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Price discovery and volatility spillovers in the French wheat market

Narjiss Araba, Alain François-Heude

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Abstract

This study contributes to the literature on the information and volatility transmissions for wheat. It investigates the relationship between the French spot market of wheat and its futures contract, through the information and volatility transfers that occur between them. The analysis of the price discovery process, i.e. the information flow between both markets is based on daily prices between 2001 and 2018, and applies a vector error correction model (VECM) for the cointegrated price series. The information share, the permanent-transitory and the component share price discovery metrics are then computed to analyze the link between both markets. Our main finding is that the futures market completely dominates the price discovery for wheat, making the French physical market and agricultural producers exposed to the effects that excessive speculation can have. Furthermore, the volatility spillovers between both markets are analyzed from 2010 to 2018 with a bivariate asymmetric quadratic GARCH model and a BEKK model. We find that volatility spillovers from the spot to futures market are stronger than from futures to spot markets.

1. Introduction

With their futures contracts, futures markets allow producers to hedge against price risks through risk transfer. They also provide information about the spot market, making futures contract an efficient estimate of the spot price. We say that futures contracts facilitate price discovery, the mechanism determining prices. According to Lehmann (2002), price discovery

is the “efficient and timely incorporation of the information into market prices”. What is meant by efficient is the avoidance of noise, whereas by timely “the speed at which the information about the fundamental value is revealed” (Janzen & Adjemian, 2017).

In this study, we discuss the relationship between European wheat futures and the French spot market. More specifically, we assess whether Euronext’s wheat futures serve as a price discovery vehicle for French spot market movements. In other words, we estimate the proportion of price discovery occurring in wheat futures markets. This topic has attracted much interest and a large number of researchers examined this relationship for different commodities, including agricultural ones, as shown for example in Oellermann, Brorsen, & Farris (1989) for cattle; Schroeder & Goodwin (1991) for livestock; Yang, Balyeat, & Leatham (2005) for different agricultural commodities; Mattos & Garcia (2004) for most commodities; Arnade & Hoffman (2015) for soybean; Adämmer & Bohl (2015) for canola, wheat and corn in Europe and Vollmer & Von Cramon-Taubadel (2017) for wheat in Europe too. All of the previous studies find that it is mostly cash markets that adjust to futures markets, except Arnade & Hoffman (2015) who find the same result only for a sub-period of the data. Janzen & Adjemian (2017) study price discovery between European and American wheat futures contract and find that the Chicago market is dominant, Euronext however plays a more important role starting 2010.

To the best of our knowledge, no study has been undertaken on the specific case of the French wheat market, although it is one of the most important ones in western Europe. And since studies show that price discovery is linked to liquidity (Janzen & Adjemian (2017), Grammig & Peter (2013) and Yan & Zivot (2010)), our study on the French wheat market will enable us to conclude which of the markets is more liquid. Furthermore, in case price discovery takes place in the futures market, a conclusion about how increased speculation affects the spot market will be set; whereas if the contrary occurs and it is revealed that the spot market that

dominates, we would conclude that the commercial producers have the bigger hand over financial actors when it comes to influencing the market. On a more practical side, knowing what market influences the other will give an indicator to French wheat producers on what market to look at when deciding on their marketing strategies.

Different measures exist for price discovery, the most widely used being Hasbrouck's information shares (IS) (Hasbrouck, 1995), the permanent-transitory decomposition (PT) (Gonzalo & Granger, 1995), and the component share (CS) (Booth et al. (1999), Chu et al. (1999), Harris et al. (2002)) that is based on Gonzalo and Granger's decomposition. In this study, all the preceding price discovery metrics have been computed.

Furthermore, we investigate how volatility is propagated between the spot and futures market of wheat in France. Volatility spillovers can be analyzed between the spot and futures markets as in this article, but also between different commodities, and different countries.

We believe that no volatility spillovers study has been carried out before, in the French or European context for agricultural commodities. In China, for the case of wheat and soybean, Liu and Wang (2006), find that volatility spillovers occur from the spot to the futures market, and so did Mahalik et al. (2009), Srinivasan (2012) and Chauhan et al. (2013) for agricultural markets in India. However, compared to Euronext, these are all emerging futures markets, hence the results can differ.

The rest of the article is organized as follows. Section 2 introduces the methodology followed by the article to reach the conclusions on the price discovery weights for each market, as well as the volatility spillovers parameters. Section 3 presents the specifications and the preliminary analysis of the data used. And finally section 4 shows the results and discusses them. Section 5 gives some concluding remarks.

2. Methodology

1. Price discovery

To derive the IS, PT and CS metrics, we first estimate a vector error correction model (VECM), a representation of a cointegrated vector autoregressive model (VAR), that is better suited in the presence of cointegration, i.e. when a market affects the other on the short and long term.

Let p^s and p^f be the spot and futures prices respectively of the same asset, milling wheat in our case. Both prices are linked by arbitrage strategies, since they represent the price of a futures and its underlying. While the spot price implies the immediate payment and delivery, the futures price comprises additional storing and delivery costs since it entails a delayed payment and delivery. In that respect, they are expected to be cointegrated, meaning that they cannot deviate from each other in the long run. Although there can be some shocks in the short run, they will end up converging to the pre-existing equilibrium. Cointegration between p^s and p^f can be written as:

$$p_t^s = \alpha + \beta p_t^f + \mu_t$$

with

$$\mu_t = \rho \times \mu_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$$

In this case, both price series that should not be stationary, can be written as different stationary linear combinations of stationary time series, integrated at the first order (Engle & Granger, 1987). To find the cointegration relationship, we use the two-step Engle and Granger (1987) procedure that fits the best α and β , and then the best ρ . Only after cointegration has been verified can we fit a VECM model.

