Strengthening European Food Chain Sustainability by Quality and Procurement Policy

**Deliverable 4.3:**

# ANALYSIS OF PRICE TRANSMISSION IN EUROPEAN FOOD QUALITY SCHEMES

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## EXECUTIVE SUMMARY

The European Union (EU) has regulated the quality schemes for agricultural food products since the 1980s, with the objective of helping producers to communicate to buyers and consumers the specific characteristics of such products and farming attributes, giving the possibility to producers to offer a unique and differentiated product of higher quality, normally sold at a higher price. Nevertheless, most of the literature focuses on price premiums that consumers pay or are willing to pay. Moreover, no study has analysed the value generated along each stage of the food chain and to what extent farmers benefit from higher consumer prices. More importantly, no study has dealt with the issue of to what extent food quality schemes (FQS) have contributed to increase competitiveness of the food chain. Probably, the main reason for this lack of empirical literature is the scarcely available data to conduct such type of analysis. In fact, to our best knowledge, no data source exists that provides systematic and continuous price information, for both FQS and conventional products, at the two extreme stages of the food supply chain (producer and retail). Hence, more efforts should be oriented towards improving the monitoring and collection of this relevant information.

Task 4.3 of the Strength2Food project deals with price transmission for FQS by analysing existing datasets to complement the investigation undertaken in WPs 5 to 9. In particular, the main objective is to assess how prices for different FQS products are transmitted along the food marketing chain and the extent to which FQS have contributed to improve the price transmission mechanism (in the long-run) with reduced asymmetries (in the short-run). Deliverable 4.3reports the main results derived from the assessment of the adjustments of prices in the marketing chain for FQS products. The methodological approach considered in this study is based on the specification and estimation of a multivariate threshold autoregressive model. Our approach allows us to investigate if there are non-linearities (asymmetries) in the adjustment mechanism of prices.

In this study, we analyse three FQS products in two Mediterranean countries, Spain and Italy. For Spain, we examine two Protected Geographical Indication (PGI) products, “Ternera de Navarra” (beef from Navarra) and “Cordero de Navarra” (lamb from Navarra). For Italy, we analyse the Protected Designation of Origin (PDO) “Parmigiano Reggiano”.

The deliverable presents a comparison of the results for the FQS and conventional marketing chains. The information obtained may provide a wider view of the differences and similarities of the two chains. From the analysis, some conclusions are drawn on the extent to which European FQS products show a better transmission mechanism in the long-run and fewer asymmetries in the short-run, and hence more market efficiency. Note that the results derived here should be used with caution and limited to these case studies. Though the usefulness and importance of this analysis is beyond doubt, analysis on more protected products will be required to generalize the performance of European FQS.

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## List of Abbreviations and Acronyms

AIC - Akaike's information criteria
APT - Asymmetric Price Transmission
ARCH - Autoregressive Conditional Heteroscedasticity
BIC - Schwarz's information criteria
ECT - Error Correction Term for the Conventional System
ECTI - Error Correction Term for the Quality System
EU - European Union
FP - Farm Price of the conventional food product
FPI - Farm Price of the food product designated with label of origin
HQ - Hannan-Quinn's information criteria
IC - Information Criteria
IRF - Impulse Response Function
MAIC - Modified Akaike's Information Criteria
MBIC - Modified Schwarz's Information Criteria
MIC - Modified Information Criteria
MSB - Modified Sargan Bhargava unit root test
NLIRF - Nonlinear Impulse Response Function
PDO - Protected Designation of Origin
PGI - Protected Geographical Indication
RC - Regulatory Council
RP - Retail Price of the conventional food product
RPI - Retail Price of the food product designated with label of origin
SETAR - Self Exciting Threshold Autoregressive Model
STVECM - Smooth Transition Vector Error Correction Model
TSG - Traditional Speciality Guaranteed
TVECM - Threshold Vector Error Correction Model
VAR - Vector Autoregressive model
VECM - Vector Error Correction Model

# *Analysis of Price Transmission in European Food Quality Schemes*

***H. Ferrer-Pérez, M. Ben-Kaabia and J.M. Gil***

## 1. INTRODUCTION

Since the 1980s, the EU has regulated the quality schemes for agricultural products and food, seeking to help producers to communicate to buyers and consumers the specific characteristics of such products and farming attributes, protecting them from inferior copycat versions. In other words, producers in these quality schemes are able to offer a unique and differentiated product of higher quality and, normally, for a higher price. Deselnicu et al (2013) explore the main factors affecting the price premium associated with Food Quality Schemes (FQS). However, most of the literature focuses on price premiums consumers pay or are willing to pay (Aprile et al, 2012). More importantly, no study has dealt with the issue of the presence of asymmetries in the price transmission mechanism along the food chain of FQS products and hence no existing studies measure the extent to which those markets are more efficient than their conventional counterparts. This is the main aim of Task 4.3 of the Strength2Food project from which this Deliverable 4.3 shows the main results.

In general, the number of farmers producing an FQS product is significantly lower than in the case of the conventional counterpart. Furthermore, retailers are not able to buy these products in geographically separated markets. This is expected to result in a reduction in market power at the retail level; an issue that has been treated extensively in the literature. As a consequence, we expect price fluctuations, which are due to unexpected supply and demand changing conditions, to be of the same magnitude both at the farm and the retail level. Moreover, we expect a quick volatility transmission along the food supply chain in the case of FQS products.

Over the last four decades, agricultural economists have dedicated much effort to measure the degree, speed and asymmetries of the price transmission mechanism in vertical markets. Substantial empirical papers and developments in theory have been published to assist economists in understanding how pricing is communicated between food consumers and agricultural producers and hence in assessing the functioning of the behaviour of chain participants (Meyer and von Cramon-Taubadel (2004), Frey and Manera (2007), McLaren (2015) and Verreth et al (2015), among others).

While concern over pricing has been substantial in conventional agricultural food products and also on the agenda of stakeholders in the value chain and policy-makers, the issue has not been explored so far for FQS products. The lack of empirical contributions dealing with FQS products may be due to the lack of available data required to conduct such analysis. What is more, no data sources exist which provide systematic and continuous pricing information for the two extremes of the food supply chain (farm and retail level). For this reason, we strongly believe that stakeholders and policy-makers involved in the food chain should direct their efforts to improving the monitoring and collection of this information.

For the current study, we managed to find a reliable database for two Mediterranean countries: Spain and Italy. For Spain, we found information for two Protected Geographical Indication (PGI) products: "Ternera de Navarra" (beef from Navarra) and "Cordero de Navarra" (lamb from Navarra). For Italy, we found information for the Protected Designation of Origin (PDO) "Parmigiano Reggiano". The dataset contains farm and retail prices for the FQS and the conventional counterpart covering a period of from 2011 to 2016 for the Spanish case study and from 2011 to 2015 for the Italian case study. The methodological framework used is based on the concept of cointegration and relies on the threshold vector error corrector model (TVECM), which has been long used as a workhorse in the analysis of the vertical price transmission mechanism.

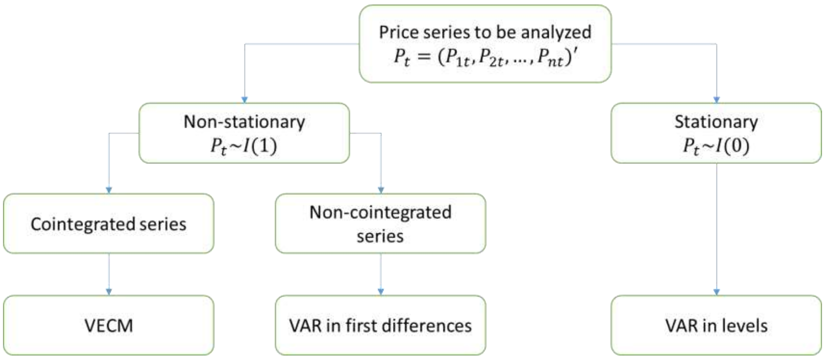
This deliverable is structured in three sections. Section 2 describes in-depth the methodological framework used. Section 3 presents the main results obtained in each of the three case studies. Section 4 concludes.

## 2. METHODOLOGICAL APPROACH

In this section, we will describe the methodological aspects of our three empirical studies. The approach entails four stages. First, price series are tested for unit roots, because if series are mischaracterized as stationary then regression analysis on nonstationary series leads to spurious outcomes, which invalidates the subsequent inferences. Assuming the series are characterized as integrated of order one, the second stage consists of determining whether price series are cointegrated and whether this long-run relationship is stable. If the variables are found to be cointegrated, then the third stage entails testing for the presence of nonlinear cointegration relationships. Once the nonlinearities are determined, the fourth stage consists of estimating the model and calculating impulse response functions to quantify short-run responses of prices to unanticipated changes from the supply/demand side in one series.

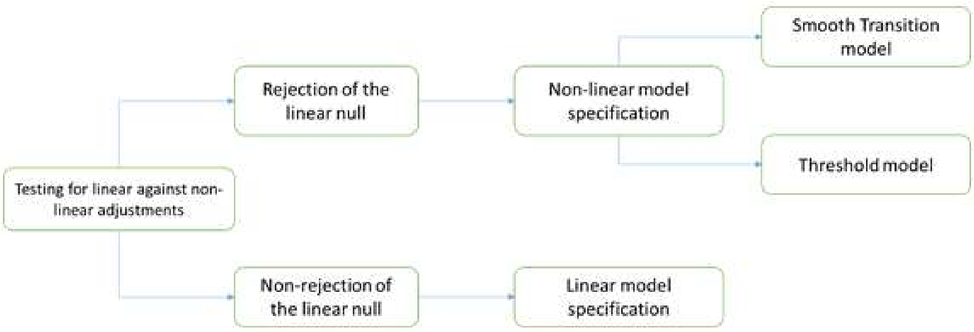
The analysis is done in two parts. In the first part, we present a detailed analysis of the stochastic properties of the price series to determine whether series contain a unit root and whether the price series are cointegrated (Figure 1). In the second part, we model the price transmission mechanism using a non-linear approach which permits us to identify non-linear adjustments in the short-run between the variables of the model (Figures 2 and 3).

**Figure 1. Guide to the computation of the first part of the analysis**



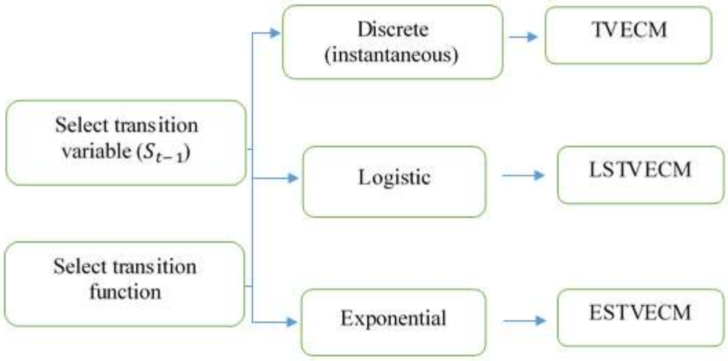

Source: Own elaboration.

**Figure 2. Guide to the computation of the second part of the analysis**




Source: Own elaboration.

**Figure 3. Strategy to specify a nonlinear model**




Source: Own elaboration.

## 2.1. Modelling nonstationary price time series

Generally, the stochastic properties of the time series or their order of integration is analysed with the use of unit root and stationarity tests. Not until the 1980s, did economists believe that economic series could be characterized as trend stationary, that is, series moving around a deterministic trend. However, this result was criticized in the influential work of Nelson and Plosser (1982) who proved that most macroeconomic time-series analysed in their paper should be treated as non-stationary in the mean. Since then, a vast number of papers focus on the analysis of nonstationary variables. Diebold (1999), Engle and Granger (1987), Hamilton (1994), Maddala and Kim (1998), Phillips and Xiao (1998), Hayashi (2000) and Choi (2015) are, among others, excellent references.

Testing for unit roots in time-series has become necessary to establish links among prices because the test statistics behave differently depending on the stationary or non-stationary nature of the variable.

Surprisingly, a detailed review of the most recent empirical studies dealing with price transmission and price volatility of agricultural commodities shows that the implementation of the (augmented) test of Dickey and Fuller (1979), DF hereafter, and the PP tests of Phillips and Perron (1988) are greatly favoured at the expense of the tests proposed by Ng and Perron (2001) as a modified version of the DF and PP tests, based on the results obtained in Elliott et al (1996). This fact is quite surprising because the unit root literature, see for instance Haldrup and Jansson (2006) and Patterson (2011), has determined that the tests proposed by Ng and Perron (2001) outperform the standard DF and PP tests.

Therefore, in this study, according to the most recent contributions to the unit root literature, we consider the tests proposed in the influential work of Ng and Perron (2001). To justify our choice, we briefly explain their contribution below. Ng and Perron (2001) attempt to resolve two issues widely discussed in the literature. The first issue concerns the low power of standard unit root tests like the test of Dickey and Fuller (1979), and Phillips and Perron (1988) when the root of the autoregressive polynomial is close to unity. The second issue concerns the size distortions of most of the standard unit root tests when the moving-average polynomial of the first difference of the series has a large negative root. Their objective is twofold. First, they enhance the power of the tests less affected by the size-distortion, the M-tests proposed by Stock

(1999), using local GLS-detrended (demeaned) data as in Elliott et al (1996)[1]. Second, they derive a modified lag length criterion to determine the truncation lag parameter of the augmented Dickey-Fuller regression required to construct the autoregressive long-run variance estimator defined as:

$$\widehat{\omega}_{AR}^2 = \hat{\sigma}_\varepsilon^2 \left(1 - \hat{\phi}(1)\right)^{-2} \tag{1}$$

where $\hat{\sigma}_\varepsilon^2 = T^{-1} \sum_{t=k+1}^{T} \hat{\varepsilon}_{tk}$ and $\hat{\phi}(1) = \sum_{i=1}^{k} \hat{\phi}_i$ with $\hat{\phi}_i$ and $\hat{\varepsilon}_{tk}$ obtained from the OLS augmented Dickey-Fuller regression:

$$\Delta \hat{y}_t = (\rho - 1)\hat{y}_{t-1} + \sum_{i=1}^{k} \phi_i \, \Delta \hat{y}_{t-i} + \varepsilon_t \tag{2}$$

where $\varepsilon_t \sim iidN(0, \sigma_\varepsilon^2)$ and $\hat{y}_t$ represents the generic filtered series. They show that the standard lag order selection methods like AIC and BIC underestimate the cost of selecting a small number of lags when the root of the moving-average polynomial is large and negative. Then, Ng and Perron propose a new class of modified information criteria which depend on a penalization factor that varies with the sample, the Modified Information Criteria (MIC) defined as:

$$MIC(k) \coloneqq \ln(\hat{\sigma}_k^2) + \frac{C_T(\tau_T(k) + k)}{T - k_{max}} \tag{3}$$

with $\tau_T(k) = (\hat{\sigma}_k^2)^{-1} \hat{\phi}_0^2 \sum_{t=k_{max}+1}^{T} \hat{y}_{t-1}^2$. If $C_T = 2$, we obtain the MAIC criterion and the MBIC is obtained with $C_T = \ln T$. Note as wel that both must satisfy $C_T / T \to 0$ as the sample size gets larger.

In our study, we apply the Modified Sargan Bhargava test, MSB henceforth, firstly proposed in Stock (1999) and improved in Ng and Perron (2001). Our choice is based on its simplicity and remarkable size-power trade-off[2]. The test is defined as follows:

$$\text{MSB} = \frac{T^{-2} \sum_{t=2}^{T} \hat{y}_t^2}{\widehat{\omega}_{AR}^2} \tag{4}$$

However, the outcome of the unit root tests developed in Ng and Perron (2001) is not valid when a structural break exists in the observed series as they are biased towards the non-rejection of the null hypothesis. To overcome this issue, it would be advisable to test for unit roots allowing for the existence of a single or multiple structural breaks.

Multiple alternatives are found in the unit root literature to address this issue[3]. In this study, we use the procedure developed in Carrion-i-Silvestre et al (2009) to test for the presence of

[1]If the local-to-unity alternative hypothesisisdefinedas$\rho_c = 1 + cT^{-1}$where $c$ reflects the noncentraltity parameter following Elliott et al (1996), these authors define the local-GLS procedure to detrend (demean) the series$\{y_t\}$ and the unknown deterministic vector $z_t$as follows: $y^{\bar{c}} = (y_1, (1 - \rho_{\bar{c}} L)y)'$ and $Z^{\bar{c}} = (z_1, (1 - \rho_{\bar{c}} L)z_{t-1})'$, being $\rho_{\bar{c}} = 1 + \bar{c}T^{-1}, \bar{c} < 0$ and $L$ the lag operator so that $Lx_t = x_{t-1}$ for any given series $x_t$. Note that $\bar{c}$ischosenso that the asymptoticlocal power functionof the unitroottestistangentto the power envelope at 50% power.

[2] See also Ferrer-Pérez (2016) for a comprehensive analysis about the properties of the MSB unit root test when there is uncertainty over the the deviation of the initial observation of the series from its deterministic part (initial condition).

[3]See Perron (2017) for an interesting editorial on the topic.

multiple unknown structural breaks in the level, intercept or intercept and slope of the series. We allow for two structural breaks at most.

As the traditional hypothesis testing favours the null hypothesis, we now consider the opposite set-up. We test the null of stationarity against the alternative of the existence of a unit root in the series. We apply the popular KPSS stationarity test developed in Kwiatkowski et al (1992).

As argued before, many commodity prices are usually characterized as co-integrated (Myers, 1994), implying that non-stationary prices share a trend in the long-run, and there are no incentives to deviate from this situation. But, if any unanticipated shock appears, there is a tendency to revert to the equilibrium.

