Recent Developments in the Econometric Analysis of Price Transmission

Islam Hassouneh, Stephan von Cramon-Taubadel, Teresa Serra and José M. Gil

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Abstract

In recent years, there have been a large number of studies that have applied time series econometric techniques to study price transmission covering both spatial and vertical aspects of this process. In this paper, we highlight some of the more recent developments and how they extend the now standard vector error correction models. Particular attention is given to threshold adjustment and smooth transition vector error correction models. We highlight the circumstances where such techniques would be applicable in analysing price transmission and we cover both parametric and non-parametric methods associated with functional forms associated with the adjustment process. We summarise the process of choosing the econometric methods when unit roots and cointegration do or do not exist.

Recent Developments in the Econometric Analysis of Price Transmission

1. Introduction

The econometric analysis of price transmission has generated a considerable number of studies covering both spatial and vertical aspects of the price transmission process. In this paper, we present a review of recent methodological approaches that can be applied to measure the process of price transmission. Since previous research has provided ample evidence of non-linearities[1] in vertical price transmission processes, the techniques employed should be flexible enough to allow for non-linear price behaviour and we therefore concentrate on methodological developments in this area. In doing so, we highlight the rationale associated with non-linear issues and how they may relate to the underlying economic issues that the non-linear processes are endeavouring to capture.

This paper is organized as follows. In the next section, we briefly discuss the preliminary data analysis that should be conducted to assess the time-series properties of the price data and to correctly specify the vertical price transmission model to be estimated. Since price time-series of interrelated markets are usually non-stationary and cointegrated, we then move on to describe the linear vector error correction model which is known to soundly represent the behaviour of this type of data (Section 3). In this section, we review factors – such as threshold effects, asymmetric price transmission due to market power, and policy interventions – that can lead to non-linear price transmission. Subsequently we show how the standard linear error correction model can be made more flexible to model such non-linearities. In Section 4, we conclude with a table that summarises the empirical methods that can be employed subject to the different possible scenarios we may encounter in addressing price transmission issues.

[1] The term "non-linearity" is used in a general sense here. We provide a more rigorous discussion of "non-linearity" and related terms such as "regime-dependent" below.

2. Preliminary Data Analysis

According to Myers (1994), commodity price series have a number of common characteristics that have important implications for sound statistical analysis. Two of these characteristics are especially relevant to our study. First, individual commodity price series generally contain stochastic trends and are non-stationary. Second, commodity prices may tend to move together over time (i.e., they may be cointegrated). In other words, though individual price series may be non-stationary, price series of interrelated markets are likely to contain the same stochastic trends. If this is the case, these stochastic trends will 'cancel' each other and a linear combination of the prices will be stationary. These statistical properties of price series must be considered in order to build an adequate framework for price analysis. We will conduct standard unit root and cointegration tests in order to determine whether price series are stationary and whether they are cointegrated, respectively.

Since the end of the 1970s, important advances have been made in developing statistical tests for the presence of unit roots in time series. The pioneers in this field were Dickey and Fuller (1979). The augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the KPSS (Kwiatkowski et al., 1992), Elliott (1999) and Perron (1997) tests will be applied to each price series in order to determine whether it has a unit root (I(1)). These tests are well known and therefore not discussed here[2].

Different methodologies have been offered in the literature in order to evaluate long-run price linkages. Engle and Granger (1987) first proposed a testing procedure for cointegration using a two-step estimator of the parameters of a bivariate single-equation model. Johansen

[2] Useful surveys on unit root testing can be found in Stock (1994), Maddala and Kim (1998), Phillips and Xiao (1998) and Zivot and Wang (2005).

(1988) developed a maximum likelihood approach for estimation and testing for multiple cointegrating vectors.

