Analysis of Price Transmission using a Nonparametric Error Correction Model with Time-Varying Cointegration

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Abstract.

Several authors have proposed using non-parametric methods to estimate price transmission rather than the currently popular piecewise linear or regime-dependent methods. However, so far only the error correction mechanism has been estimated non-parametrically using local polynomial techniques. We propose a new method for estimating price transmission relationships that combines a non-parametric error correction model with time-varying cointegration. Two applications, to wheat price transmission between Ukraine and France, and to vertical transmission between piglet and slaughter pig prices, are presented to demonstrate the complex behaviour and insights that the proposed method can reveal.

Keywords: price transmission, non-parametric methods

JEL codes: Q11, Q13, C5, C22

1. Introduction

Piecewise linear or regime-dependent cointegration methods are currently very popular in the price transmission literature. However, they have been criticised for making unrealistic assumptions about functional form and the nature of the transition process between regimes. The often-used threshold vector error correction model, for example, assumes that the price transition process between two prices changes abruptly the moment the difference between these prices crosses a certain threshold value. While this is clearly more flexible than assuming that a single price transmission process holds for all values of the difference between prices, it does not allow the price transmission process to change gradually. Other regime-dependent cointegration methods make other assumptions, but they all maintain a number of assumptions regarding functional form and the parametrisation of the transition between regimes.

In response, several authors have proposed using non-parametric methods to estimate price transmission. However, so far only the error correction mechanism has been estimated non-parametrically using local polynomial techniques. We propose a new method for estimating price transmission relationships that combines a non-parametric error correction model with time-varying cointegration. To illustrate the use of this method, we present two applications; one to wheat price transmission between Ukraine and France, and another to vertical transmission between piglet and slaughter pig prices.

He rest of this paper is structured as follows. In the following section we review the literature on price transmission using cointegration techniques to motivate the method that we propose. In section 3 we explain the theoretical background and application of this method. Section 4 presents the empirical applications mentioned above, and section 5 concludes.

2. Literature review

The current literature on price transmission relies almost entirely on the use of non-linear cointegration techniques.[1] Popular models include the asymmetric vector error correction model (AVECM; von Cramon-Taubadel, 1998), the threshold vector error correction model (TVECM;

Goodwin and Piggott, 2001; Greb et al., 2013), and the Markov-Switching vector error correction model (MSVECM; Brümmer et al., 2009; Götz et al., 2013).

All of these models can be characterised as piecewise linear; all are based on the assumption that at any given time price transmission follows one of two or more linear error correction regimes, and that transition between these regimes is governed by an endogenous or exogenous trigger. In the AVECM, for example, prices follow one of two linear error correction processes depending on whether positive or negative deviations from the long-run equilibrium relationship are being corrected. In the TVECM, which linear regime prevails depends on whether the deviation from long-run equilibrium is larger or smaller than a threshold value. The MSVECM switches between linear regimes depending on the value taken by an unobserved state variable. Another example of a piecewise linear model of price transmission is the seasonal error correction model proposed by Amikuzuno and von Cramon-Taubadel (2012), which allows for a distinct linear error correction process in each season.[2]

These models are considerably more flexible than the linear error correction models that were first introduced to price transmission analysis by Ardeni in 1989 (other examples are Gordon et al., 1993; Zanias, 1993). This flexibility has allowed researchers to generate important insights into vertical and spatial price transmission on many agricultural commodity and food markets. Nevertheless, these models are all based on the assumption that the linear error correction model is a valid parametrisation of the price transmission process within each individual regime, and each is based on some parametric assumption about the process that governs switches between regimes.

These assumptions have been criticised as being possibly too restrictive or unrealistic. Serra et al. (2006a), for example, point out that the assumption of a sharp threshold between regimes in the TVECM is only tenable if all traders face the same costs of trade. Otherwise some would respond to smaller deviations from the long-run price equilibrium than others, and the transition between regimes with and without trade would be gradual. Based on these considerations, Serra et al. (2006a; 2006b) and Hassouneh et al. (2011) propose and demonstrate the use of local polynomial regression techniques to estimate non-parametric price transmission models.

By introducing the use of non-parametric methods Serra et al. (2006a; 2006b) and Hassouneh et al. (2011) make an important contribution to the price transmission literature. We propose to continue in this direction by making two contributions. First, the non-parametric approach employed in Serra et al. (2006a; 2006b) and Hassouneh et al. (2011) maintains the assumption that the long-run equilibrium relationship between the prices being studied is constant and linear. There are many settings in which this assumption might be too restrictive. For example, policy changes such as the introduction of a tariff will affect the spatial equilibrium condition for prices in two locations and, thus, alter the long-run relationship between these prices. In the vertical price transmission setting, changes in processing technology and shifts in market power can lead to changes in the long-run equilibrium between prices at different levels of a food chain (Gardner, 1975; Lloyd et al., 2006). Finally, in both vertical and spatial settings the long-run equilibrium might display a seasonal component, for example if product qualities or the costs of transportation between markets display seasonal fluctuations (see for example Holst and von Cramon-Taubadel, 2011). Ideally one would account for such factors explicitly by including appropriate variables in the estimation of the long-run relationship.[3] However, in many cases the variables of interest are difficult or impossible to observe, especially at the high frequency (weekly or daily) at which much commodity price transmission analysis is carried out. Hence, in the following we propose a non-parametric VECM approach that allows for time-varying long-run equilibrium relationships that can capture drifting and seasonal components.

Second, while Serra et al. (2006a; 2006b) employ local polynomial techniques, in recent years non-parametric estimation has been enriched by the refinement of penalised spline techniques (Krivobokova and Kauermann, 2007; Kauermann et al., 2011). In particular, recent advances (Wiesenfarth et al., 2012) allow for estimation and simultaneous direct inference without recourse to re-sampling methods, which can reduce computational costs significantly. The non-parametric VECM approach that we propose employs these techniques.

3. A non-parametric vector error correction model with time-varying cointegration

The method we propose is analog the classical method proposed by Engle and Granger (1987) but extended to apply when the unconstrained expectation of the error correction term exhibits i) a non-linear deterministic variation over time and/or ii) a deterministic seasonal pattern. For estimation we use a two-step method. First we estimate the error correction term allowing for a time-varying cointegrating relationship following Rosales and Krivobokova (2012); and second we estimate the error correction process semi-parametrically using the penalised spline methods developed in Wiesenfarth et. al. (2012).

