Spatial Price Transmission in Major EU Pigmeat Markets: An Empirical Investigation with a Non Parametric Approach

Panos Fousekis*

Massey University, New Zealand

Abstract: This work investigates price transmission between five major EU spatial pigmeat markets using the non parametric Local Linear regression estimator and statistical tests capable of disentangling local non linearity from global linearity. The empirical results suggest that global linearity (or equivalently symmetry of price transmission) is consistent with the real world data. The speeds of price transmission, however, are generally small and the associated with them half-lives are large.

Keywords: Price Transmission, Pigmeat, EU, Non Parametric Regression
JEL Classification: Q13, C10

1. Introduction

Spatial price transmission has been a very important topic in applied microeconomics research since it is related to the functioning of geographically separated markets. When such markets are integrated (efficient) price shocks in one of them trigger responses in the others; arbitrage activities ensure that prices of a homogeneous commodity in two separate locations will differ, by at most, the cost of moving the commodity from the low- to the high-price location (e.g. Emmanoulides and Fousekis, 2012; Serra et al., 2006a; Goodwin and Piggott, 2001).

The empirical investigations typically focus on two aspects of spatial price transmission, namely, its speed and its symmetry. A high speed implies that price differentials are quickly arbitraged away and this is taken as an indication of a high degree of market integration. A symmetric (or equivalently globally linear) price transmission indicates that none of the trading partners enjoys an advantage over another. Under symmetry, positive and negative shocks (for example) in the low-price market are transmitted with the same intensity to the high-price market; that means, consumers in the importing location are equally likely to feel an increase and a decrease of the price in the exporting location.

The vast majority of econometric studies of price transmission has relied on parametric models which require the specification of an exact functional form prior to the estimation. The piecewise-linear parametric models such as the Threshold Autoregression (TAR), the Asymmetric Vector Error Correction (AVECM), and the Threshold Vector Error Correction (TVECM) allow for abrupt and discontinuous transitions from one transmission regime to the other. The smooth switching models such as the STAR (Smooth Transition Autoregression) and the STVECM (Smooth Transition Vector Error Correction Model), allow for a continuous transition between regimes[1].

A well known problem of parametric approaches is that, unless the number of regimes (in the case of the piecewise-linear models) or the smooth transition function (in the case of the continuous switching models) is correctly specified, they lead to biased and inconsistent parameter estimates (e.g. Hassouneh et al., 2012; Serra et al., 2006a)

The non parametric techniques, in contrast, are data-driven; they do not impose any functional form *a priori* and they offer a very flexible way to analyze price transmission in the physical or in the product quality space. To the best of knowledge, there has been less than a handful of empirical works on spatial price transmission using non parametric regression tools. Those were by Serra et al. (2006a) and by Serra et al. (2006b) who investigated price relationships in four EU pork markets over the period 1993 to 2004, and in four US eggs markets over the period 1882 to 1910, respectively. The above mentioned works provided certain useful insights about the patterns of price transmission in the markets examined. Those insights, however, were based exclusively on the visual graphical inspection of the non parametric regression fits (no formal statistical tests on linearity were performed). That was certainly a limitation; a non parametric regression fit may appear to be non linear in certain regions just because of the influence of few observations while the underlying data generation process may well be consistent with linear price transmission.

The objective of the present work is to investigate spatial price transmission in five major EU pigmeat markets. The investigation is based on the non parametric approach of local polynomial modeling. To avoid the potential pitfalls associated with the simple visual graphical inspection, this study exploits the fact that non parametric models "nest" their parametric alternatives and it relies on formal statistical tests to disentangle global from local linearity. In what follows section 2 presents the analytical framework and section 3 presents the data, the empirical models, and the results. Section 4 concludes.

2. Theoretical Framework

Let p_{it} and p_{jt} be the logarithmic prices at time *t* of a homogenous commodity in the geographically separated markets *i* and *j*, respectively. A focal point of the spatial price transmission literature is the relationship between the price differential in *t*-1, denoted by $p_{t-1} = p_{it-1} - p_{jt-1}$ and the adjustment of that differential in period *t*, denoted by $\Delta p_t = p_t - p_{t-1}$. Provided that price transmission is (globally) linear, p_{t-1} and Δp_t are related through the standard autoregressive AR(1) model of the form

$$\Delta p_t = \beta_0 + \beta_1 p_{t-1} \tag{1}$$

In relation (1), the slope is constant suggesting that a change in period's *t*-1 price differential causes, at the margin, an adjustment equal to β_1 for any possible value of p_{t-1}. Moreover, for stationary price differentials the slope is a negative number implying that "high" (i.e. above the long-run equilibrium value) price differentials in *t*-1 tend to adjust downwards in period *t* and "low" (i.e. below the long-run equilibrium value) price differentials in *t*-1 tend to adjust upwards in order to ensure mean reversion.