A standard long-run relationship between two I(1) price series can be expressed as follows and can be (super-)consistently estimated by ordinary least squares:

$$\alpha + P_{1,t} - \beta P_{2,t} = v_t \tag{1}$$

where $P_{1,t}$ and $P_{2,t}$ are prices at different levels of the food marketing chain and the residual v_t represents the deviation from the equilibrium relationship which is often referred to as the 'error correction term' (ECT). The existence of cointegration between the two price series depends on the nature of the following autoregressive process (Engle and Granger, 1987): $\Delta v_t = \gamma v_{t-1} + u_t$, 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. In other words, if an ADF test of the null hypothesis that the residuals in equation (1) are non-stationary (specifically, that $\gamma = 0$) leads to rejection, then we conclude that the prices $P_{1,t}$ and $P_{2,t}$ are cointegrated. Engle and Granger provide the critical values for this test, as standard ADF critical values are not applicable.

Johansen's (1988) approach has its starting point in the following so-called vector error correction model (VECM):

$$\Delta P_t = \Pi P_{t-1} + \Gamma_1 \Delta P_{t-1} + \ldots + \Gamma_{k-1} \Delta P_{t-k+1} + \varepsilon_t \tag{2}$$

where $P_t = (P_{1t}\ P_{2t})$ [3] is a vector of I(1) price variables, ε_t is the vector of error terms and the matrices Γ_i represent the short-run dynamics of price data. We discuss the interpretation of the VECM in the following section. According to the Johansen method, the VECM in (2) is estimated using maximum likelihood. Matrix Π contains the information on the cointegrating relationships between the non-stationary variables in P_t. The rank of Π indicates the number of these relationships. The rank of a matrix equals the number of its characteristic roots that differ from zero. Johansen proposes two tests for the number of significant characteristic roots, the trace test and the maximum eigenvalue test. The trace test statistic can be expressed as follows:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\lambda_i) \tag{3}$$

where T is the number of observations and λ_i are the values of the characteristic roots from Π. Equation (3) tests the null hypothesis that the rank of Π is less than or equal to r against the alternative that it is greater than r; in other words the null of r or less cointegrating vectors against the alternative of more than r cointegrating vectors. The maximum eigenvalue test statistic can be expressed as follows and tests for the null that rank(Π) = r against the alternative that rank(Π) = r+1.

$$\lambda_{max} = -T \ln(1-\lambda_{r+1}) \tag{4}$$

[3] While, for the sake of simplicity, we consider two prices, the Johansen procedure allows for multiple cointegrating vectors and thus for higher dimensional price vectors.

Neither of these test statistics follows the usual Chi-squared distribution, but alternative critical values for λ_{trace} and λ_{max} are provided by Johansen and Juselius (1990). In the following section, we take a closer look at the VECM which can adequately represent time-series behaviour in the presence of non-stationarity and cointegration, and which has become the 'workhorse' model in price transmission analysis.

3. Linear and Non-Linear Error Correction Models

3.1. The linear vector error correction model

Engle and Granger (1987) show that cointegration of non-stationary time series implies that there is a valid error correction representation of these time series. More specifically, if a set of I(1) variables is $P_{1,t}$ and $P_{2,t}$ are cointegrated, then there exists a VECM representation of these series that depicts their behaviour over time. If we are analysing the two commodity prices $P_{1,t}$ and $P_{2,t}$, then the corresponding bivariate VECM can be expressed as follows:

$$\Delta P_{1,t} = \alpha_1 + \alpha_{P1}(\alpha + P_{1,t-1} - \beta P_{2,t-1}) + \sum_{i=1}^{n} \alpha_{11}(i)\Delta P_{1,t-i} + \sum_{i=1}^{n} \alpha_{12}(i)\Delta P_{2,t-i} + \varepsilon_{P1,t}$$

$$\Delta P_{2,t} = \alpha_2 + \alpha_{P2}(\alpha + P_{1,t-1} - \beta P_{2,t-1}) + \sum_{i=1}^{n} \alpha_{21}(i)\Delta P_{1,t-i} + \sum_{i=1}^{n} \alpha_{22}(i)\Delta P_{2,t-i} + \varepsilon_{P2,t} \qquad (5)$$

