Apples versus oranges: does interdependence between the European Union juice concentrate markets exist?

J. Szenderak[1]; A. Jambor[2]; N. Potori[3]

1: University of Debrecen, , Hungary, 2: Corvinus University of Budapest, Department of Agricultural Economics and Rural Development, Hungary, 3: Research Institute of Agricultural Economics, , Hungary

Corresponding author email: attila.jambor@uni-corvinus.hu

Abstract:

A wide range of economic studies have analysed price relationships in the agri-food sectors. Initiated by a market story, this paper adds to the existing literature by investigating the co-movements of prices for orange juice concentrate and apple juice concentrates in the European Union. Different cointegration models were applied for the monthly price series made available by Flüssiges Obst for the period from December 2003 to March 2017. The results revealed statistically significant relationships between the prices of some of the apple juice concentrates but not between the prices of orange juice concentrate and apple juice concentrates.

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Introduction

Fruit production in Hungary is dominated by apples. According to Hungarian Central Statistical Office (KSH) data, during the period 2014-2016, 596 thousand tonnes of apples per year were harvested on average, accounting for 68 per cent of all fruit production. The apple-growing area totalled around 35 thousand hectares, of which over 27 thousand hectares were occupied by apple orchards.

In Hungary, foreign trade in apples is of little significance in terms of volume, except in seasons of weather extremes. Exports of apples averaged to 26 thousand tonnes per year during the period 2014-2016, with Romania, Slovakia and Austria being the major buyers. Imports of apples averaged close to 30 thousand tonnes per year, supplied by European Union (EU) Member States, including Austria, Germany, Poland and Italy, as well as by third countries, including Serbia and Macedonia.

Some 60-80 per cent of all apple production in Hungary suits primarily processing purposes. As KSH data show, 279 thousand tonnes of apples per year were purchased by processors and wholesalers on average during the period 2014-2016, and 94 thousand tonnes were processed on farm by apple producers. In seasons of average to favourable weather conditions, purchases of domestic apples by the leading fruit juice producer in the country ranges between 200 and 250 thousand tonnes (according to a statement by an industry source in FruitVeb, 2013). Most of the fruit juice production capacity in Hungary is owned by multi-national companies.

The income stability of apple production in Hungary has been low due to the relatively low yields per hectare and to the considerable fluctuations in producer prices. According to KSH data, in recent years, the monthly averages of producer prices of apples for industrial processing fluctuated in the range from HUF 12.9 (EUR 0.042) (as of September 2014) to HUF 37.2 (EUR 0.119) per kilogramme (as of November 2015). As per the 2015 Report on the Status of the Agricultural Economy (Government of Hungary, 2016), only 21 per cent of the apples were produced by members of active Producer Organisations, signalling that the selling of apples by farmers is fragmented and lacks coordination; therefore, their bargaining positions are weak. The bulk of apples for juice production are purchased by processors from the middle of August through to the end of November, parallel to the harvesting of the produce.

In November 2016, at a conference on agricultural innovations organised in Budapest by the Hungarian Agricultural and Rural Youth Association (AGRYA) for its arable and horticultural producer members, the representative of a family farm engaged in apple production for industrial processing claimed that the fruit juice producer to whom the farm had been delivering its produce kept changing the apple purchase price by insisting that adjustments in the price of frozen orange juice concentrate[1] had to be followed. At the event, the question was raised whether interdependence between the markets for orange juice concentrate and apple juice concentrates really existed. To the best of our knowledge, no study investigating the long-term price relationship between these markets has been published in recent years.

The next section of this paper provides a literature review on the co-movement of prices for agricultural and food products, and this is followed by a brief introduction to the EU fruit juice market. The subsequent section describes the data and the methodology used for the analysis, and

[1] Concentrates are made by squeezing the fruit and evaporating its natural water content before being frozen and shipped.

this is followed by the presentation of the econometric framework and the results. The last section concludes.

Literature review

Food price analysis has a long tradition in agricultural economics. The co-movement of prices of agricultural and food products are analysed under either the price transmission or the 'fuels and food' literature.