Two widely used approaches are available in the related literature. On the one hand, the approach developed by Engle and Granger (1987) which relies on a two-step estimator to test the parameters of a bivariate single-equation model; and, on the other hand, the Johansen (1988) approach, which consists of a maximum likelihood ratio test to test multiple co-integrating vectors. Here, we follow the latter.

The procedure developed by Johansen (1988) is based on the link between the rank of a matrix and its characteristic roots[4]. The starting point is the correct specification of a vector autoregressive model VAR(k) with k denoting the optimal number of lags[5]. In this model, the variables are treated as endogenous and symmetrical (Sims, 1980). We write then[6]:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_k Y_{t-k} + \varepsilon_t \tag{5}$$

being $Y_t = \left(Y_{1t}, Y_{2t}, \dots, Y_{pt}\right)'$ a $p \times 1$ vector of endogenous variables where $p$ is the number of variables; $A_i$ for $i = 1,2, \dots, k$ are $(p \times p)$ matrices of autoregressive parameters. Also, $\varepsilon_t$is the error term in array form with $E(\varepsilon_t) = 0, \forall t$ and $E(\varepsilon_t \varepsilon_s) = 0$ for $t \neq s$; $H$ for $t = s$, where H is the $(p \times p)$ variance-covariance matrix, which is positive definite.

To select the optimal truncation lag parameter, k, in the VAR(k) model, we consider information criteria as they are normally utilized for model selection (Aznar, 1989).

It is useful to rewrite equation (5) in the form of a vector error correction model (VECM) as follows:

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \cdots + \Gamma_{k-1} Y_{t-k} + \varepsilon_t \tag{6}$$

with $\Gamma_i = -\sum_{i=j+1}^{k} A_i$ for $i = 1, \dots, k-1$ and $\Pi = -\left(I - \sum_{i=1}^{k} A_i\right)$ where $I$ is the $(p \times p)$ identity matrix.

Within this context, testing for cointegration between variables implies selecting the rank $r$ of matrix Π. Thus, once we have correctly specified the deterministic components in the model (Juselius, 2006) we can arrive at three possible scenarios:

[4]One might interpretethisintuitivelyasa multivariate generalizationof the Dickey-Fuller test.
[5] The lag orderchoice in VAR modelsisnormallycarried out usingthe Akaike Information Criterion (AIC), the Schwarz Information Criterion (BIC) and/or the Hannan-Quinn Information Criterion (HQ).
[6]Toeasediscussion, the deterministictermsare not included.

- If $r = 0$, there is no cointegration, the matrix is null and we have the usual VAR model in first differences.
- If $r = p$, $Y_t$ is stationary and, hence, applying OLS to (6) will be efficient.
- If $1 \leq r < p$, $r$ denotes the number of cointegration relations with $\Pi Y_{t-1} \sim I(0)$ and so, we can decompose Π matrix as follows:

$$\Pi = \alpha\beta' \tag{7}$$

with $\beta$ the matrix of parameters from the $r$ cointegration relationships, and $\alpha$ measuring the speed of adjustment of the parameters towards the equilibrium in the long-run ($\beta' Y_{t-1}$).

Hence, selecting the cointegration rank is equal to determining the number of the characteristic roots of the matrix Π that differ from zero[7]. However, in practice, we can only estimate Π and its respective characteristic roots. Two test statistics are available in the literature and defined as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i) \tag{8}$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{9}$$

where $\hat{\lambda}_i$ represents the estimated eigenvalues, that is, the values of the characteristic roots obtained from $\hat{\Pi}$, and the sample size is indicated with T. Curiously, the null hypothesis tested differs for (8) and (9). We have for the $\lambda_{trace}$ statistic:

$$\mathrm{H}_0 : r_0 \leq r \qquad H_1 : r_0 > r \tag{10}$$

and for the $\lambda_{max}$ statistic[8]:

$$\mathrm{H}_0 : r = r_0 H_1 : r = r_0 + 1 \tag{11}$$

In the current study, we employ the Bartlett corrected trace test $\lambda^*_{trace}$ because we can ensure reduced size distortions in the trace tests due to the short-run effects of the VAR model (Johansen, 2002).

### 2.2. Modelling nonlinear adjustments

The presence of asymmetries implies for example that the price received by the farmer for a certain food product can differ depending on whether a positive or negative unexpected shock occurred in the food price. The speed and magnitude of the response may also be asymmetric.

There exist several sources that may explain this asymmetric behaviour. First, it can be that industries face different costs depending on whether prices increase or decrease (Bailey and Brorsen, 1989). Second, the existence of market power may lead industries to increase the price of the final output if the price of inputs increases and the response may be slower if the price of

[7]If the variables in $Y_t$ are not cointegrated, the rank is zero and subsequently all ofthe characteristic roots are zero.
[8]Critical values for both test statistics were computed using Monte Carlo simulations. Forfurtherdetails, the interestedreadermayconsult Johansen (1988), Juselius (2006) and Enders (2010), amongothers.

inputs decreases. Third, the asymmetric performance may be caused by the intervention of the public sector (Kinnucan and Forker, 1987).

The recognition of the importance of transaction costs and asymmetries in the price transmission mechanism has developed several nonlinear models to be able to capture the effect of these determinants on price linkages. The most used are threshold-type models, deterministic and/or stochastic (switching regime models, SRM). Among these models, the deterministic SRM (Baulch (1997) and Barret and Li (2002) among others) have been less frequent in the literature if compared to the stochastic SRMs which comprise the well-known threshold autoregressive model (TAR) of Balke and Fomby (1997), the smooth transition autoregressive (STAR) model of Teräsvirta (1994) and the markov switching autoregressive model (MSAR) developed by Hansen (1997). The last three models permit us to explain the price relationship identifying endogenously different regimes assuming an observed variable (TAR or STAR) or unobservable variables (MSAR).

All of these models are adequate to investigate the pricing transmission along the chain assuming price time series are stationary, and hence are not valid if the prices are nonstationary. However, much of the empirical evidence on the nonstationarity of price time series also showed that these series may share a stationary relationship in the long-run or are cointegrated (Engle and Granger, 1987). Thus, based on the notion of cointegration, the seminal work of Enders and Granger (1998) provides an alternative approach that allows for nonlinear and asymmetric adjustments. Likewise, based on the threshold cointegration notion, Balke and Fomby (1997) permit to test for the existence of asymmetric adjustments between variables related in the long-run equilibrium. This approach has empowered the scope of these dynamic models not only because this approach permits to solve some previous drawbacks but also because it provides new opportunities to develop more flexible and complex models to account for more than a single cointegration relationship in the model and smoother changes between regimes instead of instantaneous changes as in the TVECM. To deal with these issues, Granger and Teräsvirta (1993), Teräsvirta (1994, 1998) and van Dijk et al (2002) developed the smooth transition vector error correction models (STVECM)[9].

Following van Dijk et al (2002), a k-dimensional STVECM can be written as follows:

$$\begin{aligned} AP_t = &\left(\mu_1 + \alpha_1 z_{t-1} + \sum_{j=1}^{h-1} \phi_{1,j} \Delta \mathrm{P}_{t-j}\right)\left(1 - G(s_{t-d};\gamma,c)\right) \\ &+ \left(\mu_2 + \alpha_2 z_{t-1} + \sum_{j=1}^{h-1} \phi_{2,j} \Delta \mathrm{P}_{t-j}\right)\left(G(s_{t-d};\gamma,c)\right) + \varepsilon_t \end{aligned} \tag{12}$$

where $P_t = (P_{1t}, \dots, P_{kt})'$, $\mu_i$ is the $(k \times 1)$ vectors for $i = 1,2,\dots,k$ prices;$\alpha_i$ are the $(k \times r)$ matrices denoting the speed of the adjustment in regime i to shocks in the long-run relationship, which is represented by $z_{t-1} = \beta' P_{t-1}$ for some $(k \times r)$ matrix and $\beta$ denoting the error correction terms. Also, $\phi_{i,j}$ for $i = 1,2$ and $j = 1, \dots, p-1$ are $(k \times k)$ matrices which capture the short-run dynamics and $\varepsilon_t \sim iidN(0, \Sigma)$ with the bi-dimensional vector of white noise disturbances and Σ the variance-covariance matrix.The transition function, assumed to be a continuous function between zero and one, is represented by $G(s_{t-d};\gamma,c)$, where $s_{t-d}$ can be either a function of lagged components of $P_t$, the error correction term $(z_t)$ or lagged exogenous variables. The smoothing parameter $(\gamma)$ reflects the speed of transition from one regime to

[9]The readerisreferredtoFranses and van Dijk (2000) for an excellentintroductiontononlinear time seriesmodels.

another and $c$ represents the threshold parameter. Hence, the way these regimes reflect non-linearities is determined by the transition function selected. The two most commonly applied transition functions in practice are the second-order exponential function (ESTVECM) and the first-order logistic function (LSTVECM), respectively defined as follows:

$$G(s_{t-d};\gamma,c) = 1 - e^{\frac{-\gamma(s_{t-d}-c)^2}{\sigma^2(s_{t-d})}},\gamma > 0 \tag{13}$$

$$G(s_{t-d};\gamma,c) = \left(1 + e^{-\gamma(s_t-c)}\right)^{-1},\gamma > 0 \tag{14}$$

where the parameter $c$ can be interpreted as the threshold between the two regimes, in the sense that the logistic function changes monotonically from 0 to 1 as $s_t$ increases; and the parameter γ determines the smoothness of the change in the value of the logistic function. If $\gamma$ is large, the change becomes almost instantaneous at $s_t = 0$ and reduces to a TVECM model.

In order to specify the STVECM, we follow a strategy based on Granger and Teräsvirta (1993), Camacho (2004) and Escribano and Jordá (1999), whichcomprises the followingsteps[10]:

First step. We will specify and estimate a linear VECM for each system as benchmark models. To do so, we adapt equation (6) to our case study by considering $P_t = (P_{1t}, P_{2t})'$ as a vector of logged prices of food products at two links of the supply chain we can write:

$$\Delta P_t = \alpha[\omega_{t-1}(\beta)] + \sum\nolimits_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + u_t \tag{15}$$

being $\omega_{t-1}(\beta) = \beta' P_{t-1}$ the cointegrating vector evaluated at the default value of the cointegrating vector $\beta' = (1, \beta_2)$; $\Gamma_i$, $(2 \times 2)$ matrices measuring short-run parameters for $i = 1,2$; $\alpha$ a $(2 \times 1)$vector reflecting the departures from the cointegration relation and $u_t \sim iidN(0, \Sigma)$ with Σ as the positive definite variance-covariance matrix.

Second and third steps. Test the null that the price vector follows a linear VECM against the alternative of a STVECM. To do so, we shall rewrite (12) as follows:

$$\Delta Z_t' = X_{t-1}' B^{(1)}\left(1 - G(s_{t-d};\gamma,c)\right) + X_{t-1}'\, B^{(2)}\left(G(s_{t-d};\gamma,c)\right) + \epsilon_t \tag{16}$$

where $X_{t-1}' = \begin{pmatrix} 1 & z_{t-1}' \Delta Z_{t-1}' \cdots & \Delta Z_{t-p+1}' \end{pmatrix}$ and $B^i = \begin{pmatrix} \mu_i' \alpha_i' \phi_{i,1}' & \cdots & \phi_{i,p-1}' \end{pmatrix}$. Our interest is to test the linear null hypothesis, $H_0: \gamma = 0 \ vs \ H_1: \gamma > 0$. However, (16) is identified only under the alternative hypothesis of $\gamma > 0$ and this affects the estimation and the meaning of the LM test statistic (e.g.: Davies, 1977, 1987). This can be solved through different Taylor-order expansions (Luukkonen et al, 1988). The following table (Table 1) shows the different auxiliary regression models used to test for linearities (Camacho, 2004).

**Table 1. Auxiliary regression and linearity null hypothesis**

| $s_{t-d} \in Z_{t-1}'$ |
|---|

[10] A moredetaileddescriptioncanbefound in Mestiri (2013).

| | |
|---|---|
| $\Delta X_t = \sum_{h=0}^{3} \psi_h (Z_t' s_{t-d}^h) + \xi_t$ <br> $H_0: \psi_1 = \cdots = \psi_3 = 0 \rightarrow LM_3$ | $\Delta X_t = \sum_{h=0}^{2} \psi_h (Z_t' s_{t-d}^h) + \xi_t$ <br> $H_0: \psi_1 = \psi_2 = 0 \rightarrow LM_2$ <br> $\Delta X_t = \sum_{h=0}^{4} \psi_h (Z_t' s_{t-d}^h) + \xi_t$ <br> $H_0: \psi_1 = \cdots = \psi_4 = 0 \rightarrow LM_4$ |
| $s_{t-d} \notin Z_{t-1}'$ | |
| $\Delta X_t = \sum_{h=0}^{1} \psi_h (Z_t' s_{t-d}^h) + \xi_t$ <br> $H_0: \psi_1 = 0 \rightarrow L1$ | |

Notes: All the LM test statistics are asymptotically distributed under the null hypothesis as $\chi_f^2$ where $f = m(k(r+1) + (p-1)k^2)$ degrees of freedom where $m$ denotes the Taylor-order, $k$ is the number of endogenous variables, $r$ is the cointegration rank and $p$ is the lag order selected for the linear model.

The previous approximations have to be specified according to the transition function in the alternative hypothesis. For example, for the logistic function it is recommended to use the third-order Taylor expansion ($LM_3$). However, as the assumption of homoscedastic distributed errors is quite unrealistic, several papers recommend the use of heteroscedastic robust LM tests (e.g.: Granger and Teräsvirta, 1993; Teräsvirta, 1994; van Dijk et al, 2002).

Thus, once the linearity null has been rejected and the transition variable has been selected, we choose the transition function (logistic or exponential) using a sequence of tests of hypotheses following Escribano and Jordá (1999) (Table 2)[11].

Final step. Estimate the threshold and the smoothingparameters in the nonlinear model specified and apply usual residual tests to ensure a correct model specification that allows us to explore the mechanism by which prices move through the food marketing chain.

**Table 2. Sequence of nested hypothesis tests that should be applied to the following auxiliary regressions**

| **Test** | **Null hypothesis** | **Alternative hypothesis** | **Final decision** | |
|---|---|---|---|---|
| | | | ***Exponential*** | ***Logistic*** |
| $LM\_H_{04}$ | $\psi_4 = 0$ | $\psi_4 \neq 0$ | Reject $H_0$: exponential | Non-reject $H_0$: logistic |
| $LM\_H_{03}$ | $\psi_3 = 0 \| \psi_4 = 0$ | $\psi_3 \neq 0$ | Non-reject $H_0$: exponential | Reject $H_0$: logistic |
| $LM\_H_{02}$ | $\psi_2 = 0 \| \psi_3 = \psi_4 = 0$ | $\psi_2 \neq 0 \| \psi_3 = 0$ | Reject $H_0$: exponential | Non-reject $H_0$: logistic |
| $LM\_H_{01}$ | $\psi_1 = 0 \| \psi_2 = \cdots = \psi_4 = 0$ | $\psi_1 \neq 0 \| \psi_2 = \psi_3 = 0$ | Non-reject $H_0$: exponential | Reject $H_0$: logistic |

[11] A grid search to determine $(\gamma, c)$ that maximizes the log-likelihood function for each transition variable candidate is recommended to initialize conditions (Hansen and Seo, 2002). Recall also thatas these tests require to specify several auxiliary regressions for each regression this can yield an important problem of losing a lot degrees of freedom. To over come this issue we apply a conditional estimation which is carried out using OLS or SURE (seemingly unrelated method).

| | | | | |
|---|---|---|---|---|
| $LM\_H_e$ | $\psi_2 = \psi_4 = 0$ | $\psi_2 \neq 0 \vert \psi_4 \neq 0$ | Reject $H_0$: exponential | Non-reject $H_0$: logistic |
| $LM\_H_1$ | $\psi_1 = \psi_3 = 0$ | $\psi_1 \neq 0 \vert \psi_3 \neq 0$ | Non-reject $H_0$: exponential | Reject $H_0$: logistic |

Notes: The LM test statistics are all based on the auxiliary regression $\Delta X_t = \sum_{h=0}^{4} \psi_h \left( Z_t' s_{t-d}^h \right) + \xi_t$.

Following Lo and Zivot (2001), a three-regime TVECM model (TVECM$_3$) can be specified as:

$$\Delta P_t = \begin{cases} \alpha^1 \omega_{t-1}(\beta) + \sum_{i=1}^{k-1} \Gamma_i^1 \Delta P_{t-i} + u_t^1 \text{ ,if} z_{t-d} < \lambda^1 \\ \alpha^2 \omega_{t-1}(\beta) + \sum_{i=1}^{k-1} \Gamma_i^2 \Delta P_{t-i} + u_t^2 \text{ ,if} \lambda^1 \leq z_{t-d} \leq \lambda^2 \\ \alpha^3 \omega_{t-1}(\beta) + \sum_{i=1}^{k-1} \Gamma_i^3 \Delta P_{t-i} + u_t^3 \text{ ,if} z_{t-d} > \lambda^3 \end{cases} \tag{16}$$

with $z_{t-d}$ denoting the threshold variable which plays a crucial role in the dynamic adjustment of the price variable and can be either a function of lagged components of the endogenous variable, the error correction term $\omega_{t-1}(\beta)$or a lagged exogenous variable, and $\lambda = (\lambda^1, \lambda^2)$ the unknown threshold parameters defining the three regimes, which need to be estimated[12].