where α and β are the parameters of the cointegration vector, $\varepsilon_{P1,t}$ and $\varepsilon_{P2,t}$ are white noise disturbances that may be correlated with each other, $\alpha_1, \alpha_{2,} \alpha_{11}(i), \alpha_{12}(i), \alpha_{21}(i)$ and $\alpha_{22}(i)$ are dynamic short-run parameters, and α_{P1} and α_{P2} are parameters that measure the rate at which prices adjust to disequilibria from the long-run cointegrating relationship. This long-run relationship is given by the expression $(\alpha + P_{1,t-1} - \beta P_{2,t-1})$. If this linear combination of the $I(1)$ price variables is stationary, then all variables in (5) are stationary and the VECM is a valid representation of the long-run relationship between the prices and of the short-run dynamics that correct deviations from this long-run relationship. If $(\alpha + P_{1,t-1} - \beta P_{2,t-1})$ is not stationary (i.e. the prices are not cointegrated), then (5) contains terms of different degrees of integration and is not a valid specification.

3.2. Non-linearity in vector error correction models

The VECM in equation (5) is linear in two senses of the word that are relevant in price transmission analysis. First, it is linear in the sense that all of the parameters in the model are assumed to be constant over the entire sampling period. Second, it is linear in the sense that the left-hand-side (LHS) variables react linearly to changes in the right-hand-side (RHS) variables. Numerous studies have shown that in many settings one or both of these types of linearity cannot be expected to hold (von-Cramon-Taubadel, 1998; Serra and Goodwin, 2003; Serra *et al*. 2006; Ben-Kaabia and Gil, 2007; Hassoneh *et al*., 2010).

For example, a policy change or a new technology can lead to a structural break in the long- and/or short-run dynamics depicted in (5). In this case, the first type of linearity referred to above will not hold and a more appropriate specification would link two individual VECMs – one that depicts price behaviour before the break, and one that depicts behaviour after. The result could be termed a 'piecewise' linear VECM; in the literature this sort of price transmission is often referred to as 'regime-dependent'. Regime dependence can take on more complex forms than the two-regime, one-jump example just given. Furthermore, the trigger that determines when the system switches from one regime to another need not be an observable exogenous variable, like a policy change, but could instead be endogenous (for example, the sign or magnitude of the ECT) or an unobservable latent state variable (for example, the business climate).

The other type of non-linearity referred to above obtains when the price changes on the LHS react in a non-linear manner to changes in the RHS variables. For example, the error correction response to a deviation from the long-run equilibrium could be an increasing function of the magnitude of this deviation. To account for this one could specify a non-linear functional form (for example, by including the term $(\alpha + P_{1,t-1} - \beta P_{2,t-1})^2$ on the RHS of (5)) or one might employ non-parametric estimation techniques.

An almost limitless number of combinations of the many possible forms of regime-dependence and non-linear response can be imagined. Each of these combinations corresponds to a specific non-linear (in the general sense) VECM. In the field of price transmission analysis, a few of these models have become relatively popular and are employed in a large proportion of the published articles and studies. The popularity of a particular model depends partly on the availability of a theoretical justification. For example, as explained below, so-called asymmetric VECMs are often justified by referring to the possible exercise of market power in the food chain. However, as non-linear models often involve complicated issues of estimation and inference, popularity also hinges on the availability of econometric techniques and software.

A number of established as well as emerging non-linear VECM models can be utilised in order to assess how prices for different agricultural commodities are transmitted along the food marketing chain. In the following, we present and discuss these models, focussing on both their theoretical underpinnings and questions of estimation and interpretation.

3.3. Common non-linear error correction models in price transmission analysis

3.3.1. The asymmetric vector error correction model

In the context of vertical price transmission, asymmetry usually refers to differences in price transmission that depend on whether prices are increasing or decreasing. For example, farmers often suspect that when the prices of agricultural raw products increase, these increases are more rapidly and/or more completely passed on to consumers than corresponding decreases in agricultural raw product prices. This suspicion is generally based on concerns about concentration and imperfect competition in the food chain, in other words that relatively few processors and retailers are able to exercise market power to take advantage of relatively many farmers. However, a variety of other explanations for possible asymmetric price transmission have been proposed, including menu costs, product storage and perishability, and the influence of support policies on expectations. Meyer and von Cramon-Taubadel (2004) and Frey and Manera (2007) provide reviews of the causes and estimation of asymmetric price transmission.