3.1 Theory

Consider the following extension of the system in Engle and Granger (1987):

$$x_{1,t} + \bar{\gamma} x_{2,t} = e_t + g(t), \tag{1}$$

$$x_{1,t} + \bar{\beta} x_{2,t} = W_t + h(t),$$

measured at times $t = \{1, \ldots, n\}$ for functions $g(t)$ and $h(t)$. Assume $e_t = \vartheta(e_{t-1})e_{t-1} + \mu_t$ and $W_t = W_{t-1} + \nu_t$, with $\mu_t \overset{iid}{\sim} \mathcal{N}(0, \sigma_\mu^2)$, $\nu_t \overset{iid}{\sim} \mathcal{N}(0, \sigma_\nu^2)$ and $\operatorname{cov}(\mu_t, \nu_t) = 0$. Hence e_t is characterized as a smooth transmission auto regressive (STAR) model, where $|\rho(e_{t-1})| \leq 1$ (in fact for the non-reaction regime one would expect $\rho(e_{t-1}) = 1$ so that e_t behaves like a random walk). More specifically $\vartheta(\cdot)$ is a transition function, e.g. logistic or exponential. Both $\bar{\gamma}$ and $\bar{\beta}$ are fixed in time. In this setting $g(t)$ can be seen as a time varying intercept that modulates the long term relationship between $x_{1,t}$ and $x_{2,t}$. As defined here, e_t and W_t contain no seasonality. If the processes defined in (1) contain deterministic seasonal patterns, e.g. $\varsigma_i(t)$ in $X_{i,t} = x_{i_t} + \varsigma_i(t)$ for each $i = \{1,2\}$, these can be removed independently. Equation (1) can be rewritten as:

$$X_{1,t} + \bar{\gamma} X_{2,t} = e_t + \{\varsigma_1(t) + \bar{\gamma}\varsigma_2(t)\} + g(t), \tag{2}$$

$$X_{1,t} + \bar{\beta} X_{2,t} = W_t + \{\varsigma_1(t) + \bar{\beta}\varsigma_2(t)\} + h(t),$$

where the first equation is of special interest since it accounts for common features mentioned in the previous section, i.e. a remainder with a drifting (possibly nonlinear) component and a seasonal pattern in the error correction term, see e.g. Holst and von Cramon-Taubadel (2011). Solving (2) for between $x_{1,t}$ and $x_{2,t}$ leads to:

$$x_{2,t} = +\left(\frac{1}{\bar{\gamma}-\bar{\beta}}\right)e_t - \left(\frac{1}{\bar{\gamma}-\bar{\beta}}\right)W_t + \left\{\frac{g(t)-h(t)}{\bar{\gamma}-\bar{\beta}}\right\}.$$

Since the seasonalities cancel out in the derivation of (3), subsequent analysis can focus on the deseasonalized series. This is not a surprising feature, as a number of authors have suggested that whenever determinisitic seasonality is present, it should be removed (e.g. Box and Jenkins, 1970; Engle and Granger, 1987; Hylleberg et. al., 1990).

From (3) we obtain the error correction representation by taking differences:

$$\Delta x_{1,t} = \varrho_1(e_{t-1}) + \tau_1(t) + \varepsilon_{1,t}, \qquad (4)$$

$$\Delta x_{2,t} = \varrho_2(e_{t-1}) + \tau_2(t) + \varepsilon_{2,t},$$

where $\varrho_i(e_{t-1}) = \rho_i(e_{t-1})e_{t-1}$, $\tau_1(t) = -(\bar{\beta}\Delta g(t) - \bar{\gamma}\Delta h(t))/(\bar{\gamma}-\bar{\beta})$, $\tau_2(t) = (\Delta g(t) - \Delta h(t))/(\bar{\gamma}-\bar{\beta})$, $\varepsilon_{1,t} = (\bar{\gamma}\nu_t - \bar{\beta}\mu_t)/(\bar{\gamma}-\bar{\beta})$ and $\varepsilon_{2,t} = (\mu_t - \nu_t)/(\bar{\gamma}-\bar{\beta})$ so that in general $\mathrm{cov}\,(\varepsilon_{1,t}, \varepsilon_{2,t}) \neq 0$ unless $-\bar{\gamma}/\bar{\beta} = \sigma_\mu^2/\sigma_\nu^2$ holds.[4] Moreover, the adjustment speeds can be computed as the first derivatives of $\varrho_i(e_{t-1})$, $i = \{1,2\}$.

3.2 Estimation

Once the data is deseasonalized (if necesary), estimation of the non-parametric VECM can be conducted in two steps. In the first step the error correction term is computed non-parametrically from (1), and in the second step the adjustment speeds are computed semi-parametrically from (4).

The first step is equivalent to the estimation of $\bar{\gamma}$ and $g(t)$. A direct semi-parametric estimation to compute both $\bar{\gamma}$ and g(t) simultaneously would be ideal. However, methods that use non-intrusive/data-driven smoothing parameter selection suffer from an indentification problem in this setting: the magnitude of $\bar{\gamma}$ tends to be underestimated since the inherent flexibility of g(t) allows it to explain most of the variance in $x_{1,t}$.[5] Estimating $\bar{\gamma}$ first by OLS and then estimating

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[4] This condition is equivalent to $\varepsilon_{1,t} = -\bar{\gamma}\bar{\beta}\varepsilon_{2,t}$.

g(t) non-parametrically is also not possible as omiting g(t) in the initial OLS estimation of $\bar{\gamma}$ would induce bias.

To solve this problem consider the decomposition $x_{i,t} = f_i(t) + \epsilon_{i,t}$ for $i = \{1,2\}$ as presented in Rosales and Krivobokova (2012), where $f_i(t)$ represents the trend of each series. Define $\eta_i(t) := f_i(t) - f(t)$, where $f(t)$ is the common factor defined as $f(t) := 0.5f_1(t) + 0.5f_2(t)$, so that it portrays the co-movement of the two series. To identify the second equation in model (1), its connection and the previous decomposition scheme can be seen after taking expectations and dividing by $(1+\bar{\beta})$, so that $h(t) = (1+\bar{\beta})f(t)$ for $\bar{\omega}_1 = 1/(1+\bar{\beta})$ and $\bar{\omega}_2 := \bar{\beta}/(1+\bar{\beta})$.

To identify the first equation in model (1) we suggest to estimating the long-run relationship between $x_{1,t}$ and $x_{2,t}$ by solving:

$$(x_{1,t} - \eta_{1,t}) + \tilde{\gamma}(x_{2,t} - \eta_{2,t}) = \tilde{e}_t + \tilde{g}$$

via Engle and Granger (1987) for constants $\tilde{\gamma}$ and $\tilde{g}$ and error term $\tilde{e}_t$. This is equivalent to setting $\bar{\gamma} = -1$ and estimating the time varying intercept as $\hat{g}(t) = \hat{\eta}_1(t) - \hat{\eta}_2(t)$ in (1), leading to an unbiased estimate of e_{t-1}.