On the one hand, economists have developed many analytical tools to better understand the magnitude, nature, direction and speed of price transmission in global markets. Von Cramon-Taubadel (1998) was probably the first to use modern econometric techniques to investigate price transmission in agricultural markets. Peltzman (2000) was among the early researchers to apply such techniques to a large producer and consumer goods dataset in the United States, concluding that prices tend to rise faster than they fall. The evolution of time-series econometric techniques since the Millennium has then boosted price transmission analysis in agri-food sectors.

Conclusions from empirical research on price transmission vary greatly depending on the sector tested, the methodology chosen and the frequency of the data used in the analysis (von Cramon-Taubadel et al. 2006). However, price transmission is generally found to be imperfect, meaning that a price change at the producer level is not fully transmitted to consumers. Moreover, price transmission is often asymmetric, meaning that price decreases are relatively slowly and not fully transmitted, while price increases are relatively quickly and fully transmitted from producers to consumers (Drabik et al. 2016).

One of the most important parts of the price transmission literature seeks to understand the behaviour and dynamics of commodity prices. Bakucs and Fertő (2016) analysed the validity of various sale theories through assessing Hungarian milk prices and showed that durable and perishable products have similar pricing patterns, contrary to theoretical predictions. They also showed that retailers and not processors determine price promotions. Dai et al. (2017) investigated food scares and asymmetric price transmission in the Chinese pork market using monthly data from 2001 to 2014 and showed that the same food scare events can influence prices and price transmissions to different extents. Adachi and Liu (2009) identified four structural breaks in farm-retail prices in the Japanese pork market, implying the existence of asymmetric price transmission. Arshad and Hameed (2014) examined the cointegration and causality relationships between Malaysian fruit market farm and retail prices and used Granger causality tests for monthly data from January 2000 to December 2010. Their results showed evidence of a long-term bidirectional causal relationship between farm and retail prices for banana and watermelon, but not for jackfruit and durian. Bakucs et al. (2014), by applying a meta-analysis to the existing literature, showed that asymmetries are more likely to exist in sectors with larger shares of fragmented producers, stronger political interests and higher concentration of retailer powers.

Another part of the literature focuses on the link between food and fuel prices. An extensive literature review by Serra and Zilberman (2013) concludes that energy prices drive long-term agricultural price levels and that instability in energy markets is transferred to food markets. However, Lucotte (2016) found that strong positive co-movements between crude oil and food prices could be detected for the period 1990-2006 but not for the period 2007-2015. Kristoufek et al. (2014) investigated price movements between biofuel markets and related commodities and found both ethanol and biodiesel prices to be responsive to their production factors. Ciaian and Kancs (2011) used a cointegration analysis in a search for interdependencies in the energy-bioenergy-food price systems for 1994-2008 monthly price data. Their results show that prices for crude oil and agricultural commodities are interdependent: an increase in oil price by USD 1 per barrel increases the agricultural commodity prices by between USD 0.10 and USD 1.80 per tonne. Avalos (2014) investigated the possible existence of a structural break in the stochastic properties of the maize and soybean price processes. The results suggest that structural stability is rejected and cointegration between oil and corn prices was found after 2006.

In general, there are different theoretical bases for the analysis of agricultural prices in the literature. Co-movement of two agricultural commodities is relatively poorly studied and this article contributes to addressing this gap.

The EU fruit juice market in brief

The global consumption of fruit juices (100 per cent fruit content) and nectars (25-99 per cent fruit content) was slightly less than 36 billion litres in 2016, with the EU as the principal consumption region with 9.3 billion litres (AIJN, 2017). In the EU, the consumption of fruit juices and nectars by flavour is led by orange with an almost 37 per cent share, while flavour mixes rank second with a share of just over 19 per cent, and apple comes third with an approximately 15 per cent share. Apple remains a staple flavour for consumers in the large apple-growing EU Member States, e.g. Germany and Poland. In Hungary, apple flavour is the second most popular behind orange, with shares of around 16 and over 25 per cent respectively, while flavour mixes are third, with only a 10 per cent share (AIJN, 2016).