Early empirical analyses of asymmetric price transmission involved the use of variations of a variable splitting technique introduced by Wolffram (1971) and later refined by Houck (1977) and Ward (1982). This technique splits a variable x_t into its positive and negative components such that $x_t^+ = x_t$ for all $x_t > 0$ and 0 otherwise and $x_t^- = x_t$ for all $x_t < 0$ and 0 otherwise. The Wolffram-type specifications, however, pre-dated the development of cointegration techniques and thus did not explicitly consider the problems related to nonstationary data. To solve this problem, Granger and Lee (1989) extended the ECM specification to allow for asymmetric adjustments by applying the splitting technique described above to the ECT. The resulting asymmetric VECM (AVECM) is:

$$\Delta P_{1,t} = \alpha_1 + \alpha_{P1}^{+} v_{t-1}^{+} + \alpha_{P1}^{-} v_{t-1}^{-} + \sum_{i=1}^{n} \alpha_{11}(i) \Delta P_{1,t-i} + \sum_{i=1}^{n} \alpha_{12}(i) \Delta P_{2,t-i} + \varepsilon_{P1,t}$$

$$\Delta P_{2,t} = \alpha_2 + \alpha_{P2}^{+} v_{t-1}^{+} + \alpha_{P2}^{-} v_{t-1}^{-} + \sum_{i=1}^{n} \alpha_{21}(i) \Delta P_{1,t-i} + \sum_{i=1}^{n} \alpha_{22}(i) \Delta P_{2,t-i} + \varepsilon_{P2,t} . \qquad (6)$$

Since $v_t^{+} + v_t^{-} = v_t$, the standard symmetric VECM is nested in the AVECM and an F-test can be used to test the null hypothesis of symmetry $(\alpha_{Pi}^{+} = \alpha_{Pi}^{-})$, i = 1 and 2 (see von Cramon-Taubadel, 1998, for an application of this model to pork markets in Germany).

The AVECM is an example of what we referred to above as a piecewise linear model in which there is one regime of linear price response whenever the ECT is greater than 0, and another such regime whenever the ECT is less than 0. If the variables being modelled are prices at different levels in the marketing chain for some product (e.g. producer prices and retail prices), then a positive (negative) ECT indicates that the marketing margin is above (below) its long run equilibrium. The suspicion expressed by farmers that producer price increases are passed on faster than producer price decreases would then be equivalent to the testable hypothesis that positive ECT values are corrected more rapidly than negative ECT values.

3.3.2. Threshold vector error correction models

There are many situations in economics in which a response is only triggered, or the nature of a given response changes significantly, when some variable crosses a threshold. Due to search and information costs, for example, consumers will not switch from the store that they habitually visit to another store in response to a price increase unless this increase exceeds a certain threshold value. Threshold effects of this nature are often hypothesised to occur in price transmission. Indeed, asymmetric price transmission (see above) can be considered a threshold phenomenon in which the ECT is the trigger variable that changes the nature of price transmission whenever it crosses the threshold value of 0.

Tong (1978) introduced threshold time series models. Tsay (1989) proposed a method to test for threshold effects in autoregressive models and to model threshold autoregressive (TAR) processes, and Balke and Fomby (1997) extended TAR models to a cointegration framework. Goodwin and Holt (1999) first proposed the use of threshold vector error correction models (TVECM) to allow for threshold effects in vertical price transmission, and Goodwin and Piggott (2001) is the seminal paper on the use of the TVECM in the analysis of spatial price transmission.

In spatial price transmission, it is often hypothesised that due to transaction costs traders will only respond to a deviation from the long-run price equilibrium between two locations if this deviation exceeds a certain threshold value. This was suggested first by Heckscher (1916) who hypothesised a band of inaction in which small deviations from the law of one price are not adjusted because transaction costs are higher than potential earnings due to the price differential. Heckscher termed the threshold values at the boundaries of this neutral band, within which prices at different locations move independently of one another, commodity points. This idea was later formalised in spatial equilibrium theory (Takayama and Judge, 1971). Similar effects can be imagined in vertical price transmission if, for example, due to menu costs a processor only adjusts the wholesale price of his products in response to a change in the price of a key input if this change exceeds a certain threshold value.

