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In search of attention in agricultural commodity markets[☆]

Tomáš Mišečka [a], Pavel Ciaian [b,*], Miroslava Rajčániová [a,c], Jan Pokrivčák [a,c]

[a] Slovak Agricultural University in Nitra, Faculty of Economics and Management, Department of Economic Policy, Slovakia
[b] European Commission, Joint Research Centre (JRC), Seville, Spain
[c] University of West Bohemia, Faculty of Economics, Pilsen, Czech Republic

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ABSTRACT

This paper investigates the impact of attention driven behaviour on agricultural commodity prices. We proxy attention driven behaviour using search queries for the commodity names in Google. We apply the ARDL model to estimate the impact of search queries on three internationally traded agricultural commodities – corn, wheat and soybean – using weakly data for the period 2009–2015. The results show that there is causal and permanent relationship between Google search queries and prices of corn and wheat confirming the presence of the attention driven behaviour. However, the estimates do not confirm this relationship for soybean price.

1. Introduction

There is a significant body of literature attempting to explain the determinants of agricultural price developments. In addition to the traditional macroeconomic drivers (global growth in population and incomes, interest rates, exchange rates) (Headey and Fan, 2008; Gohin and Chantret, 2010), trade policies (Bellmann and Hepburn, 2017) and fundamental sectorial determinants (e.g. commodity stocks, supply shocks caused by weather changes) (Brunner, 2002; Hochman et al., 2014; Ott, 2014; Wang and McPhail, 2014), the literature proposed additional drivers in an attempt to explain the agricultural commodity price developments. The rise of policy intervention in biofuel market in past decades is argued to have created a tighter link between energy markets and agricultural commodity markets (de Gorter and Just, 2009; Ciaian and Kancs, 2011; Serra and Zilberman, 2013; Drabik et al., 2014; Wang and McPhail, 2014; Ahmadi et al., 2016; Fowowe, 2016). The speculative trading and the financialization of agricultural commodity markets through the increased role played by the commodity investment funds and the financial derivatives markets are also argued to have a strong impact on both the level of agricultural prices and their volatility (Dwight et al., 2010; Cheng and Xiong, 2013; Gutierrez, 2013; Isakson, 2014; Henderson et al., 2015).

A less explored driver of the agricultural commodity price developments in the literature is the online activity of internet users and the role of mass-media. In general, the access to information on the state and prospects of markets is not free. There are significant search costs to obtain information based on which trading and investment decisions can be made. Given that searching for information for available trading or investment opportunities is costly, those commodities or assets which are under attention in the mass media might be preferred by investors because activity of mass-media reduces the search costs for some investors, specifically those that do not look for information systematically but rather trade those commodities or assets that catch their attention. Media attention is frequently coupled with the intensity of activity on internet search engines (e.g. Google, Yahoo, Baido). This effect causes capital flowing to trading or investment opportunities that are under more attention (O'Hara, 1995; Barber and Odean, 2008). In general, the attention-based behaviour is expected to shape the price levels of different assets including prices of commodities. The attention-driven behaviour of market agents was found in the literature to affect stock prices (Bank et al., 2011; Chan, 2003; Da et al., 2011; Barber and Odean, 2013; Kristoufek, 2015), exchange rates (Goddard et al., 2015), cryptocurrency prices (Kristoufek, 2013; Ciaian et al., 2015, 2018) and food consumption (Rieger et al., 2016).

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* Correspondence to: European Commission, Joint Research Centre, C/ Inca Garcilaso, 3, 41092 Seville, Spain.
E-mail address: pavel.ciaian@ec.europa.eu (P. Ciaian).

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The objective of this paper is to estimate the impact of the attention-driven behaviour on the agricultural commodity prices. To our knowledge there are no studies available in the literature analysing the implications of the attention-driven behaviour of market participants on agricultural commodity markets. In this paper we proxy the attention-driven behaviour by search queries in Google. That is, we attempt to estimate the linkage between the number of searched keywords attached to the specific agricultural commodities in Google and agricultural commodity price movements. Currently, information sources were market participants can search for information are significantly more extensive than they were in the past. In the past market participants were often taking actions based on information obtained from newspapers, radio, television, extension services or interpersonal communication with peers (Mondria et al., 2010). Nowadays market participants often search for information on the internet using search engines (e.g. Google). This allows to measure their attention for specific key words searched on the search engines. The search queries in Google is extensively used in the literature to explain the attention driven behaviour particularly in financial markets (Da et al., 2011; Preis et al., 2013; Kristoufek, 2013, 2015; Goddard et al., 2015; Welagedara et al., 2017; Ciaian et al., 2018). Da et al. (2011) show that Google search queries capture attention more timely compared to other well-established attention proxies.