Once the model has been estimated, we check whether the dynamics and the adjustments towards the equilibrium in the long-run are linear or nonlinear. So, we will testthe null of a linear VECM against a three-regime TVECM and the null of two-regime TVECM against the alternative of a three-regime TVECM using the two following sup-likelihood ratio test statistics:

$$LR_{13} = T\left(\ln\left|\hat{\Sigma}\right| - \ln\left|\hat{\Sigma}_3\left(\hat{\lambda}\right)\right|\right) \tag{17}$$

$$LR_{23} = T\left(\ln\left|\hat{\Sigma}_2\left(\hat{\lambda}\right)\right| - \ln\left|\hat{\Sigma}_3\left(\hat{\lambda}\right)\right|\right) \tag{18}$$

where $\hat{\Sigma}$ are respectively the residual variance-covariance matrices of each respective model. If the linear null is rejected with $LR_{13}$ then we have to confirm whether a two-regime or three-regime threshold model is more appropriate with the $LR_{23}$ test statistic.

## 2.3. Measuring short-run dynamics

After having assessed the long-run dynamics, we now explore the adjustments of the deviations from the equilibrium in the short-run by computing the impulse response functions (IRFs) because they provide information about the size and persistence of the response of a specific variable to an unanticipated change in the other variable over time. This is particularly useful

[12] The reader is referred for example toBen-Kaabia and Gil (2007) for a detailed explanation of the estimation procedure.

in order to provide a better understanding of the dynamic relationships between prices along the food supply chain.

However, given the non-linear cointegration framework used in this study, Koop et al. (1996) claim that we cannot directly apply the computation of the linear IRFs and we should compute instead the generalization of the IRFs suggested in Potter (1995) and Koop et al. (1996) in order to capture the asymmetry in the different responses of the variables to one standard deviation of positive and negative unanticipated shocks in non-linear models.

Similar to the generalization of the IRFs, the non-linear IRFs (NLIRFs) are defined but considering the conditional expectation instead of the standard linear predictor. Hence, let $u_t = \delta$ be a specific unexpected shock and the history of the model $P_{t-1} = \varphi_{t-1}$. We can define

$$\begin{aligned} NLIRF(n, \delta, \varphi_{t-1}) & \\ &= E[P_{t+n} \mid u_t = \delta, u_{t+1} = \cdots = u_{t+n} = 0, \varphi_{t-1}] \\ &- E[P_{t+n} \mid u_t = 0, u_{t+1} = \cdots = u_{t+n} = 0, \varphi_{t-1}] \end{aligned} \quad (19)$$

for $n = 0,1,2, \ldots, N$. In the above expression we can see two important drivers of the NLIRF: the magnitude of the shock ($\delta \in u_t$) and the combined magnitude of the history ($\varphi_{t-1} \in \Omega_{t-1}$). Given that $\delta$ and $\varphi_{t-1}$ are realizations of the random variables$\Omega_{t-1}$ and $u_t$, Koop et al. (1996) pointed out the fact that NIRFs are realizations of stochastic variables given by:

$$NLIRF(n, \delta, \varphi_{t-1}) = E[P_{t+n} \mid u_t, \Omega_{t-1}] - E[P_{t+n} \mid \Omega_{t-1}] \quad (20)$$

Finally, in order to measure the extent of the responses to positive and negative unexpected shocks and the significance of asymmetries over time, we compute the following measure proposed in Potter (1995):

$$ASY(n, u_t, \varphi_{t-1}) = NLIRF(n, +\delta_i, \varphi_{t-1}) + NLIRF(n, -\delta_i, \varphi_{t-1}) \quad (21)$$

which is basically defined as the sum of NLIRFs for any particular shock (positive and negative), given a particular history $\varphi_{t-1}$.

## 3. THREE CASE STUDIES

### 3.1. Protected Geographical Indication "Cordero de Navarra"

The PGI "Cordero de Navarra" (lamb from Navarra) was designated with the EU PGI label in 2003. This quality designation only protects lambs from the Navarra and Lacha breeds. We can distinguish two types of lambs: the suckling lamb ("cordero lechal"), which is only fed with milk from the suckler lamb, and the light lamb ("cordero ternasco"), which is fed with milk at least until 45 days after birth for Navarra breeds and 25-30 for Lacha breeds, after which they are fattened with white cereal straw and a concentrate made mainly from cereals, legumes, vitamins and minerals. Both types of lamb are raised following traditional methods linked to territory based on extensive-type or semi-extensive-type systems, in which the diet is based on grass, fodder and cereals.

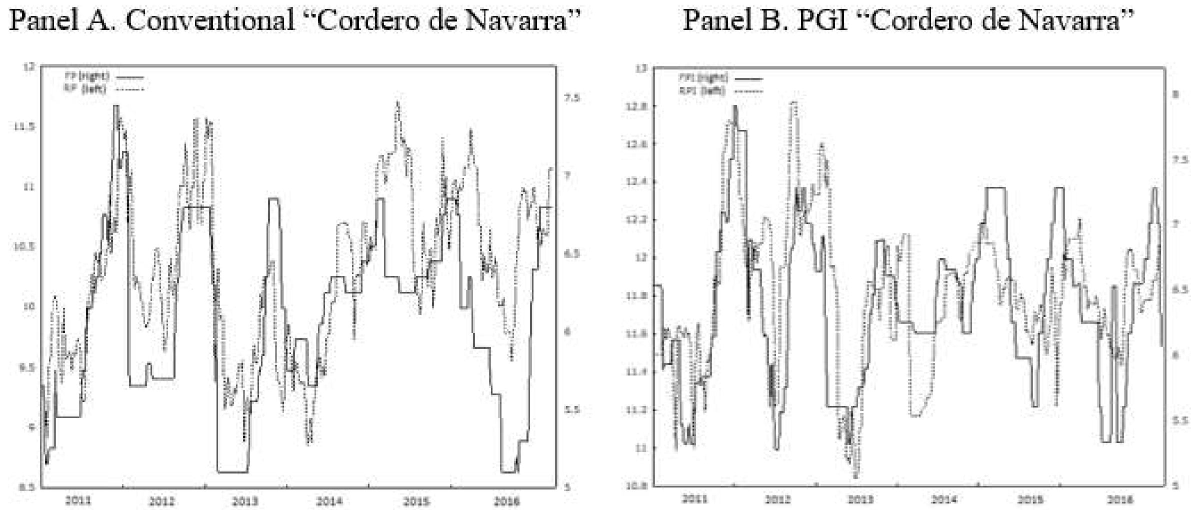
The Regulatory Council (RC) registered more than 200 families that make a living from raising PGI lambs, more than 50.000 lambs certified with the PGI label and 89 butchers authorized for commercialization in the region of Navarra.

### *3.1.1. Empirical results*

Navarra is located in the West Pyrenees leaning towards the river Ebro sharing a border in the north with France, in the south with La Rioja and Zaragoza (Spain); in the east with Zaragoza and Huesca (Aragón) and with Álava and Guipúzcoa (País Vasco), in the west. The area spans in total, 10.506 km, mostly mountainous terrain. This geography together with the weather and agricultural characteristics makes Navarra a region of contrasts which favours the development of the lamb of Navarra.

Data were extracted from the official statistics supplied by the Observatory of Agricultural Prices of the Government of Navarra (Spain) which includes a recent five-year period after prices started to rise again in2011, following the 2007/2008 price crisis. Specifically, the period covers 2011-2016 with a total of 312 observations. Weekly prices, expressed in Euros, are available at the farm and retail levels for the PGI "Cordero de Navarra"[13] and for its conventional counterpart. We will use the following notation for the prices to be analyzed: FPI and RPI for farm and retail prices of the PGI lamb respectively, and FP and RP for farm and retail prices of the conventional lamb, respectively.

**Figure 4. Lamb price series**




Source: Own calculation based on Regional Government of Navarra (Spain), Observatory of Agricultural Prices database. Vertical axes are measured in €/kg carcass.

Nominal prices are illustrated in Figure 4, with the conventional lamb shown in Panel A and the PGI lamb in Panel B. All the price series were transformed into natural logs according to theory. Prices of conventional lamb seem to suggest a co-movement over time with more fluctuation periods at retail level and lagged responses in some periods of farm prices after changes in retail prices. In Panel B, again, we can identify more volatile episodes at retail level than at farm level. From visual inspection of the two panels, prices display an increasing pattern over time.

A summary of basic statistics of all of the price series are reported in Table 3. The statistics indicate that the trend, though extremely small, is only significant in the conventional system not in the FQS system. All the prices seem to strongly reject the null hypothesis of no ARCH effects.

[13]In the remainder of the section we use indistinctly light lamb and lamb.

**Table 3. Summary of descriptive statistics for the Spanish lamb price series**

| | FP | RP | FPI | RPI |
|---|---|---|---|---|
| Mean | 6.080 | 10.301 | 6.380 | 11.818 |
| Median | 6.150 | 10.299 | 6.321 | 11.842 |
| Minimum | 5.100 | 8.843 | 5.285 | 10.840 |
| Maximum | 7.450 | 11.703 | 7.912 | 12.822 |
| Standard deviation | 0.580 | 0.685 | 0.606 | 0.393 |
| Skewness | -0.058 | -0.033 | 0.110 | 0.050 |
| Kurtosis (excess) | -0.899*** | -0.905*** | -0.620** | 0.240 |
| Jarque-Bera test | 10.576*** | 10.602*** | 5.622* | 0.881 |
| Engle (1982)'s test | 257.347*** | 187.593*** | 229.903*** | 221.897*** |
| Trend | $7.059e^{-04}$* | $2.489e^{-03}$*** | $5.059e^{-03}$ | $-1.907e^{-04}$ |
| # observations | 312 | 312 | 312 | 312 |

Notes: We have considered logarithmic transformations of the prices in our application. The use of the test of Engle (1982) allows us to check whether there are ARCH effects. In this case, we have used 2 lags. ***, ** and * denote statistically significant at 1%, 5% and 10% level of significance.

Unit root tests and stationarity tests are applied to analyze the order of integration of all the series. Results reported in Table 4 point out that the series can be characterized as non-stationary that is, integrated of order 1. The presence of a unit root in all the series is robust to the presence of possible structural changes according to Carrion-i-Silvestre et al (2009).

**Table 4. Results of the integration order for the Spanish lamb price series**

Panel A. Unit root and stationarity tests

| | MSB | KPSS |
|---|---|---|
| FP | 0.185 (1) | 0.680 (0)** |
| RP | 0.184 (5) | 1.189 (0)** |
| FPI | 0.155 (1) | 0.319 (1)** |
| RPI | 0.158 (1) | 0.349 (1)** |

Panel B. Unit root tests allowing for structural breaks (Carrion-i-Silvestre et al, 2009)

| | ADF | MSB | $\ell$ | Tb |
|---|---|---|---|---|
| FP | -2.521 (-3.347) | 0.195 (0.146) | 0 | 2011:47 (47) |
| RP | -3.246 (-3.451) | 0.147 (0.142) | 5 | 2012:52 (104) |
| FPI | -2.950 (-3.378) | 0.173 (0.145) | 0 | 2012:05 (57) |
| RPI | -4.022 (-4.142) | 0.131 (0.119) | 0 | 2012:05 (57)<br>2013:03 (107)<br>2013:41 (145) |

Notes: In Panel A, we apply the MSB unit root test as in Ng and Perron (2001) and the KPSS stationarity test. The truncation lag parameter, k, presented in parentheses and is estimated using the MAIC. Also, ** denotes statistically significant at 5% level of significance since the asymptotic critical values at 5% level for the constant (trend) case are respectively 0.233 (0.168) for the MSB, and 0.463 (0.146) for the KPSS. As for the prices in the conventional system we have applied the tests in their respective trend version. In Panel B, $\ell$ reflects the bandwidth parameter for the KPSS test selected with the automatic bandwidth procedure of Andrews (1991) for the kernel-based estimator of the long-run variance. The critical value at the 5% significance level of each test is shown in parentheses. Tb reflects the time breaks, that is, the date when a structural break was endogenously detected and the corresponding number of observation is presented in parentheses.

Since all the price series are nonstationary, we can assess whether there is cointegration between each pair of prices in each system. As our cointegration testing approach is based on the unrestricted VAR model we first estimate the lag order which ensures the presence of no autocorrelation in the system. Results are reported in Table 5.

Based on the lag order choice for the two VAR model specifications, we test for cointegration rank following Johansen (2002)[14]. Table 6 shows the results and the respective long-run relationships for each system. The coefficients can also be interpreted as price elasticities since the prices have been transformed into logs. In the conventional system, there is a strong positive relationship (42.3%) which implies that an increase in farm prices will lead to an increase in retail prices. For the FQS system, the results imply a slightly weaker relationship between prices, around 20% of price elasticity.

**Table 5. VAR lag length selection for the Spanish lamb sector**

Panel A. Conventional System

| IC | k |
|---|---|
| BIC; AIC; HQ | 1; 6; 1 |

Panel B. FQS System

| IC | k |
|---|---|
| BIC; AIC; HQ | 1; 1; 1 |

Notes: k denotes the number of lags of the unrestricted VAR model. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

**Table 6. Results of the cointegration analysis for the Spanish lamb sector**

Panel A. Conventional System

| Rank | Eigen value | $\lambda^*_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.073 | 24.494 | 0.001 |
| 1 | 0.021 | 6.328 | 0.172 |

Cointegration relationship: $ECT = RP_t - 1.568^{***} - 0.423^{***}FP_t$

Panel B. FQS System

| Rank | Eigen value | $\lambda^*_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.079 | 34.032 | 0.000 |
| 1 | 0.027 | 8.450 | 0.069 |

Cointegration relationship: $ECTI = RPI_t - 2.103^{***} - 0.198^{***}FPI_t$

[14] The use of the approach of Engle and Granger (1987) also concludes in favour of the presence of cointegration relationships in each system.

Notes: *** denotes statistically significant at 1% level of significance. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

After having identified the existence of a stationary relationship in the long-run between each pair of prices in the two systems, we examine whether the adjustment process exhibits non-linearities. To do so, we test the null that the adjustment is linear against the alternative of the threshold model specification. But first, we determined in Table 7 that the threshold variable ($\omega_{t-1}$) in the conventional system is $RP_{t-1}$ and in the FQS system is $ECTI_{t-1}$.

Now, we estimate the LSTVECM but since the estimated value of the smoothing parameter is very large in both systems ($\gamma \approx 500$), the model becomes TVECM[15]. Subsequently, we test in Table 8 which threshold model best suits in the two systems given their respective threshold variables. Results indicate that we can characterize the two systems by the $TVECM_3$. The middle panel shows the estimated threshold parameters for each system. In particular, for the conventional system, $\hat{\lambda}(CS) = (-0.027, 0.029)$ splitting the adjustment mechanism depending on if the RP lies below 10%, between 10% and 79%, and above 79%; whereas in the FQS system, $\hat{\lambda}(QS) = (-0.010,0.029)$ indicates that the adjustment process is described if the ECT lies below 37%, above 46%, or between 37% and 46%.

**Table 7. Threshold variable selection**

| | **Conventional System** | | **FQS System** | |
|---|---|---|---|---|
| **Test** | **Variable** | **p-value** | **Variable** | **p-value** |
| $LM_1$ | $RP_{t-1}$ | 3.29E-05 | $ECTI_{t-1}1$ | 0.0247 |
| LM_W1 | $RP_{t-2}$ | 0.0642 | $ECTI_{t-1}$ | 0.0287 |
| $LM_2$ | $RP_{t-1}$ | 2.38E-11 | $ECTI_{t-1}$ | 0.0349 |
| LM_W2 | $RP_{t-1}$ | 0.167 | $ECTI_{t-1}$ | 0.0168 |
| $LM_3$ | $RP_{t-1}$ | 3.94E-10 | $ECTI_{t-1}$ | 0.0935 |
| LM_W3 | $RP_{t-1}$ | 0.149 | $ECTI_{t-1}$ | 0.0457 |
| $LM_4$ | $RP_{t-1}$ | 2.14E-09 | $ECTI_{t-1}$ | 0.0711 |
| LM_W4 | $RP_{t-1}$ | 0.243 | $ECTI_{t-1}$ | 0.0667 |
| LMH_1 | $RP_{t-1}$ | 3.29E-05 | $ECTI_{t-1}$ | 0.0247 |
| LMH_W1 | $RP_{t-2}$ | 0.0642 | $ECTI_{t-1}$ | 0.0287 |
| LMH_2 | $RP_{t-1}$ | 3.80E-08 | $ECTI_{t-1}$ | 0.249 |
| LMH_W2 | $RP_{t-1}$ | 0.0273 | $ECTI_{t-1}$ | 0.216 |
| LMH_3 | $RP_{t-2}$ | 0.182 | $FP_{t-1}$ | 0.0699 |
| LMH_W3 | $RP_{t-2}$ | 0.0219 | $FP_{t-1}$ | 0.0941 |
| LMH_4 | $ECT_{t-1}$ | 0.14 | $ECTI_{t-1}$ | 0.19 |
| LMH_W4 | $ECT_{t-1}$ | 0.0625 | $ECTI_{t-1}$ | 0.309 |

Notes: LM denotes the standard Lagrange multiplier, and LM_W is the heteroscedastic robust LM test statistic.

Table 9 reports the estimated results for the three-regime TVECM specified for the conventional and FQS systems, which have passed usual residual tests to ensure a correct model specification.

Now, we pay attention to the adjustment mechanism of the two systems. This is useful to show how prices react to revert to the equilibrium after an unexpected shock that surpasses a certain threshold and changes the long-run relation between prices. This behaviour depends on whether the shock generates a decrease or an increase.

[15]Results are omitted to save some space but available from authors upon request.

Note first that not all the adjustment coefficients are statistically significant. Thus, for the conventional system, when a shock makes RP decrease, FP does not react because the estimated adjustment coefficient is not statistically significant ($\alpha_2^1 = -0.028$). However, when the shock makes RP decrease, RP strongly reacts ($\alpha_1^1 = -0.463$) by decreasing almost 46%. This is also valid when the shock generates an increase in RP or a decrease in FP. When prices seem not to suffer from significant decreases (second regime), the response of the upstream level is small but significant ($\alpha_2^2 = 0.057$) and the response in the downstream level is not significant. For the FQS system, the discussion is quite similar but the significant adjustments are smaller in magnitude except for the reaction of the FPI against a slight decrease in RPI (second regime), which results more strongly($\alpha_2^2 = 0.718$) compared to that reported in the conventional system.