Two approaches of fitting a VECM model exist: Engle and Granger (1987), and Johansen's maximum likelihood estimation (Johansen, 1988). For this analysis, we choose the latter method. As detailed in (Baillie et al., 2002) the VECM model can be represented as:

$$\Delta p_t = \alpha \beta' \times p_{t-1} + \Gamma_1 \times \Delta p_{t-1} + \dots + \Gamma_k \times \Delta p_{t-k} + \varepsilon$$

Where $\alpha \beta' \times p_{t-1}$ translates into the long-term relationship, and $\sum \Delta p_{t-i}$ into the short-run term. In addition, α is the error correction coefficient, that represents the speed of adjustment. In other words, it allows the system to adjust back to the equilibrium. ε is the serially uncorrelated residuals vector.

Once the VECM estimated, we can start deriving the price discovery metrics by first obtaining the vector moving average (VMA) from the VECM equation:

$$\Delta p_t = \Psi(L) \times \varepsilon_t$$

Where L is the number of lags and ε a vector of the price innovations of mean zero and variance matrix Ω . Ψ is the matrix that reveals the impact of the innovations on the price change. This equation can be rewritten as:

$$\Delta p_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \dots$$

Where $\psi \varepsilon_t$ is the change in prices that is due to new information.

Integrated, it becomes:

$$p_t = \Psi(1) \sum_{s=1}^t \varepsilon_s + \Psi^*(L) \varepsilon_t$$

The matrix $\Psi(1)$ contains the sum of the moving average coefficients, I being the identity matrix:

$$\Psi(1) = I + \psi_1 + \psi_2 + \dots$$

Hasbrouck's (1995) information share can be written as the market j 's proportion in the total variance:

$$IS_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi'}$$

With j =spot or futures; $\psi \Omega \psi'$ is the variance of $\psi \varepsilon_t$, and ψ_j the j^{th} element of the matrix ψ .

In case Ω is not diagonal, IS is written as:

$$IS_j = \frac{([\psi' F]_i)^2}{\psi \Omega \psi'}$$

With $FF' = \Omega$.

An alternative price discovery measure is Gonzalo and Granger's (1995) permanent-transitory measure. In their decomposition of the VECM equation, Gonzalo and Granger get a permanent component: $W_t = \alpha'_{\perp} X_t$

X_t is decomposed into:

$$X_t = A_1 \alpha'_{\perp} X_t + A_2 \beta X_t$$

$$A_1 = \beta_{\perp} (\alpha'_{\perp} \beta_{\perp})^{-1}$$

$$A_2 = \alpha (\beta' \alpha)^{-1}$$

We get:

$$PT_j = \frac{\alpha^j}{\alpha^j - \alpha^i}$$

Alternatively, (Harris et al., 2002) propose the component share as a price discovery measure.

They use Gonzalo and Granger's decomposition and obtain as presented by Yan & Zivot (2007), the "weighted average of observed prices with component weights":

$$CS_j = \frac{\psi_j}{\psi_j + \psi_i}$$

Each measure has certain drawbacks and we would like to note that the information share cannot be used when there is a strong correlation of the innovations. This happens when prices are

observed at a low frequency. However, no study has been carried out on the best sampling frequency. Another advantage of PT and CS over IS, is that they result in a unique price discovery weight, while IS provides a lower and higher bound.

2. Volatility spillovers

Different multivariate conditional volatility models are available to estimate volatility spillovers, but it is advised to use a model that takes into account the asymmetry of the returns volatility, i.e. when a negative shock has a different effect from a positive one. The model we start with, that is multivariate and asymmetric is the Bivariate Asymmetric Quadratic GARCH model (BaqGARCH), developed by Schmidbauer (2008) and used by Schmidbauer & Rösch (2008).

This model is in fact a combination of the GJR model (Glosten, Jagannathan, & Runkle, 1993) that takes into account the asymmetry but that is univariate, and the BEKK model developed by Baba, Engle, Karft and Kroner and defined in Engle & Kroner (1995) that does not capture asymmetry but that is multivariate.

The BEKK and the BaqGarch models are similar, except the latter has an additional weight function.

The matrix H_t is a conditional variance-covariance of a random coefficient autoregressive process, and is given by the BEKK model as:

$$H_t = C'C + \sum_{i=1}^k A'_i \varepsilon_{t-i} \varepsilon'_{t-i} A_i + \sum_{i=1}^k B'_i H_{t-i} B_i$$

Where k is the number of lags, C is a triangular $N \times N$ matrix of constants. A and B are also $N \times N$ matrices, but A is the ARCH parameters matrix and B is the GARCH matrix.

On the other hand, the baqGARCH model with its weight function S_w is written as:

$$H_t = C'C + \sum_{i=1}^k A'_i \varepsilon_{t-i} \varepsilon'_{t-i} A_i + \sum_{i=1}^k B'_i H_{t-i} B_i + \sum_{i=1}^k S_w \varepsilon_{t-i} \Gamma' \varepsilon_{t-i} \varepsilon'_{t-i} \Gamma$$

This way, the weight w and the Γ matrix add the asymmetry component to the BEKK model. Details about the computation of the weight function S_w can be found in Schmidbauer & Rösch (2008).