A one-threshold, two-regime bivariate TVECM can be expressed as follows:

$$\Delta P_t = \begin{cases} \alpha^{(1)} + \alpha_p^{(1)} v_{t-1} + \sum_{i=1}^{n} \alpha_i^{(1)} \Delta P_{t-i} + \varepsilon_t^{(1)} & if \quad z_t \leq c \\ \alpha^{(2)} + \alpha_p^{(2)} v_{t-1} + \sum_{i=1}^{n} \alpha_i^{(2)} \Delta P_{t-i} + \varepsilon_t^{(2)} & if \quad z_t > c \end{cases} \tag{7}$$

where $P_t = (P_{1t}\ P_{2t})$ is the vector of prices being analyzed, $\alpha^{(m)}, \alpha_i^{(m)}$, $m = 1$ and 2 are vectors of parameters that capture short-run dynamic price responses, and $\alpha_p^{(m)}$ are the adjustment parameters that measure the adjustment of prices to deviations from the long-run equilibrium. c is the threshold that delineates the different regimes, and z_t represents the variable that triggers the threshold behaviour. In price transmission analysis z_t is usually specified as the lagged value of the error correction term v_{t-1}. In this case, if the threshold c = 0, then the TVECM in (7) is identical to the AVECM in (6). Alternatively, the AVECM can be interpreted as a special case of the TVECM in which the threshold value is restricted to equal 0. Note that if the threshold value c ≠ 0, then the resulting model is necessarily asymmetric in the sense that price transmission will differ depending on whether prices are increasing or decreasing, even if all the parameters on the RHS of the two equations in (7) are identical.

Like the AVECM, the one-threshold, two-regime TVECM is piecewise linear. Several studies have used this model to study price behaviour (e.g. Obstfeld and Taylor, 1997). This basic model can be generalised to *m* thresholds and *m+1* linear regimes, and in spatial price transmission analysis the two-threshold, three-regime TVECM has proven especially popular (see Goodwin and Piggott, 2001; Serra and Goodwin, 2004). This model is able to capture Hechsher's idea of a central band of inaction or 'neutral bank' between two commodity points or thresholds. One of these thresholds is positive and when the ECT exceeds this threshold arbitrage in one direction is triggered and reduces the ECT until it is once again within the neutral band;

the other threshold is negative and ECT values below it trigger equilibrating trade in the opposite direction. In the case of vertical price transmission, a similar constellation can arise if margins must be either squeezed or stretched by more than a certain amount to trigger price responses. For example, in an oligopolistic setting, firms may be reluctant to increase their output prices when input prices climb because they worry about losing market share; and they might be reluctant to reduce their output prices when input prices fall because they are concerned about triggering a price war.

Clearly, the two thresholds in such a two-threshold, three-regime model need not be of equal absolute value. The transaction costs of trade from market A to market B can differ from the transaction costs of trade from B to A (for example due to the difference in costs of moving goods up- as opposed to down-river). Hence, the TVECM with two thresholds allows for an additional type of asymmetry in price transmission; even if all the parameters in the outer regimes of such a TVECM are identical, price transmission will be asymmetric if these outer regimes do not both begin at the same distance from 0.

To date, TVECMs have been estimated using profile likelihood methods. According to this method, the TVECM is estimated for each possible value of the threshold variable, and the value of the threshold that corresponds to the TVECM with the best fit is taken to be the estimate of the threshold. In the popular two-threshold TVECM, the model is thus estimated for all possible combinations of the two threshold values. This amounts to searching for the TVECM with the best fit on a two-dimensional grid of possible threshold values which explains why many authors refer to the 'grid search method'. However, the underlying method is actually profile likelihood in which all of the parameters of the TVECM (the so-called 'nuisance parameters'[4]) except for the thresholds are concentrated out to generate a profile of the best possible fits for each possible (combination of) threshold value(s).