**Table 8. Results for the tests for non-linearities in price adjustments in both systems**

| | **Conventional System** | | | **FQS System** | | |
|---|---|---|---|---|---|---|
| | $LR_{13}$ | | $LR_{23}$ | $LR_{13}$ | | $LR_{23}$ |
| **Test statistic (p-value[a])** | 112.998 (0.03) | | 40.318 (0.00) | 42.461 (0.03) | | 20.596 (0.00) |
| **Estimated threshold parameters** | | | | | | |
| $\hat{\lambda}^1$ | -0.027 | | | -0.010 | | |
| $\hat{\lambda}^2$ | 0.029 | | | 0.029 | | |
| **Percentage of observations** | *First regime* | *Second regime* | *Third regime* | *First regime* | *Second regime* | *Third regime* |
| | 10.032% (31 obs) | 78.964% (288 obs) | 11.003% (34 obs) | 36.57% (113 obs) | 46.278% (143 obs) | 17.152% (53 obs) |

Notes: $LR_{13}$ tests the null hypothesis of linearity against the alternative hypothesis of TVECM model (Lo and Zivot, 2001). $LR_{23}$ tests the null hypothesis of TVECM$_2$ model against the alternative hypothesis of TVECM$_3$ (Lo and Zivot, 2001).

[a]Critical values at the 5% significance level were obtained by using the FR bootstrapping technique (Hansen and Seo, 2002) or the PR bootstrap algorithm (Hansen and Seo, 2002).

**Table 9. Estimated results for the TVECM$_3$**

**Conventional System**

| **Estimated parameters** | *First regime* | *Second regime* | *Third regime* |
|---|---|---|---|
| $\begin{pmatrix} \alpha_1^i \\ \alpha_2^i \end{pmatrix}$ | $\begin{pmatrix} -0.463^{***}\ (0.156) \\ -0.028\ (0.020) \end{pmatrix}$ | $\begin{pmatrix} -0.014\ (0.016) \\ 0.057^{*}\ (0.034) \end{pmatrix}$ | $\begin{pmatrix} -0.605^{***}\ (0.101) \\ 0.156\ (0.183) \end{pmatrix}$ |

**FQS System**

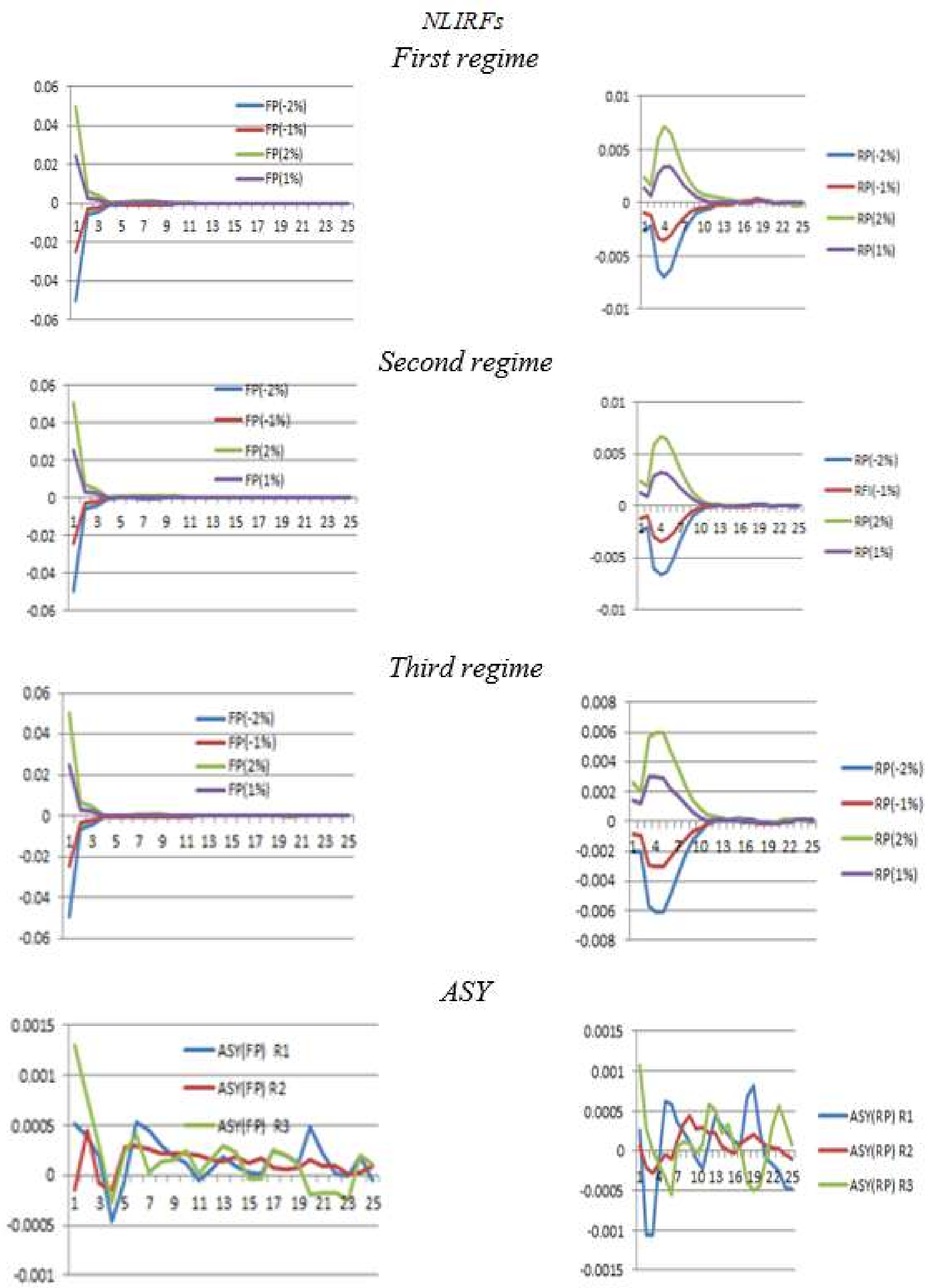
| **Estimated parameters** | *First regime* | *Second regime* | *Third regime* |
|---|---|---|---|

| | | | |
|---|---|---|---|
| $\begin{pmatrix}\alpha_1^i \\ \alpha_2^i\end{pmatrix}$ | $\begin{pmatrix}-0.134^{***}\ (0.041) \\ 0.192\ (0.118)\end{pmatrix}$ | $\begin{pmatrix}-0.071\ (0.061) \\ 0.718^{**}\ (0.302)\end{pmatrix}$ | $\begin{pmatrix}-0.133^{**}\ (0.068) \\ 0.021\ (0.116)\end{pmatrix}$ |

Notes: Values presented in parentheses for the estimated parameters of adjustment coefficients $(\alpha_1^i, \alpha_2^i)$ are standard deviations robust to heteroscedasticity. *** (**, *) stands significance at 1% (5%, 10%) level.

The previous results have given us an idea on how the price transmission mechanism works in the long-term in both systems. Now, we complete this analysis by examining the short-run dynamics by means of the computation of the non-linear impulse response functions in order to determine whether the transmission mechanism is symmetric or asymmetric.

**Figure 5. Responses of FP and RP to a shock in FP**



Notes: In the left (right) panels, the conventional FP (RP) response to a shock in FP for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is provided for the three regimes (R1, R2, and R3).

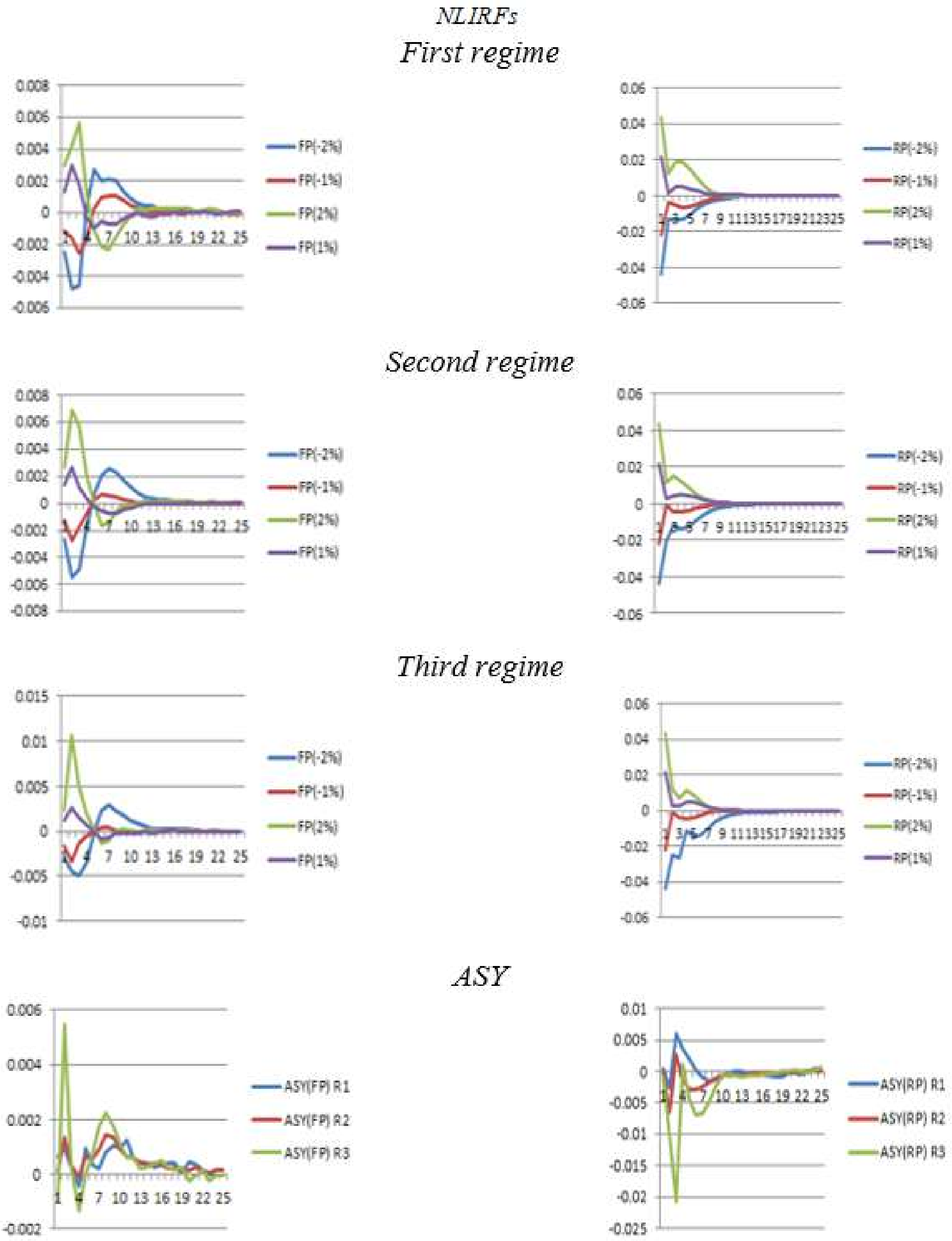
We illustrate in Figures 5 and 6 the performance of the price adjustments specific-regime by computing the NLIRFs for $\delta = (\pm 1, \pm 2)$ along with Potter's measure (ASY) for the conventional system. Results for the FQS system are presented in Figures 7 and 8. All figures follow the same structure and show the responses in FP in the left-hand panel whereas those in the RP are reported in the right-hand panel. In the upper panel we illustrate the short dynamics calculated for two positive and two negative shocks of the same magnitude when a shock occurs in the first regime; the second panel shows the short dynamics when a shock takes place in the second regime; the next panel shows results for the third regime; and, finally, the lower panel illustrates the asymmetric Potter's measure.

Some comments are worthy to mention with respect to the conventional system. As can be seen in Figure 5, we can distinguish three phases in which responses are quite similar regardless of the regime. Thus, in the first phase, both prices decrease but the response in RP is less than half of the FP, so the gross margin[16] does not decrease. In the second phase, while the FP maintains its downward trajectory, RP notably increases before decreasing and entering in the third phase, in which both prices go down to reach the equilibrium by week 4 (FP) and 13 (RP). For both prices, the asymmetry in the short-run tends to be positive with some periods in which Potter's measure reverts to negative before reaching the equilibrium after 25 weeks or so. Moreover, it can be seen that retailers slightly benefit from positive asymmetries as FP increases are transmitted more rapidly than decreases.

In Figure 6, unlike what was plotted in Figure 5, farm responses differ from retail responses because the former exhibit a cyclical asymmetric pattern that is not present in the latter, which seems to be quite symmetric. Moreover, farm responses are much smaller in magnitude compared to retail responses, which may indicate the existence of retail market power to some extent as the decreases of farm prices are not significant enough to reduce the margin in the case of demand shocks. In this case, the reaction to a shock in RP is positive asymmetric in the downstream level and negative asymmetric in the upstream level, which suggests that decreases in RP are transmitted much less through the chain than increases, pointing to some retail market power.

[16]Gross margin defined as the difference in absolute value between RP and FP.

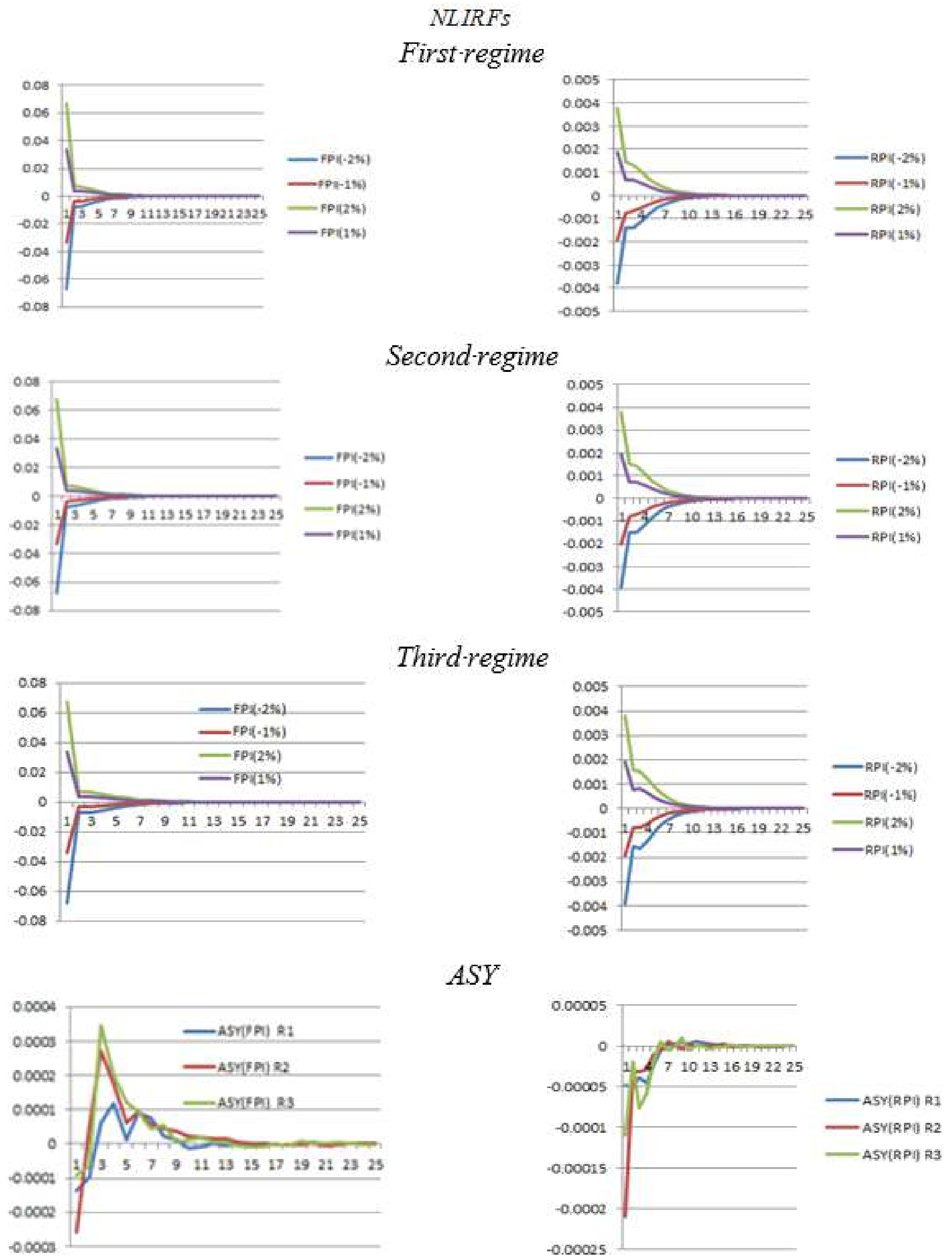
**Figure 6. Responses of FP and RP to a shock in RP**




Notes: In the left (right) panels, the conventional farm (retail) prices response to a shock in FP for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is provided for the three regimes (R1, R2, and R3).

Now, we analyze the responses of the two prices to shocks in the FQS system. As can be seen from Figure 7 and regardless of the regime, the responses to a positive or a negative shock exhibit a symmetric decreasing pattern, for which the initial responses are immediate. Also, the responses in FPI to any shock are higher than those in RPI, which indicates that retailers do not exert market power as we expected a priori. In this case, the convergence of the responses in FPI is not as fast as in FP (9 weeks), and time to converge responses in RPI is similar to that in RP. Moreover, the magnitudes in FPI responses are slightly superior to those illustrated for FP in Figure 5, but the magnitudes in RPI are smaller than in RP. In general, we can observe that for each regime, the FPI response exhibits negative asymmetries during the first two weeks before benefiting from positive asymmetries which last more than12 weeks before reaching the equilibrium. On the contrary, RPI responses only show negative asymmetries until reverting to equilibrium by week 5.