3. Data

Our study aims to analyze first the price discovery mechanism of wheat in France between the cash market on one hand, and futures market on the other, between September 2001 and October 2018, the period in which our spot prices data are available. Second, we attempt to analyze volatility spillovers between January 2010 and October 2018. Our data for the cash market covers the daily prices in the port of Rouen, the first western European port for grain trade (INSEE, 2018) and is made available online by the National Institution of Agricultural and Sea Products (FranceAgriMer). Strategically located in the north of France, near the productive agricultural areas of Normandie, Picardie and Ile-de-France, it represents 40% of grain exports and 55% of milling wheat and barley exports (Passions Céréales, 2016). Different qualities are available, and we choose the standard quality (“supérieur A2”). As for the futures market, we take Euronext’s milling wheat contract n°2, traded as EBM. It is exchanged in large amounts, making it a liquid contract (for 2016, more than 450,3 millions of tons were traded, 16 times the French wheat production of the same year).

The mentioned EBM contract is also considered as a “global price benchmark for the European underlying physical markets” by Euronext (Raavel & Porte, 2016). This argument is partially what we aim to clarify, by analyzing the price discovery function between the futures contract and its underlying. Accordingly, we use the settlement prices of milling wheat available on Euronext’s website to construct two continuous price vectors, to get rid of any liquidity anomalies due to the expiration effects, also known as Samuelson effects (Samuelson, 1965). Samuelson (1965) noted that during expiration months the traded volumes are low and price

movements are irregular, which led him to warn about the volatility creation due to the use of the last day before delivery as the rollover date.

Over the years, the delivery months of EBM's futures contract has seen several changes (Table 1 EBM's delivery dates during the covered period) and omitting the first days of the delivery months by switching to the second nearby contract on the 1st day of the delivery month, as is often done in similar studies (Vollmer & Von Cramon-Taubadel, 2017 and Adämmer & Bohl, 2015 amongst others), will lead to irregularities in the data.

Table 1 EBM's delivery dates during the covered period

	<i>Jan</i>	<i>Feb</i>	<i>Mar</i>	<i>Apr</i>	<i>May</i>	<i>Jun</i>	<i>Jul</i>	<i>Aug</i>	<i>Sep</i>	<i>Oct</i>	<i>Nov</i>	<i>Dec</i>
2001	10/01/01		12/03/01		10/05/01		10/07/01		10/09/01		12/11/01	
2002	10/01/02		11/03/02		10/05/02		10/07/02		10/09/02		11/11/02	
2003	10/01/03		10/03/03		12/05/03		10/07/03		10/09/03		10/11/03	
2004	12/01/04		10/03/04		10/05/04		12/07/04		10/09/04		10/11/04	
2005	10/01/05		10/03/05		10/05/05		11/07/05		12/09/05		10/11/05	
2006	10/01/06		10/03/06		10/05/06		10/07/06		11/09/06		10/11/06	
2007	10/01/07		12/03/07		10/05/07				10/09/07		12/11/07	
2008	10/01/08		10/03/08		12/05/08			11/08/08			10/11/08	
2009	12/01/09		10/03/09		11/05/09			10/08/09			10/11/09	
2010	11/01/10		10/03/10		10/05/10			10/08/10			10/11/10	
2011	10/01/11		10/03/11		10/05/11			10/08/11			10/11/11	
2012	10/01/12		12/03/12		10/05/12			10/08/12			12/11/12	
2013	10/01/13		11/03/13		10/05/13						11/11/13	
2014	10/01/14		10/03/14		12/05/14						10/11/14	
2015	12/01/15		10/03/15		11/05/15				10/09/15			10/12/15
2016			10/03/16		10/05/16				12/09/16			12/12/16
2017			10/03/17		10/05/17				11/09/17			11/12/17
2018			12/03/18		10/05/18				10/09/18			10/12/18

Different studies tried to surpass this problem by omitting from the data, the month of delivery (Junkus, 1986), or the last week before delivery (Östermark et al., 1995) and (Martikainen & Puttonen, 1996). However, the literature produces contradictory results as to the importance of the rollover day on the results. Ma et al. (1992) find biases according to the day chosen. Carchano & Pardo (2009) test this claim and find no significant effect of the rollover day; therefore, they use the last day before delivery as a rollover date. In this article, and in order to

keep one data per day, we construct an artificial futures contract with a constant horizon of a 180 days (6 months), which to our knowledge, has not been used before in a similar context. The new contract that we call forward180 (*Fwd180*) is continuous and constructed as a weighted mean of the next and second-next contract settlement prices:

$$Fwd180 = Price_{\tau_1} + (Price_{\tau_2} - Price_{\tau_1}) \times \frac{\tau_1 - 180}{\tau_1 - \tau_2} \quad (1)$$