The literature on spatial price transmission has cited a number of factors which may render the relationship between Δp_t and p_{t-1} a non linear one (meaning that the slope of (1) and, in turn, the *speed of price transmission* is not constant but it depends on the value of p_{t-1}). These include, among others, possession of local market power, asymmetric information between central (hub) and peripheral (spoke) markets, and asymmetric transaction costs (e.g. Meyer and von Cramon Taubadel, 2004). The presence of non linearity affects the intensity at which price shocks in *t*-1 are transmitted to period *t*. For example, positive price shocks may be transmitted with higher intensity (speed) than the negative ones or large positive and large negative shocks may be transmitted but small price shocks may not.

The *Local Polynomial* (LP) modeling (e.g. Cleveland, 1979; Fan and Gijbels, 1996; Li and Racine, 2007) which does not require any restrictive assumptions about the functional form of the relationship between Δp_t and p_{t-1} offers a flexible way to investigate the nature of price transmission. Given a set of observations $(\Delta p_t, p_{t-1})$ for t = 2, …, n, the idea behind LP modeling is to estimate for every individual u (focal point) in the set of p_{t-1} values the following regression

$$\Delta p_t = m(u) + e_t = E(\Delta p_t / p_{t-1} = u) + e_t \tag{2}$$

where *m* stands for the smooth conditional mean function, E for the expectation operator, and *e* for the error term. Because *m* is unknown but smooth, it may be locally approximated by a Taylor series expansion

$$m(p_{t-1}) = \beta_0(u) + \beta_1(u)(p_{t-1} - u) + ... + \beta_k(u)(p_{t-1} - u)^k \tag{3}$$

Relative theoretical research showed that odd order *k* polynomials are preferable to even order ones (e.g. Fan and Gijbels, 1996; Racine, 2008). Among the odd order polynomials the most popular involves *k*=1 which leads to the *Local Linear* (LL) non parametric regression estimator. Note that exactly the same estimator has been employed by the earlier works of Serra et al. (2006a) and Serra et al. (2006b). With *k*=1 the value of the regression at the focal point is $\beta_0(u)$ and its slope is $\beta_1(u)$.

Observations closer to u contain more information about the behavior of regression line at the point of evaluation compared to more remote ones. Therefore, the regression function at the neighborhood of u is estimated by weighted least squares where weights $w_l(p_l)$ are assigned through a *kernel function* (*K*)

$$w_l(u) = K(\frac{p_l - u}{h(u)}) \tag{4}$$

with *h* being the *bandwidth* and *l* = 2, …, *n*. The parameters $\beta_0(u)$ and $\beta_1(u)$ are then obtained by solving the following optimization problem

$$\hat{m}(u) = \min_{\beta_0(u), \beta_1(u)} \sum_{l=2}^{n} (\Delta p_l - \beta_0(u) - \beta_1(u)(p_l - u))^2 w_l(p_l) \tag{5}$$

The fitted value at the focal point u may be written as

$$\hat{m}(u) = \theta^T(u)\Delta p \tag{6}$$

where $\theta^T(u) = (\theta_2(u), ..., \theta_n(u))$ is the *projection* (smoothing) *row* that converts vector Δp into $\hat{m}(u)$. In accordance with (6), the vector of all fitted values may be written as

$$\hat{M} = \Theta \Delta p \tag{7}$$

where Θ is the *projection* (smoothing) *matrix* having as rows the $\theta^T(u)$ vectors for all individual focal points *u* [2].

The *equivalent number* of parameters from the LL regression is $df_{MOD} = tr(\Theta\Theta^T)$, the residual degrees of freedom are $df_{RES} = (n-1) - df_{MOD}$, the estimated error variance is $S^2 = \frac{\sum_{l=2}^{n}(\hat{e}_l)^2}{df_{RES}}$, and the estimated variance of the fitted value at the focal point u is $\hat{Var}(\hat{m}(u)) = S^2 \sum_{l=2}^{n} \theta_l^2(u)$ (Loader, 1997; Fox, 2005). Note that, in contrast with parametric regression models, the equivalent number of parameters for a LL model is not necessarily an integer. Connecting the predicted values at all possible focal points produces the non parametric regression fit. Pointwise, 95-percent confidence intervals around each $\hat{m}(u)$ may be approximated as $\hat{m}(u) \pm 2\hat{Var}(\hat{m}(u))$.

A non parametric model "nests" its parametric alternatives. Therefore, in testing for the nature of the relationship between Δp_t and p_{t-1} (globally linear vs non linear) the LL model described by the equations (3) to (7) is the unrestricted while the parametric (globally) linear model in equation (1) is the restricted; the idea is of course that a linear relationship is a special case of a potentially non linear relationship. The relevant test statistic is

$$F = \frac{(RSS_R - RSS_U)/(df_{MOD} - 2)}{RSS_U / df_{RES}} \qquad (8)$$

where RSS_R and RSS_U are the residual sum of squares from the restricted (globally linear) and the unrestricted (LL) models, respectively; 2 is the number of parameters of the globally linear model (Fox, 2005). The statistic given in (8) follows the *F*-distribution with $df_{MOD} - 2$ and df_{RES} degrees of freedom. The null hypothesis (global linearity) is rejected for large values of the test statistic.