The second step can be performed by a direct semiparametric extension of (4) following Wiesenfarth et. al. (2012). Specifically we solve:

$$\Delta x_{i,t} = \varrho_i(e_{t-1}) + \tau_i(t) + \varepsilon_{i,t}, \quad (5)$$

with $\varepsilon_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\varepsilon_i})$ and assuming $\mathrm{cov}\,(\varepsilon_{i,t}, \varepsilon_{j,t}) = \delta_{i,j}$ for $\delta_{i,j}$ the kronecker delta and $i = \{1,2\}$. From the estimation of (5) the adjustment speeds can be directly obtained as $\hat{\rho}_i(e_{t-1}) = \partial\hat{\varrho}_i(e_{t-1})/\,\partial e_{t-1}$, so that $\beta(e_{t-1})$ can be recovered as $-\hat{\rho}_1(e_{t-1})/\hat{\rho}_2(e_{t-1})$.

4. Applications

In the following we present two applications that demonstrate the use of the proposed non-parametric VECM. The first application considers the spatial transmission of wheat prices between Ukraine and France, and the second application considers vertical transmission between

4.1 Spatial wheat price transmission between Ukraine and France

The first application is based on nine years of weekly observations of wheat prices in France and Ukraine from 2005 to 2013 (figure 1). The French price is for class 1 soft wheat fob Rouen (HGCA). The Ukrainian price is an ex-warehouse price for class III milling wheat (APK-Inform).[6] Both prices are in US$/t.

(Figure 1)

France and Ukraine are major exporters of wheat, and wheat prices in both countries are influenced by conditions on world markets. However, the relationship between these two prices might vary over time in a complex manner for a number of reasons. First, changes in the costs of international trade (for example due to varying energy costs but also due large investments in Ukrainian port facilities in recent years) can affect the transaction costs that link these two prices to world market prices and, thus, each other. Second, the importance of different export destinations for French and Ukrainian wheat can vary from year to year, as importers' specific needs and the qualities and volumes produced in France, Ukraine and competing exporting countries (such as the US, Canada and Russia) change from year to year. This can also affect the relevant transaction costs between each of these prices and world market prices over time. Third, while the EU has effectively liberalised its wheat export regime and made no use of price distorting measures such as export subsidies during the sample period, Ukraine has periodically implemented export restrictions such as taxes and quotas (von Cramon-Taubadel and Raiser, 2006; Berlin Economics, 2011). These factors might cause both the long-run relationship between French and Ukrainian wheat prices, and the mechanism which ensures that they respond to correct deviations from this long-run relationship, to vary over time. For example, Götz et al. (2013) employ an MSVECM to study the effect of export restrictions on price transmission between Ukrainian and world market prices for grain.

Figure 1 displays the series-specific trends $f_i(t)$ for $i = \{\text{France}, \text{Ukraine}\}$. These trends are used to purge each price of its series-specific deviation, and the resulting series are depicted in Figure 2. The adjustment responses estimated semi-parametrically using these purged prices are presented in Figure 3, together with the corresponding 95% confidence intervals. For comparison, the regularized Bayesian method proposed by Greb et al. (2013, 2014). Detailed TVECM results are presented in Table 1.

(Figure 2)

In figure 3 we see that only French prices respond significantly to positive deviations from the long-run equilibrium relationship (i.e. when prices in France are too high relative to prices in Ukraine, on the right hand sides of panels a and b). This was the case for example in late 2007-early 2008 and late 2010-early 2011 (see figure 2). In both of these periods Ukraine imposed export restrictions for wheat, so the finding that Ukrainian prices were not adjusting to large disequilibria is very plausible. We also see that only the Ukrainian prices respond significantly to negative deviations (i.e. when prices in Ukraine are too high relative to prices in France – on the left hand sides of panels a and b). This was the case for example in early 2006 and early 2010 (see figure 2).

French price adjustment becomes significant when the deviation from equilibrium exceeds roughly 60 $/t, and reaches values of approximately 20%/week for large deviations (figure 3, panel a). Ukrainian price adjustments becomes significant when the deviation from equilibrium falls below roughly -20 $/t, and attains 30%/week for large negative deviations (figure 3, panel b). Comparison with the TVECM estimates of the adjustment parameters (in red in figure 3) shows that the non-parametric estimates provide a much richer depiction of price transmission behaviour between these two markets. The TVECM results suggest that French prices do not adjust at all to deviations from the long-run equilibrium, and that the Ukrainian prices display some, comparatively weak adjustment, but only to a small number of large negative deviations from equilibrium (see also Table 1).

(Figure 3)

(Table 1)

4.2 Vertical transmission between piglet and slaughter pig prices in Germany

Our second application considers transmission between piglet and slaughter pig prices in is an average price for the main classes of slaughter pig in Euro/kg also in Lower Saxony, which is the largest pork producing region in Germany (Land- und Forstwirtschaftliche Zeitung; Holst and von Cramon-Taubadel, 2011).

Slaughter pig producers in Germany generally purchase piglets from specialised farrowing operations located in Germany but increasingly also in Denmark and the Netherlands. After feed, which accounts for roughly one-half of the cost of slaughter pig production, piglets are the second largest cost component with a share of roughly 40%. While slaughter pig producers are largely price takers on the markets for inputs such as feed, energy and labour, piglets are a specialised input for which there is essentially no alternative demand. Hence, piglet prices depend heavily on the expected profitability of slaughter pig production and, thus, slaughter pig prices. This, in turn, depends on conditions on pork markets, which are subject to well-known cyclical fluctuations (Berg and Huffaker, 2014).

Holst and von Cramon-Taubadel (2011) hypothesise that when pork prices are in the declining phase of a cycle, slaughter pig producers will be less interested in purchasing piglets, leading, ceteris paribus, to oversupply. On the resulting buyers' market for piglets, slaughter pig producers will be able to pass negative price shocks on to piglet producers more rapidly than positive shocks; i.e. price transmission between slaughter pig and piglet prices will be characterised by negative asymmetry (Meyer and von Cramon-Taubadel, 2004). The opposite will hold when pork prices are in the increasing phase of a cycle: slaughter pig producers will be eager to expand production, and the resulting sellers' market for piglets will be characterised by positive asymmetry – sometimes referred to as the "rockets and feathers" phenomenon (Bacon, 1991) – whereby piglet prices react quickly when slaughter pig prices increase, but slowly when they fall. Holst and von Cramon-Taubadel test this hypothesis by means of a piecewise linear error correction model. They first use the Hodrick-Prescott (1997) filter to extract a smooth cyclical component from the series of slaughter pig prices and divide their dataset into increasing and decreasing phases of pork prices. They then estimate a separate AECM for each of these phases and find support for the hypothesis of alternating regimes of positive and negative asymmetric price transmission.