Since the TVECM is piecewise linear, for given values of the threshold and on the assumption that the error terms are normally distributed, profile likelihood can be implemented using ordinary least squared (OLS). Seeming unrelated regression (SUR) estimation can be used, but as long as all equations in the TVECM have the same RHS variables (which is usually the case), SUR and equation-by-equation OLS produce identical results. To test for the significance of the differences in parameters across the regimes in a TVECM, a sup-LR test developed by Hansen and Seo (2002) can be used. This test compares the fit of a linear VECM with the fit of the 'best' estimated TVECM. The sup-LR statistic has a non-standard distribution because the threshold parameters are not identified under the null hypothesis (i.e. if each piece of the TVECM has the same parameters, the model reduces to a simple VECM and has no thresholds). Hence, to calculate the p-value of the sup-LR statistic, bootstrapping techniques developed by Hansen and Seo (2002) can be used.

Recent work (Greb *et al*, 2011a) has demonstrated that the profile likelihood estimator produces biased estimates of the threshold in a set of generalised threshold models. This bias is a result of two shortcomings. First, the variance of the nuisance parameters in the TVECM is not taken into account when choosing the 'best' estimate of the threshold value(s). Second, in order to ensure that estimation is feasible it is necessary to impose the restriction that each regime contains sufficient observations to permit estimation of all of the nuisance parameters. This can lead to exclusion of the true threshold value from the search grid. Greb *et al*. (2011a) propose a regularised empirical Bayesian (REB) estimator and demonstrate that it has less bias and a lower

[4] The term 'nuisance parameter' makes sense from an econometric perspective, but is misleading in the sense that the parameters in question (for example, the adjustment parameters) are certainly of interest from an economic point of view.

variance than the profile likelihood estimator in Monte Carlo experiments. Greb *et al*. (2011b) demonstrate that the REB estimator also has these properties in the specific case of TVECM models. This estimator accounts for the variance of the nuisance parameters and does not require any arbitrary restrictions on the number of observations in each regime.

3.3.3. Smooth transition vector error correction models

In the piecewise linear threshold models described in the previous section, transition between regimes takes place in a discontinuous and abrupt fashion whenever a threshold is crossed. With reference to the economic mechanisms that can lead to threshold behaviour discussed above, this implies that all economic agents exhibit identical responses. In spatial equilibrium, for example, an abrupt threshold implies that all traders face the same transaction costs and therefore begin to engage in arbitrage at the same time. In vertical price transmission it implies that all market participants respond to the exact same change in margins and have identical conjectures about the responses of the other participants. If, more realistically, we assume a (for example normal) distribution of transaction costs and behavioural parameters across participants, the transition from one regime to another will be gradual as first a few, then progressively more and ultimately all participants respond to changes in the threshold variable.

The Smooth Transition Vector Error Correction Model (STVECM), originally developed by Teräsvirta (1994), allows for transition to occur in a smooth fashion. Following van Dijk *et al*. (2002), a two-dimensional STVECM can be expressed as:

$$\Delta P_t = \left(\alpha^1 + \alpha_p^{(1)} v_{t-1} + \sum_{j=1}^{p-1} \alpha_{i,j}^{(1)} \Delta P_{t-i} \right) (1 - G(v_{t-1}; \gamma, c)) + \left(\alpha^2 + \alpha_p^{(2)} v_{t-1} + \sum_{j=1}^{p-1} \alpha_{i,j}^{(2)} \Delta P_{t-i} \right) (G(v_{t-1}; \gamma, c)) + \varepsilon_t \tag{11}$$

where all variables and parameters are as defined above and $G(v_{t-1};\gamma,c)$ is a smooth transition function which is assumed to be continuous and bounded between zero and one. The transition function depends on the transition variable v_{t-1}, as well as on the speed of transition and threshold parameters γ and c, respectively. Unlike the AVECM and the TVECM, the STVECM is not piecewise linear; it is therefore non-linear in both of the senses discussed in section 3.2. It can be considered a continuously regime-switching model in which price transmission at any one point is a unique mixture of the extreme regimes associated with the extreme values of the transition function, $G(v_{t-1};\gamma,c)=0$ and $G(v_{t-1};\gamma,c)=1$. The transition from one regime to the other takes place in a smooth way as values of $G(v_{t-1};\gamma,c)$ within the (0,1) interval define a range of intermediate regimes, each of which is a linear combination of the two extreme regimes.