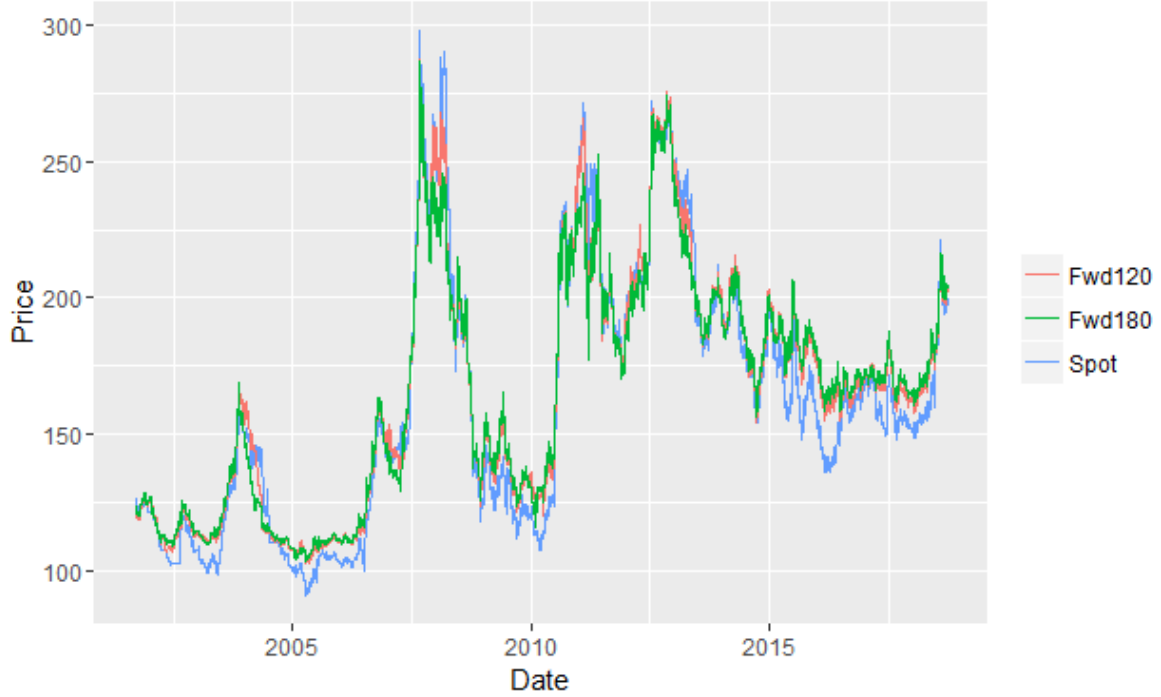
τ_1 and τ_2 denote the number of days until the next and second next delivery dates, such that they are the successive immediate lower and upper bounds of 180. This way, an interval containing 180 days is created. For robustness checks of the price discovery measures, we construct the same price vector for 120 days (*Fwd120*). We end up with a database of 4365 observations for the price discovery part, and 2258 observations for the volatility spillover analysis.

4. Results and discussion

1. Price discovery

Figure 1 Price evolution shows the common trend followed by the spot and futures prices, as well as the mutual spikes. Four major peaks can be detected: one in the end of 2003 to 2004 (which is less significant compared to the others), the price peak of 2007/2008, the one of 2010/2011 and finally the one of 2012/2013. The peak of 2007/2008 was the largest and the most debated in accordance to the reasons that led to it, whether they be speculative or related to the fundamentals of demand and supply. During that episode, prices nearly reached 300 euros per ton not only for the milling wheat futures, but on the physical market as well.

Figure 1 Price evolution



First, to help induce homoskedasticity and normally distributed errors, and for ease of interpretation, we take the log of all of our daily prices (the spot and forward prices). We then decompose our data to remove the seasonal component and test for stationarity using the augmented Dickey-Fuller (ADF) test to detect unit-roots, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for trend stationarity. As displayed in Table 2 Empirical results of the stationarity tests the null hypothesis of the existence of a unit root is not rejected with the ADF test, and the KPSS test show that the prices series are not trend stationary.

Table 2 Empirical results of the stationarity tests

	ADF	KPSS
<i>Spot</i>	-2.32***	2.17***
<i>Fwd120</i>	-2.50***	2.28***
<i>Fwd180</i>	-2.49***	2.34***

Where *** denotes significance at the 1% level.

We also compute the number of differences necessary to make the series stationary and find that they should be differenced once.

We then examine the short run and long run relationship between the spot and futures prices. The short run relationship is examined by the Granger causality test. The results that are not shown in this analysis indicate that both futures prices Granger cause the spot price, which is why we choose to model the spot price as a function of the futures price.

Next, we verify that a cointegration relationship exists, for the long term link, using Engle-Granger's cointegration procedure and find that the spot is cointegrated with both futures prices (*Fwd180* and *Fwd120*).

Table 3 Cointegration results

	α	β	ρ
Spot and <i>Fwd120</i>	0.55***	0.90**	0.96***
Spot and <i>Fwd180</i>	0.71***	0.86**	0.98***

Where *** denotes significance at the 1% level, and ** at the 5% level.

We find that the series are cointegrated Table 3 Cointegration results but the residuals do not seem to be well fitted by the auto-regressive series of order 1 used in the model. Hence the parameters of the residuals (ρ) may not be the best specification.

Since the series are not stationary but need to be differenced once to be so, and are cointegrated (I(1)), we can estimate two VECM models, using Johansen's approach for both the *Fwd180* and *Fwd120* with the spot price.

We start by estimating the number of lags by estimating a VAR model using OLS and trying with different lags. We obtain that, for both equations that 6 and 2 lags are optimal. We fit VECM models using the 2 lags, and find that the best models are obtained with 2 lags (best Akaike and Bayesian information criteria (AIC and BIC)).