Figure 4 displays the series-specific trends $f_i(t)$ for $i = \{\text{piglets}, \text{slaughter pigs}\}$. In this case the common trend and the series specific trend for slaughter pig prices are almost identical (not shown), indicating that common trend is largely driven by the slaughter pig prices and that the piglet prices mostly follow. Inspection of figure 4 also reveals that the piglet and the slaughter pig prices both display seasonal fluctuations. De-seasonalising following Rosales and Krivobokova (2012) and subtracting the series-specific deviation from each price results in the series depicted in figure 5. The adjustment responses estimated semi-parametrically using these series are presented in figure 6, together with the corresponding 95% confidence intervals. We again include estimated adjustment parameters from a TVEMC for comparison.

(Figure 5)

Figure 6 shows that slaughter pig prices do not react significantly to any deviations from the long-run equilibrium – the estimated adjustment response is very close to 0 over the entire range of deviations (panel b). Hence, as expected the burden of adjustment to disequilibrium is borne by the piglet prices, which react to positive and negative deviations. The adjustment of piglet prices is significant for negative deviations beginning at roughly -0.1 and increased from a rate of roughly 7%/week to 23%/week (left side of panel a). The adjustment of piglet prices to positive deviations is weaker and not significant at the 5% level, but is significant at the 10% level for deviations greater than or equal to roughly 0.05, reaching rates of 10-13%/week for larger deviations. These results suggest that piglet prices react more strongly when they are too high vis-à-vis slaughter pig prices, i.e. when the slaughter pig producers' margins are squeezed. When piglet prices are too low, which increases slaughter pig producers' margins, the reaction of piglet prices is smaller and less significant.

5. Conclusions

The current price transmission literature largely draws on piecewise-linear or regime-dependent VECM specifications such as the threshold VECM and the Markov-switching VECM. While these specifications are more flexible than the linear VECM, they are all based on the assumption that the linear VECM is a valid parametrisation of the price transmission process within each individual regime, and each is based on some parametric assumption about the process that governs switches between regimes. These assumptions have been criticized as too restrictive, leading some authors (Serra et al., 2006a and 2006b; Hassouneh et al., 2011) to propose the use of non-parametric estimation techniques. We propose a fully data-driven non-parametric VECM estimation method that allows for non-parametric error correction but also a time varying long-run equilibrium relationship. Application to two examples illustrates that the proposed method generates interesting and intuitive insights in to the complex nature of price transmission processes.

Ongoing work is looking into the generalization of the method beyond pairs of prices to the multivariate analysis of spatial price networks or multiple-link vertical food price chains. A fundamental issue that requires further exploration is the distribution of smoothing/flexibility between the long-run equilibrium relationship and the error correction process in a VECM. Further applications of the proposed method will provide more information on its strengths and limitations.

References

Amikuzuno, J., von Cramon-Taubadel, S., 2012. Seasonal Variation in Price Transmission between Tomato Markets in Ghana. Journal of African Economics 21, 669–686.

APK-Inform. Unpublished data. Dnipropetrovsk, Ukraine.

Ardeni, P. G., 1989. Does the law of one price really hold for commodity prices? American Journal of Agricultural Economics 71, 661–669.

Bacon, R. W., 1991. Rockets and feathers: The asymmetric speed of adjustment of UK retail gasoline prices to cost changes. Energy Economics 13, 211-218.

Barrett, C. B., Li, J. R., 2002. Distinguishing between equilibrium and integration in spatial price analysis. American Journal of Agricultural Economics 84, 292–307.

Berg, E., Huffaker, R., 2014. What drives the German hog price cycle? Diagnostic modelling of a nonlinear dynamic system. Paper presented to the European Association of Agricultural Economists Congress, Ljubljana, August 2014.

Berlin Economics, 2011. Turning Ukrainian Agriculture into an Engine of Growth: A Strategy for the Development of the Grains and Oilseeds Sector. Study prepared for the American Chamber of Commerce and the European Business Association, Kiev.

Box, G. E. P., Jenkins, G. M., 1970. Time Series Analysis - Forecasting and Control. Holden Day, San Francisco.

Brümmer, B., von Cramon-Taubadel, S., Zorya, S., 2009. The impact of market and policy instability on price transmission between wheat and flour in Ukraine. European Review of Agricultural Economics 36, 203–230.

Dillon, B. M., Barrett, C. B., 2013. The Impact of World Oil Price Shocks on Maize Prices in East Africa. Paper presented to the Australian Agricultural & Resource Economics Society Meetings, Sydney, May 2013.

Engle, R. F., Granger, C. W. J., 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica 55, 251–276.

Gardner, B. L., 1975. The Farm-Retail Price Spread in a Competitive Food Industry. American Journal of Agricultural Economics 57, 399–409.

Götz, L., Glauben, T., Brümmer, B., 2013. Wheat export restrictions and domestic market effects in Russia and Ukraine during the food crisis. Food Policy 38, 214–226.

Goodwin, B. K., Piggott, N., 2001. Spatial market integration in the presence of threshold effects. American Journal of Agricultural Economics 83, 302–317.

Gordon, D. V., Hobbs, J. E. Kerr, W. A., 1993. A test for price integration in the EC lamb market. Journal of Agricultural Economics 44, 126–134.

Greb, F., von Cramon-Taubadel, S., Krivobokova, T., Munk, A., 2013. The Estimation of Threshold Models in Price Transmission Analysis. American Journal of Agricultural Economics 95, 900–916.

Greb, F., Krivobokova, T., Munk, A., von Cramon-Taubadel, S., 2014. Regularized Bayesian estimation of generalized threshold regression models. Bayesian Analysis 9, 171–196.

Hassouneh, I., Serra, T., Gil, J. M., 2011. Non-parametric and Parametric Modeling of Biodiesel - Sunflower Oil - Crude Oil Price Relationships. Paper presented at the EAAE Congress , Zurich, August 30 to September 2, 2011.

HGCA (Home Grown Cereals Authority). Internet database.