There are different specifications of the transition function $G(\dot{})$ that lead to different patterns of regime change. The most popular are the logistic and the exponential functions (van Dijk *et al.*, 2002). The exponential transition function can be expressed as follows:

$$G(v_{t-1};\gamma,c) = 1 - \exp\left(-\frac{\gamma (v_{t-1} - c)^2}{\sigma^2 (v_{t-1})} \right),\ \gamma > 0\ . \tag{12}$$

Combining (11) and (12) produces the exponential STVECM (ESTVECM) in which γ determines the speed of the transition from one regime to the other, c is the midpoint between the two regimes, v_{t-1} is the transition variable and $\sigma(v_{t-1})$ is the sample standard deviation of v_{t-1} used as a normalisation variable. Under this approach, the adjustment is symmetric around the parameter c, and differs for large and small absolute values of v_{t-1}. In other words, $G(v_{t-1};\gamma,c)$ approaches zero as v_{t-1} approaches c, and approaches one as v_{t-1} becomes large with respect to c. In most analyses, the transition variable is assumed to be the lagged ECT, but other transition variables are possible. As $\gamma \to 0$, the transition function becomes a constant and thus the ESTVECM reduces to a VECM. Conversely, as $\gamma \to \infty$, the change of $G(v_{t-1};\gamma,c)$ from 0 to 1 becomes instantaneous resulting in a one-threshold, piecewise linear TVECM.

The logistic transition function can be expressed as follows:

$$G(v_{t-1};\gamma,c) = \frac{1}{1+\exp\left(-\frac{\gamma(v_{t-1}-c)}{\sigma(v_{t-1})}\right)},\ \gamma>0\,. \tag{13}$$

Combining this function with (11) produces what is called a logistic STVECM (LSTVECM).

Which of these two transition functions performs better in a given setting can be determined using a sequence of nested tests proposed by Teräsvirta (1994) and Luukkonen *et al.* (1988). The parameters of the STVECM model can be estimated by using non-linear least squares (NLS).

3.3.4. Multivariate local polynomial fitting

The models discussed so far (AVECM, TVECM and STVECM) are all parametric models that require the specification of exact functional form of the model prior to estimation. If the functional form (e.g. the number of thresholds or the shape of the transition function) is specified incorrectly, estimation will lead to misleading results. Non-parametric regression techniques are data-driven methods that do not impose any restriction on the functional form that characterises price transmission. They thus make it possible to explore price data in a more flexible way. Local polynomial techniques by which the data are segmented into small overlapping sections are widely used to estimate regression functions non-parametrically (Fan and Gijbels, 1996; Li and Racine, 2007).

Consider a set of observations $\left(Y_t, \mathbf{X}_{t-1}\right)$ for $t = 1, \ldots, n$ from a population $\left(Y, \mathbf{X}_{-1}\right)$, where $Y_t = \Delta P_{it},\ Y_t \in \mathbb{R}$, represents price *i* in first differences, *i* = 1, *2* is an index representing the prices being analyzed, and $\mathbf{X}_{t-1} = (\Delta P_{1t-1}, \Delta P_{2t-1}, v_{t-1}),\ \mathbf{X}_{t-1} \in \mathbb{R}^d$ is a vector containing lagged price differences, and the lagged error correction term, being $d = 3$. Hence, the LHS in this model are, as in the VEC mechanism, expressed as a function of the lagged price changes and the ECT. Of interest is to estimate the multivariate non-parametric regression problem $m(\mathbf{x}_k) = E(Y_t \mid \mathbf{X}_{t-1} = \mathbf{x}_k)$.

