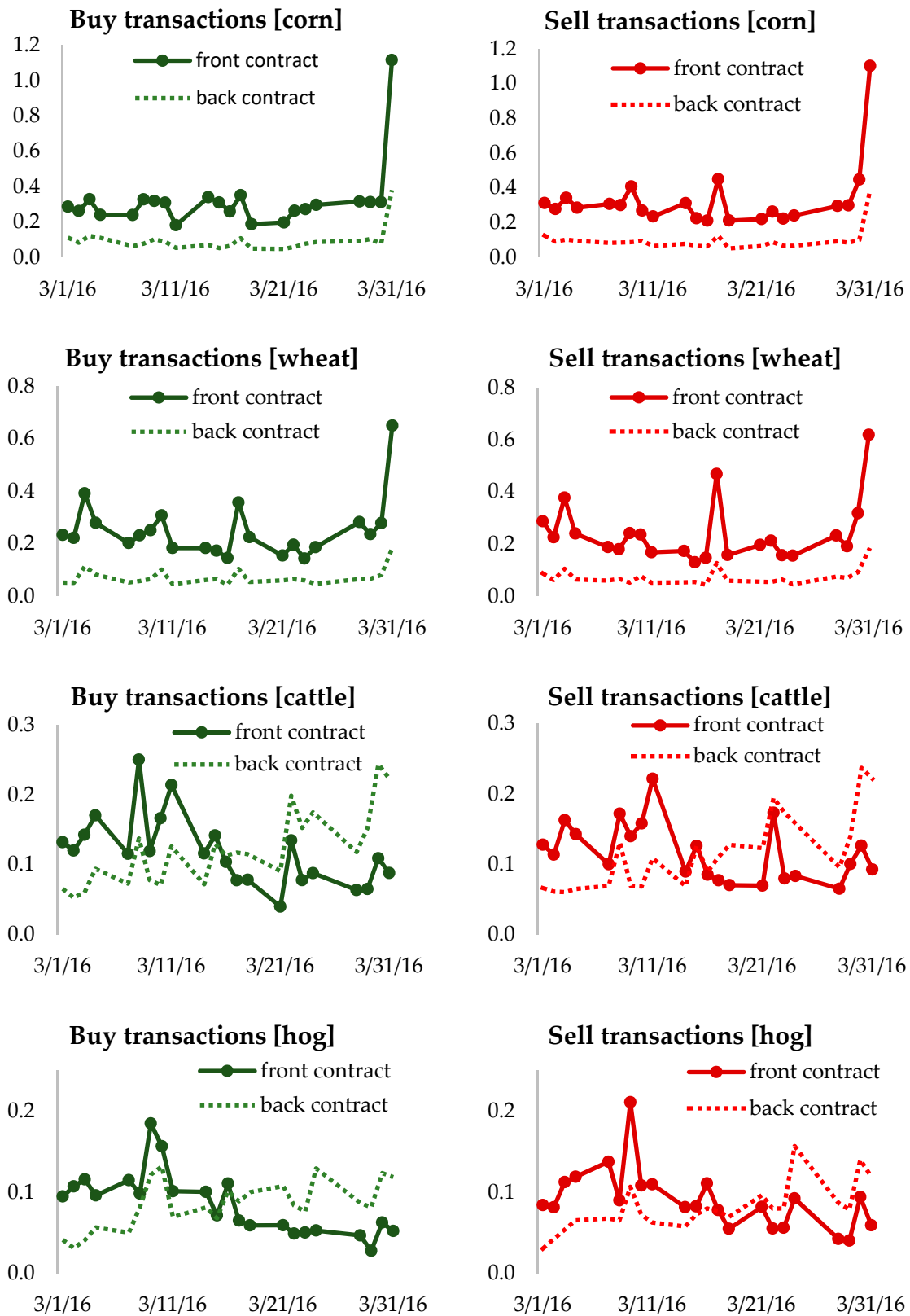
Figure 2. Evolution of average intensities (*y*-axis) in both buy and sell transactions for corn, wheat, live cattle, and lean hog in March 2016.