The attention driven behaviour is particularly relevant for agricultural commodity markets due to the growth of internet penetration in rural areas in the last decades both in developed and developing countries. Developing countries are particularly impacted by the expansion in the use of mobile phones in rural areas in recent period which provides cheaper information access to many small farmers and traders from these countries as compared to the traditional forms of information dissemination (e.g. extension services) (Asenso-Okyere and Mekonnen, 2012). According to Da et al. (2011), Kristoufek (2015) and Goddard et al. (2015), the impact of Google search queries tends to reflect more attention driven behaviour from those market participants that devote less time and resources for information search such as from non-professional market participants. In contrast, professional market participants (e.g. large trading companies, global food companies, institutional investors) usually use well established sources for information which are not necessarily obtained through the internet search engines. Indeed, the agricultural sector is characteristic for the presence of many small (non-professional) market participants such as small farmers, small traders and small food processing plants who as argued by Da et al. (2011), Kristoufek (2015) and Goddard et al. (2015) are more susceptible to the attention driven behaviour. This is especially the case since internet access became more available thus leading to a greater exposure of these agents to information diffused through the mass media. On the one hand, the availability of information, among other, allows these small agents to improve their market performance by improving bargain position, better respond to market signals, increase spatial arbitrage between different markets or to better coordinate supply and demand for agricultural commodities (e.g. stock management, timing of harvest, packaging, planting, etc.). The market performance can be improved in particular if agents access timely market information where internet plays a key role (Shepherd, 1997; Jensen, 2007; Muto and Yamano, 2009; Lokanathan et al., 2011). On the other hand, with a greater internet access, small (non-professional) market agents are prone to attention driven behaviour because they are more exposed to the mass media as compared to the past period before the advent of the internet and mobile phones. Better access to mass media through internet reduces information search costs, while small economic size of the many players in agriculture do not provide them sufficient resources to set-up a systematic method for collecting and processing information. This is reinforced by the fact that small farmers and traders in rural areas are usually less educated and credit constrained which reduces their ability to process and analyse the information. As a result, those commodities under attention in the mass will tend to catch attention of these market agents and potentially affect their production and trading decisions. Overall these characteristics of the agri-food sector are expected to cause the attention driven behaviour impacting agricultural commodity prices.

The paper is organized as follows. In Section 2 we describe the empirical approach. Section 3 presents data used in the paper. In Section 4 we explain the estimated results and Section 5 summarizes our findings and concludes.

2. Methodology

We apply the Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration developed by Pesaran et al. (2001) to analyse the dynamic relationship between agricultural commodity prices and their determinants. The advantage of this approach is that it enables to estimate the long and short-run parameters simultaneously, it addresses endogeneity problems and can be applied irrespective of whether underlying regressors are purely I(0), purely I(1) or mutually cointegrated variables (Pesaran et al., 2001). That is, an important advantage is that the ARDL approach to cointegration works even when having endogenous regressors. Pesaran and Shin (1999, p. 16), contend that "*appropriate modification of the orders of the ARDL model is sufficient to simultaneously correct for residual serial correlation and the problem of endogenous regressors*". This issue is relevant for our estimations because the endogeneity problem could be particularly present in our data given that agricultural commodity prices and Google search queries are likely mutually interdependent which might lead to biased estimates if standard regression models are applied.

According to Ouattara (2004) in the presence of I(2) variables the computed F statistics provided by Pesaran et al. (2001) become invalid. Therefore, before applying ARDL bounds test, we determine the order of integration of all variables using the unit root tests, to make sure that none of the variable is integrated of order I(2) or beyond. We use five unit root tests to determine the stationarity of time series: the augmented Dickey–Fuller (ADF) test, the Dickey–Fuller GLS test (DF-GLS), Phillips–Perron (PP) test, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and Elliott–Rothenberg–Stock (ERS) test. The appropriate number of lags for the model is determined by the Akaike Information Criterion (for more details see Appendix).

3. Data

We consider three internationally traded agricultural commodities in this paper: corn, wheat and soybean. We use weekly prices of these agricultural commodities for the period 2009–2015 from the statistical data portal Index Mundi.

