Nonlinearities in the Slovenian Apple Price Transmission

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Abstract

This paper assesses price linkages and patterns of transmission among producer and consumer markets for apple in Slovenia using nonlinear vector error correction models. Nonlinearities are allowed by means of threshold and multivariate local linear regression estimation techniques. Monthly prices over the period 2000-2011 are used in the empirical application. Both techniques provide evidence of non-linearities in price adjustments. Findings suggest that producer and consumer prices tend to increase rather than decrease. Results also indicate that parametric threshold approaches may have difficulties in adequately representing price behavior dynamics.

Key words: Local linear regression, threshold model, price transmission, Slovenia.

JEL classification: C22, Q11

1. Introduction

Since they are considered to be relevant to understand market performance, price transmission analyses along the food marketing chain have long attracted considerable research interest (Goodwin and Holt, 1999). The price instability observed in the last decade in global food markets has increased the interest in price studies (FAO, 2008). While a rich empirical literature has analyzed price linkages and price transmission patterns along the food marketing chain in both the United States (US) and the European Union (EU) (see, for example, Hassouneh et al., 2010; Reziti and Panagopoulos, 2008; Ben Kaabia and Gil, 2007; Goodwin and Holt, 1999), the Central and Eastern European Countries (CEECs) have received less research attention. A few notable exceptions are reviewed in this paper.[3] Brümmer et al. (2009) analyze the relationship between wheat and wheat flour prices in Ukraine using Markov-Switching Vector Error Correction Models (MSVECM). Bakucs and Fertő (2006) utilize an Asymmetric Vector Error Correction Model (AVECM) in order to study beef price transmission within the beef Hungarian market. The paper by Bojnec and Peter (2005) studies the meat sector in Slovenia using a Johansen (1988) cointegration framework. We add to this scarce literature by analyzing price linkages and patterns of transmission among producer and consumer markets for apple in Slovenia.

According to planted areas, number of apple trees, value of production and sales, the apple sector is the most important fruit market in Slovenia (Statistical Office of the Republic of Slovenia, SORS, 2012). It is also one of the few agricultural sectors in Slovenia with trade surplus. Relevance of exports as a market outlet make it specially interesting to study how prices in this sector behave, and particularly to identify any possible patterns that could harm its competitiveness.

Literature on price transmission has typically relied on parametric methods which require the specification of a functional form characterizing price dynamics prior to estimation. A parametric method that is not correctly specified may lead to misleading results. To our knowledge, this is the first attempt to analyze price linkages along the Slovenian apple marketing chain. The lack of previous studies on this market makes it even more difficult to select an appropriate functional form to represent price dynamics. Non-parametric regression models do not impose any restriction on the functional form. Instead, the data speak for themselves when characterizing the nature of the relationship among the time series studied. In this paper, both parametric and non-parametric techniques are employed and compared. To our knowledge, no previous study has

[3] Our empirical review focuses on the literature on vertical price transmission along the food marketing chain. Readers interested in spatial price analysis in CEECs are referred to Goodwin et al. (1999).

utilized multivariate non-parametric approaches to analyze price linkages along the food marketing chain, which represents another important contribution of our work to the existing literature.[4]

The paper is organised as follows. Section 2 presents an overview of the apple sector in Slovenia. After describing both the parametric and non-parametric techniques (in section 3), in section 4 we present the results of the empirical applications. Finally, the paper ends with the concluding remarks (section 5).

2. The Apple sector in Slovenia

The apple sector, as the most important fruit production sector, has a long tradition in the Slovenian agriculture. Apple is produced both in intensive systems and using extensive production methods. Around one third of apple production in 2010 came from traditionally extensive apple orchards and was mostly used for processing. Intensive apple orchard plantations generated two-thirds of 2010 production that was mostly consumed as table apples (Statistical Office of the Republic of Slovenia, SORS, 2012).

While the area under intensive apple orchard plantations has experienced a slight decline, the number of apple trees has increased and is now rather stable (Table 1). Since in traditional extensive orchards, apple trees are bigger than in intensive plantations, average yield per apple tree is higher in extensive plantations. However, due to lower apple quality, areas under extensive orchards have been reduced. Apple production, while fluctuating from year to year, tends to decline over time. Annual variability in production is related to changing weather conditions, as only a small part of production in intensive plantations is irrigated and protected against hail and

[4] Serra et al. (2006a and 2006b) used univariate non-parametric techniques to analyze spatial price transmission in EU and US markets, respectively.

other possible impacts on yields. While apple production in Slovenia is important for around one-third of agricultural households, 73% of the farms producing apples dedicate less than 2 hectares (ha) to this production. A small proportion of orchard farms, around 9%, are bigger than 10 ha (SORS, 2012).