Imports of fruit juices into the EU, including intra-EU imports, totalled 7.4 million tonnes in 2016. Of these, the largest share is accounted for by concentrated orange juice, followed by tropical fruit juices, mixtures of fruit juices and apple juice. The leading trade hubs for fruit juices are Belgium and the Netherlands, and other major importers include France, Germany, and the United Kingdom (CBI, 2017). The supply of concentrated orange juice to the EU is dominated by Brazil, with a share of over 90 per cent (Morris, 2011), or 750-800 thousand tonnes a year. Exports of NFC (not from concentrate) orange juice from Brazil to the EU come near to this volume (AIJN, 2012).

Data and methodology

To assess the long-term price relationship between the markets for orange juice concentrate and apple juice concentrates in the EU, five price series for the period from December 2003 to March 2017 were used. The data, kindly provided by Flüssiges Obst, consisted of the monthly prices for orange juice concentrate (OSK (65 °Brix[2]), USD/kilogramme, CIF[3] Rotterdam), acid-rich apple juice concentrate (ASKR (70 °Brix), EUR/kilogramme DDP[4]), acid-poor apple juice concentrate (ASKP (70 °Brix), EUR/kilogramme DDP), bio-orange juice concentrate (OSKBIO (65 °Brix),

[2] Sugar content of an aqueous solution.
[3] Cost, insurance and freight: the seller paying for costs, freight and insurance against the buyer's risk of loss or damage in transit to destination.
[4] Delivered duty paid: including paying for shipping costs, export and import duties, insurance and any other expenses incurred during shipping.

USD/kilogramme, CIF Rotterdam), and acid-rich bio-apple juice concentrate (ASKBIO (70 °Brix), EUR/kilogramme DDP).

Most economic time series exhibit non-stationary behaviour; therefore, the data need to be pre-tested for a unit root. If a unit root exists, to remove the stochastic trend, it should be differenced out. By doing this, the data will be stationary with well defined, finite mean and variance. To detect a unit root, the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1979; Dickey and Fuller, 1981) was used with constant and trend, and without any of the deterministic variables. Then the first difference of the price series was tested for the presence of a unit root. To assess the strength of price co-movements, the correlation coefficients of the variables were calculated. Since the existence of constant correlations during the sample period was not a plausible idea, the rolling correlation coefficients with a rolling window of 24 months were calculated, where the window size was arbitrary. Furthermore, by applying the procedure by Johansen (1988) and Johansen (1991), the cointegration rank of the system was determined. To identify structural breaks in the single time series, the Zivot and Andrews (1992) unit root test was used. Finally, to estimate break points endogenously, the residual based cointegration test with regime change model (C/S) by Gregory and Hansen (1996) was applied. The calculations were done in the R programming environment.

Econometric framework and results

Following Pfaff (2008), firstly the $\tau = 0$ hypothesis was tested, where τ denotes the parameter of the lagged value of the price series in the ADF regression. Rejecting the null hypothesis means that the price series do not have a unit root. In the case of non-rejection, the ϕ_2 hypothesis was tested for the absence of drift, where H_0: $\tau = 0$ and H_0: $\beta_1 = \tau = 0$. Finally, the ϕ_3 combined hypothesis was tested, where ϕ_3: H_0: $\tau = 0$ and H_0: $\beta_1 = \beta_2 = \tau = 0$. β_1 and β_2 denote the drift and the trend parameters. In the case of non-rejection, the price series have a unit root with no drift and trend. If so, to achieve stationarity, the first differences of the price series were tested.

The results showed that the level variables have a unit root at the 5 per cent level of significance (tested both with and without deterministic variables), but by taking their first differences, the unit root was removed. The correlation analysis requires stationary data; therefore, the first difference of the price series was used (Table 1).