**Figure 7. Responses of FPI and RPI to a shock in FPI**

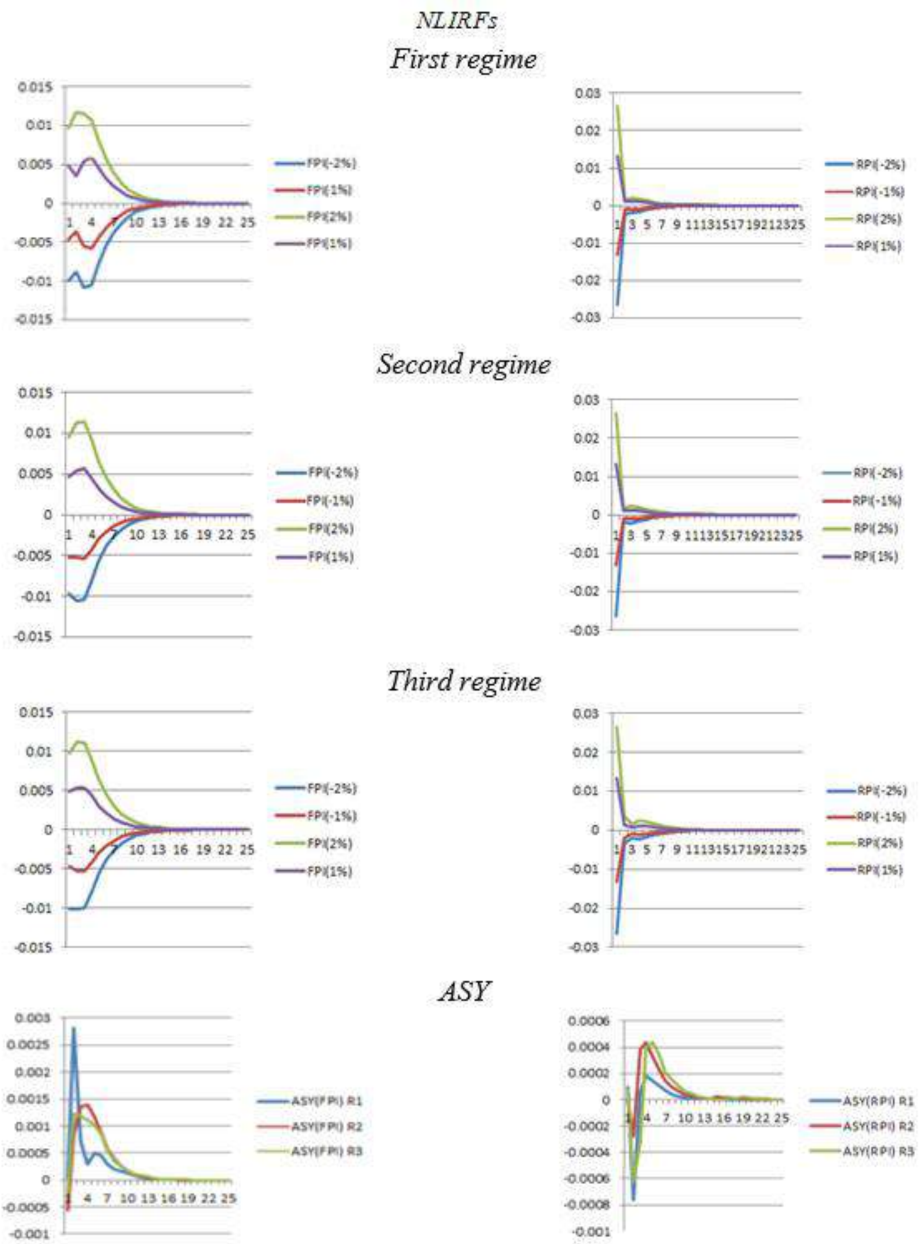



Notes: In the left (right) panels, the FQS farm (retail) prices response to a shock in FPI for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is provided for the three regimes (R1, R2, and R3).

Looking at the responses of a shock in RPI, the picture plotted in Figure 8 is quite different from that illustrated in Figure 7 for the conventional system. In particular, we first notice that responses of the retailers in the FQS system are smaller in magnitude than those reported in the conventional system, and the magnitude of the responses of the farmers slightly superior.

Moreover, the responses plotted in Figure 8 show a symmetric pattern regardless of the regime and the magnitude of the shock. The FPI responses seem to be less than half of RPI responses. In this case, the cumulative responses are clearly positive asymmetric for FPI and greater than those for RPI, which show quite small negative asymmetries during the first three weeks before reverting to positive for about 6-9 weeks to reach the equilibrium between week 9 and 13. The evidence reported in this case does not support the idea of market power exerted by retailers.

**Figure 8. Responses of FPI and in RPI to a shock in RPI**




Notes: In the left (right) panels, the FQS farm (retail) prices response to a shock in RPI for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is provided for the three regimes (R1, R2, and R3).

Based on these results, we can draw the following general conclusions. The responses in both systems are immediate regardless of their sign and magnitude. In general, prices exhibit quite symmetric pattern responses to any shock and regime considered, except for the case of FP responses to a shock in RP for which the pattern slightly differs. We can also claim that after positive and negative shocks in the upstream price level, responses in this level are higher than in the downstream price level, being slightly higher in the FQS system than in the conventional system which we had expected a priori. However, those responses in the downstream level are lower in the FQS system than in the conventional system. Farm responses are much smaller than retail responses in the conventional system which may indicate that retailers may exert some level of market power and benefit during a short time when prices change. In the FQS system, the data does not support this. Moreover, the time spent to revert to equilibrium is slightly lower in the FQS system than in the conventional system. Finally, and despite the fact that the magnitude of the cumulative responses was small, we found negative asymmetries in the retail price of the FQS product, as was also the case for its conventional counterpart.

## 3.2. Protected Geographical Indication "Ternera de Navarra"

PGI "Ternera de Navarra" (beef from Navarra) was created in 1994 as a label of origin with the objective of protecting and promoting an underestimated foodstuff produced traditionally so that the consumer may perceive this system as ensuring the superior quality of the beef meat. The method of production is based on the sustainable exploitation of natural resources and the environment along with exhaustive controls realized by ENAC (national body that certifies the reliability of these controls). In 2000 Ternera de Navarra was designated with the European PGI label. The area of the Navarra region designated for breeding the beef from Navarra represents almost 96% of the total territory.

In 2016, the Regulatory Council (RC) registered 513 farms, 15 more than in the year 2015, and had 180 butchers authorized for commercialization. Farms raise the Pirenaica, Blonde, Parda Alpina, Charolais breeds and their crossbreeds. Suckling is compulsory at least during the first four months after birth, when the suckler cow is allowed to graze as usual, and be fed a supplementary nutrition composed by maize, barley, soya, wheat, beans, and concentrated foodstuffs authorized by the RC. The RC guarantees the quality of the PGI Beef of Navarra by controlling the maturing period of the beef (at least one week) until gaining the optimal conditions of colour, taste, aroma and tenderness with a pH always less or equal than 5.8, and by controlling the traditional cutting process. The RC has 4 slaughterhouses which slaughter 6.856 animals, producing around 2,177.246 tonnes of beef, mostly commercialized in the domestic market with small export figures to international markets.

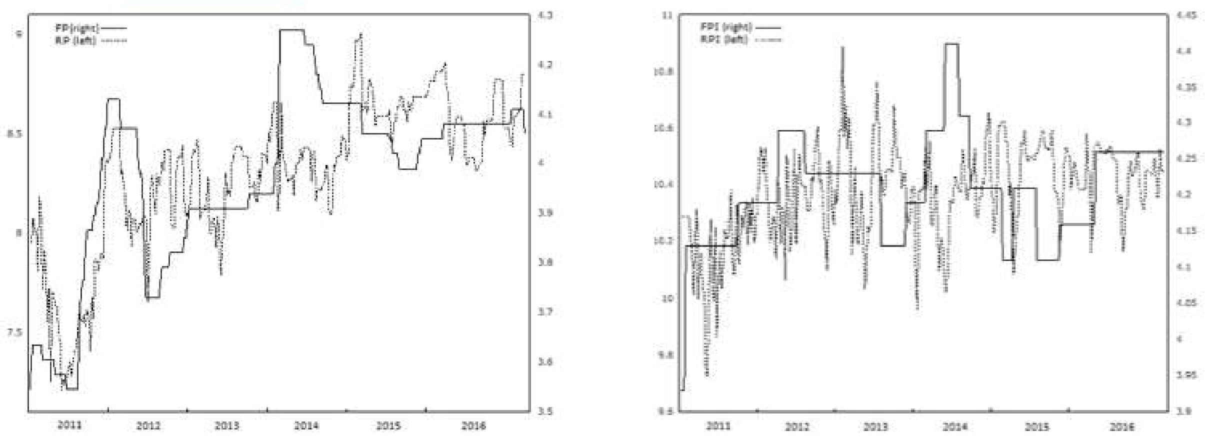
### *3.2.1. Empirical results*

As in the previous case study, data were collected from the Observatory of Agricultural Prices of the Government of Navarra. Data are available for the PGI "Ternera de Navarra" and its conventional counterpart so that we can compare both systems. Prices time-series are expressed in Euros, and available at farm level (price paid to the farmer) and retail level (price paid by the consumer). Our choice follows the natural selection commonly used in the price transmission literature (Goodwin and Piggott, 2001).

Weekly prices are available for the period from 2011 to 2016. For the quality system, we have farm (FPI) and retail (RPI) prices whereas for the conventional system, we have farm (FP) and retail (RP) prices. Again, our data set covers the important period after the recent rise in prices in 2011 after the first food crisis of 2007/2008. We present nominal prices in Figure 1, in which Panel A illustrates the conventional beef and Panel B illustrates the PGI beef. All price series were transformed into natural logs according to theory (Banerjee et al, 1993). In Panel A, prices show a similar trend pattern during the period, which may suggest an equilibrium relationship in the long-run, but with more volatile periods at the retail level than at the farm level. In Panel B, prices also seem to obey a long-term relationship, again with more significant volatile episodes for retail than for farm prices. In this case, farm prices tend to adjust only a bit slower after a change at the retail level. Every price series exhibits a growth trend over the whole sample period.

**Figure 9. Beef price series**

Panel A. Conventional "Ternera de Navarra" Panel B. PGI "Ternera de Navarra"



Source: Own calculation based on Regional Government of Navarra (Spain), Observatory of Agricultural Prices database. Vertical axes are measured in €/kg carcass.

Table 10 shows a summary of the descriptive statistics of the price series for each system. The statistics indicate that the trend is significant in both the conventional and the FQS price series but almost negligible. All the prices are found to exhibit non-normality and ARCH effects. In all, we have 312 observations for each series.

**Table 10. Summary of descriptive statistics for the Spanish beef price series**

| | FP | RP | FPI | RPI |
|---|---|---|---|---|
| Mean | 3.975 | 8.305 | 4.207 | 10.370 |
| Median | 4.050 | 8.379 | 4.210 | 10.385 |
| Minimum | 3.545 | 7.204 | 3.930 | 9.729 |
| Maximum | 4.270 | 9.010 | 4.410 | 10.888 |
| Standard deviation | 0.179 | 0.371 | 0.072 | 0.166 |
| Skewness | -0.788*** | -0.916*** | -0.024*** | -0.644*** |
| Kurtosis (excess) | 0.120 | 0.590** | 1.880*** | 0.990*** |
| Jarque-Bera test | 32.487*** | 48.176*** | 45.941*** | 34.307*** |
| Trend | $1.325e^{-03}$*** | $3.159e^{-03}$*** | $1.981e^{-04}$*** | $8.231e^{-04}$*** |
| # observations | 312 | 312 | 312 | 312 |

Notes: We have considered logged prices in our application. The use of the Engle (1982)'s test allows us to test for ARCH effects. We have used 2 lags. *** (**) denotes statistically significant at 1% (5%) level(s) of significance.

We move to the preliminary analysis of the univariate stochastic properties of the series considered. Unit root tests and stationarity tests confirm the existence of a unit root in the series of each system, and this result does not change when testing for unit roots when allowing for structural breaks (Table 11).

**Table 11. Results of the integration order for the Spanish beef price series**

Panel A. Unit root and stationarity tests

| | MSB | KPSS |
|---|---|---|
| FP | 0.284 (3) | 0.471 (1)** |
| RP | 0.337 (3) | 0.673 (0)** |
| FPI | 0.284 (3) | 0.471 (1)** |
| RPI | 0.337 (3) | 0.673 (0)** |

Panel B. Unit root tests allowing for structural breaks (Carrion-i-Silvestre et al, 2009)

| | ADF | MSB | $\ell$ | Tb |
|---|---|---|---|---|
| FP | -1.978 (-3.092) | 0.300 (0.161) | 3 | 2016:20 (281) |
| RP | -2.368 (-3.098) | 0.201 (0.160) | 5 | 2016:19 (280) |
| FPI | 2.521 (-3.172) | 0.398 (0.157) | 3 | 2011:32 (32) |
| RPI | -3.097 (-3.827) | 0.152 (0.130) | 1 | 2012:44 (96)<br>2015:21 (229) |

Notes: In Panel A, we apply the MSB unit root test as in Ng and Perron (2001) and the KPSS stationarity test. The truncation lag parameter, k, presented in parentheses and is estimated using the MAIC. Also, ** denotes statistically significant at 5% level of significance since the asymptotic critical values at 5% level for the trend case are respectively 0.168 (MSB) and 0.146 (KPSS). In Panel B, $\ell$ reflects the bandwidth parameter for the KPSS test selected with the automatic bandwidth procedure of Andrews (1991) for the kernel-based estimator of the long-run variance. The critical value at the 5% significance level of each test is shown in parentheses. Tb reflects the time breaks, that is, the date when a structural break was endogenously detected and the corresponding number of observation is presented in parentheses.

Now, we address the first step to model non-linear adjustments. According to theory, cointegration exists when two or more nonstationary variables, prices in our case, show a tendency to move together in the long term and deviations from this equilibrium due to unanticipated shocks tend to revert eventually. Further, recall that the cointegration analysis is based on the unrestricted vector autoregressive (VAR) model. See Juselius (2006) for an excellent illustration of the co-integrated VAR model. Thus, before testing for cointegration, it is necessary to determine the number of lags to be included in the unrestricted VAR model. Table 12 reports the results.

Based on the lag choice for each system, we test for cointegration using the likelihood ratio test developed by Johansen (1988, 2002) and determine the cointegration rank[17] using the Bartlett corrected trace test $\lambda^*_{trace}$. Furthermore, the cointegrating vector can still be estimated superconsistently in the presence of neglected non-linearity in the adjustment process. Before determining the cointegration rank, the system has to be correctly specified. More precisely, we determine which deterministic components must be included and what the optimum lag is that ensures that residuals are approximately white noise and have zero autocorrelations for all lags.

[17] Note that if we apply the method suggested in Engle and Granger (1987) we also found the existence of respective co-integration relationships in the two systems.

**Table 12. VAR lag length selection for the Spanish beef sector**

Panel A. Conventional System

| IC | lags |
|---|---|
| BIC; AIC; HQ | 2; 5; 2 |

Panel B. FQS System

| IC | lags |
|---|---|
| BIC; AIC; HQ | 1; 3; 1 |

Notes: Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

Results, which are reported in Table 13, show the respective relationships in each system. As prices are considered in logs, we can read the cointegration parameters as price elasticities. In both cases, we can observe a positive relationship, which is especially strong in the conventional system (97.9%) implying that an increase in farm prices will lead to a rise in retail prices. Whereas for the FQS system, farm prices exert very low influence on retail prices, about 7% of price elasticity.

**Table 13. Cointegration analysis for the Spanish beef sector**

Panel A. Conventional System

| Rank | Eigen value | $\lambda^{*}_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.037 | 14.811 | 0.062 |
| 1 | 0.011 | 3.297 | 0.069 |

Cointegration relationship: $ECT = RP_t - 0.979^{***} FP_t$

Panel B. FQS System

| Rank | Eigen value | $\lambda^{*}_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.089 | 36.601 | 0.000 |
| 1 | 0.027 | 8.404 | 0.070 |

Cointegration relationship: $ECTI = RPI_t - 2.240^{***} - 0.068\, FPI_t$

Notes: *** denotes statistically significant at 1% level of significance. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

Having identified the existence of a stationary relationship in the long-run between each pair of prices in the two systems, we examine whether the adjustment process exhibits non-linearities in both systems. To do so, we test the null that the adjustment is linear against the alternative of the threshold model specification. But, first, the transition variable must be selected by running several LM tests.

For the conventional system, results are reported in Table 14and as can be seen the results reject the linear null in all the situations indicating that $RP_{t-1}$ is the transition variable. However, the following calculations for the LSTVECM are excessive and meaningless so we have to impose the $ECT_{t-1}$ as threshold variable, and assume the threshold model. For the quality system, we cannot find convergence when selecting the transition variable even if the number of lags changes. So, again, we check the results considered $RP_{t-1}$, $RP_{t-1}$ and $ECTI_{t-1}$ as transition variables. Estimated results for the LSTVECM assumed that the two first variables are excessive, and makes no sense. Results for the latter indicate that $\gamma \approx 500$ and hence, the model becomes a threshold model. So, we must estimate a threshold model for the two systems. Results are reported in Table 15.