Hodrick, R. J., Prescott, E. C., 1997. Post-War U.S. Business Cycles: A Descriptive Empirical Investigation. Journal of Money, Credit, and Banking 29, 1–16.

Holst, C., von Cramon-Taubadel, S., 2011. Einfluss des Schweinezyklus auf die Preistransmission zwischen Ferkel- und Schlachtschweinepreisen in Niedersachsen, in M. Banse et al., eds. Möglichkeiten und Grenzen der wissenschaftlichen Politikanalyse. Schriften der

Hylleberg, S., Engle, R. F., Granger, C. W. J., Yoo, B. S., 1990. Seasonal integration and cointegration. Journal of Econometrics 44, 215–238.

Kauermann, G., Krivobokova, T., Semmler, W., 2011. Filtering time series with penalized splines. Studies in Nonlinear Dynamics & Econometrics 15, Article 2.

Krivobokova, T., Kauermann, G., 2007. A note on penalized spline smoothing with correlated errors. Journal of the American Statistical Association 102: 1328–1337.

Land und Forstwirtschaftliche Zeitung. Amtliche Preismitteilungen für Niedersachsen. Deutscher Landwirtschaftsverlag, Hannover.

Lloyd, T., McCorriston, S., Morgan, W., Rayner, A. J., 2006. Food Scares, Market Power and Price Transmission: the UK BSE Case. European Review of Agricultural Economics 33, 119–147.

Meyer, J., von Cramon-Taubadel, S., 2004. Asymmetric price transmission: A Survey. Journal of Agricultural Economics 55, 581–611.

Miller, D. J., Hayenga, M. L., 2001. Price Cycles and Asymmetric Price Transmission in the U.S. Pork Market. American Journal of Agricultural Economics 83, 551–562.

Rosales, F. and Krivobokova, T., 2012. Instant trend-seasonal decomposition of time series with splines. Working paper. Courant Research Center for Poverty Equality and Growth in Developing Countries.

Serra, T., Gil, J. M., Goodwin, B. K., 2006a. Local polynomial fitting and spatial price relationships: price transmission in EU pork markets. European Review of Agricultural Economics 33, 415–436.

Serra, T., Goodwin, B. K., Gil, J. M., Mancuso, A., 2006b. Non-parametric modelling of spatial price relationships. Journal of Agricultural Economics 57, 501–522.

Teräsvirta, T., Eliasson, A.C., 2001. Non-linear error correction and the UK demand for broad money, 1878–1993. Journal of Applied Econometrics 16, 277–288.

von Cramon-Taubadel, S., 1998. Estimating asymmetric price transmission with the error correction representation: An application to the German pork market. European Review of Agricultural Economics 25, 1–18.

von Cramon-Taubadel, S., Raiser, M., 2006. The Quotas on Grain Exports in Ukraine: ineffective, inefficient, and non-transparent. German Advisory Group on Economic Reform and The World Bank Country Office Ukraine, Kiev.

Wiesenfarth, M., Krivobokova, T., Klasen, S., Sperlich, S., 2012. Direct simultaneous inference in additive models and its application to model undernutrition. Journal of the American Statistical Association 107, 1286–1296.

Zanias, G. P., 1993. Testing for integration in European Community agricultural productmarkets. Journal of Agricultural Economics 44, 418–427.

Figure 1: Wheat prices in France and Ukraine (US$/t, 2005-2013)

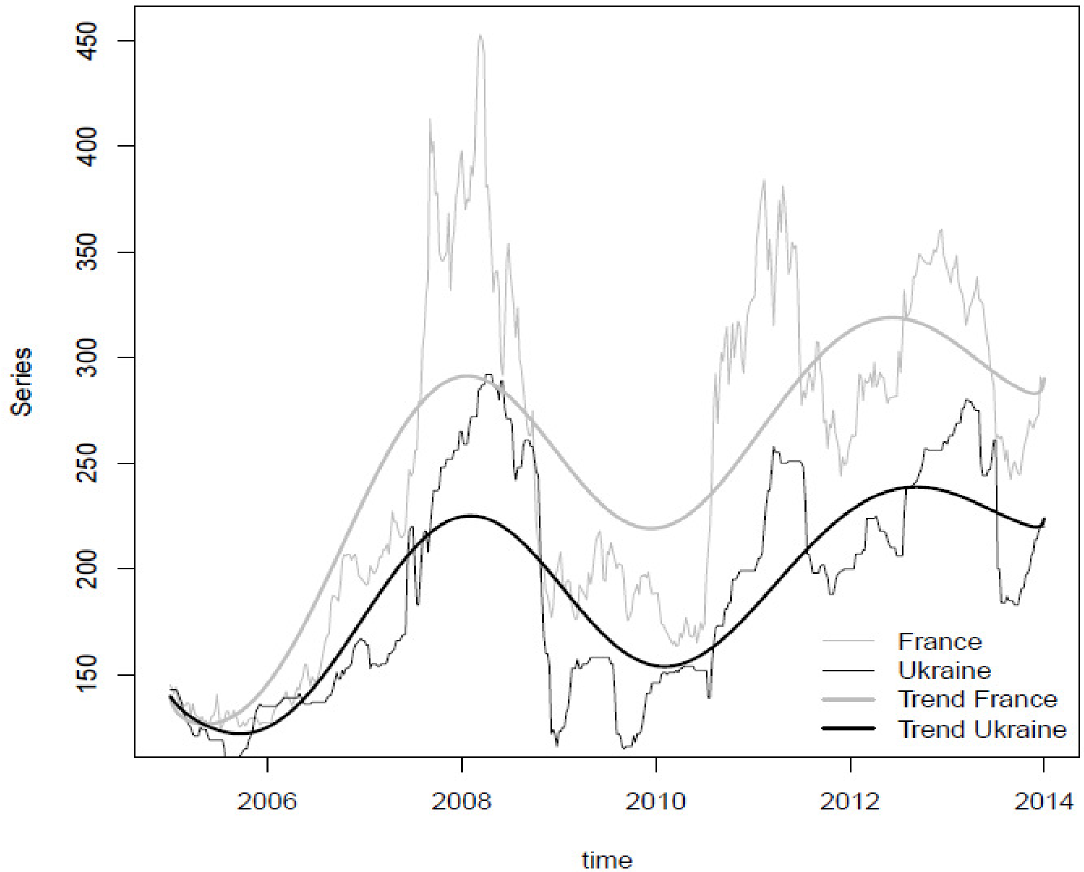


Figure 2: Wheat prices in France and Ukraine minus their series-specific deviations (US$/t, 2005-2013)