We proxy the media attention using search queries in Google – which is the most widely used search engine (Sterling, 2015) – with the number of weekly searches taken from the Google Trends database. The Google Trends provides information on how often a specific expression is searched relatively to the total search volume. We use the global searches based on the filtering options attention for news. More specifically we consider the name of agricultural commodities (corn, wheat, soybean) in four languages (English, German, French and Spanish) for the period

Table 1
Descriptive statistics.
Source: Own calculation based on the data from Index Mundi, Google Trends and the National Bank of Slovakia

	Obs.	Mean	Median	Maximum	Minimum	Std. Dev
Corn price	324	523.14	478.88	818.75	323.12	145.64
Wheat price	324	636.49	633.69	943.88	435.38	118.01
Soybean price	324	1222.58	1269.25	1758.38	855.63	223.37
Gold price	324	1399.07	1338.25	1873.70	1056.20	210.85
Crude oil price	324	85.22	91.39	113.93	34.73	19.01
Search for Corn	324	60.84	60.00	91.00	30.00	10.70
Search for Wheat	324	25.15	25.00	50.00	17.00	4.13
Search for Soybean	324	71.20	72.00	100	37.00	12.04
Inflation in DE	324	1.27	1.30	2.40	−0.30	0.68
Inflation in USA	324	1.69	1.70	3.90	−0.20	1.01
Temperature in DE	324	9.13	8.40	20.30	−3.70	6.46
Temperature in USA	324	8.54	8.64	22.44	−11.06	9.48
US, DE, UK bonds	324	16.08	16.20	31.33	1.15	8.83
SAP adjusted close	324	1556.11	1435.55	2126.64	1022.58	352.14
SAP traded volume	324	3.79E+9	3.72E+9	7.68E+9	1.93E+9	7.70E+8

Notes: number of searches are transposed data to 0–100 interval, commodity prices are in USD, inflation is in %, temperature in °C, bonds index, rate of S&P 500 adjusted close and number of trades of S&P 500 are dimensionless.

Table 2
Stationarity tests results.
Source: Own calculation.

Variable	ADF		DF-GLS		PP		KPSS		ERS		Summary
	level	1st dif.	Level	1st dif.	Level	1st dif.	Level	1st dif.	Level	1st dif.	
Corn price	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Wheat price	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Soybean price	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Gold price	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Crude oil price	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Search for Corn	S	S	S	S	S	S	S	S	S	S	I(0)
Search for Wheat	S	S	S	S	S	S	S	S	S	S	I(0)
Search for Soybean	S	S	S	S	S	S	S	S	S	S	I(0)
Inflation in DE	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
Inflation in USA	NS	S	NS	S	NS	S	S	S	NS	S	I(1)
Temperature in DE	NS	S	S	S	S	S	S	S	NS	S	I(0)
Temperature in USA	S	S	S	S	S	S	S	S	S	S	I(0)
US, DE, UK bonds index	S	S	NS	S	S	S	S	S	NS	S	I(1)
SAP adjusted close	NS	S	NS	S	NS	S	NS	S	NS	S	I(1)
SAP traded volume	NS	S	NS	S	S	S	NS	S	S	S	I(1)

Notes: S means stationary, NS means non-stationary time series.

2009–2015 extracted from the financial portal Investing.com.[1] The search query time series from the Google Trends are normalized and rescaled from 0 to 100 interval that represents the proportion of searched terms in the searched period.

We also include additional variables to account for the developments of the fundamental factors (temperature), macro-financial markets (inflation, stock index) prices of non-agricultural commodities (gold and crude oil) — temperature in Germany and USA, inflation in Germany and USA, US, German and UK bonds index, the adjusted close value of S&P 500 index, the traded volumes of S&P 500 index and gold and crude oil prices — all extracted from the databases of the Slovak National Bank as explanatory variables. These variables were argued in the literature to potentially impact agricultural commodity prices (e.g. Brunner, 2002; Gohin and Chantret, 2010; Hochman et al., 2014; Ott, 2014). The descriptive statistics of the variables are provided in Table 1.

4. Results

The necessary precondition to use the ARDL model is that all variables are stationary at levels or at first differences. To check for the stationarity of all variables we use Augmented Dickey–Fuller test, Dicky–Fuller GLS (DF-GLS) test, Phillip–Perron (PP) test, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, and Elliot–Rothenberg–Stock Point-Optimal (ERS) test. The results of the tests are summarized in Table 2. All variables except for Google search queries and temperature variables are stationary in first differences.