**Table 14. Threshold variable selection**

| | Conventional System | |
|---|---|---|
| **Test** | **Variable** | **p-value** |
| $LM_1$ | $RP_{t-1}$ | 6.82E-06 |
| LM_W1 | $RP_{t-2}$ | 0.10 |
| $LM_2$ | $RP_{t-1}$ | 8.57E-12 |
| LM_W2 | $RP_{t-1}$ | 0.05 |
| $LM_3$ | $RP_{t-1}$ | 1.96E-15 |
| LM_W3 | $RP_{t-1}$ | 0.03 |
| $LM_4$ | $RP_{t-1}$ | 6.72E-22 |
| LM_W4 | $RP_{t-1}$ | 0.06 |
| LMH_1 | $RP_{t-1}$ | 6.82E-06 |
| LMH_W1 | $RP_{t-2}$ | 0.10 |
| LMH_2 | $RP_{t-1}$ | 6.77E-08 |
| LMH_W2 | $RP_{t-1}$ | 0.15 |
| LMH_3 | $RP_{t-2}$ | 1.25E-05 |
| LMH_W3 | $RP_{t-2}$ | 0.03 |
| LMH_4 | $ECT_{t-1}$ | 1.3E-08 |
| LMH_W4 | $ECT_{t-1}$ | 0.03 |

Notes: LM denotes the standard Lagrange multiplier, and LM_W is the heteroscedastic robust LM test statistic.

In Table 15, we can see for the conventional and FQS system that the linear null is rejected at 10% and 5% significance levels respectively, and that the null of a two-regime TVECM against the alternative of a three-regime TVECM is rejected too. So, we can confirm that both systems can be modelled by means of a three-regime TVECM (TVECM$_3$). In particular, for the conventional system, $\hat{\lambda}(CS) = (0.701, 0.772)$ splitting the adjustment mechanism depending on if the RP lies below 18%, between 18% and 67%, and above 67%; whereas in the FQS system, $\hat{\lambda}(QS) = (-0.020{,}0.014)$ indicates that the adjustment process is described if the ECT lies below 12%, above 72%, or between 12% and 72%.

**Table 15. Results for the nonlinear tests**

| | Conventional System | | FQS System | |
|---|---|---|---|---|
| | $LR_{13}$ | $LR_{23}$ | $LR_{13}$ | $LR_{23}$ |
| **Test statistic (p-value[a])** | 64.357 (0.10) | 11.843 (0.00) | 50.642 (0.03) | 11.821 (0.00) |
| **Estimated threshold parameters** | | | | |
| $\hat{\lambda}^1$ | 0.701 | | -0.020 | |
| $\hat{\lambda}^2$ | 0.772 | | 0.014 | |

| **Percentage of observations** | *First regime* | *Second regime* | *Third regime* | *First regime* | *Second regime* | *Third regime* |
|---|---|---|---|---|---|---|
| | 18.12% (56 obs) | 66.99% (207 obs) | 14.89% (46 obs) | 11.69% (36 obs) | 72.40% (223 obs) | 15.91% (49 obs) |

Notes: $LR_{13}$ tests the null hypothesis of linearity against the alternative hypothesis of TVECM model (Lo and Zivot, 2001). $LR_{23}$ tests the null hypothesis of $TVECM_2$ model against the alternative hypothesis of $TVECM_3$ (Lo and Zivot, 2001).

[a]Critical values at the 5% significance level were obtained by using the FR bootstrapping technique (Hansen and Seo, 2002) or the PR bootstrap algorithm (Hansen and Seo, 2002).

Table 16 reports the estimated results for the $TVECM_3$ specified for both the conventional and FQS systems. We briefly discuss the adjustment mechanism of the two systems as it is of interest to show how prices revert to the equilibrium after an unanticipated shock that surpasses a certain threshold, changing the relation between prices in the long term. This behaviour depends on whether the shock generates a decrease (first regime) or an increase (third regime). Thus, for the conventional system, when a shock makes RP decrease, FP does not react because the estimated adjustment coefficient is not statistically significant ($\alpha_2^1 = 0.047$), and when the shock makes FP increase, RP neither reacts($\alpha_1^1 = -0.246$). Thus, when prices seem not to suffer from remarkable increases (decreases), that is, the second regime, the response of the upstream level is small but not significant ($\alpha_2^2 = -0.007$) but the response in the downstream level is statistically significant ($\alpha_2^1 = -0.096$). Finally, when prices increase, only RP reacts ($\alpha_2^2 = -0.542$).The discussion in the FQS system is quite similar but we can also find in the first regime a significant response from the RP ($\alpha_2^2 = -0.264$). Adjustments are of similar magnitude when compared with the results from the conventional system.

We complete this analysis by examining the short-run dynamics by means of the computation of the non-linear impulse response functions in order to determine whether the transmission mechanism is symmetric or asymmetric.

Figures 10 and 11 illustrate the performance of the price adjustments specific-regime by computing the NIRFs for $\delta = (\pm 1, \pm 2)$ along with the cumulative Potter's measure (ASY) for each regime for the conventional system. Similarly, Figures 12 and 13 show the results for the FQS system. Figures follow the same structure: the responses in FP are reported in the left-hand panel whereas those of RP are in the right-hand panel; the upper panel illustrates the short dynamics calculated for two positive and two negative shocks of the same magnitude when a shock occurs in the first regime; the second panel shows the short dynamics when a shock takes place in the second regime; the next panel shows the results for the third regime; and, the lower panel illustrates the asymmetric Potter's measure for each regime.

**Table 16. Estimated results for the $TVECM_3$**

**Conventional System**

| **Estimated parameters** | *First regime* | *Second regime* | *Third regime* |
|---|---|---|---|
| $\begin{pmatrix} \alpha_1^i \\ \alpha_2^i \end{pmatrix}$ | $\begin{pmatrix} -0.246\ (0.162) \\ 0.047(0.050) \end{pmatrix}$ | $\begin{pmatrix} -0.096^{*}(0.051) \\ -0.007\ (0.023) \end{pmatrix}$ | $\begin{pmatrix} -0.542^{***}(0.221) \\ 0.027\ (0.063) \end{pmatrix}$ |

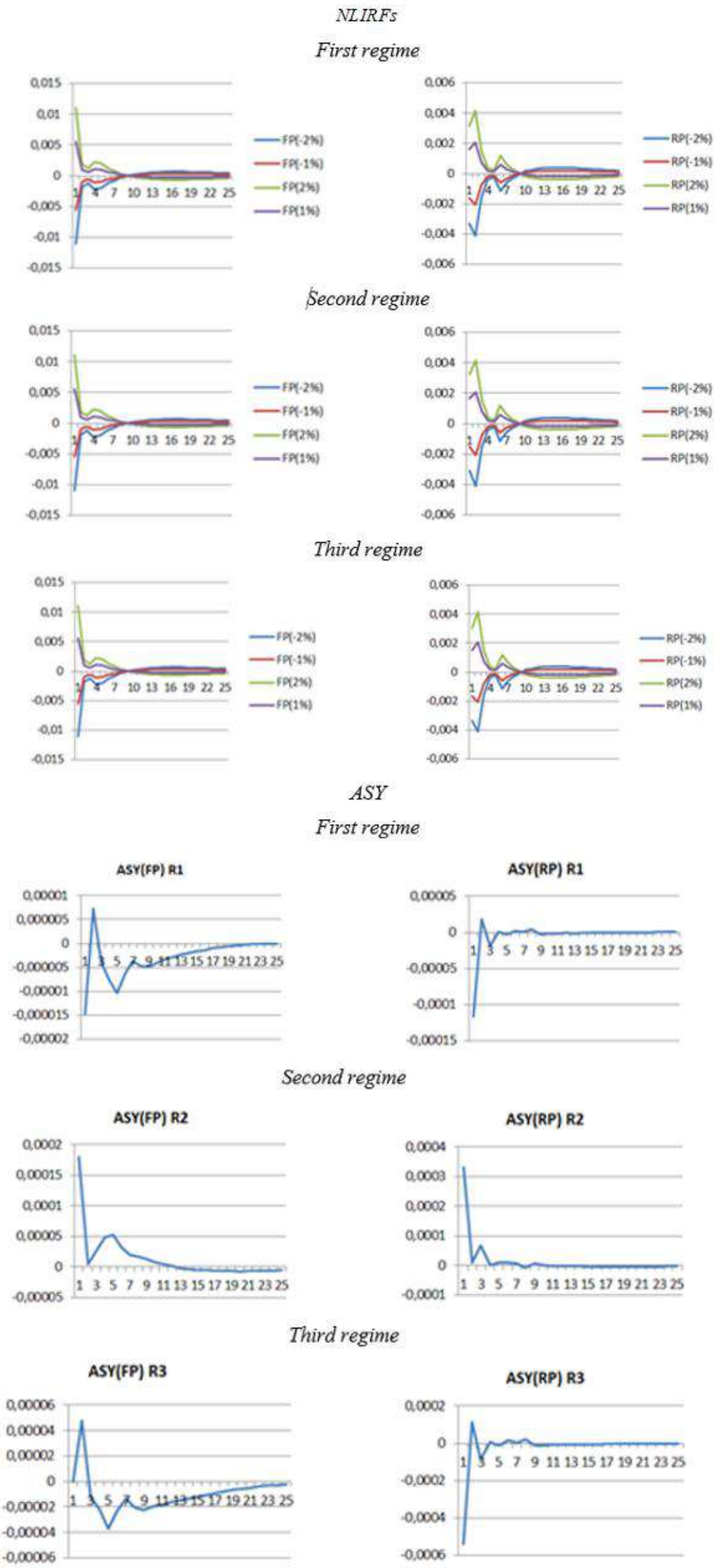
**FQS System**

| **Estimated parameters** | | | |
|---|---|---|---|
| | *First regime* | *Second regime* | *Third regime* |
| $\begin{pmatrix}\alpha_1^i \\ \alpha_2^i\end{pmatrix}$ | $\begin{pmatrix}-0.264^{**}(0.123) \\ -0.035\ (0.035)\end{pmatrix}$ | $\begin{pmatrix}-0.119\ (0.075) \\ -0.034\ (0.023)\end{pmatrix}$ | $\begin{pmatrix}-0.541^{***}(0.115) \\ 0.016\ (0.030)\end{pmatrix}$ |

Notes: Values presented in parentheses for the estimated parameters of adjustment coefficients $(\alpha_1^i, \alpha_2^i)$ are standard deviations robust to heteroscedasticity. *** (**, *) stands significance at 1% (5%, 10%) level. P-values are presented in parentheses for the residual tests.

We first observe in Figure 10 that all of the reactions are immediate regardless of the sign and the magnitude of the shock. In general, the RP reactions in the three regimes are less than half of the FP responses, and as occurred in the lamb case, three phases can be distinguished. Thus, while FP responds by decreasing towards equilibrium before showing a period of 3-4 weeks characterized with a slight increase prior to achieving the equilibrium by week 10, the RP reacts with a slight increase for 2-3 weeks before showing a significant decrease followed by a two-week period characterized by another small increase before reaching momentarily the equilibrium by week 10 but not reverting to it until after 25 weeks. A comparison of the cumulative responses indicates that those for RP are slightly greater than those for FP. Moreover, for both prices, the cumulative responses show some sort of oscillation from negative to positive in the two extreme regimes (prices decreasing and increasing) before reverting to the equilibrium by week 5 for RP and by week 25 for FP. So, in this case, farmers benefit from these positive asymmetries when FP prices increase. In the second regime, positive asymmetry is evidenced for RP before achieving the equilibrium by week 5, and positive for the FP during the first 13 weeks but slightly negative until week 25.

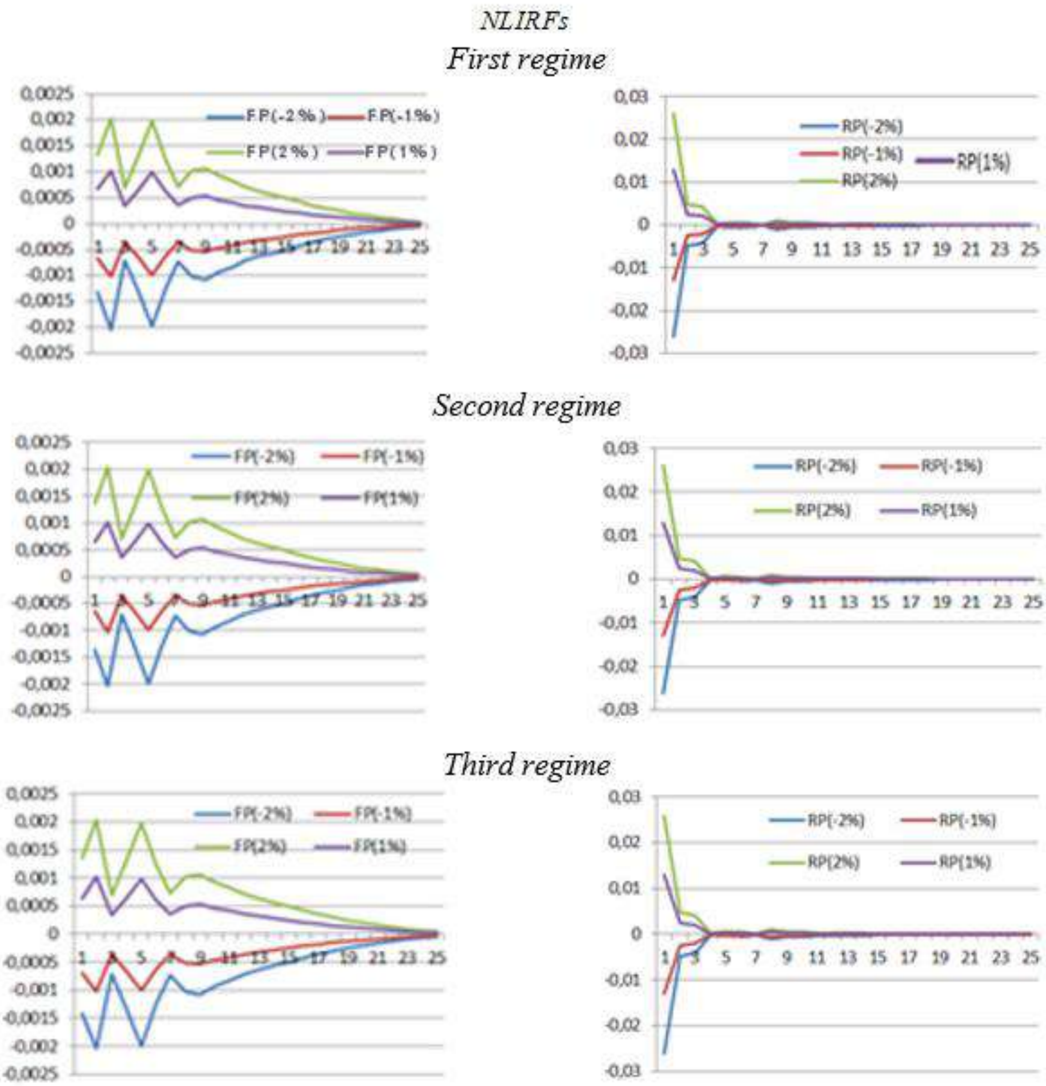
**Figure 10. Responses of FP and RP to a shock in FP**

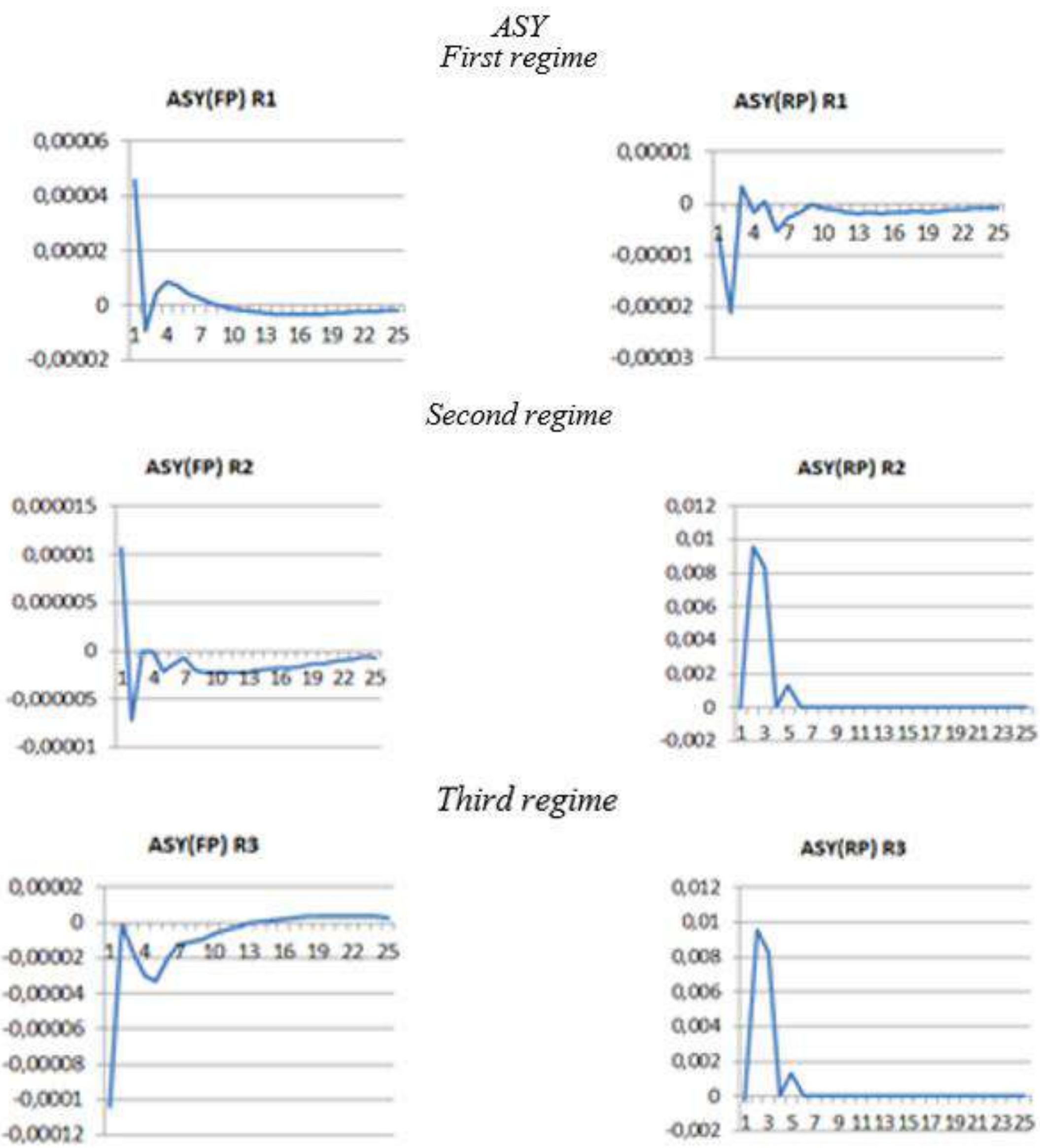



Notes: In the left (right) panels, the FP (RP) response to a shock in FP for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is also provided for the three regimes.