Table 1. Area, apple trees and apple production

	Orchard plantations			Extensive orchards	
	Area (ha)	Number of apple trees	Production (t)	Number of apple trees	Production (t)
Ø 2001–2005	3,095	6,953,252	78,450	753,913	33,963
Ø 2006–2010	2,867	7,402,704	76,728	665,344	32,289
2006	3,099	7,086,469	79,878	664,712	39,298
2007	2,874	7,481,763	86,977	663,828	27,516
2008	2,874	7,481,763	71,613	663,828	31,280
2009	2,722	7,481,763	72,587	663,828	23,075
2010	2,765	7,481,763	77,291	670,524	40,278

Source: SORS (2011).

Market balances for apple clearly indicate that Slovenia has a surplus in apple production (Table 2), with exports being above imports. While apple exports fluctuate over time and have increased slightly, imports have experienced a rapid increase during the most recent years. According to household expenditures survey (SORS, 2012), annual apple consumption per household member in Slovenian households is rather stable around 18 kg per year. About one-third of apple consumption represents home produced apple consumption (SORS, 2012). A majority of marketed apple production are table apples. While marketed apple quantities vary by years, around a half of production from intensive apple orchards is sold through vertically integrated marketing channels, and to a lesser extent through sales at free markets.

Table 2. Market balance for apples in Slovenia (in 1000 tones)*

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Index 2010/2000 (%)
Available*	70.75	34.51	89.73	51.81	85.22	65.82	68.39	59.92	61.39	66.66	63.56	89.8
Production from intensive orchards	84.14	50.79	93.90	70.15	92.94	84.47	79.88	86.98	71.61	72.59	77.29	91.9
Import	4.32	4.33	8.68	2.74	5.55	6.81	8.83	6.95	17.16	17.95	20.13	466.2
Export	17.70	20.61	12.84	21.09	13.28	25.46	20.32	34.01	27.38	23.88	33.87	191.3
Domestic consumption	70.75	34.51	89.73	51.81	85.22	65.82	68.39	59.92	61.39	66.66	63.56	89.8
Self-sufficiency rate (%)	118.9	147.2	104.6	135.4	109.1	128.3	116.8	145.1	116.7	108.9	121.6	102.3
Per capita consumption (kg)	35.5	17.3	45.0	25.9	42.7	32.9	34.0	29.7	30.4	32.6	31.0	87.3

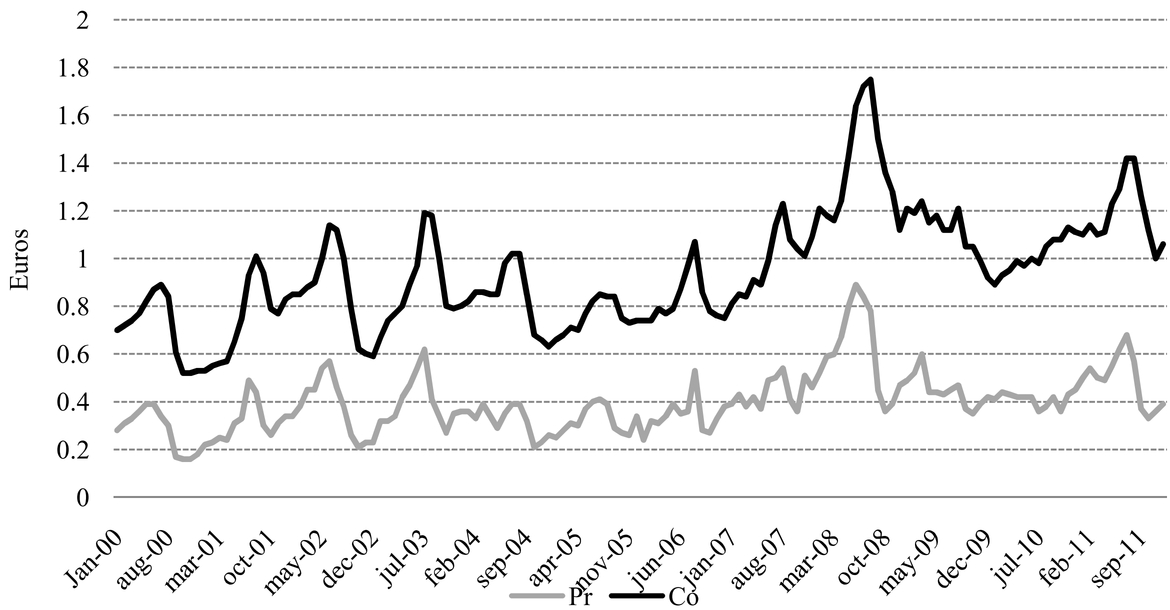
* Assumption that apples from intensive orchards are table apples, while from extensive are used for processing. Change in stock is not considered.