3. The Data and the Estimation Results

The data for the empirical analysis are monthly wholesale prices (expressed in Euro per 100 kg) for the period 2006:1 to 2014:4. They have been obtained from the European Commission and they come from the five major pigmeat producing EU member states; namely, Germany (DE), Spain (ES), France (FR), Poland (PL), and Denmark (DK). Table 1 presents the respective production shares for the year 2012; these five countries taken together account for 65 percent of the total pigmeat production in EU-27. The trade flows among them involve fresh and frozen pigmeat, live animals, and processed pigmeat. As known, the existence of trade flows is a necessary condition for the transmission of price shocks from one spatial market to the other. DE is a net importer of pigmeat from DK (primarily) and to a lesser extend from ES and FR; it is, however, a net exporter of pigmeat to PL. FR is a net importer of pigmeat from ES, and PL is a net importer of pigmeat from DK; PL exports to DE and to DK live animals.

Figure 1 (panels (a) to (e)) presents the natural logarithms of prices in the five major EU pigmeat markets. The prices appear to move generally together which is an indication of spatial market integration. We note that recently Emmanouilides and Fousekis (2012) found that pigmeat prices in DE, ES, FR, and DK were cointegrated using data from 1990 to 2011. On the average, ES is the market with the highest prices followed closely by DE; DK is the market with the lowest prices.

For the empirical implementation of the LL non parametric regression one has to select a kernel function and a bandwidth. The choice of the kernel function is not very important, provided that it will involve continuous and smooth weights. Here we work with the Epanechnikov kernel which ensures that weights have the desirable properties. The bandwidth affects the bias-variance trade off. A small bandwidth (each local regression is estimated from a small number of observations) produces a large variance; a large bandwidth results in oversmoothing, that is, in a large bias (Fox, 2005; Racine, 2008). There are two types of bandwidths, namely, the constant bandwidth where $h(u) = h$ for all focal points and nearest neighborhood bandwidth where $h(u)$ varies so that all local regressions are estimated with exactly the same number of observations (or equivalently, with the same proportion of the total observations in the sample) (Altman, 1992). In the latter case, the bandwidth is termed as *span*. In the present work, the span (denoted by α) has been selected in such as way as to minimize the *Integrated Mean Squared Error* (IMSE) of the non parametric regression fit using the *Generalized Cross Validation* (GCV) Criterion

$$GCV = n\frac{\sum_{l=2}^{n}(\Delta p_l - \hat{m}(p_{l-1}))^2}{(n - tr(\Theta))^2} \tag{9}$$

(Loader, 1997; Schafer and Wasserman, 2013) [3]. The best global goodness of fit is achieved for the value of α that minimizes GCV in (9).

Given that the number of countries considered is five, there are (5x4)/2 market pairs and, therefore, ten transmission functions to be estimated. Table 2 presents the results from the search of the optimal span for each individual price transmission function, based on the GCV Criterion [4]. The optimal spans range from a low of 0.42 to a high of 0.83 (values that are very common in empirical non parametric regression analysis). The equivalent number of parameters range from a low of 2.59 to a high of 4.49 suggesting that the selected LL models use (effectively) from 0.6 to 2.5 more parameters than their respective globally linear parametric models.

Figure 2 (panels (a) to (j)) present the estimated non parametric regression lines along with the approximated pointwise 95-percent confidence bands. The simple visual inspection provides for a number of market pairs (notably DE-DK, DK-PL, and FR-PL) some indication of non linear price transmission. This, however, comes primarily from the behavior of the regression lines at the extremes of the respective distributions of the price differentials in *t*-1 where the confidence bands are wide (i.e. the conditional means of the changes in price differentials are estimated with low precision).

Table 3 presents the empirical values of the *F*-statistic along with the associated with them *p*-values for the null hypothesis of global linearity. The *p*-values for all market pairs are well above the conventional levels of statistical significance. We conclude, therefore, that the null hypothesis of globally linear price transmission is consistent with the real world data. As mentioned in the Introduction, non parametric regression models are more flexible than the parametric ones; they are, however, less efficient in the sense that they converge to the true (but unknown relationship) at a slower rate than the correctly specified parametric alternatives. Given that global linearity has not been rejected, Table 4 presents the estimation results from the parametric models. All slopes are negative and statistically significant at the five percent level (or less) suggesting that the underlying data generation processes are indeed mean reverting. The adjusted coefficients of determination range from a low of 0.054 for the pair of markets ES-PL to a high of 0.287 for the pair of markets DE-FR.