The responses plotted in Figure 11are quite similar to those presented in Figure 6 for the lamb case with two significant differences: the magnitudes are much smaller in this case (less than half) and the equilibrium is reached with a significant delay in FP (by week 24) and sooner in RP (by week 4). As for the cumulative responses, FP shows positive-negative-positive-negative asymmetries in the first regime, whereas RP mainly shows negative asymmetries. In the second regime, FP shows positive-negative asymmetries and no equilibrium but comes close to it after 25 weeks and RP reports positive asymmetries with equilibrium by week 7. In this case, retailers benefit because the margin increases. Finally, in the third regime when prices rise, FP exhibits negative asymmetries during the first 10 weeks before showing a small positive asymmetry failing to achieve the equilibrium after 25 weeks, the RP shows positive asymmetries before reaching the equilibrium by week 7.

**Figure 11. Responses of FP and RP to a shock in RP**



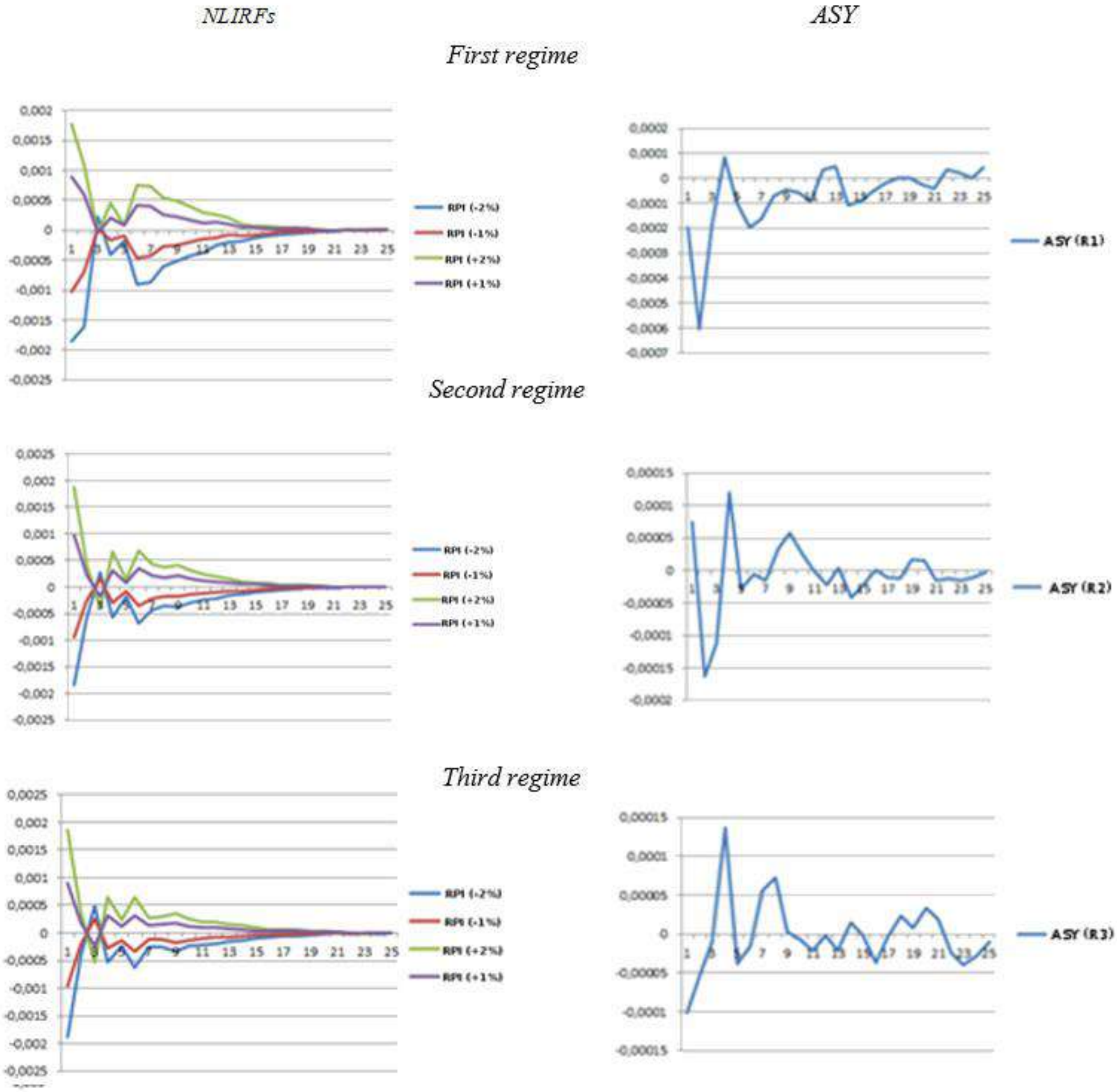



Notes: In the left (right) panels, the conventional farm (retail) prices response to a shock in FP for $\delta = (\pm 1, \pm 2)$under the three regimes. Potter's measure (ASY) is also provided for the three regimes.

As to the FQS system, the respective cross responses to a shock in RPI and in FPI are plotted respectively in Figures 12 and 13. In general, it can be seen that the magnitudes of the responses are smaller than in the conventional system for all the cases.

Looking at the RPI reaction to a shock in FPI in Figure 12, we first can observe that these responses are immediate and two phases can be identified in the three regimes. The first phase comprises a marked decrease until reaching momentarily the equilibrium in week 3 before entering in the second phase which shows during the first 4 weeks an increasing pattern followed by a long decrease that lasts 10 weeks until the equilibrium is achieved by week 20. Furthermore, a quite erratic asymmetric pattern and no equilibrium are found for all the regimes, so it is difficult to see who takes the most benefit from each situation. As the magnitudes are very small, we cannot say that retailer market power exists.

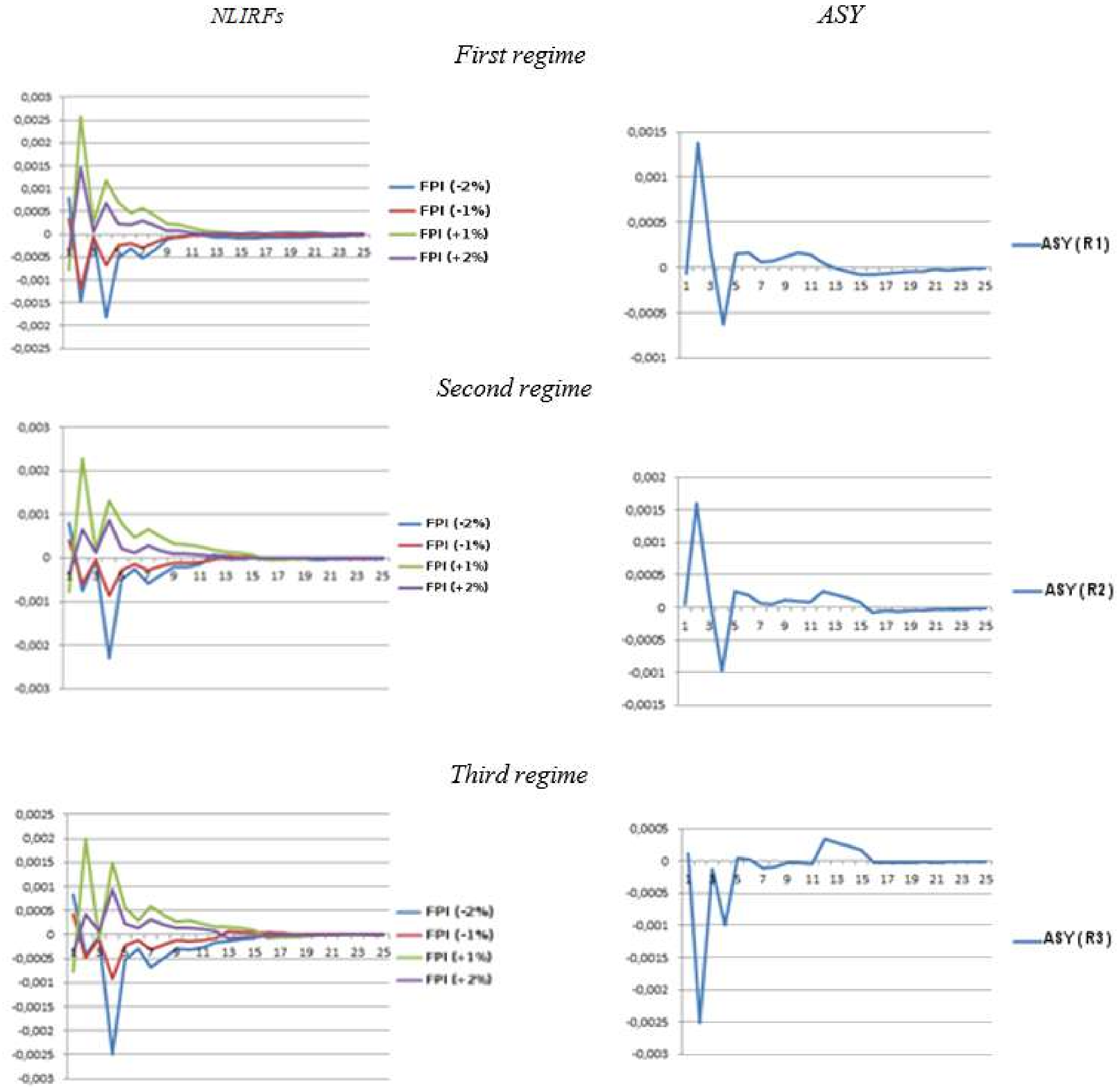
**Figure 12. Responses of RPI to a shock in FPI**




Notes: FQS retail prices response to a shock in FPI for $\delta = (\pm 1, \pm 2)$ under the three regimes. Potter's measure (ASY) is also provided for the three regimes.

From Figure 13, the FPI initial responses to a shock in RPI show no delay and in this case, though the previous two-phase behaviour is also found, the equilibrium is achieved earlier, by week 13-19, depending on the regime. Also, positive asymmetry characterizes the adjustment process but reverts to negative before changing to positive before reaching the equilibrium by week 25. When prices go up (third regime), negative asymmetric behaviour characterizes the process.

**Figure 13. Responses of FPI to a shock to RPI**




Notes: FQS farm prices response to a shock in RPI for $\delta = (\pm 1, \pm 2)$ under the three regimes. Potter's measure (ASY) is also provided for each regime.

In the end, it can be highlighted that the reactions to any shock show no delay, they are immediate as in the previous case. The magnitude of the responses for the FQS product is in general smaller than those presented for the conventional system. The results suggest that in this case, while retailers may slightly benefit from some market power in the conventional system, data cannot corroborate this fact for the retailers in the FQS system.

### 3.3. Protected Denomination of Origin "Parmigiano Reggiano"

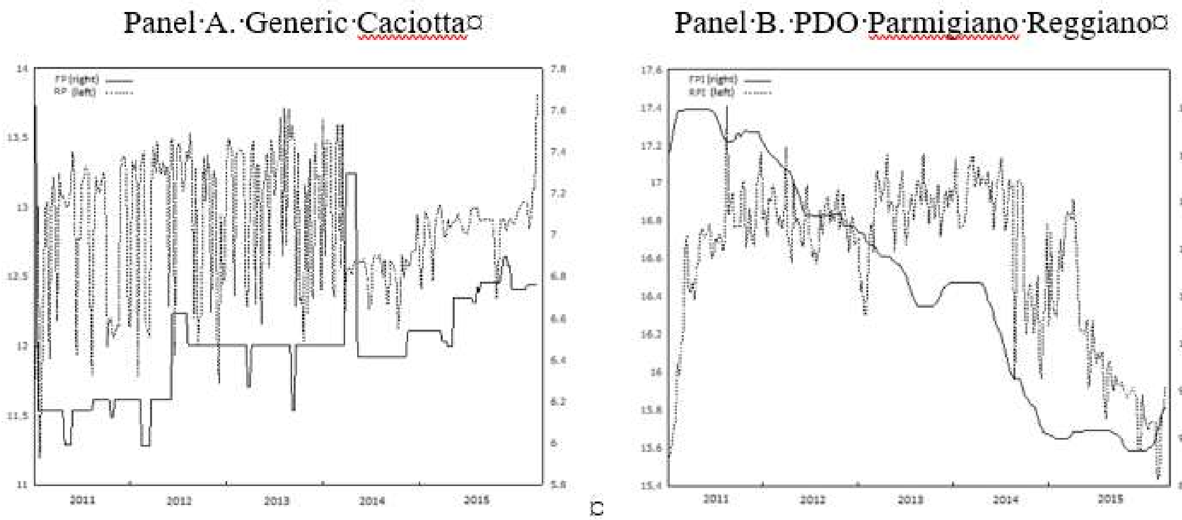
The Parmigiano Reggiano is one of the most valued cheeses in Italy with a long tradition and history, which goes back to ancient times circa 1200 in the Benedictine monasteries that settled close to the river Po and the Apennines. Undoubtedly, it can be said that this product is strictly linked not only to the territory but also to all the people who manufacture it, on whose knowledge the product crucially depends.

The Parmigiano Reggiano is designated as a Protected Designation of Origin (PDO) food. Its manufacturing is carried out according to the PDO specifications reflected in the respective bid specifications and strictly controlled by official institutions. Furthermore, the PDO Parmigiano Reggiano can only designate cheeses produced and processed in the place of origin, and manufactured according to strict standards that require precise production methods, controlled feeding of cows, and qualitative selection and designation (Parmigiano Reggiano official website, 2012).

### *3.3.1. Empirical results*

Parmigiano Reggiano (18-24 months) prices, expressed in Euros, at the farm (FPI) and retail (RPI) levels are observed weekly from 2011 to 2015. Prices for the Generic Caciotta cheese (the conventional counterpart considered for this study) are also observed at farm (FP) and retail (RP) levels for the same period. All of the four series are obtained from the Istituto di Servizi per il Mercato Agricolo Alimentare (ISMEA) database. Nominal prices are illustrated in Figure 9, in which Panel A illustrates the Generic Caciotta cheese and Parmigiano Reggiano in Panel B. In both panels, prices seem to obey a long-term relationship, with the retail prices being much more volatile than farm prices. Furthermore, all the prices exhibit visible fluctuations along with a positive growth in the case of the conventional cheese and a decreasing patter for the FQS cheese.

**Figure 14. Cheese price series**




Source: Own calculation based on ISMEA database. Vertical axes are measured in €/kg.

Table 17 reports a summary of the descriptive statistics of the series for each system. In the table we observe that the trend is significant for RP, and FPI and RPI but negative and rather small. Non-normality and ARCH effects are found in all the series.

As before, we examined whether the logged price series contain a unit root and it can be concluded that all the series are integrated of order 1. The results are reported in Table 18.

**Table 17. Summary of descriptive statistics for the Italian cheese price series**

| | FP | RP | FPI | RPI |
|---|---|---|---|---|
| Mean | 6.45 | 12.860 | 10.654 | 16.605 |
| Median | 6.473 | 12.910 | 10.655 | 16.752 |
| Minimum | 5.988 | 11.192 | 8.875 | 15.435 |

| | | | | |
|---|---|---|---|---|
| Maximum | 7.620 | 13.824 | 12.485 | 17.412 |
| Standard deviation | 0.253 | 0.473 | 1.222 | 0.419 |
| Skewness | 0.988*** | -0.503*** | -0.068 | -0.948*** |
| Kurtosis | 2.733*** | -0.298 | -1.328*** | -0.138 |
| Jarque-Bera test | 123.240*** | 11.945*** | 19.300*** | 39.139*** |
| Engle (1982)'s test | 220.225*** | 20.924*** | 257.906*** | 208.045*** |
| Trend | -7.682e$^{-05}$ | 0.002*** | -0.003*** | -0.016*** |
| # observations | 260 | 260 | 260 | 260 |

Notes: We have considered logarithmic transformations of the prices in our application. The use of the test of Engle (1982) allows us to check whether there are ARCH effects. In this case, we have used 2 lags. *** denotes statistically significant at 1% level.