Table 1: Results of the ADF test

	OSK	ASKR	ASKP	OSKBIO	ASKBIO
			ADF test with drift and trend for the level series		
τ	-2.62	-2.81	-2.71	-1.97	-2.21
ϕ_2	2.70	2.70	2.58	1.66	1.69
ϕ_3	3.48	4.01	3.79	2.08	2.44
			ADF test with drift for the level series		
τ	-2.27	-2.48	-2.73	-2.04	-2.22
ϕ_2	3.13	4.07	3.81	2.49	2.55
			ADF test without drift and trend for the level series		
τ	0.48	-0.43	-0.31	0.42	0.02
			ADF test for the first differences		
τ	-4.84*	-5.01*	-5.92*	-10.07*	-8.57*

Critical values at the 5 per cent level of significance for testing $\tau = 0$ is -1.95; for testing ϕ_2 is -2.88, and 4.63; and for testing ϕ_3 is -3.43, 4.75, and 6.49.

* Significant at the 5 per cent level of significance.

Source: own calculations

The values of the correlation coefficients for the first differences of the price series ranged between -0.05 and 0.63, representing the extremes. The correlation between OSK and ASKR, and OSK and ASKP was weak, and it was close to zero between OSK and OSKBIO. Between OSK and ASKBIO, a stronger correlation existed than between OSK and OSKBIO. A strong correlation was found between ASKR and ASKP, and the values of the correlation coefficients for ASKR and ASKBIO, and for ASKP and ASKBIO were the same. Finally, the correlation between OSKBIO and ASKBIO was very weak (Table 2).

Table 2: Correlation table for the first differences of the time series

	OSK	ASKR	ASKP	OSKBIO	ASKBIO
OSK	**1**	0.12	0.08	-0.05	0.23
ASKR		**1**	0.63	0.13	0.19
ASKP			**1**	0.05	0.19
OSKBIO				**1**	-0.02
ASKBIO					**1**

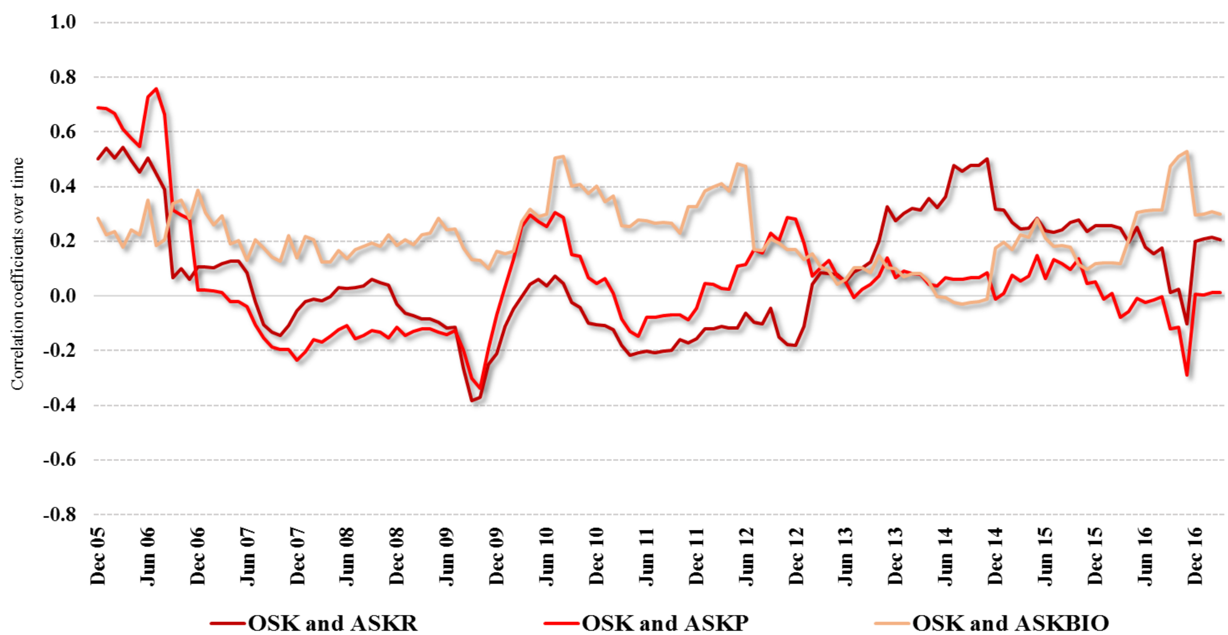
For abbreviations see text.