We use Bounds test to check for the long-run relationship between the commodity prices (corn, wheat or soybean), lagged values of prices and the rest of variables including Google search queries. The F-statistics values of the Bounds test are significantly higher than the critical values for corn and wheat prices, so we rejected the null hypothesis of no long-run relationship in these two models and ran the cointegrated ARDL. However, for soybean prices we were not able to reject the null hypothesis of no long-run relationship, thus only the short-run elasticities were estimated. Further, the post-estimation tests were performed to test results for the heteroscedasticity, normality and serial correlation. The test results show that the residuals are homoscedastic and all models are stable and do not show any serial correlation.

Using error correction representation of the ARDL model, we estimated short-run and long-run elasticities for corn and wheat prices as reported in Table 3. The cointegrated models for corn and wheat prices bring not only short-run coefficients explaining short-run fluctuations but also long-run coefficients accounting for the equilibrium effects of the independent variables on the dependent variable as well as adjustment parameters (*ADJ* in

[1] Investing.com provides news, analysis, and streaming quotes about the global financial markets. Advantage of this trading platform is the free access to the historical quotes that are recorded at a weekly frequency.

Table 3
Short-run and long-run elasticities for corn and wheat (EC representation of ARDL model).

	Corn	Wheat
Short-run effects		
D (corn price)	–	0.618***
LD (corn price)	−0.168***	–
D (wheat price)	0.457***	–
LD (wheat price)	0.089**	–
D (soybean price)	0.510***	−0.100***
LD (soybean price)	0.186***	–
D (gold price)	0.056	0.003
D (crude oil price)	0.016	−0.134***
D (search for corn)	0.034*	–
D (search for wheat)	–	0.058***
D (inflation in DE)	0.003	−0.002
D (inflation in USA)	0.017	−0.029***
D (US, DE, UK bonds)	−0.002	0.002
D (S&P 500 adj. close)	−0.145**	−0.031**
D (S&P volume)	−0.011	0.000
Temperature in DE	−0.004	−0.014
Temperature in USA	−0.004	0.010*
ADJ	−0.078***	−0.193***
Long-run effects		
L (corn price)	–	0.188
L (wheat price)	1.334***	–
L (soybean price)	−0.307	0.519***
L (crude oil price)	−0.344**	0.150*
L (gold price)	0.599**	0.014
L (search for corn)	0.432*	–
L (search for wheat)	–	0.301***
L (inflation in DE)	−0.009	−0.010
L (inflation in USA)	0.206**	−0.148***
L (US, DE, UK bond index)	−0.049	0.012
L (S&P 500 adj. close)	−0.302	−0.162**
L (S&P 500 volume)	−0.176	−0.001

Note: L denotes lagged values, D are differences and LD lagged difference of a variable.

Table 4
Short-run elasticities for soybeans (ARDL model).

	Soybeans
Corn price	0.491***
L (corn price)	−0.290***
L2 (corn price)	−0.135***
Wheat price	−0.031
L (soybean price)	0.783***
L2 (soybean price)	0.159***
Gold price	−0.049**
Crude oil price	0.034***
Search for soybean	0.000
Inflation in DE	0.007
Inflation in USA	−0.012*
US, DE, UK bonds	0.003*
S&P 500 adj. close	0.234***
S&P volume	0.004
Temperature in DE	0.006
Temperature in USA	−0.004

Note: L denotes lagged values and L2 s lag of a variable.

Table 3) representing the speed of adjustment of the dependent variable to a deviation from the equilibrium relationship. The estimated adjustment parameters are −0.078 and −0.193 for the corn price and wheat price models, respectively, both significant at 1% level. This indicates that 7.8% and 19.3% of the dis-equilibrium due to the previous period shocks is adjusted back to the long-run equilibrium in one week. As the bounds test for the soybean model does not reject the null hypothesis of no long-run relationship, we can only estimate an ARDL model in first differences (Table 4).

The estimated results for corn and wheat show that the variables capturing the impact of the media attention – Google search queries – have a statistically significant short and long-run impact on their prices (Table 3). We find statistically stronger impact of the Google search queries on wheat price than on corn price. These results suggest the presence of the causal effect of the attention-driven behaviour in these two commodity markets both in the short-run and in the long-run. That is, the Google search queries determine the short-run adjustments as well as they have permanent effect on the corn and wheat price developments. In the case of soybean prices, there is no long-run relationship between soybean prices and explanatory variables, thus we estimate only the short-run elasticities. As reported in Table 4, for soybean prices the shot-run media attention effect is statistically insignificant.