Table 4 VECM results

	ECT	Intercept	P^s_{t-1}	P^F_{t-1}	P^s_{t-2}	P^s_{t-2}
Spot & Fwd120	-0.0225***	-0.0126***	-0.2489***	0.5634***	-0.0281**	0.0330**
Spot & Fwd180	-0.0142***	-0.0105***	-0.2322***	0.5674***	-0.0159**	0.0143**

Where ECT is the error correction term; *** denotes significance at a 1% level and ** at a 5% level.

First, we see that the error correction term is negative and lies between 0 and 1 in absolute terms, which entails that the process is converging in the long run, i.e. that the estimated model is stable and a long-run relationship exists between the spot and futures prices. The other coefficients indicate the short-run relationship. To better interpret these results, we plot the impulse response functions, i.e. the response of the spot and futures prices after an impulse on the spot prices to study the dynamics between them.

We see that (Impulse response function for the Fwd120 Figure 2) a positive shock on the spot price led to an immediate reaction of the spot price itself, with a 1,45% increase of the spot price fluctuations. It stayed roughly the same, at its maximum level, until the last period. The reaction of the futures price (*Fwd120*) to the shock on the spot price, is very similar but at a lower magnitude. An increase of the fluctuations of 0.5% initially, until it reached 0.7% at the second period and then stagnated. As for the *Fwd180* (Figure 3), the reaction remained similar. As time passes, the shock does not decay to 0.

Table presents the price discovery metrics and we note a clear domination of the futures market, according to the IS, PT and CS measures between 2001 and the end of 2018. According to the IS measure, the futures market is responsible for between 70 and 99% of price discovery (for both price vectors), that is on average 84.5%. Likewise, the CS and PT measures are of a similar magnitude, and indicate a domination of approximately 93% in favor of futures prices (both price vectors), while the spot prices are responsible of less than 8% of the price discovery. This consistency between the three measures and both price vectors is a sign of the assertive role the futures market plays. It is also in line with the literature findings on the general context of

agricultural commodities, where it is mostly the spot market that adjusts to the futures markets, and to the European framework as highlighted by Vollmer & Von Cramon-Taubadel (2017) and Adämmer & Bohl (2015) for Germany.

Table 5 Price discovery results

		PT	Component Share	IS bounds
Fwd120	<i>Spot</i>	6,00%	5,88%	[0;0,31]
	<i>Futures</i>	94,00%	94,12%	[0,69;0,99]
Fwd180	<i>Spot</i>	7,16%	6,77%	[0;0,30]
	<i>Futures</i>	92,84%	93,23%	[0,70;0,99]

We also study the reaction of the spot prices after a shock in the futures prices with impulse response functions (Figures 4 and 5), we find that for both *Fwd120* and *Fwd180*, the response of the spot price is quick and positive.

Figure 2 Impulse response function for the Fwd120

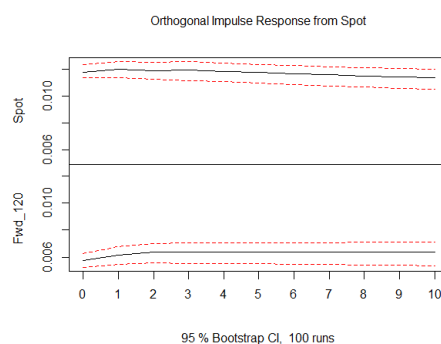
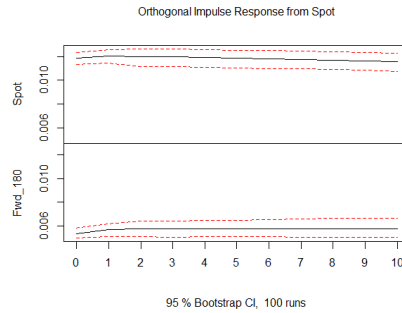


Figure 3 Impulse response function for the Fwd180



Dimpfl et al. (2017) make an interesting link between price discovery and speculation in their analysis, from which we can draw a commentary regarding our findings. The fact that it is the futures market that determines the efficient price for wheat in France, and not the fundamentals of supply and demand is an important point that implies the extensive role financial actors play. There is a disagreement in the financial literature on the role played by financial actors compared to commercial producers, especially when it comes to explaining what led to the 2007-2008 price peak of agricultural commodities. It has long been believed that each actor has a specific role in the financial market: commercial producers hedge, and financial agents speculate, hence creating liquidity to the commercials. However, more recent work (Guilleminot et al., 2012) undermined this argument by analyzing US commodities markets according to the positions taken by each type of agent (hedgers, index investors and hedge funds). The authors find that it is the hedgers that provide liquidity to index investors that since 2004, when the latter became the first financial participants.

Furthermore, since market liquidity provides more efficient price discovery, we can conclude that the financial market is more liquid than the spot market. This is in agreement with general beliefs on the EBM contract with its important trading volumes and facility to find a trading counterparty.