Source*: own calculations*

It is unrealistic to assume that the correlation coefficients remained constant over the sample period, therefore 24-month rolling window correlations were calculated for the price series. With the five price time series, the number of pairs in the correlation tests were $\frac{1}{2}n(n-1)$, thus $\frac{1}{2}5(5-1) = 10$. (The correlation matrix is symmetric, therefore it is sufficient to consider only the upper or the lower triangular matrix).

The rolling correlation between OSK and ASKR, and OSK and ASKP proved strongest at the beginning of the sample period. By the autumn of 2006, the values of both coefficients declined steeply, and then varied, except for a few short breaks, similarly within the range of -0.20 and 0.20 until the autumn of 2013. The rolling correlation between OSK and ASKR became much stronger by the end of 2013, with its coefficient values changing mostly within the range of 0.20 and 0.40 afterwards. The highest negative values for both OSK – ASKR, and OSK – ASKP occurred in the autumn of 2009. The rolling correlation between OSK and ASKBIO exhibited more stability and more strength throughout the sample period (Figure 1).

Figure 1: Development of the rolling correlation coefficients between OSK and ASKR, OSK and ASKP, and OSK and ASKBIO, December 2005 – March 2017

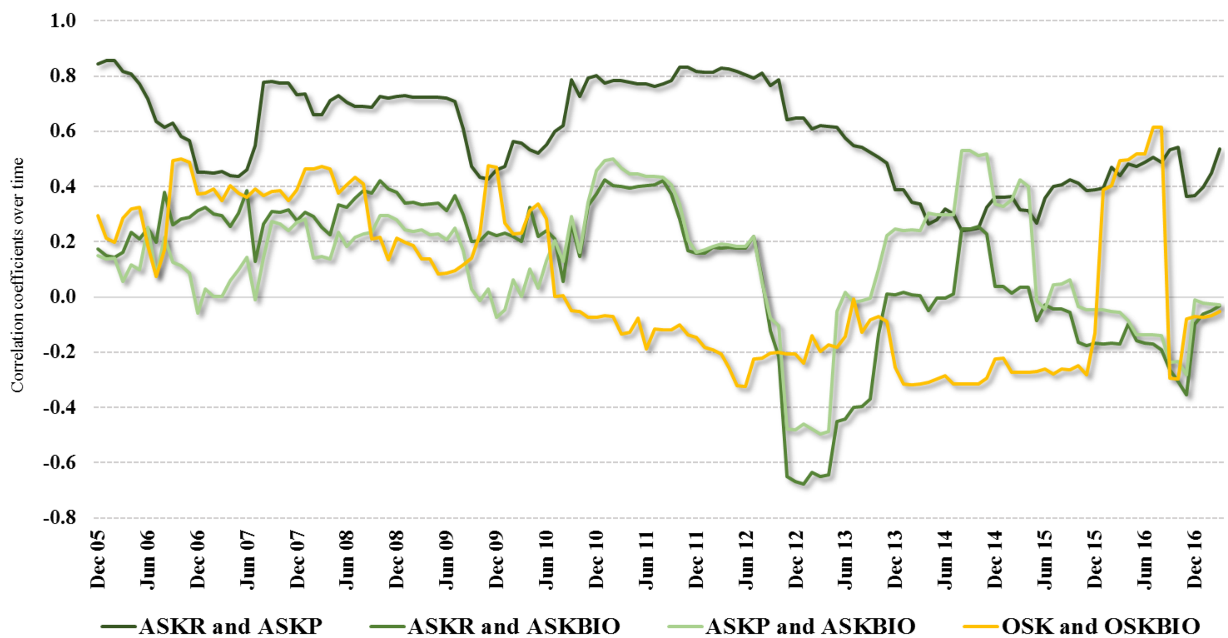


For abbreviations see text

Source*: own calculations*

The values of the rolling correlation coefficients for ASKR – ASKP varied mostly between 0.4 and 0.8 until 2012, then declined continuously, only to become negative by the summer of 2015. The rolling correlation between ASKR and ASKBIO, and ASKP and ASKBIO exhibited mostly similar movements through these years, both reaching their highest negative values between December 2012 and April 2013. The rolling correlation between OSK and OSKBIO changed from positive to negative by the autumn of 2010, then for most of 2016, its coefficient values became positive again, exhibiting the strongest connection for the sample period (Figure 2).