Source: SORS (2012).

Apple producer and consumer prices, the objective of our research interest, have explored variations over the years (Figure 1), which also causes variations in marketing margins. Apple import prices are usually higher than export prices (SORS, 2012). Lower export prices are likely to be related to a lack of investment in technological advances for orchard farms, in apple varieties, classification, packaging, marketing and organizational activities that are demanded by the markets.

To sum up, small and fragmented apple family farms face difficulties in marketing their product, a problem that typically characterizes small-scale producers that are not integrated in marketing channels. Promoting more integrated production and distribution methods, increased cooperation in marketing activities and improved quality should improve these farms' economic performance. In addition to finding appropriate marketing outlets, another challenging issues are exports and the lack of competitiveness in the international market.

Figure 1. Monthly nominal price series.



3. Econometric methods

Previous research has provided ample evidence of non-linearities in vertical price transmission processes in food markets (Goodwin and Piggott, 2001; Serra and Goodwin, 2003; Hassouneh et al., 2010). As a result, to assess price links along the Slovenian apple marketing chain, we rely on sufficiently flexible models that allow for nonlinearities, while containing linear price adjustment as a special case. Threshold Vector Error Correction models (TVECMs) constitute one of the most widely used nonlinear technique in the literature. TVECMs allow for (a limited number of) different price behavior regimes characterizing different economic conditions, each represented by a specific linear Vector Error Correction model (VECM). The whole set of VECMs are combined piecewise into a TVECM. Threshold models not only allow for a limited number of price-behavior regimes, but they also rely upon the assumption that transition from one regime to another is discontinuous and abrupt. The sudden reversion assumption imposed by threshold models may be too restrictive in a wide array of situations, since it involves that price differences motivating price adjustments are common across economic agents (Serra et al., 2006a). To evaluate to what extent these assumptions can fit the price series studied, a non-parametric model is also applied. Contrary to parametric models, non-parametric regression techniques are data-driven methods that do not require any specification of the functional form characterising price transmission and thus make it possible to explore price series in a more flexible manner. Fan and Gijbels (1996) argue that applying both parametric and non-parametric methods allows exploring many interesting data features that are difficult to identify by only utilizing a single approach. We now proceed to describe both the parametric and non-parametric techniques used in this paper.

3.1 Threshold Vector Error Correction Model

Time-series models are usually non-stationary (i.e., they contain a stochastic trend). However, when related, these time series may show a tendency to co-move in the long run. In other words, while individual prices may not be stationary, they may have a stable long-run relationship. Co-movement of price time series is termed as cointegration. The use of autoregression and cointegration methods has been key in time-series modeling to represent non-stationarity and co-movements of time-series. As is well known, Tong (1978) introduced nonlinear threshold time-series models. Tsay

(1989) developed a method to test for threshold effects in autoregressive models and to model threshold autoregressive (TAR) processes. Balke and Fomby (1997) extended TAR models to derive a threshold error correction model (TECM). Goodwin and Holt (1999) proposed the use of TVECM to allow for nonlinear and threshold-type price adjustments in multivariate settings. TVECMs constitute a multivariate version of TECMs.

A standard long-run cointegration relationship between two I(1) price series can be expressed as follows:

$$P_{Pr,t} - \beta P_{Co,t} = v_t \tag{1}$$

where $P_{Pr,t}$ and $P_{Co,t}$ are producer and consumer prices at time t and v_t represents the deviation from the long-run equilibrium relationship between these two prices. Existence of cointegration between the two price series depends on the nature of the residual autoregressive process $\Delta v_t = \gamma v_{t-1} + u_t$, where Δ is a first difference operator and $\gamma \neq 0$ implies that deviations from the equilibrium are stationary and that the price series are cointegrated.