The estimated intercept terms of the globally linear models provide information about the long-run price differentials [5]. A positive (negative) and statistically significant $\hat{\beta}_0$ implies a positive (negative) differential. From Table 4 it appears, for example, that in the long-run the price in DE will higher than in DK, the price in DK will be lower than in FR, and the price in ES will be (statistically) no different from the price in FR. The signs and the statistical significance of the estimated intercept parameters are in line with the time series of logarithmic prices shown in Figure 1.

Simple functions of the slope parameter β_1 can provide useful insights about the speed of price transmission and the time required for a given part of a shock in period *t*-1 to be transmitted from one spatial market to the other. In particular, the speed of price transmission per unit of time (here month) can be obtained as $-\ln(1+\beta_1)$ while the time required for a half of a shock to be transmitted (termed as *half- life*) can be obtained as $-\ln(2)/\ln(1+\beta_1)$ (Barro and Sala-i-Martin, 2003). Table 5 presents the speeds of price transmission and the half-lives for the five major EU pigmeat markets.

The speed of price transmission ranges from 0.137 per month for the market pair ES-PL to 0.896 per month for the pair DE-FR; for the overwhelming majority of pairs, however, it lies in the neighborhood of 0.21. The figure 0.137 implies that 13.7 percent of the gap between the price differential in *t*-1 and the long-run price differential is corrected (arbitraged away) in a time period of one month. From Table 4 it is obvious that correction of price differentials in the DE-FR market pair is much more faster than for any other market pair; for example, it is almost two and a half times as fast as the correction for the market pair DK-FR and it is almost seven times as fast as for the market pair ES-PL. The above imply that, in the short-run, DE and FR is the most well integrated pair (followed by DK and FR) while ES and PL is the least well integrated pair among all ten pairs of spatial markets considered here.

The differences in the speed of price transmission are reflected in the estimated half-lives (the higher the speed, the lower the half-life). For the market pair DE-FR, 50 percent of the price differential in *t*-1 and the long-run price differential is arbitraged away in a time period of about 23 days (0.77 months). The same correction percentage for the market pair DK-FR requires 1.9 months while for the pair ES-PL it requires 5.07 months. Note that differences in the speed of transmission and in the half-lives do not preclude the achievement of a long-run equilibrium for all prices in the spatial markets. They only suggest that each logarithmic price ratio will approach the common to all long-run equilibrium (provided that such an equilibrium exists) at a different pace.

One would *a priori* expect that proximity and trade intensity are important determinants of the speed of price transmission in spatial commodity markets. This expectation, is only partly verified by our empirical results. DE and FR are neighboring countries with intense trade in pigmeat which may be an explanation for the estimated high speed of price transmission. ES and PL are away from each other with limited trade flows which may also explain the low speed of price transmission between them. DK and DE, however, are also neighboring countries with intense trade in pigmeat. The speed of price transmission for the pair DE-DK is far more smaller than that for the pair DE-FR; exactly the same observation holds for the pair of markets ES-FR.

Possession of market power may be behind the differences in speed of price transmission. Firms in multinational oligopolies or oligopsonies are often capable of adjusting prices when faced with demand or supply shocks in different markets in such as way as to retain their margins. Pig slaughtering in a number of major EU producing countries is indeed dominated by few multinational companies (Brossard and Montage, 2012). For example, Danish Crown which operates in DK and PL accounts for 20 percent of EU slaughtering, Tonnies Fleisch which operates in DE and DE accounts for 13 percent of EU slaughtering, while Cooperl Arcantlantique accounts for 20 percent of slaughtering in France.

Finally, from the five countries considered in this study only three have adopted Euro as their currency; DK and PL have not. The price relationships (including price transmission) between DK and PL and the remaining three countries are probably more complicated because they may reflect both developments in the respective commodity markets as well as changes in the nominal exchange rates between Euro and the national currencies.

4. Conclusions

The objective of the present work has been to investigate price transmission in five major EU pigmeat markets. The investigation relied on the Local Linear non parametric regression estimator and on formal statistical tests capable of disentangling local non linearity from global linearity. According to the empirical results:

(a) The price transmission functions are globally linear suggesting that price differentials are transmitted with the same intensity regardless of their initial magnitude. Therefore, no trading partner appears to enjoy an advantage over another.