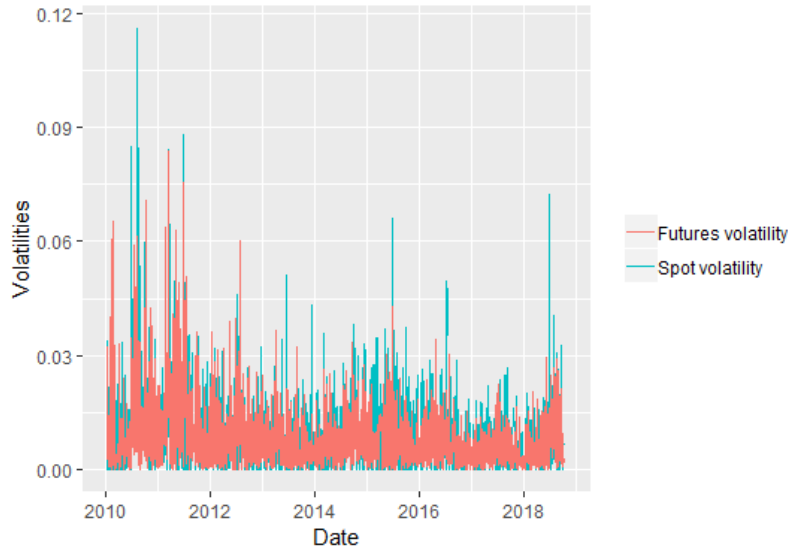
2. Volatility spillovers

Computation of returns is necessary to analyze volatility spillovers between both markets. We first compute the spot returns, by taking the difference of the log of the price at time t , and the log of the price at time $t-1$. We do the same for the futures return with the Fwd180 price

$$r_j = \log(p_t^j) - \log(p_{t-1}^j)$$

where j is either the spot or the futures price.

Figure 4 Volatilities

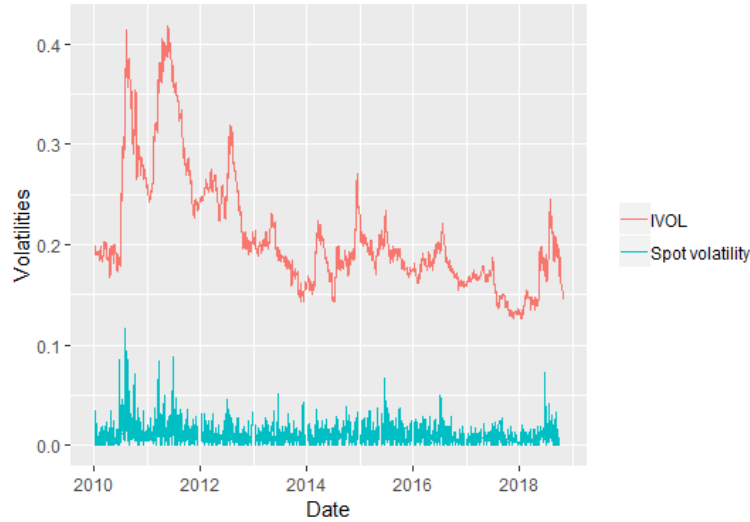


We note from Figure 4 Volatilities that both volatilities have a similar pattern with the spot volatility having higher swings. This might be due to the fact that the futures prices used to compute the volatilities are transformed to get rid of the expiration effect while the spot prices are not.

We also compute the implied volatility for the futures contract volatility (Figure 5) from Euronext's options on milling wheat futures (OBM), as an indicator of the futures volatility during the lifetime of the option. Like for the futures prices, the implied volatility is scaled to

have a constant horizon of 180 days. We note that although the implied volatility is higher, both volatilities show a similar trend and coinciding peaks.

Figure 5 Volatilities



Correlation tests of the futures and spot volatilities using Pearson's method give us a correlation of 0.38 for when the futures volatility is computed using the returns, and 0.32 for when it is the implied volatility.

Further analysis of the relationship between both volatilities leads us to test the Granger causality and modelling the conditional volatilities. Before, the returns are deseasonalized, detrended and tested for seasonality.

Table 5 Stationarity tests for the returns

	ADF	KPSS
r_s	-12.009***	0.0602
r_f	-12.426***	0.3339

Where *** denotes significance at the 1% level.

The tests show that both returns are unit root stationary according to the ADF test, and are trend stationary according to the KPSS test.

We first perform a Granger causality test to understand the interdependencies between the returns of the futures and spot markets. We first select the number of lags to be taken into account using a vector autoregressive (VAR) process, and find that 6 is the optimal number of lags. Exploring granger's causality via the Wald test, we find that there is a significant bi-causal relationship between futures and spot markets, since the spot returns Granger cause the futures returns and vice versa.

Table 6 Granger causality tests for the returns

Hypothesis	Wald statistic	p-value
The spot returns Granger cause the futures returns	28.284	$< 2.2e-16$
The futures returns Granger cause the spot returns	2.3512	0.0288

However, the Granger test does not take into account the autoregressive second moment which is why we also analyze the conditional volatility with multivariate conditional volatility models.

We start with the BaqGARCH model to capture the asymmetry and find the following results with the t values in parenthesis:

$$\begin{aligned}
 C &= \begin{pmatrix} -0.008 & -0.006 \\ (-) & (-) \\ 0.000 & -0.003 \\ (-) & (-) \end{pmatrix} \quad A = \begin{pmatrix} 0.239 & 0.046 \\ (-) & (0.455) \\ 0.104 & 0.422 \\ (2.12) & (8.979) \end{pmatrix} \quad B = \begin{pmatrix} 0.456 & -0.662 \\ (-) & (-17.843) \\ 0.024 & -0.126 \\ (-) & (-0.863) \end{pmatrix} \\
 \Gamma &= \begin{pmatrix} 0.182 & 0.530 \\ (2.275) & (8.116) \\ -0.371 & -0.188 \\ (-12.367) & (-1.39) \end{pmatrix} \\
 w &= 0.201 \\
 & (0.646) \\
 AIC &= -13968.45
 \end{aligned}$$

Contrary to Koutmos & Booth's finding regarding the asymmetry of volatility transmission in a stock market context (1995), our asymmetry parameters are not significant. Indeed, the weight parameter w is not significant, and two of the Γ parameters are not significant either. Hence we cannot reject the null hypothesis that there is no asymmetric interaction between spot and futures returns. Consequently, without interpreting the BaqGARCH results, we model the

conditional volatility with the Full BEKK model, since it is equivalent to the previous model without asymmetry parameters, but also because the AIC value of the BEKK model is better.