Following the methods proposed by Balke and Fomby (1997) and Goodwin and Holt (1999), this simple analysis can be extended to threshold frameworks. A two-regime bivariate TVECM can be expressed as follows:

$$\Delta P_t = \begin{cases} \alpha^{(1)} + \alpha_p^{(1)} v_{t-1} + \sum_{i=1}^{n} \alpha_i^{(1)} \Delta P_{t-i} + \varepsilon_t^{(1)} & if \quad v_{t-d} \leq c \\ \alpha^{(2)} + \alpha_p^{(2)} v_{t-1} + \sum_{i=1}^{n} \alpha_i^{(2)} \Delta P_{t-i} + \varepsilon_t^{(2)} & if \quad v_{t-d} > c \end{cases} \tag{2}$$

where $P_t = (P_{\Pr,t}\ P_{Co,t})$ is the vector of prices being analyzed, $\alpha^{(m)}, \alpha_i^{(m)}$, $m = 1,2$ are parameters showing the short-run dynamics, $\alpha_p^{(m)}$ represents the speed of price adjustments to long-run disequilibrium, c is the threshold that delineates the different regimes, and v_{t-d} represents the variable relevant to the threshold behaviour (as is usual in the literature we assume $d = 1$).

To estimate parameters of the bivariate TVECM, sequential multivariate least squares in two steps is used. This estimation process is well known and we refer the reader to Hansen and Seo (2002) for further detail. To test for the significance of the differences in parameters across the regimes in a TVECM, the sup-LR test developed by Hansen and Seo (2002) is applied. The sup-LR statistic has a non-standard distribution because the threshold parameter is not identified under the null hypothesis. Hansen and Seo (2002) suggest using the residual bootstrap technique to compute the p-value of the sup-LR statistic. In our empirical application, a total of 1,000 simulations are run. Prior to the estimation of the TVECM, preliminary analyses were conducted to evaluate the time-series properties of price data. Specifically, standard unit root tests were applied in order to determine whether price series are stationary or not. The Johansen (1988) test for cointegration was then used to test for the existence of a long-run relationship.

3.2 Multivariate local polynomial fitting

Parametric methods are perhaps the most widely used tools in the price transmission literature. As noted above, these approaches require the specification of a functional form characterizing price relationships prior to estimation. Failure in selecting an appropriate functional form will lead to unreliable results. Non-parametric methods are not subject to restrictive functional forms. Price links are instead determined from data. Hence, local polynomial fitting has been typically used in the literature to explore data structure (see, Mancuso et al., 2003; Serra et al., 2006b; Hassouneh et al., 2012b). In this article, we apply this approach to estimate a non-parametric version of the TVECM. To the best of our knowledge, multivariate non-parametric approaches have not yet been used to characterize price transmission along the food marketing chain.

Let $(Y_t, \mathbf{X}_{t-1})$, $t = 1,...,n$, be a set of observations from a population $(Y, \mathbf{X}_{-1})$, where $Y_t = \Delta P_{it}$, $Y_t \in \mathbb{R}$, represents price i in first differences, i = $Pr\,, Co$ is an index representing producer and consumer price series respectively, and $\mathbf{X}_{t-1} = (\Delta P_{Prt-1}, \Delta P_{Cot-1}, v_{t-1})$, $\mathbf{X}_{t-1} \in \mathbb{R}^d$ is a vector containing lagged producer and consumer prices in first differences and the lagged error correction term, being $d = 3$. Of interest is to study the relationship between the response variable Y_t and the vector of covariates $\mathbf{X}_{t-1}$ via $m(\mathbf{x}_k) = E(Y_t \mid \mathbf{X}_{t-1} = \mathbf{x}_k)$. The basic idea behind local fitting is to estimate the function m at point $\mathbf{x}_k$, i.e. $\hat{m}(\mathbf{x}_k)$, using the observations that are relatively close to $\mathbf{x}_k$. To estimate the entire function $\hat{m}(\mathbf{X}_{t-1})$, the process is repeated for a number of grid values of $\mathbf{X}_{t-1}$ (Serra et al., 2006a). Since the regression function $m(\mathbf{x}_k)$ is unknown, a Taylor series expansion is used to approximate it locally by a polynomial model of order p :

$$m(\mathbf{x}) \approx \sum_{j=0}^{p} \boldsymbol{\beta}_j^{'} (\mathbf{x} - \mathbf{x}_k)^j \tag{3}$$

where the local parameter vector $\boldsymbol{\beta}_j = m^{(j)}(\mathbf{x}_k) / j!$ depends on $\mathbf{x}_k$. The $m^{(j)}$ term is the jth derivative of function m. Li and Racine (2007) strictly recommend using an odd polynomial order, since even orders generate bias at the boundary areas. In our analysis and following previous literature (see, Cleveland, 1979; Heij et al., 2004; Wu and Zhang 2006), we set a polynomial of order $p = 1$, which leads to the following minimization problem:

$$\sum_{t=1}^{n}(Y_t - \beta_0 - \boldsymbol{\beta}_1'(\mathbf{X}_{t-1} - \mathbf{x}_k))^2 K_{\mathbf{h}}\left(\mathbf{X}_{t-1} - \mathbf{x}_k\right) \tag{4}$$