(b) Expect for the market pair DE-FR (and to a lesser extend for the pair DK-FR) the speed of price transmission from one spatial market to the other is generally low. As a result, in a number of cases, it takes more than three months for 50 percent of an initial price shock to be transmitted. This finding alone creates concerns about the degree of integration among the five major pigmeat markets in the EU. Given that pigmeat is a highly homogeneous commodity and that policy interventions in the EU pigmeat market are virtually non existent, higher speeds of price transmission have been expected. Possible explanations for the low speeds and the large half-lives are first, market power (pig slaughtering is concentrated in the hands of few abattoirs; just 5 percent of abattoirs conduct 65 percent of total pig slaughtering in the EU 27) and second, not all countries examined here have adopted Euro as their currency. Under these circumstances price shocks associated with real market fundamentals such as that supply and demand changes may be confounded with changes in the nominal exchange rates between the Euro, the Danish Krone, and the Polish Zloty.

Besides its findings regarding price interrelationships in the spatial EU pigmeat markets, this study also demonstrates the importance of drawing implications for global versus local non linearity from formal statistical tests rather from simple graphical visual inspection of the non parametric regression fits (a practice common to earlier relevant empirical studies). Of course, additional empirical substantiation is necessary and further work on this important topic is warranted.

Endnotes

The author would like to thank an anonymous referee for helpful comments

Panos Fousekis, Associate Professor, School of Economics and Finance, Massey University, New Zealand. E-mail: p.fousekis@massey.ac.nz

1. For a recent review of the econometric analysis of price transmission see Hassouneh et al. (2012).
2. For details on the construction of the smoothing matrix see Fox (2005) and Schafer and Wasserman (2013).
3. The IMSE is defined as $\int_u (\hat{m}(u) - m(u))^2 du$
4. The determination of the optimal spans and the estimation of the non parametric regressions have been carried out using the Package Locfit in R.
5. In the long run equilibrium, $\Delta p = 0 \Rightarrow p = -\beta_0 / \beta_1$ (with $\beta_1 < 0$).

References

Altman, N. 1992. "An Introduction to Kernel and Nearest-Neighbor Non Parametric Regression", *The American Statistician*, 46, 175-185.

Barro, R. and X. Sala-i-Martin. 2003. *Economic Growth.* MIT Press, Massachusetts,USA.

BPEX. 2013. Agriculture and Horticulture Development Board. Country Report, August.

Brossard, L. and L. Montage. 2012. An Overview of Pig Production in the EU. CAPES-COFECUB n°Sv 687/10, Brazil.

Cleveland, W. 1979. "Robust Locally Weighted Regression and Smoothing Scatterplots", *Journal of the American Statistical Association*, 74, 829–836.

Emmanouilides, C. and P. Fousekis. 2012. "Testing the for the LOP Under not Linearity: An Application to Four Major EU Pork Markets", *Agricultural Economics*, 45, 715-723.

Fan, I. and I. Gijbels. 1996. *Local Polynomial Modelling and its Applications*. London, UK Chapman and Hall.

Fox., J. 2005. *Introduction to Non Parametric Regression*. Economic and Social Research Council.

Goodwin, B. and N. Piggott. 2001. "Spatial Market Integration in the Presence of Threshold Effects", *American Journal of Agricultural Economics*, 83, 302-317.

Hassouneh, I, S. von Cramon-Taubadel, T. Serra and J. Gil. 2012. Recent Developments in the Econometric Analysis of Price Transmission. TRANSFOP, Working Paper No 2, January.

Kmenta, J. 1986. *Elements of Econometrics*. MacMillan, NY.

Loader, C. 1997. Locfit: An Introduction. *Statistical Computing and Graphics Newsletter*, April.

Li, Q. and J. Racine. 2007. *Non Parametric Econometrics: Theory and Practice*. Princeton University Press: Princeton, NJ.

Meyer, J. and S. von Cramon-Taubadel. 2004. 'Asymmetric Price Transmission: A Survey", *Journal of Agricultural Economics*, 55, 581–611.

Newey, W. and K. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix" *Econometrica*, 55, 703–708.

Racine, J. 2008. 'Non Parametric Econometrics: A Primer". *Foundations and Trends in Econometrics*, 3, 1-88.

Schafer, C. and L. Wasserman. 2013. Tutorial on Non Parametric Inference with R. Carnegie Mellon University.

Serra, T., J. Gil and B. Goodwin. 2006a. 'Local Polynomial Fitting and Spatial Price Relationship: Price Transmission in EU Pork Markets", *European Review of Agricultural Economics*, 33,415-436.

Serra, T., B. Goodwin, J. Gil and A. Mancuso. 2006b. 'Non Parametric Modeling of Spatial Price Relationships", *Journal of Agricultural Economics*, 33, 415-436.

Table 1. Pigmeat Production Shares (2012) in EU-27 *

Country	Share (%)
DE	24.8
DK	7.3
ES	16.1
FR	8.9
PL	7.8

* Calculated from production data available in BPEX, Country Report, EU Summary (August, 2013).