Several other variables considered in the estimations have a statistically significant impact on wheat and corn prices. However, this is more often the case in the short-run than in long-run. In the short-run, own and cross prices, crude oil price, inflation in USA, the close value of S&P 500 index and the temperature in USA are statistically significant for wheat price. Similar holds for soybeans, except that gold price is statistically significant, while the temperature in USA is not significant. For corn price, alongside own and cross prices only the close value of S&P 500 index has statistically significant short-run effect. In the long-run the statistical significant drivers of corn and wheat prices are cross prices, crude oil price, gold price, the inflation in USA and the close value of S&P 500 index (Tables 3 and 4).

5. Conclusions

This paper provides evidence for the presence of the attention driven behaviour of participants on agricultural commodity markets. That is, the estimated results show that there is a strong long-run link between Google search queries and corn and wheat prices. We do not find a long-run relationship between google search queries and soybean price. In the short-run we find that the Google search queries impact corn and wheat prices but not soybean prices. This result confirms that the attention driven behaviour of market participants by searching information about individual agricultural commodities on internet plays an important role in their price formation mechanism. That is, the attention driven behaviour is not only present in financial markets as shown in the literature but as our estimates suggest, it also impacts agricultural commodity markets. This attention in mass media has both some implications for short-run price movements but also tends to be reflected in a permanent effect on the commodity prices particularly for corn and wheat.

A caveat of our analyses is that due to the data unavailability, we were not able to differentiate in our estimations type and quality of information that was queried and obtained through the Google search engine (e.g. whether it was positive or negative news, fake news) and how the information was assessed and perceived (e.g. the presence of judgement bias, capability to understand and use information) by different market percipients (e.g. farmers, traders). The analyses of potential impact of different type of information and their perception/assessment by different market participants on agriculture commodity prices is a promising avenue for further research.

Appendix. Estimation approach

We apply both ADF and DF-GLS tests, as the DF-GLS test is considered to be a more efficient univariate DF-GLS test for autoregressive unit root recommended by Elliott et al. (1996). The test is a simple modification of the conventional augmented Dickey–Fuller (ADF) t-test as it applies generalized least squares

(GLS) detrending prior to running the ADF test regression. Compared with the ADF tests, the DF-GLS test has the best overall performance in terms of sample size and power. It "has substantially improved power when an unknown mean or trend is present" (Elliott et al., 1996). *PP* test was used, as it has one advantage over the ADF tests to be robust to general forms of heteroskedasticity in the error term. Another advantage is that the user does not have to specify a lag length for the test regression. Contrary to most unit root tests, in the KPSS test the presence of a unit root is not the null hypothesis but the alternative. Additionally, in the KPSS test, the absence of a unit root is not a proof of stationarity but, by design, of trend-stationarity. This is an important distinction since it is possible for a time series to be non-stationary, have no unit root yet be trend-stationary.

To investigate the presence of long-run relationships among the series, bound testing under Pesaran et al. (2001) procedure is used. The ARDL bound test is based on the Wald-test (F-statistic). The asymptotic distribution of the Wald-test is non-standard under the null hypothesis of no cointegration among the variables. Two critical values are given by Pesaran et al. (2001) for the cointegration test. The lower critical bound assumes all the variables are I(0) meaning that there is no cointegration relationship between the examined variables. The upper bound assumes that all the variables are I(1) meaning that there is cointegration among the variables. The empirical representation of $ARDL(p, q, \ldots, q)$ model is the following:

$$y_t = c_0 + c_1 t + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{i=0}^{q} \beta_i x_{t-i} + u_t$$

Where p and q is the optimum lag length, y_t is autoregressive lagged values of itself and x_t is distributed lag component (explanatory variable), u_t is a random "disturbance" term (random walk), c_0, c_1, and$t$ represent deterministic variables, intercept term and time trend, respectively. When there is a long run relationship between variables, there should exist an error correction representation. Therefore, the error correction model is estimated:

$$\begin{aligned}\Delta y_t &= c_0 + c_1 t - \alpha\,(y_{t-i} - \theta x_{t-i}) \\ &\quad + \sum_{i=1}^{p-1} \varphi_{yi} \Delta y_{t-i} + \omega \Delta x_t + \sum_{i=1}^{q-1} \varphi_{xi} \Delta x_{t-i} + u_t\end{aligned}$$

where α is the speed of adjustment, θ are the long run coefficients and φ are the short-run coefficients.

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