Figure 3 depicts the evolution of the baseline intensity μ on 31 March 2016 for corn. The figure is based on 24 intervals of 10 min. 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.
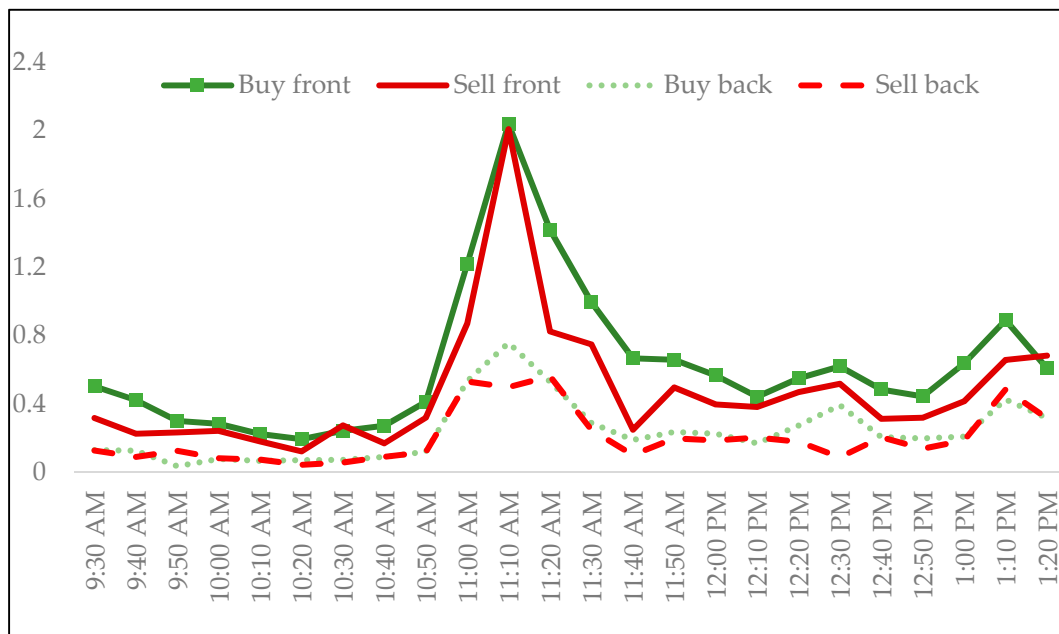
Figure 3. Evolution of the baseline intensity (*y*-axis) for corn on 31 March 2016.

The evolution of the baseline intensity for corn on 31 March 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.

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

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

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

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 31 March 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 31 March 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.