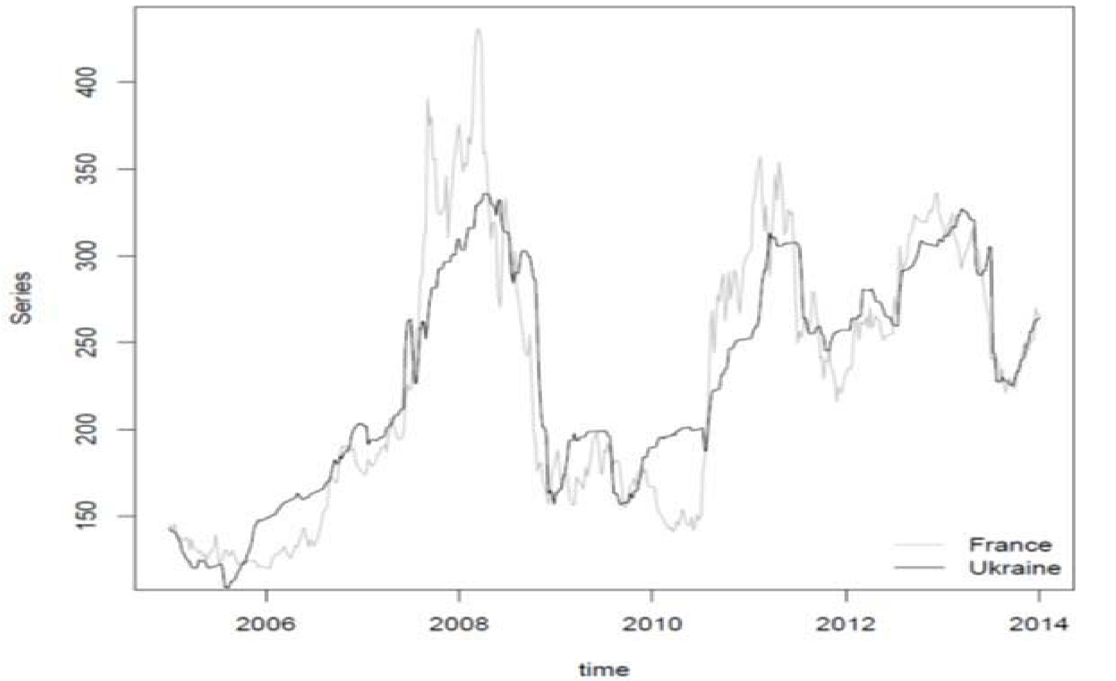
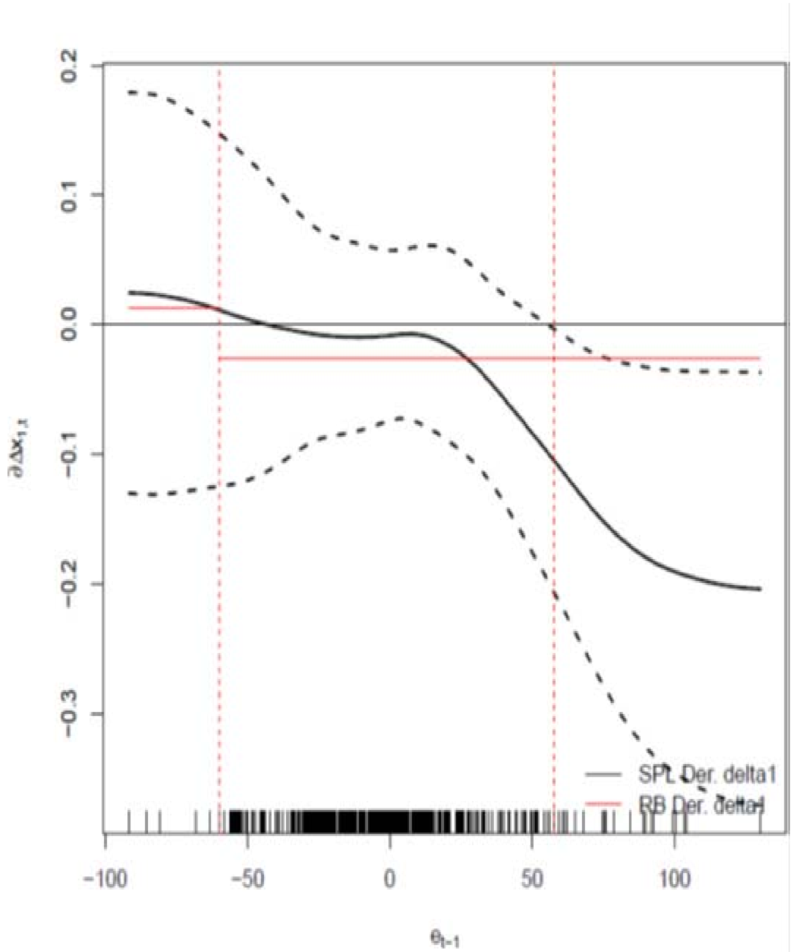


Figure 3: Estimated non-parametric adjustment of French and Ukrainian wheat price

a) Adjustment of French prices



b) Adjustment of Ukrainian prices

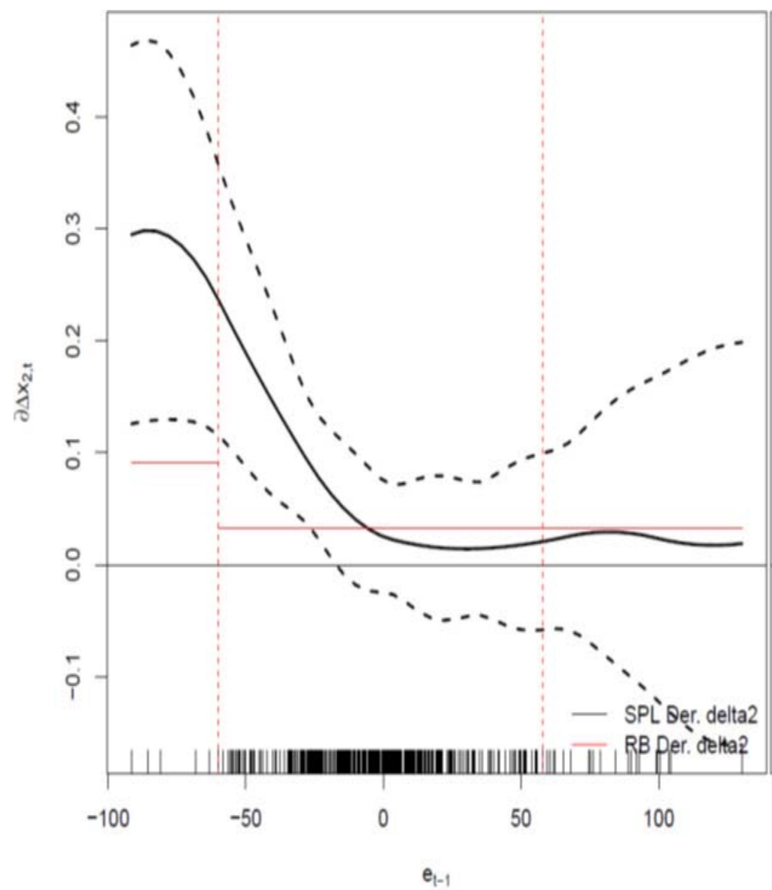


Figure 4: Piglet and slaughter pig prices in Germany (Euro/piglet and Euro/kg, 1996-2013)