Table 2. Optimal Span Selection

Market Pair	Minimum GCV Value	Span	df_{MOD}
DE-DK	0.0011	0.69	2.87
DE-ES	0.0018	0.55	3.39
DE-FR	0.0012	0.83	2.59
DE-PL	0.0013	0.55	3.87
DK-ES	0.0021	0.52	3.58
DK-FR	0.0013	0.73	2.97
DK-PL	0.0017	0.53	3.92
ES-FR	0.0013	0.68	2.99
ES-PL	0.0022	0.42	4.49
FR-PL	0.0017	0.54	3.87

Table 3. Test for Global Linearity of Price Transmission

Market Pair	*F*- Statistic	p-value
DE-DK	1.56	0.21
DE-ES	0.99	0.35
DE-FR	1.67	0.19
DE-PL	1.94	0.15
DK-ES	0.76	0.44
DK-FR	1.18	0.28
DK-PL	1.12	0.33
ES-FR	0.25	0.62
ES-PL	0.24	0.82
FR-PL	1.93	0.15

Table 4. Estimation Results from the Parametric Models

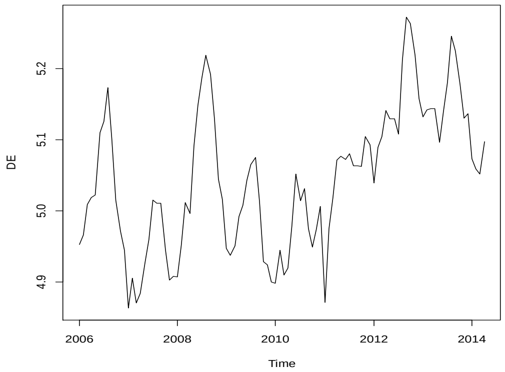
Market Pair	Coefficients		R^2 (adjusted)
	β_0	β_1	
DE-DK	0.027*	-0.193*	0.097
	(0.007)	(0.045) +	
DE-ES	-0.003	-0.185*	0.077
	(0.009)	(0.055)	
DE-FR	0.051*	-0.592*	0.287
	(0.007)	(0.082)	
DE-PL	0.007*	-0.171*	0.078
	(0.003)	(0.067)	
DK-ES	-0.036*	-0.234*	0.101
	(0.011)	(0.048)	
DK-FR	-0.016*	-0.307*	0.151
	(0.005)	(0.039)	
DK-PL	-0.018*	-0.188*	0.085
	(0.007)	(0.057)	
ES-FR	0.021*	-0.214*	0.097
	(0.007)	(0.046)	
ES-PL	0.008	-0.128*	0.054
	(0.005)	(0.049)	
FR-PL	-0.008*	-0.193*	0.091
	0.004	(0.051)	

***** Statistically significant at the 5 percent level (or less); the *F*-tests for individual regressions are also significant at the 1 percent level (or less).
+ Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors in parentheses

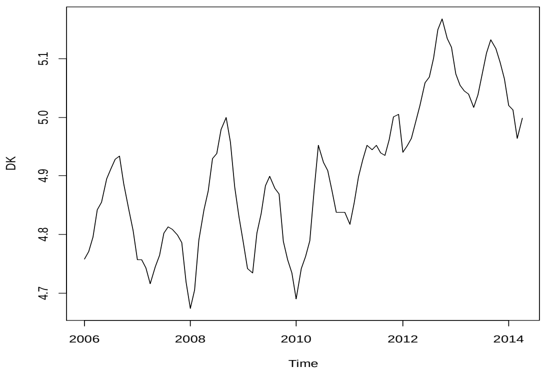
Table 5. Speed of Price Transmission and Half-Life

Market Pair	Speed (per month)	Half-Life
DE-DK	0.214*	3.234*
	(0.074)	(1.117)
DE-ES	0.205*	3.378*
	(0.075)	(1.241)
DE-FR	0.896*	0.773*
	(0.232)	(2.001)
DE-PL	0.187*	3.711*
	(0.062)	(1.332)
DK-ES	0.226*	2.601*
	(0.086)	(0.835)
DK-FR	0.367*	1.892*
	(0.103)	(0.532)
DK-PL	0.208*	3.327*
	(0.072)	(1.165)
ES-FR	0.240*	2.882*
	(0.086)	(0.962)
ES-PL	0.137*	5.072*
	(0.057)	(2.117)
FR-PL	0.211*	3.284*
	(0.071)	(1.113)

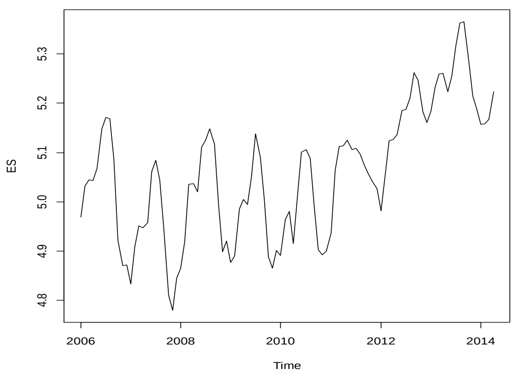
***** Statistically significant at the 5 percent level (or less)
+ Standard errors in parentheses, computed with the Delta Method (Kmenta, 1986)