Figure 2: Development of the rolling correlation coefficients between ASKR and ASKP, ASKR and ASKBIO, ASKP and ASKBIO, and OSK and OSKBIO, December 2005 – March 2017



For abbreviations see text

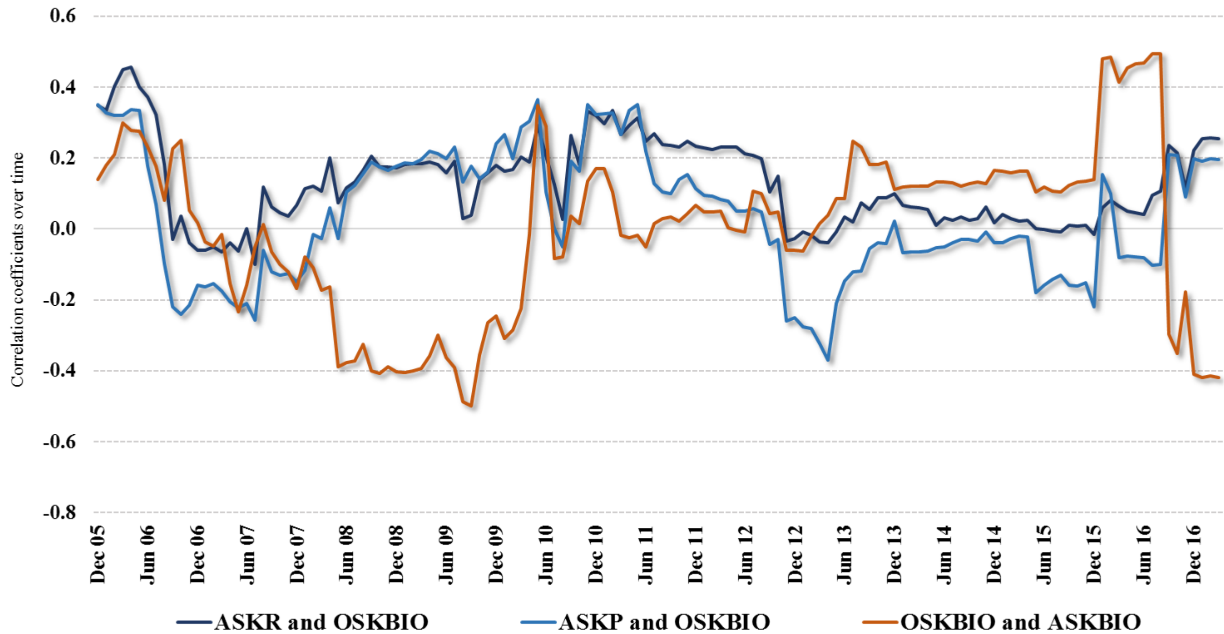
Source*: own calculations*

For most of the time, the rolling correlation between ASKR and OSKBIO developed similarly to that of between OSK and ASKBIO (Figure 1), with its extreme values being very similar.

The rolling correlation trend between ASKP and OSKBIO closely followed that of ASK – OSKBIO during the sample period, except for reaching substantially higher negative values.

Finally, the values of the rolling correlation coefficients for the two bio-juice concentrates, OSKBIO and ASKBIO varied within a relatively wide range of -0.49 and 0.49 (Figure 3).