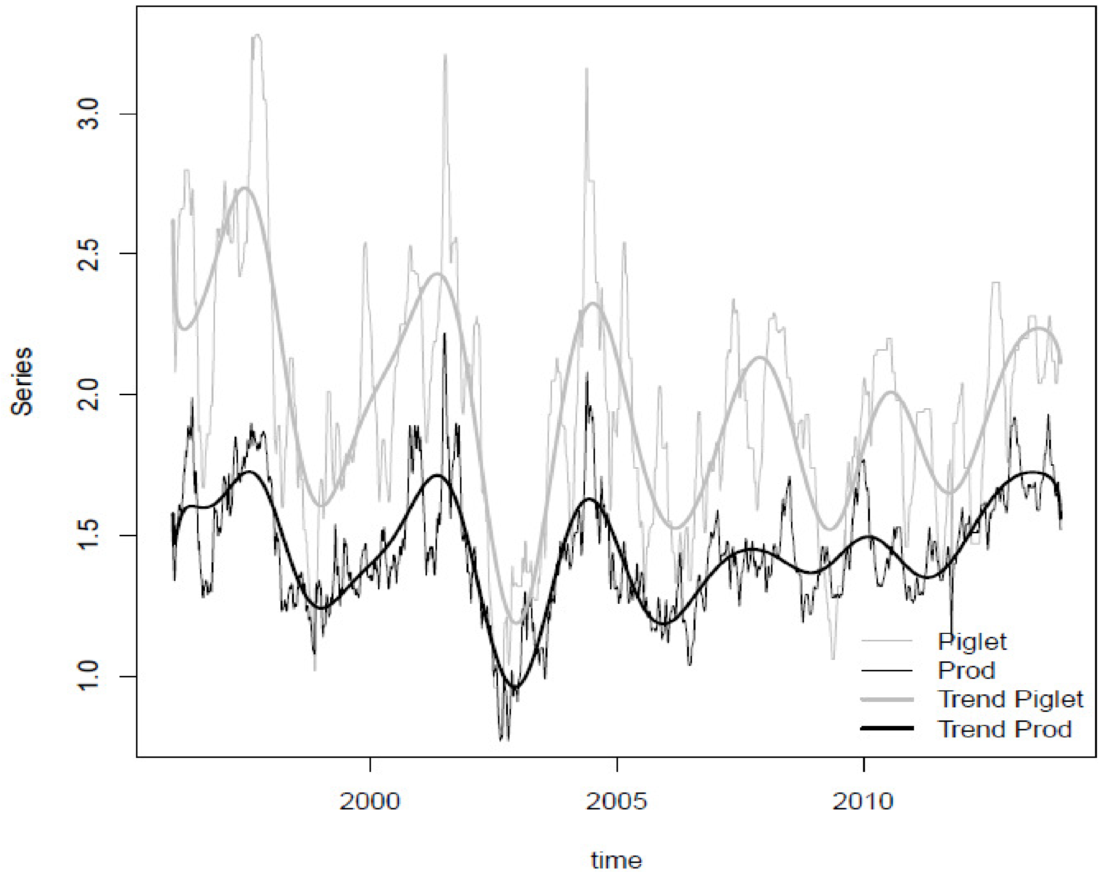


Figure 5: Piglet and slaughter pig prices in Germany, de-seasonalised and minus their series-specific deviations