The matrices of the fitted BEKK model are the following, with the t values in parenthesis:

$$C = \begin{pmatrix} -0.005 & -0.006 \\ (-5.556) & (-9.677) \\ 0.000 & -0.007 \\ (-) & (-8.434) \end{pmatrix} \quad A = \begin{pmatrix} 0.237 & 0.158 \\ (5.780) & (3.080) \\ 0.081 & 0.402 \\ (2.508) & (11.983) \end{pmatrix} \quad B = \begin{pmatrix} -0.569 & -0.371 \\ (-7.679) & (-6.543) \\ -0.417 & -0.273 \\ (-6.079) & (-3.917) \end{pmatrix}$$

$$AIC = -13986.56$$

The first row of all the matrices is for the futures market while the second row is for the spot market. Similarly, the first column is the futures market's column and the second is the spot market's one.

We first start by examining the matrix A, more precisely its squared elements. They correspond to the ARCH parameters, meaning the volatility's response to the squared standardized residuals of the markets (Mohammadi & Tan, 2015). The element (1,1) becomes 0.056 when squared, implying that the response of the futures market volatility to its own innovations is estimated to be 0.056. Likewise, the response of the spot market to its own innovations (squared element (2,2)) is 0.162. The off-diagonal parameters of matrix A tell us more about the response of one market to the innovations of the other market. Thus the response of the futures market's volatility to the shocks from the spot market (squared element (2,1)) is 0.007, and the response of the spot market's volatility to the shocks from the futures markets is 0.025.

On the other hand, the GARCH parameters matrix (matrix B) tell us about the past volatilities effect on the volatilities. We obtain that the response of the futures market to its own past volatility is 0.324, the response of the spot market to its own past volatility is 0.074, the response of the futures market to past spot market's volatility is 0.174, and the response of the spot market to past futures market's volatility is 0.138.

In light of the above and since all parameters are statistically significant (both ARCH and GARCH), we first conclude that the conditional variances of both markets are impacted by their own previous shocks. The spot market reaction to its own innovation being larger. In addition, the conditional variances of both markets are affected the shocks coming from the other market: the futures market past shocks affect the spot market and vice versa. However, the spot market's reaction to the futures market shocks is 3.6 times larger. Second, from the GARCH parameters we note that both market respond to their own volatility, as well as to the other market's volatilities. Interestingly, the spot market responds more to the volatility of the futures market rather than to its own volatility.

In other words, the futures market leads the french spot market, yet it is slightly more impacted by the spot volatility. Nevertheless, it is more impacted by its own volatility rather than by that of the spot market, as opposed to the spot market, that has a stronger reaction to the futures volatility rather than to its own.

3. Conclusion

In this study we examined the relationship between EBM's futures prices and the French spot price for wheat using Hasbrouck's information share (1995), Gonzalo and Granger's permanent-transitory component (1995) and the component share of Harris et al. (2002). The three measures are consistent with eachother and point to the futures market being the price discovery vehicle for the spot market's movement. The complete domination of futures markets translates into the fact that speculation is an important factor in the wheat price determination. This conclusion is relevant to the agricultural producers who use the futures markets to hedge against price risk, because it implies that futures market is efficient and liquid, yet heavily influences the spot market. And most importantly, since it is not the agricultural producers who play the biggest role in the physical market, they should pay more attention to the futures market

when deciding on marketing strategies. Further, we found that one unit shock in the futures price leads to a quick and positive response of the spot price.

On the other hand, with regards to the volatility spillovers, the results indicate that the innovations in the futures markets affect the spot market and vice versa and that volatility spillovers occur from the futures market to the spot market and vice versa. But the futures market reaction to the innovations and to the volatility of the spot market is slightly higher, even though it is the leading market in terms of price discovery. Therefore, the spot market is also a source of volatility.

The distortions created in the future markets do spill over to the French spot market, where the producers end up with an additional risk transferred through the spot and the futures markets. Encouraging French wheat producers to use the futures markets can help increase the number of hedgers compared to the speculators, in order to stabilize the prices.

References

- Adämmer, P., & Bohl, M. (2015). Price Discovery in European Agricultural Markets: When Do Futures Contracts Matter? *Center for Quantitative Economics (CQE), University of Muenster*, No. 4415.
- Arnade, C., & Hoffman, L. (2015). The Impact of Price Variability on Cash/Futures Market Relationships: Implications for Market Efficiency and Price Discovery. *Journal of Agricultural and Applied Economics*, 47(4), 539-559.
- Baillie, R., Booth, G., Tse, Y., & Zobotina, T. (2002). Price discovery and common factor models. *Journal of financial markets*, 5(3), 309-321.
- Booth, G., So, R., & Tse, Y. (1999). Price discovery in the German equity index derivatives. *Journal of Futures Markets*, 19(6), 619-643.
- Carchano, Ó., & Pardo, Á. (2009). Rolling over stock index futures contracts. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 29(7), 684-694.
- Chauhan, A. K., Singh, S., & Arora, A. (2013). Market efficiency and volatility spillovers in futures and spot commodity market: The agricultural sector perspective. *Samvad*, 6(2), 61-84.
- Chu, Q., Hsieh, W., & Tse, Y. (1999). Price discovery on the S&P 500 index markets: An analysis of spot index, index futures and SPDRs. *International Review of Financial Analysis*, 8(1), 21-34.
- Dimpfl, T., Flad, M., & Jung, R. (2017). Price discovery in agricultural commodity markets in the presence of futures speculation. *Journal of Commodity Markets*, 5, 50-62.