Figure 3: Development of the rolling correlation coefficients between ASKR and OSKBIO, ASKP and OSKBIO, and OSKBIO and ASKBIO, December 2005 – March 2017



For abbreviations see text

Source*: own calculations*

Table 3: Dates for the maximum and the minimum values of the rolling correlation coefficients

	OSK – ASKR	**OSK – ASKP**	**OSK – OSKBIO**	**OSK – ASKBIO**	**ASKR – ASKP**
Minimums	September 2009	October 2009	June 2012	August 2014	August 2014
Maximums	March 2006	July 2006	July 2016	November 2016	February 2006
	ASKR – OSKBIO	**ASKR – ASKBIO**	**ASKP – OSKBIO**	**ASKP – ASKBIO**	**OSKBIO – ASKBIO**
Minimums	July 2007	January 2013	April 2013	March 2013	September 2009
Maximums	April 2006	January 2011	May 2010	September 2014	July 2016

For abbreviations see text

Source*: own calculations*

The level variables were used for the cointegration analysis, since it requires data integrated of order one. The automatic lag selection procedure based on different information criteria (IC) indicated one or two lags length in the Johansen procedure (Table 4).

Table 4: Optimal lag lengths according to the different information criteria

	Akaike's (AIC)	Hannan – Quinn (HC)	Schwartz (SC)	Final Prediction Error (FPE)
Optimal lag	2	1	1	2
Value of the IC	-21.60547	-21.19592	-20.83842	4.414415e-10

Source*: own calculations*

The results of the Johansen cointegration test with two lags length indicated that in this five variables system, there was only one cointegration relation. However, by analysing the residuals, it became evident that these were not free from autocorrelation. To get white noise residuals, the number of lags was increased to three, but with three lags no cointegration was found. The test statistics (λ) of 31.46 were smaller than the 34.40 critical value at the 5 per cent level of significance, thus the null hypothesis of no cointegration (r=0) could not be rejected. Since the presence of white noise residuals would be essential to get meaningful results, it was concluded that by applying the Johansen procedure, no cointegration could be detected in the system (Table 5). The sensitivity of the Johansen procedure for the lag length is well known; furthermore, the low frequency of the available price data and the relatively short sample period limit the results.

Table 5: Results of the Johansen cointegration test

		Level of significance		
	Test statistics (λ)	**10 per cent**	**5 per cent**	**1 per cent**
r <= 4	3.66	7.52	9.24	12.97
r <= 3	5.73	13.75	15.67	20.20
r <= 2	11.60	19.77	22.00	26.81
r <= 1	25.95	25.56	28.14	33.24
r = 0	31.64	31.66	34.40	39.79

Source*: own calculations*

The lack of cointegration may be due to the presence of structural breaks in the data. Furthermore, several outliers were detected in the single series. A possible solution could be the use of dummy variables; however, owing to the high number of outliers, the data were analysed for breaks in the series and in the cointegration relations. To identify structural breaks in the single time series, the Zivot and Andrews (1992) unit root test was applied. Since the power of the ADF test falls sharply in the presence of breaks, the Zivot and Andrews test offers an efficient alternative: it includes a break dummy variable in the artificial regression to detect a unit root. The dummy variable is looped over the sample points and the test statistics with the strongest evidence against the null hypothesis will be the final results. If the null hypothesis of a unit root is rejected, the series is trend stationary with a break. The Zivot and Andrews test allows for the use of three models by which a break in the intercept (level shift), a break in the trend, or both at the same time can be tested for. In our case, a break both in the trend and the intercept was tested for first. None of the test statistics were significant at the 5 per cent level of significance, meaning that the series were non-stationary without a break. Table 6 shows the results for the model where a break both in the intercept and the trend was allowed for. Testing for a break only in the trend, or in the intercept produced similar results.

Table 6: Results of the Zivot and Andrews unit root test

	Test statistics	Selected lag by AIC	Break date
OSK	-2.55	0	October 2007
ASKR	-4.09	1	March 2008
ASKP	-3.53	2	March 2008
OSKBIO	-4.97*	0	June 2011
ASKBIO	-4.79	0	April 2008

Critical values at 1, 5, and 10 per cent level of significance: -5.57, -5.08, and -4.82, respectively.