where $K_{\mathbf{h}}\left(\mathbf{X}_{t-1} - \mathbf{x}_k\right) = \prod_{j=1}^{d} K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right) h_j^{-1}$ is a multivariate multiplicative kernel function whose role is to smooth data points in the given local neighborhood. More specifically, K is a weighting scheme to the local least squares problem that places large weights on neighboring observations and reduces such weights as the observations move away from $\mathbf{x}_k$. The bandwidth h_j controls the amount of local information used (the local sample size) and is defined in our analysis as $h_j = h_{base} s_x n_t^{-1/5}$ (Serra and Goodwin, 2009) where s_x is the standard deviation of the covariate and n is the number of observations (Fan and Gijbels, 1996).[5] The local linear estimate of $m(\mathbf{x}_k)$ is $\hat{\beta}_0$, while the gradient vector $m'(\mathbf{x}_k)$ is $\hat{\boldsymbol{\beta}}_1$.

Fan and Gijbels (1996) stress that choosing an appropriate bandwidth is a critical step in multinomial local polynomial fitting. While a large bandwidth may cause an important modeling bias, selecting a small bandwidth can lead to noisy estimates. In this paper we select an optimum constant base bandwidth h_{base} using the least squares cross-validation approach. This frequently used approach (Fan and Gijbels, 1996; Li and Racine, 2007) chooses h to minimize the squared prediction error: $\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2$. In our empirical analysis and following previous literature (Serra et al., 2006a), the predicted values for Y_t are obtained using the leave-one-out local constant kernel estimator originally proposed by Nadaraya (1964) and Watson (1964):

[5] This is known as the "rule of thumb" bandwidth estimator which was originally suggested by Silverman (1986).

$$\hat{Y}_t = \frac{\sum_{t=1}^{n} Y_t \prod_{j=1}^{d} K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right)}{\sum_{t=1}^{n} \prod_{j=1}^{d} K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right)} \tag{5}$$

In addition to the selection of the bandwidth approach, the choice of the kernel function is required. The Epanechnikov kernel is used, since it has been shown to be an optimal kernel (Fan and Gijbels, 1996).

4. Results

To assess price linkages and patterns of vertical transmission among producer and consumer markets for apple in Slovenia, monthly prices from January 2000 to December 2011 are used. Data on monthly apple producer and consumer prices are obtained from the SI-STAT of SORS (2012). Prices are expressed in euros per kilogram.[6]

Graphs of the nominal price series considered are presented in Figure 1. The patterns in nominal price developments reflect four main price behavior characteristics. First, nominal apple prices have a slight positive trend, which is partly due to an inflationary process. Second, seasonal variability characterized by lower prices during the harvesting period between September and November is also observed. Third, important increases prior to 2008 harvest due to adverse weather conditions are noteworthy. Fourth, the producer-to-consumer price differential, that captures marketing margins, shows a tendency to increase over time.

[6] Slovenia adopted the euro on 1st January 2007, which replaced the Slovenian tolar, the national currency before the euro adoption.

Logarithmic transformations of the price data are used in the empirical application. Unit-root testing suggests that prices are non-stationary.[7] Johansen's (1988) test supports the existence of a long-run relationship between producer and consumer prices (see Table 3).[8] The parameter representing the consumer price in the cointegration equation, that is virtually equal to 1, suggests that changes in consumer prices are fully transmitted to producer price levels in the long-run. This might imply competitive vertically integrated apple market.

Table 3. Johansen λ_{trace} test for cointegration and cointegration relationship.

Ho	Ha	λ_{trace}	p-value
$r = 0$	$r > 0$	42.656	0.000
$r \leq 1$	$r > 1$	7.770	0.101
Cointegration relationship			
$P_{Pr} - 1.046^{**} P_{Co} + 0.887^{**} = Ect$ (0.061) (0.015)			

Note: r is the cointegration rank.

** denotes statistical significance at the 5% level.

The TVECM is then estimated using the error correction term derived from the cointegration regression. The threshold derived from the grid search and the sup-LR statistic are presented in Table 4. Results indicate that nonlinearities are statistically significant at the 96% confidence level. This involves the existence of different price behavior regimes in the Slovenian apple sector,

[7] Details on unit root testing are available from the authors upon request.