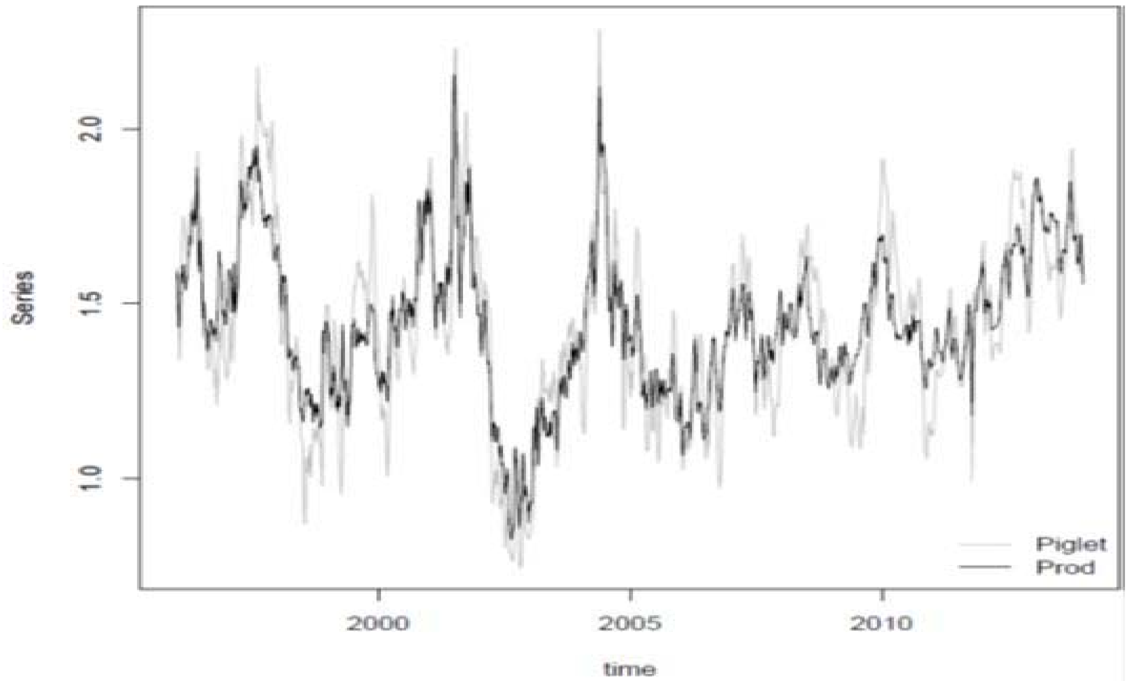
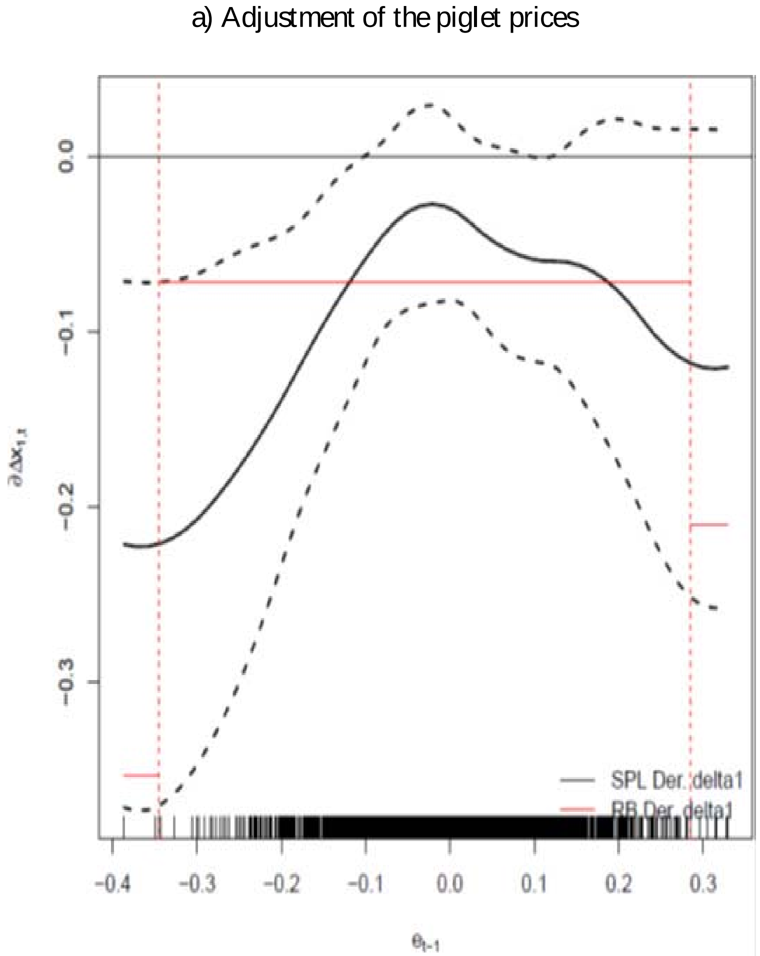


Figure 6: Estimated non-parametric adjustment of piglet and slaughter pig prices



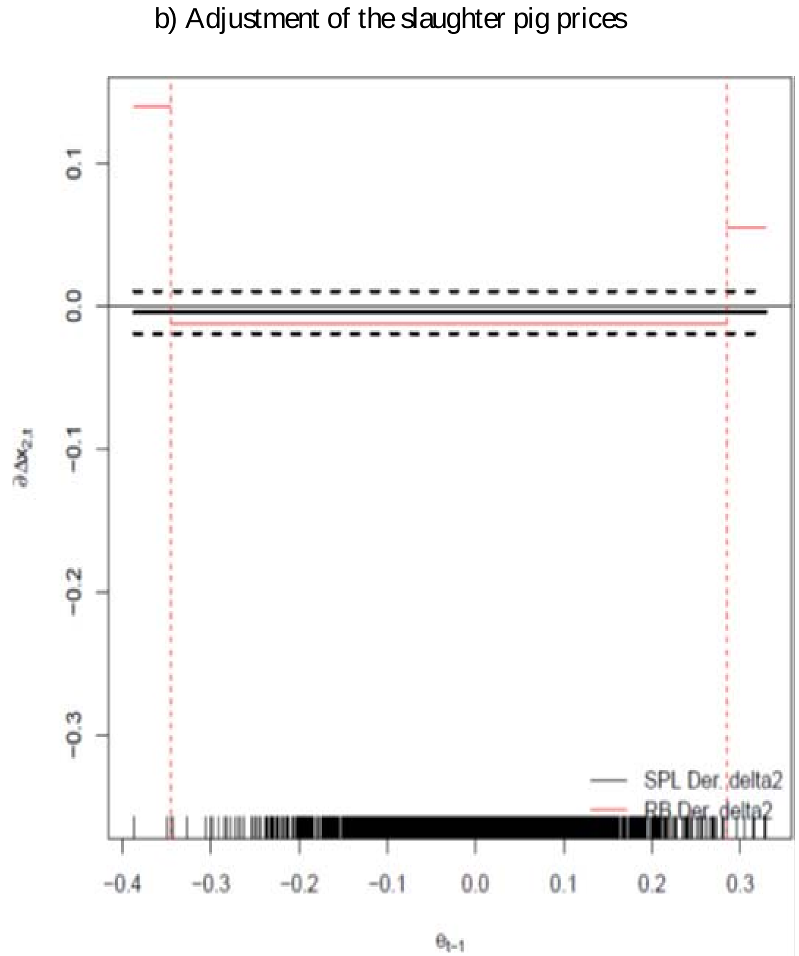


Table 1: Results of the threshold vector error correction model estimation

		France[1]	Ukraine[2]	Piglet[3]	Slaughter pig[4]
Step 1	Theta1	1,4510	1,4600	0,0047	0,0035
	Gamma	-1,0000	-	-1,0000	-
Step 2	Threshold 1	-60	-	-0,34	-
	Threshold 2	57	-	0,28	-
	Rho1 (lower)	0,0129	0,0819	-0,3534	0,0535
	Rho1 (middle)	-0,0259	0,0164	-0,0722	0,0095
	Rho1 (upper)	-0,0259	0,0164	-0,2097	0,0481
	Rho2 (lower)	0,0907	0,0662	0,1399	0,0661
	Rho2 (middle)	0,0324	0,0088	-0,0127	0,0079
	Rho2 (upper)	0,0324	0,0088	0,0549	0,0509

[1] Lags dx1.1, dx1.2 and dx2.4 were statistically significant and included in the regression

[2] Lags dx1.1 and dx2.1 were statistically significant and included in the regression

[3] Lags dx1.1, dx2.1 and level dx2 were statistically significant and included in the regression

[4] Lags dx1.1, dx1.3, dx2.1, dx2.2, dx2.3 and level dx1 were statistically significant and included in the regression.