The main 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*., 2006). Since the regression function $m(\mathbf{x}_k)$ is unknown, a Taylor series expansion is used to approximate it by a simple polynomial model:

$$m(\mathbf{x}) \approx \sum_{j=0}^{p} \boldsymbol{\beta}_j^{'} (\mathbf{x} - \mathbf{x}_k)^j \tag{14}$$

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. Previous research argues that odd order polynomial fits are preferable to even order polynomial fits, (see, Fan and Gijbels, 1996). Moreover, several authors recommend choosing a polynomial of order $p = 1$, which leads to the Multivariate Local Linear Regression Estimator (MLLRE), an estimator that has been shown to provide adequate smoothed points and computational ease (Cleveland, 1979; Heij *et al*., 2004).

The observations with most information about $m(\mathbf{x}_k)$ should be those at locations closest to $\mathbf{x}_k$ compared to more remote points. Weighted least squares is used to give more weight to neighbouring observations than to more distant ones. Weights are assigned through a kernel function as follows:

$$\sum_{t=1}^{n} (Y_t - \beta_0 - \boldsymbol{\beta}_1^{'} (\mathbf{X}_{t-1} - \mathbf{x}_k))^2 K_{\mathbf{h}} \left(\mathbf{X}_{t-1} - \mathbf{x}_k \right) \tag{15}$$

where $K_{\mathbf{h}} \left(\mathbf{X}_{t-1} - \mathbf{x}_k \right) = \prod_{j=1}^{d} K \left(\dfrac{X_{j,t-1} - x_{j,k}}{h_j} \right) h_j^{-1}$ is a multivariate multiplicative kernel function assigning weights to each datum point and $K \left(\dfrac{X_{j,t-1} - x_{j,k}}{h_j} \right)$ is a univariate kernel function. The bandwidth h_j controls for the size of the local neighbourhood (Fan and Gijbels, 1996) and is equal to $h_j = h_{base} s_x n,^{-1/5}$ where s_x is the standard deviation of the covariate and n is the number of observations (Serra and Goodwin, 2009). The local linear estimate of $m(\mathbf{x}_k)$ is $\hat{\beta}_0$, while the gradient vector $m'(\mathbf{x}_k)$ is $\hat{\boldsymbol{\beta}}_1$.

Previous literature argues that selecting an appropriate bandwidth is a key issue of multinomial local polynomial fitting. In order to find an appropriate bandwidth, one can select an optimum constant base bandwidth h_{base} using the least squares cross-validation method. This widely used technique (Fan and Gijbels, 1996; Li and Racine, 2007) chooses h to minimize the squared prediction error $\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2$. Following Kumbhakar *et al.* (2007), the predicted values for Y_t will be obtained using the "leave one out" version of the local linear estimator.

Fan and Gijbels (1996) argue that the choice of the kernel function is less crucial since the modeling bias is primarily controlled by the bandwidth. However, they recommend using the Epanechnikov kernel which has been shown to be optimal under general conditions.

To conclude this section, we would like to note that, since they do not impose any *a priori* parametric restriction, non-parametric models will always fit the data better than their parametric counterparts. The less sure we are about the theoretical restrictions that underpin parametric specifications, the better off we are not imposing these restrictions and the greater the possible advantages of non-parametric estimation. However, if we have a useful theory, not imposing it on the estimation means not using available information, and the resulting estimates can be correspondingly inferior. Furthermore, interpreting the results of a non-parametric estimation is difficult. For example, a non-parametric VECM will always produce results that are asymmetric about 0. But whether this asymmetry is statistically significant cannot be determined.

4. Methodological framework summary

We conclude this paper with a summary of the proposed methodological framework for the analysis of price transmission highlighting the steps from the basic analysis of the properties of the underlying price data through to the applicability of the more recent time series econometric developments. For each set of prices representing a food marketing chain, the following steps will be followed in order to determine the final model to be estimated:

Step	**Test**	**Result**	**Econometric model to be estimated**
1	Unit root	No	VECM with stationary data or VAR using level prices
		Yes	Move to step 2
2	Cointegration	No	VAR using prices in first differences
		Yes	VECM, AECM, TVECM, STVECM or MLLRE

Hence, depending on the properties of the prices being studied, different models will need to be estimated. In any case, research results will be comparable across different models, since they are all based on the same underlying vector autoregressive specification..

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