[8] Hansen and Johansen's (1999) test for constancy of the cointegration parameters is implemented and indicates constancy of these parameters throughout the time period considered. These results are supported by the eigenvalues fluctuation test proposed by the same authors and also implemented. The existence of a cointegration relationship is backed by results from the Engle and Granger (1987) test. Results are available from the authors upon request.

depending on the magnitude and sign of error correction term. Specifically, price behavior can be classified into two regimes,[9] one mainly corresponding to negative and very small positive error correction term values (ECT<=0.097), and a second regime corresponding to ECT>0.097.

Table 4. TVEC model: Thresholds and Sup-LR test.

Threshold (C)	Sup-LR test (p-value)
0.09668	19.0495 (0.040)

Table 5 presents the TVECM parameter estimates across the two different regimes.[10] Parameter estimates suggest that both producer and consumer prices are endogenous for long-run parameters and adjust to deviations from the long-run equilibrium relationship. Adjustments however, do not occur in the same price regime. While the producer price adjusts to system disequilibrium in regime I, the consumer price responds to long-run disequilibrium when the ECT is above the threshold (regime II). Specifically, -48% producer price adjustments are observed when the ECT is lower than 0.097. Negative error correction values characterizing price regime I, are registered when the producer price is too cheap and thus when this price has to increase to maintain market equilibrium. In contrast, positive values of the ECT (mainly found in regime II) indicate that the producer price is too expensive and should decline. Hence, producer prices are mainly found to react to market disequilibriums when equilibrating price movements are favorable to apple producers.

[9] It is worth mentioning that a three-regime TVECM was tested against a VECM and results suggest no significant differences between the two models.

[10] The Akaike Information Criterion (AIC) as well as the Schwartz Bayesian Criterion (SBC) are used to select the optimal number of lags. When these two criteria differ, we use the more parsimonious SBC criteria (Enders, 1995; Wang and Liu, 2006). According to test results, one lag is applied in the estimation.

Table 5. TVEC model: parameter estimates.

Dependent variables	**Producer price equation**		**Consumer price equation**	
	Regime I	Regime II	Regime I	Regime II
ΔP_{Prt-1}	0.403** (0.132)[a]	-0.551** (0.262)	0.110* (0.059)	-0.101 (0.117)
ΔP_{Cot-1}	0.239 (0.253)	-0.354 (0.503)	0.200* (0.113)	0.060 (0.224)
ECT_{t-1}	-0.478** (0.187)	0.324 (0.270)	0.127 (0.083)	0.320** (0.120)
Constant	0.006 (0.019)		0.001 (0.009)	
Number of observations	Obs. in Regime I [99]		Obs. in Regime II [44]	

Notes: [a] Numbers in parentheses are standard errors.
*(**) denote statistical significance at the 10 (5) per cent level.

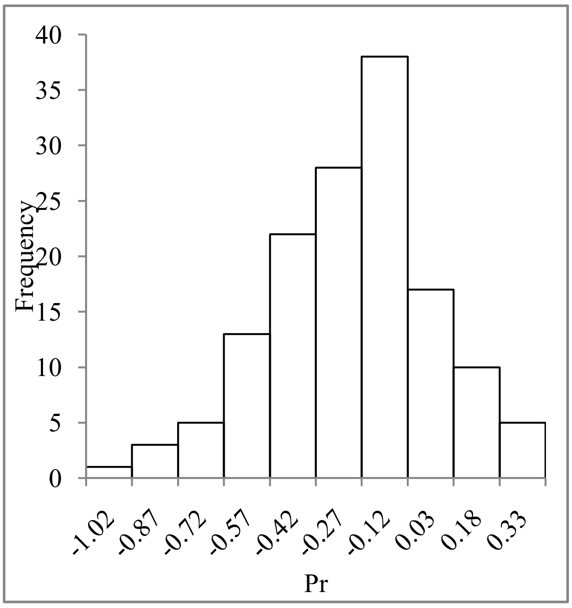
Conversely, the consumer price equation indicates that consumer prices only respond to deviations from the long-run parity in the second regime. Positive error correction values entail too cheap consumer prices and require these prices to increase. These results are expected and are consistent with previous literature that has suggested that price increases are more prone to occur than price declines (Peltzman, 2000). Parameters also indicate that the degree of producer price response to long-run disequilibrium is higher than consumer price adjustment. The tendency of both prices to increase, but not to decrease, can harm the competitiveness of the sector and slow down its restructuring process.