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 exemplarily for corn and live cattle. The figure is based on mean values of 528 intervals of 10 min. 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 $\hat{\lambda}_i$.
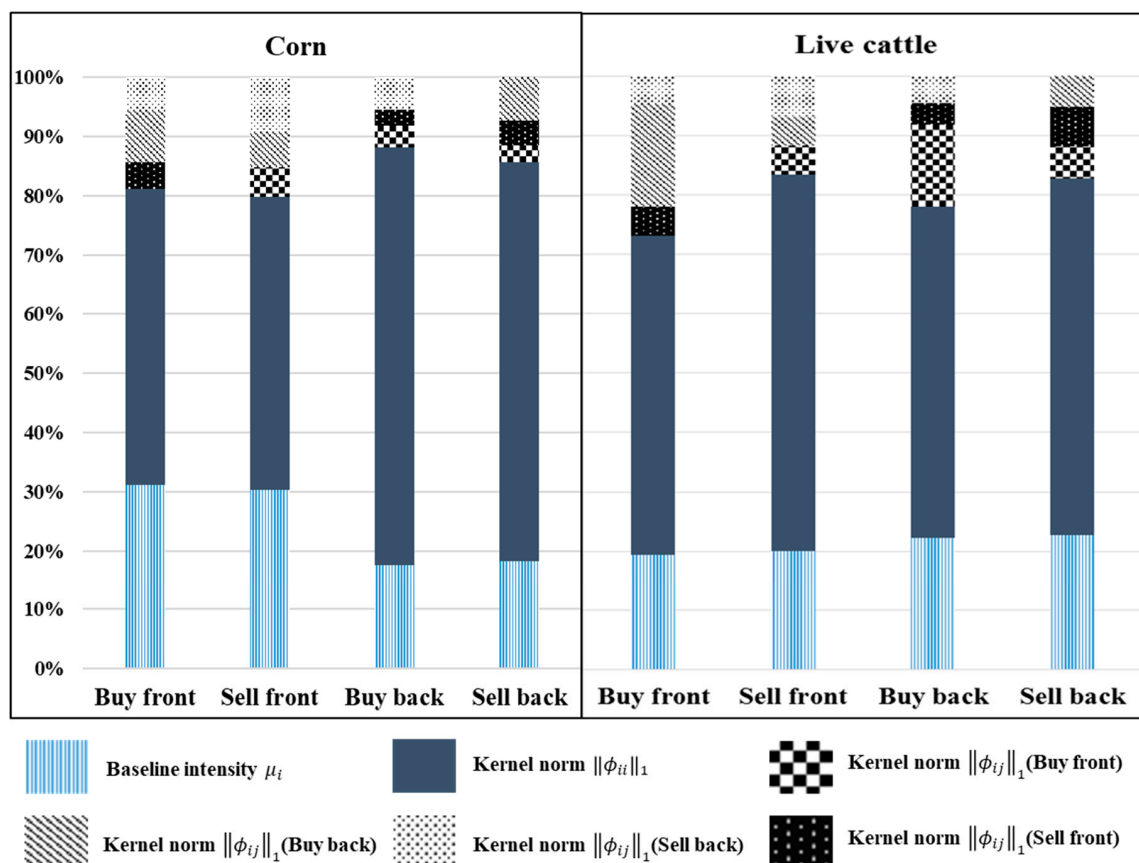
Figure 5. Composition of the estimated intensity for corn and live cattle.

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 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 (1982), the composition of the estimated intensity suggests that interdependencies of current and subsequent supply might link futures contracts of different maturities to 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. We conjecture that the degree of reflexivity is related to the trading intensity and the amount of automated trading. Endogeneity results from backward-looking trading strategies, which exploit information from previous trading activities. Most likely, this source of endogeneity is more prevalent in liquid markets than in thin markets. Storable commodities are more frequently traded compared with non-storable commodities, but this holds only for the front contract (c.f. Table 1). Moreover, grains show a higher share of automated trading than livestock contracts (e.g., Haynes and Roberts 2015; Couleau et al. 2019). It appears that these differences are reflected in the endogeneity of the price formation process.

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 the 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.

Appendix A

Table A1. Estimated baseline intensities, average intensities, and exogeneity ratios (corn, lean hog) for a 30-min interval.

Contract	Front		Back		Front		Back	
Transaction	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
Commodity	Corn (30-min interval)				Lean Hog (30-min interval)			
Baseline intensity	0.164	0.163	0.054	0.056	0.052	0.058	0.054	0.052
Average intensity	0.303	0.312	0.089	0.093	0.087	0.091	0.087	0.082
Exogeneity ratio	0.567	0.565	0.643	0.638	0.669	0.681	0.683	0.697

Table A2. Residual analyses (corn, lean hog) for a 30-min interval.

Contract	Front		Back		Front		Back	
Transaction	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
Commodity	Corn (30-min interval)				Lean Hog (30-min interval)			
Kolmogorov–Smirnov	0.460	0.465	0.758	0.757	0.830	0.800	0.794	0.790
Ljung–Box	0.373	0.374	0.791	0.770	0.807	0.785	0.829	0.860

Figure A1. Estimated matrices of kernel norms (corn, lean hogs) for a 30-min interval.

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