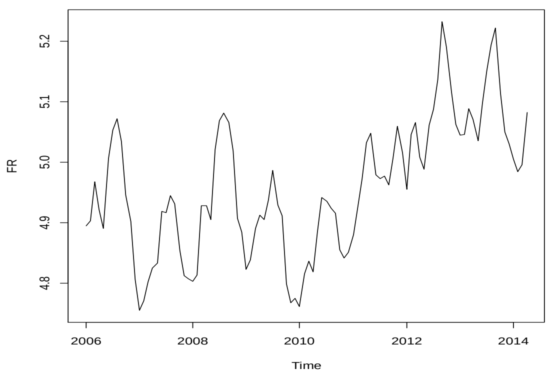
(a) Germany



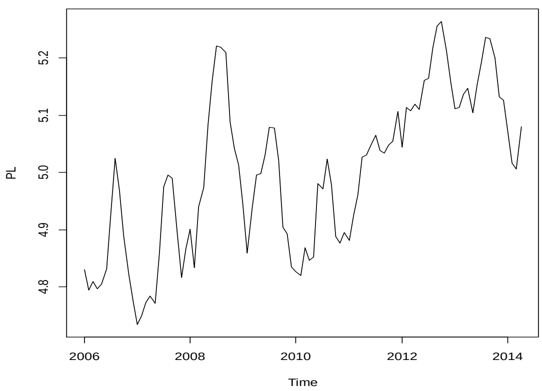
(b) Denmark



(c) Spain

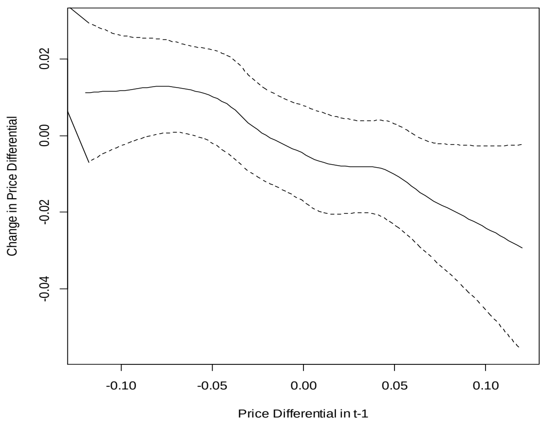


(d) France

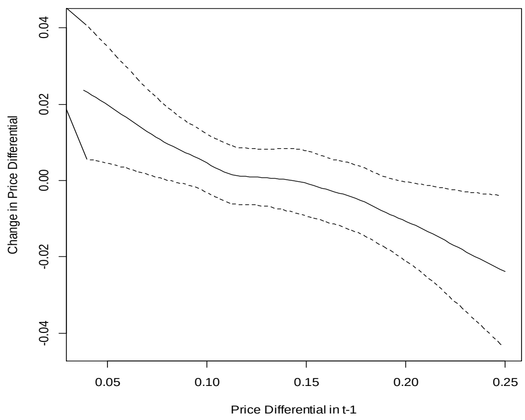


(e) Poland

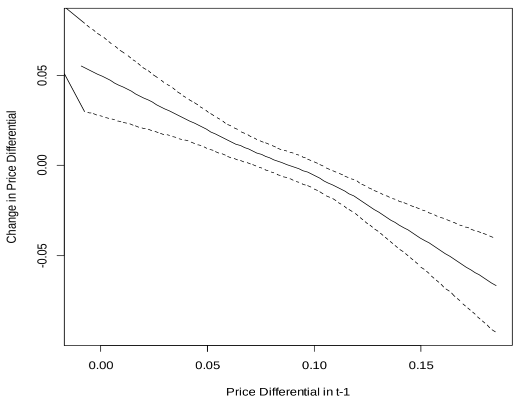
Figure 1. Logarithmic Prices in Major EU Pigmeat Markets