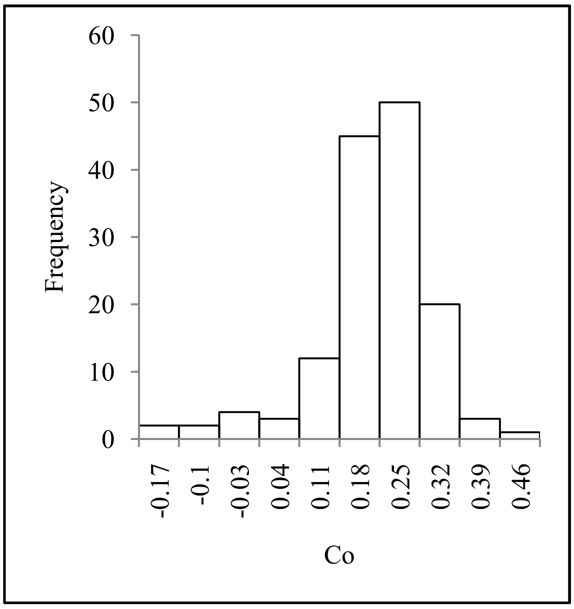
As explained above, TVECMs rely on the assumption that transition from one price behavior regime to another takes place in a discontinuous and abrupt fashion. Also, they involve a limited number of regimes to capture price adjustment. Usually, however, price behavior has been found to be of a smoother nature and to require higher flexibility than the one allowed by a few number of regimes (Serra et al., 2011; Hassouneh et al., 2012a). It is thus important to use more flexible techniques that restrict discontinuities to a special case. The nonparametric method is used as a flexible methodological alternative. Results derived from the Multivariate Local Linear Regression (MLLR) method described in section 3.2. are presented in Figure 2.[11]

The flexibility of the MLLR method is such that it allows deriving a different set of parameter estimates for each observation in the sample. The figure illustrates the MLLR estimates of the parameters representing long-run price dynamics. High variation in local estimates confirms that a two-regime model is too restrictive to represent changes in price behavior during the period studied. Producer and consumer prices response to long-run disequilibrium can range from -102% to 33% and -17% to 46%, respectively. In any case, the MLLR coincides with the TVECM in that both producer and consumer prices mainly increase when their levels are too low.

[11] The optimal base smoothing parameters h_{base} are searched utilizing a grid of values following the least squares cross-validation approach. The optimal bandwidth that minimizes the squared error of producer and consumer price equations is $h_{base} = 6$.

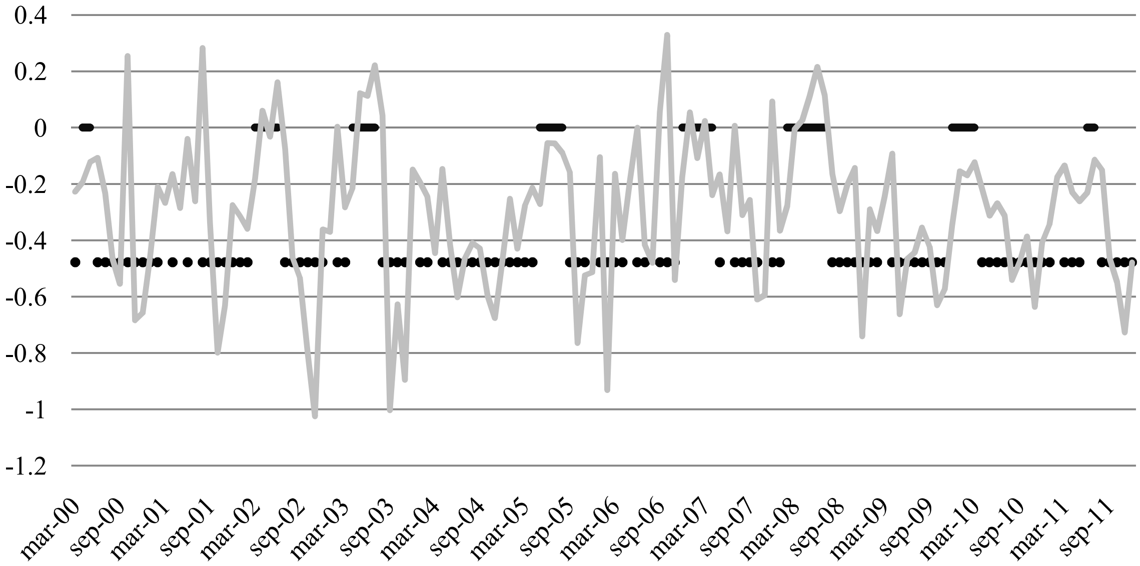
Figure 2. Distribution of localized estimates of the parameters showing the response of producer and consumer prices to long-run disequilibrium.