- Engle, R., & Granger, C. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.
- Engle, R., & Kroner, K. (1995). Multivariate simultaneous generalized ARCH. *Econometric theory*, 11(1), 122-150.
- Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48(5), 1779-1801.
- Gonzalo, J., & Granger, C. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics*, 13(1), 27-35.
- Grammig, J., & Peter, F. (2013). Telltale tails: A new approach to estimating unique market information shares. *Journal of Financial and Quantitative Analysis*, 48(2), 459-488.
- Guilleminot, B., Ohana, J., & Ohana, S. (2012). *Les nouveaux modes d'investissement sur les marchés dérivés de matières premières agricoles. Décryptage et impact.*
- Harris, F., McInish, T., & Wood, R. (2002). Security price adjustments across exchanges: An investigation of common factor components for Dow stocks. *Journal of Financial Markets*, 5(3), 277-308.
- Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The journal of Finance*, 50(4), 1175-1199.
- INSEE. (2018). *Plus de 460 000 emplois liés à la logistique dans la Vallée de la Seine.*
- Janzen, J., & Adjemian, M. (2017). Estimating the location of world wheat price discovery. *American Journal of Agricultural Economics*, 99(5), 1188-1207.
- Janzen, J., & Adjemian, M. (2017). Estimating the location of world wheat price discovery. *American Journal of Agricultural Economics*, 99(5), 1188-1207.
- Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, 12(2-3), 231-254.
- Junkus, J. C. (1986). Weekend and day of the week effects in returns on stock index futures. *Journal of Futures Markets*, 6(3), 397-407.
- Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of international Money and Finance*, 14(6), 747-762.
- Lehmann, B. N. (2002). Some desiderata for the measurement of price discovery across markets. *Journal of Financial Markets*, 5(3), 259-276.
- LIU, Q. F., & WANG, H. M. (2006). Price Discovery in the Spot-Futures Markets: An Empirical Analysis in Chinese Agricultural Products. *Research on Financial and Economic Issues*, 4, 44-51.
- Ma, C., Mercer, J., & Walker, M. (1992). Rolling over futures contracts: A note. *Journal of Futures Markets*, 12(2), 203-217.
- Mahalik, M. K., Acharya, D., & Babu, M. S. (2009). Price discovery and volatility spillovers in futures and spot commodity markets: Some empirical evidence from India. *IGIDR Proceedings/Project Reports Series*, (062-10).
- Martikainen, T., & Puttonen, V. (1996). Sequential information arrival in the Finnish stock index derivatives markets. *The European Journal of Finance*, 2(2), 207-217.
- Mattos, F., & Garcia, P. (2004). Price discovery in thinly traded markets: Cash and futures relationships in Brazilian agricultural futures markets. *NCR-134 Conference on*

- Applied Commodity Price Analysis, Forecasting, and Market Risk Management*,. St. Louis.
- Mohammadi, H., & Tan, Y. (2015). Return and volatility spillovers across equity markets in mainland China, Hong Kong and the United States. *Econometrics*, 3(2), 215-232.
- Oellermann, C., Brorsen, W., & Farris, P. (1989). Price discovery for feeder cattle. *Journal of Futures Markets*, 9.2: 113-121.
- Östermark, R., Martikainen, T., & Aaltonen, J. (1995). The predictability of Finnish stock index futures and cash returns by derivatives volume. *Applied Economics Letters*, 2(10), 391-393.
- Passions Céréales. (2016). *LE PORT DE ROUEN SÈME POUR L'AVENIR*.
- Raevel, O., & Porte, L. (2016). *The functioning of the futures markets: new regulation, challenge and opportunities*.
- Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial management review*, 6(2).
- Schmidbauer, H. (2008). *News Impact in Bivariate GARCH Models*. . Research report, Istanbul Bilgi University.
- Schmidbauer, H., & Rösch, A. (2008). Volatility spillovers between crude oil prices and US dollar to Euro exchange rates. *Unpublished Research Paper*.
- Schroeder, T., & Goodwin, B. (1991). Price Discovery and Cointegration for Live Hogs. *Journal of Futures Markets*, 11.6: 685–96.
- Srinivasan, P. (2012). Price Discovery and Volatility Spillovers in Indian Spot-Futures Commodity Market. *IUP Journal of behavioral finance*.
- Vollmer, T., & Von Cramon-Taubadel, S. (2017). Price discovery in the European wheat market. *International Congress of the European Association of Agricultural Economists*. Parma.
- Yan, B., & Zivot, E. (2007). The Dynamics of Price Discovery. *AFA 2005 Philadelphia Meetings*.
- Yan, B., & Zivot, E. (2010). A structural analysis of price discovery measures. *Journal of Financial Markets*, 13(1), 1-19.
- Yang, J., Balyeat, B., & Leatham, D. (2005). Futures Trading Activity and Commodity Cash Price Volatility. *Journal of Business Finance & Accounting*, 32(1) & (2).