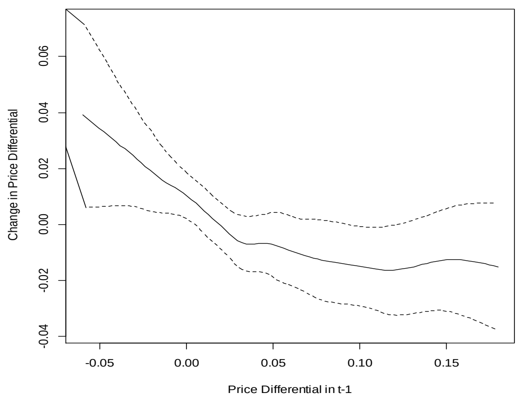
(a) Market Pair: DE - ES



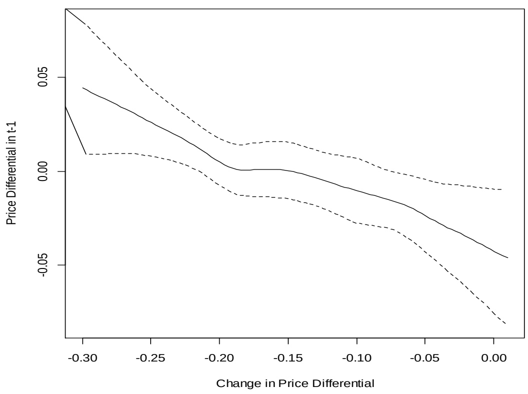
(b) Market Pair: DE -DK



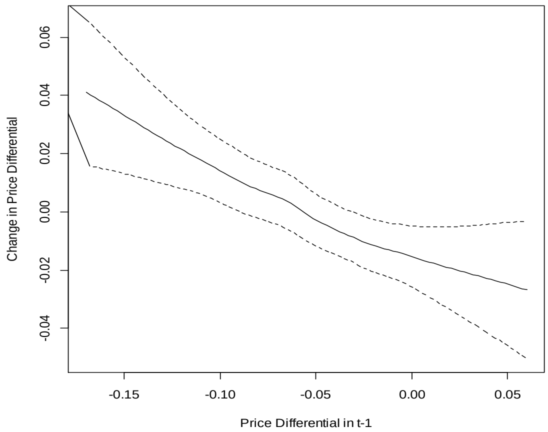
(c) Market Pair: DE-FR



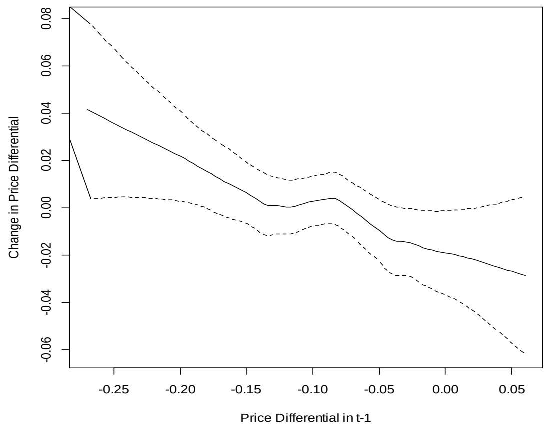
(d) Market Pair: DE-PL



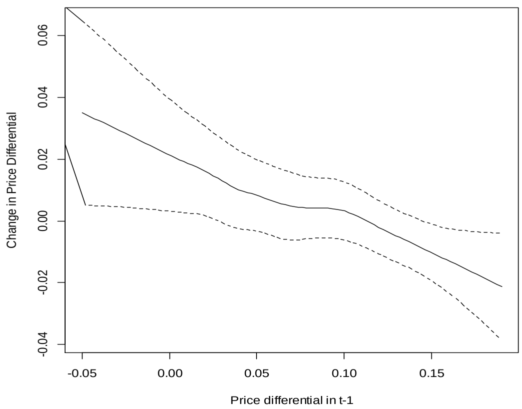
(e) Market Pair: DK-ES



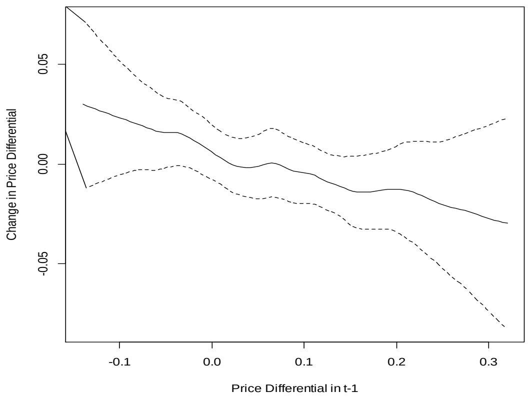
(f) Market Pair: DK-FR



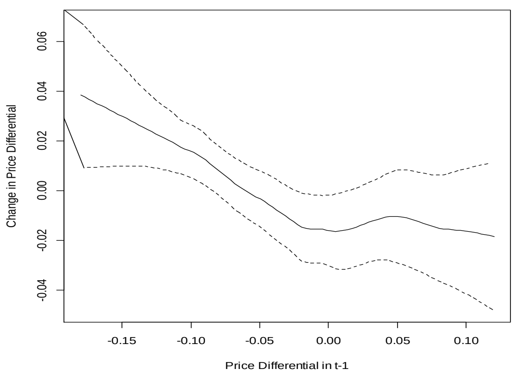
(g) Market Pair: DK-PL



(h) Market Pair: ES-FR



(i) Market Pair: ES-PL



(j) Market Pair: FR-PL

Figure 2: Non Parametric Regression Lines