A comparison between the TVECM and MLLR techniques is presented in Figures 3 and 4. More specifically, these figures contain the parameters representing the long-run dynamics of producer and consumer prices, respectively. Regarding the TVECM parameters, the responses of the producer price in regime II as well as the consumer price in regime I, are set to zero in these figures since they are not statistically significant. Consistent with the threshold method, the non-parametric approach implies that the deviations from long-run equilibrium are adjusted in a non-linear manner. The non-parametric approach, however, displays a very different picture by showing much less abrupt price adjustment changes. The inaccuracy of simplifying long-run dynamics to an on-off switching mechanism implied by the TVECM is patent.

Figure 3. Non-parametric and parametric adjustments of producer price.

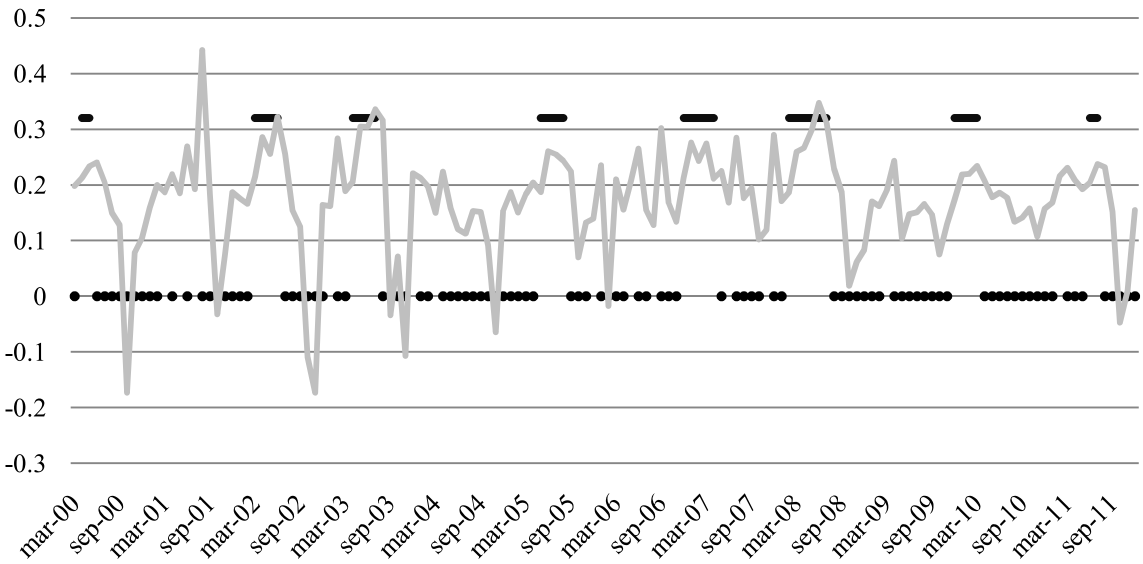


Where ● represents TVECM in regime I

▬ represents TVECM in regime II

▬ represents MLLR approach

Figure 4. Non-parametric and parametric adjustments of consumer price



Where ● represents TVECM in regime I

▬ represents TVECM in regime II

▬ represents MLLR approach

In short, our results suggest that our parametric results may not be reliable enough relative to MLLR. The restriction of abrupt price behavior changes seems too stringent in light of the smoother price behavior captured by the non-parametric estimator. It is thus very relevant to use price analysis methods that are flexible enough to get rid of restrictive aprioristic assumptions.

5. Concluding remarks

In this paper we analyze price linkages and patterns of vertical transmission among producer and consumer markets for apple in Slovenia. Previous studies on price time series data have provided ample evidence of the non-linear nature of price relationships. Parametric threshold models have frequently served to analyze these non-linearities in price relationships. Threshold models may involve too restrictive or unrealistic assumptions about the relationships between the variables. Non-parametric regression models such as local polynomial fitting are fully flexible in a way that they allow data to completely determine the relationships between price series studied. To our knowledge, no previous study has applied the MLLR to characterize vertical price transmission along the food marketing chain. Another contribution of this work to the literature relies on the fact that this is the first attempt to model the Slovenian apple market.

Both parametric and non-parametric approaches suggest that apple prices respond to deviations from long-run equilibrium in a non-linear fashion. Results also provide evidence that producer prices tend to increase at a faster speed than consumer prices. Both nominal prices are reluctant to fall, which may harm the Slovenian net exporter position in apple international trade. These findings are in line with previous research that suggests that nominal prices tend to rise and not to fall (see Peltzman, 2000). Non-parametric techniques further suggest that threshold models may have difficulties in adequately representing the actual links between the variables. These results are also consistent with the findings by Serra et al. (2006) which demonstrate that non-parametric techniques suggest smoother price adjustments than parametric methods.

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