* Significant at the 10 per cent level of significance.

For abbreviations see text

Source*: own calculations*

Although the price series had no structural breaks, the cointegrating vector might not have remained constant during the sample period. Long-term equilibrium may hold over a long time, but it might change due to market developments. The Gregory and Hansen (1996) method is a residual based cointegration method where the cointegrating regression involves a dummy variable which is 0 before and 1 after the break. The advantage of the test is that the break point is estimated endogenously, thus it is not known a priori. The point where the estimated statistics provide the strongest evidence again the null hypothesis of no cointegration will be the candidate for the break.

To test the residuals from the cointegration regression, Gregory and Hansen used a modified version of the ADF test (denoted as ADF*) and the Phillips and Perron (1988) unit root test (denoted as Z^*_t, and Z^*_α). In our case, the general version of the Gregory and Hansen cointegration test, the regime change model (C/S) was applied, which allows for both the intercept and the trend to shift. For the ADF* test 10 was set as an upper bound for the lag, where the optimal lag was selected according to the AIC criterion. The Johansen procedure failed to reject the null hypothesis of no cointegration between the variables. However, by the Gregory and Hansen method, cointegration was found between ASKR and ASKP, and ASKR and ASKBIO. All three tests gave strong evidence against the null of no cointegration, i.e. cointegration existed at the 1 per cent or the 5 per cent significance level. But most importantly, between OSK and ASKR, cointegration was indicated by the ADF* test only at the 10 per cent level of significance, with a break in February 2009.

Conclusions

The paper aimed at investigating the co-movements of prices for orange juice concentrate and apple juice concentrates in the EU. Based on the monthly price series made available by Flüssiges Obst for the period from December 2003 through March 2017, the results of the applied cointegration tests provided no convincing evidence for the existence of interdependence between the markets for these juice concentrates, except for some of the apple juice concentrates. Our findings do not support arguments for changing the purchase price of apples for industrial use in Hungary due to changes in the price of orange juice concentrate. The paper has limitations, i.e. the low frequency of the available price data and the relatively short sample period. Therefore, the results should be generalised with caution. Future research might extend our analysis with higher frequency of price data for the respective markets, longer sample periods and further products included, such as pineapple and grapefruit juice concentrates, to better understand the long-term price relationships between the markets for these products.

Table 7: Results of the Gregory and Hansen cointegration test (C/S regime change model)

	OSK - ASKR	**OSK - ASKP**	**OSK - OSKBIO**	**OSK - ASKBIO**	**ASKR - ASKP**	**ASKR - OSKBIO**	**ASKR - ASKBIO**	**ASKP - OSKBIO**	**ASKP - ASKBIO**	**OSKBIO - ASKBIO**
t-statistics	**-4.81***	-4.51	-2.32	-4.64	**-6.52*****	-4.51	**-5.24****	-3.77	**-4.90***	-3.38
ADF* lag	6	4	3	4	0	6	4	4	0	0
Estimated break date for ADF*	February 2009	April 2009	March 2012	February 2009	July 2011	January 2008	February 2010	October 2007	June 2010	October 2008
Z^*_t	-3.14	-2.82	-2.30	-3.65	**-6.54*****	-2.97	**-5.27****	-2.43	**-4.84***	-3.18
Z^*_α	-20.82	-16.77	-10.06	-24.94	**-67.82*****	-17.51	**-49.21****	-11.66	**-41.34**	-18.91
Estimated break date for Z^*_t and Z^*_α	January 2009	November 2009	December 2013	September 2009	July 2011	September 2007	June 2010	February 2011	June 2010	November 2008

Critical values at 1, 5, and 10 per cent level of significance for the ADF* and Z^*_t tests: -5.47, -4.95, and -4.68, respectively; and for Z^*_α test: -57.17, -47.04, and -41.85.

* Significant at the 10 per cent level of significance.

** Significant at the 5 per cent level of significance.

*** Significant at the 1 per cent level of significance.

For abbreviations see text

Source: own calculations

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