**Table 18. Results of the integration order for the Italian cheese price series**

Panel A. Unit root and stationarity tests

| | MSB | KPSS |
|---|---|---|
| FP | 0.248 (1) | 0.404 (0)** |
| RP | 0.353 (10) | 0.759 (0)** |
| FPI | 0.247 (1) | 2.656 (0)** |
| RPI | 0.253 (3) | 2.820 (0)** |

Panel B. Unit root tests allowing for structural breaks (Carrion-i-Silvestre et al, 2009)

| | ADF | MSB | $\ell$ | Tb |
|---|---|---|---|---|
| FP | -2.775 (-3.312) | 0.300 (0.161) | 1 | 2014:27 (183) |
| RP | -2.041 (-3.289) | 0.201 (0.160) | 10 | 2011:27 (27) |
| FPI | -2.342 (-3.835) | 0.224 (0.129) | 7 | 2013:5 (107); 2014:3 (169) |
| RPI | -2.216 (-3.443) | 0.229 (0.143) | 3 | 2013:4 (106) |

Notes: In Panel A, we apply the MSB unit root test as in Ng and Perron (2001) and the KPSS stationarity test. The truncation lag parameter, k, presented in parentheses and is estimated using the MAIC. Also, ** denotes statistically significant at 5% level of significance since the asymptotic critical values at 5% level for the constant (trend) case are respectively 0.233 (0.168) for the MSB, and 0.463 (0.146) for the KPSS. In Panel B, $\ell$ reflects the bandwidth parameter for the KPSS test selected with the automatic bandwidth procedure of Andrews (1991) for the kernel-based estimator of the long-run variance. The critical value at the 5% significance level of each test is shown in parentheses. Tb reflects the time breaks, that is, the date when a structural break was endogenously detected and the corresponding number of observation is presented in parentheses.

Prior to testing for cointegration, we select the number of lags of the unrestricted VAR model. Table 19 reports the results.

**Table 19. VAR lag length selection for the Italian cheese sector**

Panel A. Conventional System

| **IC** | **lags** |
|---|---|
| BIC; AIC; HQ | 1; 1; 1 |

Panel B. FQS System

| IC | lags |
|---|---|
| BIC; AIC; HQ | 2; 5; 3 |

Notes: Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

Once the lag order has been determined for each system, we test for cointegration and select the cointegration rank using the Bartlett corrected trace test $\lambda^*_{trace}$ as in Johansen (2002)[18]. Results are presented in Table 20. Recall that prices are considered in logs. For this reason, we can interpret the cointegration parameters as price elasticities. Subsequently, we find a positive relationship for the FQS system (11%) implying that an increase in farm prices will lead to a rise in retail prices. However, for the conventional system, the relationship seems only significant at 20% with low influence of farm prices on retail prices, around 2%.

**Table 20. Results of the cointegration analysis for the Italian cheese sector**

Panel A. Conventional System

| Rank | Eigen value | $\lambda^*_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.208 | 68.082 | 0.000 |
| 1 | 0.035 | 8.995 | 0.053 |
| Cointegration relationship: $ECT = RP_t - 2.586^{***} + 0.018\, FP_t$ | | | |

Panel B. FQS System

| Rank | Eigen value | $\lambda^*_{trace}$ | p-value |
|---|---|---|---|
| 0 | 0.082 | 28.699 | 0.002 |
| 1 | 0.029 | 7.207 | 0.119 |
| Cointegration relationship: $ECTI = RPI_t - 2.554^{***} - 0.108^{***} FPI_t$ | | | |

Notes: *** denotes statistically significant at 1% level of significance. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

Once the presence of a stationary long-run relationship is correctly identified for the two systems, we examine whether the adjustment process exhibits nonlinearities.

Unlike to what we have found in the two previous case studies, the results confirm the absence of nonlinearities in the models specified for the two systems[19]. Consequently, we were forced to choose a linear model as the best specification for both systems. Specifically, we estimate two VECM for the conventional and FQS system, respectively. Tables 21 and 20 report the results, which also ensure the absence of remaining residual autocorrelation.

We analyse the estimated coefficients as they are relevant to describe which prices adjust to equilibrium and which do not. The results derived from the two systems indicate that only RP and FP respond in the conventional and FQS system respectively, and that the response in the FQS system is extremely low (0.09%).

[18] Note that if we apply the method suggested in Engle and Granger (1987) we also found the existence of respective cointegration relationships in the two systems.

[19]Wefound multiple problemsofconvergencewhenfacing the estimationstrategyof the twosystems,and the residual testscould not beachieved due tomatrixsingularity. And whatismore, the testsforselecting the transition variable and functioncontradicteachother, and the linear null cannotberejected.

**Table 21. Estimated VECM for conventional system**

Short-run parameters for the Conventional System

$$\begin{pmatrix}\Delta \mathrm{RPI_t}\\ \Delta \mathrm{FPI_t}\end{pmatrix} = \begin{pmatrix}\alpha_1\\ \alpha_2\end{pmatrix}\mathrm{ECTI}_{t-1} + \begin{pmatrix}\delta_{111} & \delta_{121}\\ \delta_{211} & \delta_{221}\end{pmatrix}\begin{pmatrix}\Delta \mathrm{RPI_{t-1}}\\ \Delta \mathrm{FPI_{t-1}}\end{pmatrix} + \begin{pmatrix}\delta_{112} & \delta_{122}\\ \delta_{212} & \delta_{222}\end{pmatrix}\begin{pmatrix}\Delta \mathrm{RPI_{t-2}}\\ \Delta \mathrm{FPI_{t-2}}\end{pmatrix} + \begin{pmatrix}\delta_{113} & \delta_{123}\\ \delta_{213} & \delta_{223}\end{pmatrix}\begin{pmatrix}\Delta \mathrm{RPI_{t-3}}\\ \Delta \mathrm{FPI_{t-3}}\end{pmatrix} + \varepsilon_t$$

| | $i = 1$ | $i = 2$ | $i = 3$ |
|---|---|---|---|
| $\alpha_i$ | -0.626*** (0.095) | 0.006 (0.039) | - |
| $\delta_{11i}$ | -0.146* (0.086) | -0.106 (0.076) | -0.118** (0.06) |
| $\delta_{12i}$ | -0.084 (0.155) | 0.019 (0.155) | 0.026 (0.23) |
| $\delta_{21i}$ | -0.027 (0.04) | -0.01 (0.03) | -0.034 (0.03) |
| $\delta_{22i}$ | 0.003 (0.06) | -0.079 (0.06) | -0.006 (0.05) |

Source: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. The residuals pass the multivariate test of Hosking (1981): 37.31 (p-value: 0.87) and hence indicates that there all autocorrrelations and lagged cross correlations are zero. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

**Table 22. Estimated VECM for FQS system**

Short-run parameters for the Quality System

$$\begin{pmatrix}\Delta \mathrm{RPI_t}\\ \Delta \mathrm{FPI_t}\end{pmatrix} = \begin{pmatrix}\alpha_1\\ \alpha_2\end{pmatrix}\mathrm{ECTI}_{t-1} + \begin{pmatrix}\delta_{111} & \delta_{121}\\ \delta_{211} & \delta_{221}\end{pmatrix}\begin{pmatrix}\Delta \mathrm{RPI_{t-1}}\\ \Delta \mathrm{FPI_{t-1}}\end{pmatrix} + \begin{pmatrix}\delta_{112} & \delta_{122}\\ \delta_{212} & \delta_{222}\end{pmatrix}\begin{pmatrix}\Delta \mathrm{RPI_{t-2}}\\ \Delta \mathrm{FPI_{t-2}}\end{pmatrix} + \varepsilon_t$$

| | $i = 1$ | $i = 2$ |
|---|---|---|
| $\alpha_i$ | -0.020 (0.022) | -0.009** (0.004) |
| $\delta_{11i}$ | -0.280*** (0.064) | -0.200*** (0.063) |
| $\delta_{12i}$ | 0.313 (0.323) | -0.016 (0.321) |
| $\delta_{21i}$ | 0.001 (0.012) | 0.010 (0.012) |
| $\delta_{22i}$ | 0.546*** (0.062) | 0.198*** (0.062) |

Source: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parenthesis. The residuals pass the multivariate test of Hosking (1981): 37.31 (p-value: 0.87) and hence indicates that there all autocorrrelations and lagged cross correlations are zero. Results are obtained with CATS (Dennis et al, 2006) in RATS 9.0.

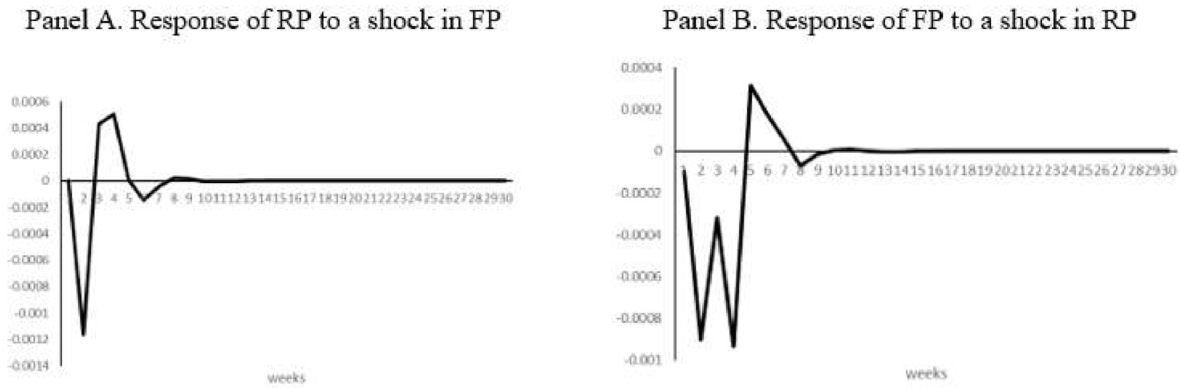
Now, we examine the short-run dynamics by means of the computation of the orthogonalized impulse response functions (IRFs). In this case, Figures15 and 16plot the IRFs for the conventional and the FQS systems, respectively. Here, we only show the cross responses to any given shock. Figures follow the same structure: in Panel A (left panel) we show the retail price reaction to a shock in the downstream level and Panel B (right panel) shows the farm price level response to a shock in the upstream level.

As we can see from Panel A of Figure 15, the RP reaction to a shock in FP is not immediate and for the first three weeks is negative before reverting to positive and briefly fluctuates around the zero-line until the equilibrium is achieved by week 10. Note that the magnitude in the positive response is less than half of the negative one. Similarly, the response of FP to a shock in RP is immediate and negative until the fifth week where it reverts to positive until week 8 before reverting again to negative for two more weeks to reach the equilibrium in week 10. Again the period with the negative reaction is more significant and longer than being positive, which may imply that when retail prices go up, farmer prices decrease and hence the margin increases, which benefits the retailer.

In Figure 16, for the FQS system, the RPI response (Panel A) is immediate, negative and small in magnitude for the first two weeks when it reverts to positive after which it shows a decreasing pattern that collapses to the equilibrium around week 16. The FPI reaction plotted in Panel B is immediate too but slightly higher and positive at each time responsive period, which benefits the farmer for the responsive period by squeezing the margin. The value reaches the equilibrium with some delay, that is, by week 19.

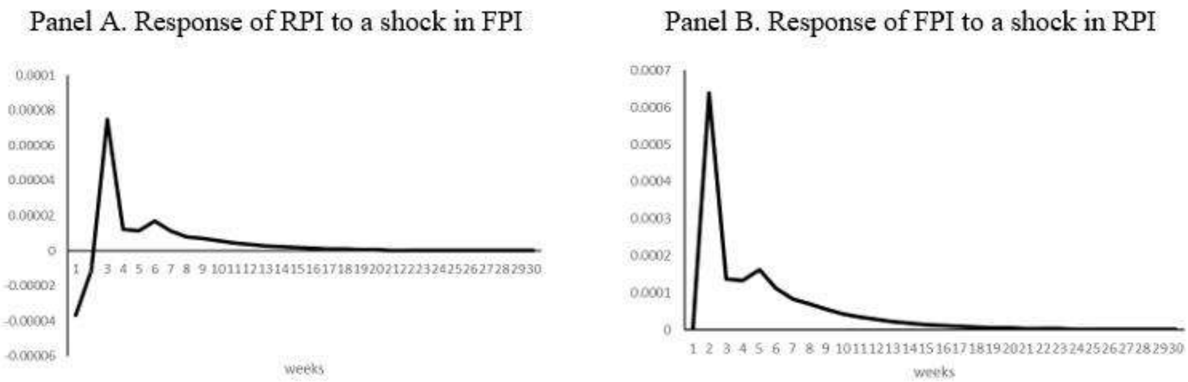
In this case, responses in the conventional system indicate that retailers may be benefiting when prices increase, and that responses in the FQS system suggest that farmers may not be very much affected when retail prices go up as they react positively for a long period in which the margin is relatively squeezed.

**Figure 15. Impulse Response Function in the Conventional System**




Source: Own calculations based on an orthogonal unitary shock.

**Figure 16. Impulse Response Functions in the FQS System**




Source: Own calculations based on an orthogonal unitary shock.

## 4. CONCLUDING REMARKS

This study provides insights in the analysis of the price transmission mechanism along the marketing chain of food products protected with European food quality schemes. We focused on food quality products because of the growing interest of consumers, producers and food policy makers in the potential of these schemes to increase competitiveness in both domestic and international markets and to maintain social and territorial cohesion.

The literature dealing with price relationships in agricultural and food markets is vast and has mainly focused on studying how pricing information is transmitted between chain actors, especially for conventional products. However, there is a gap in the literature since food quality schemes have not been examined yet. Our study contributes to fill this gap and provides novel results on price transmission within the supply chain for FQS designated goods.

Our study comprises three case-studies. The first and second studies examine the Spanish meat sector whereas the third focuses on the Italian cheese sector. In particular, we study the PGI "Cordero de Navarra" (lamb from Navarra), the PGI "Ternera de Navarra" (beef from Navarra), and the PDO Parmigiano Reggiano. To provide a better understanding of the FQS markets and to assess the differences in the transmission of the pricing information among chain actors, we compare the results for the FQS to their conventional counterparts.

Weekly prices were observed at two levels of the food supply chain for each system, farm and retail. Prices cover a recent period after the rise in prices that took place in 2011. To achieve our main objective, we have used a multivariate non-linear approach and estimated a threshold autoregressive model which allows us to assess possible asymmetries in the price transmission. In what follows, we offer a summary of the results obtained:

- The results derived from the lamb case study indicate that retail and farm prices are cointegrated in both the conventional and the FQS system. This long-run relationship seems stronger in the conventional system than in the FQS system although faster adjustments are reported in the latter. As to the short-run dynamics, we have shown that the responses in both systems are immediate, regardless of their sign and magnitude. Price responses exhibit in general a symmetric pattern to any shock and regime. While farm responses are much smaller than retail responses in the conventional system - indicating some level of retail market power- this cannot be supported for the FQS system. Responses in the FQS system revert to equilibrium sooner than those for the conventional system. In the two systems, we found negative asymmetries in the retail prices.
- From the beef case study, our results suggest a long-run relationship between the two prices in both systems, though stronger in magnitude in the conventional system. Retail prices, and not farm prices, are found to respond to deviations in each system from the parity in the long-run equilibrium. The responses to any shock are immediate, and those for the FQS product are in general lower than those presented for the conventional system. In this case, conventional farmers seem to be benefiting from positive asymmetries when FP prices increase and retailers when RP prices increase. Moreover, data can only corroborate the existence to some extent of retail market power in the conventional system but not in the FQS system.
- In the cheese case study, our results reveal a long-run equilibrium relationship between farm and retail prices in the two systems. The relationship in the former is not significant but that in the latter is quite strong and statistically significant. Conventional retail prices are characterized by a faster adjustment compared to conventional farm prices, which are characterized by slow adjustments to deviations from the equilibrium implying retail market power. Conversely, for the FQS, farm prices are characterized by a very low adjustment and retail prices do not respond. As to the short-run dynamics, the computed linear impulse response functions suggest that retailers may benefit when prices rise and responses for the FQS system indicate that farmers may not be very much affected when retail prices increase as their positive response remains for quite a long period in which the margin is reduced.

Taking into account the three case studies, it is difficult to highlight some definite conclusions. In the two meat sectors, which are located in the same territory and with similar market structures and governance, it seems that FQS have contributed to reduce market power at the retail level, mainly in the case of lamb. In the cheese sector, results are less conclusive, although in this case, we have to take into account the nature of the data available. In any case, results have to be interpreted with caution. Further research is needed before generalizing this result to the rest of EU FQS across products and Member States. However, to allow such analyses, more data should be available. The efforts that have been made in the EU to increase market transparency along the food supply chain have not included FQS. There has not been any systematic data collection for these kinds of products, even when the EU is providing significant support for FQS promotion. We hope transparency will also extend to FQS in the future so that more studies can be carried out to assess if these schemes have been a useful tool to increase farmers' market power and to improve the functioning of markets allowing prices to be quickly and fully transmitted along the food supply chain.

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**The Strength2Food project in a nutshell**

Strength2Food is a five-year, €6.9 million project to improve the effectiveness of EU food quality schemes (FQS), public sector food procurement (PSFP) and to stimulate Short Food Supply Chains (SFSC) through research, innovation and demonstration activities. The 30-partner consortium representing 11 EU and four non-EU countries combines academic, communication, SMEs and stakeholder organisations to ensure a multi-actor approach. It will undertake case study-based quantitative research to measure economic, environmental and social impacts of FQS, PSFP and SFSC. The impact of PSFP policies on nutrition in school meals will also be assessed. Primary research will be complemented by econometric analysis of existing datasets to determine impacts of FQS and SFSC participation on farm performance, as well as understand price transmission and trade patterns. Consumer knowledge, confidence in, valuation and use of FQS labels and products will be assessed via survey, ethnographic and virtual supermarket-based research. Lessons from the research will be applied and verified in 6 pilot initiatives which bring together academic and non-academic partners. Impact will be maximised through a knowledge exchange platform, hybrid forums, educational resources and a Massive Open Online Course.

**www.strength2food.eu**