Spatial Price Transmission, Transaction Costs, and Econometric Modelling: How Inference Can Be Improved When Transaction Costs Are Observed?

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Background and Previous Studies

The study of spatial price transmission and market efficiency has long been of interest for several agricultural commodities and has been performed with the objectives of evaluating market integration and the degree and speed of transmission of prices across markets (Lo and Zivot 2001; Hassouneh, Serra, and Gil 2010; Goodwin 2006; Brosig et al. 2011; Esposti and Listorti 2013). Spatial price transmission theory is mostly backed on the concept of "Law of One Price (LOP)", which should be a theoretical condition for markets to be integrated (Goodwin 2006). According to the LOP, prices of a homogeneous good must be the same across markets, net of transaction costs. When there is price difference between regions greater than costs of transporting and selling goods from one market to another, arbitrage becomes profitable so that prices are driven back to an equilibrium, in which price differences are equal or lower than transaction costs (Sexton, Kling, and Carman 1991). Therefore, in order to study price transmission and market efficiency, it is imperative to account for transaction costs. Barrett (1996) affirms that inference on price transmission and the LOP hypothesis is only possible when transaction costs, and preferably trade flow data, are incorporated in the model. Such data, however, is not easily available and is seldom observed.

To overcome the problem of unobserved transaction costs, the threshold vector error correction model (TVECM) that allows for the presence of thresholds in the cointegrating vector has arisen. These thresholds would be consistent with the existence of varying transaction costs, which induces different corrections (regimes) towards the established long-run equilibrium (Fackler and Goodwin 2001; Listorti and Esposti 2012). Although the model is able to account for transaction costs, one can argue that such estimators are biased, as actual transaction costs are omitted from the equations (Barrett 2001).

When incorporating both transaction cost data, trade flow and prices, Barrett and Li (2002) using a maximum likelihood estimation of a mixture distribution model demonstrated that at least one assumption among stationary transfer costs, and constant and unidirectional trade was violated in every direction-specific market pair, underscoring the need for incorporating transaction costs and using more flexible methods to model price transmission.

Despite its popularity in the price transmission literature, some recent work have demonstrated that the TVECM is fragile, as determination of thresholds is much dependent on the methodology used and may not truly represent transaction costs, as well as corrections towards the long run equilibrium may not be immediate but rather smooth (Frey and Manera 2007; Goodwin, Holt and Prestemon 2011).

Although several modelling methods have been proposed to better adjust price behavior to specific markets' characteristics, it is still unclear how the dynamics of transaction costs impact spatial price transmission, as few of these studies have explicitly incorporated transaction cost data into the modelling framework. Bekkerman, Goodwin and Piggott (2009), revisiting the work of Goodwin and Piggott (2001) by incorporating diesel prices in the model and specifying a variable transaction costs framework, showed that the asymmetric variable thresholds model outperformed the alternative constant and symmetric variable thresholds specification, which might have implied an underestimation of the overall post-shock price effects in evaluated markets, as viewed through nonlinear impulse response functions.

Lence et al.(2017) evaluated the performance of a Band-TVECM through a Monte Carlo experiment and proved that the model failed to represent the true underlying data generating process, systematically underestimating the transference costs, while counterintuitively providing poor inference on possible trade occurrence (as viewed through percentage of observations within different price regimes) and therefore suggesting lower than expected market integration, as well as biasing downwards the speed of price transmission.

Although underscoring the weaknesses of the Band-TVECM, the authors did not evaluate any alternative econometric modelling which could theoretically better represent the dynamics of the transaction costs and the price correction mechanism (e.g. the assumption of time-varying co-integration and smooth transition). This paper did not evaluate the addition of potential sources of observed transaction costs into the modelling framework or dealt with the problem of thresholds estimation. In our study, we model price transmission between regions by using the same Band-TVECM with two thresholds and three regimes as defined in Greb et al. (2013) or one threshold and two regimes, but we explicitly incorporate transaction costs into the modelling framework. Following the rationale provided by Greb et al. (2014), in our empirical application, we use a regularized Bayesian estimator to estimate the thresholds and we compare a time varying threshold model with a constant threshold model in a Monte Carlo experiment. We observed a potential significant model misspecification due to results of the test for linear cointegration against threshold cointegration, specially when true underlying DGP was of three price regimes (two thresholds). We observed that specifying a time varying threshold model dependent on lagged transportation costs improved inference in terms of both estimation of transaction cost (as viewed by threshold estimation) as well as in the speed of price adjustment to the long run equilibrium and identification of number of violations to spatial price equilibrium. Our findings suggest that a varying threshold model using transportation costs outperformed the constant threshold specification specifically under the assumption of endogenous transportation cost. The empirical application using Brazilian farm gate hog prices and freight indices revealed threshold effects in price transmission, which were significantly different when accounting for time variation in transaction costs. Our paper follows with a Literature review explaining the theory behind the TVECM and its use to evaluate spatial price transmission in agricultural markets. We then provide detailed specification on modelling procedure, data generation and results for our MC experiment, concluding with our empirical application and directions for future research.

Literature Review

Spatial price analysis is based on the assumptions of the Law of One Price, which states that prices of a given commodity must be the same across regions, net of transaction costs. Therefore, the Law of One Price is a consequence of spatial arbitrage, and also one possible explanation for cointegration (Goodwin and Schroeder 1991). The concept of cointegration, on the other hand, relates to the property of a function of a given pair of nonstationary variables to be stationary. For the case of price series, cointegration means that two nonstationary price series share a common long run mean, to which prices tend to return in the long run.

Methodologies based on co-integration have been widely used to evaluate market integration and price transmission in agricultural and other commodities markets (Frey and Manera 2007). As price series tend to be nonstationary, cointegration models are able to represent how non-stationary variables are linked by a stationary long-run relationship, allowing them to diverge from it in the short run.

This provides the distinction between short and long run dynamics of the prices of interest. One of the most popular methodologies used for such purpose is the vector error correction model (VECM). In the VECM, a long run relationship is established by the presence of co-integration between the analyzed prices. If this hypothesis is not confirmed, then the dependence of prices is limited to short run responses to shocks (Listorti and Esposti 2012). This long run relationship expresses the LOP, which assume the price spreads to be constant or in constant proportions. This may be regarded as a caveat of the methodology, as prices may not be cointegrated in given integrated markets, as transaction costs and other factors contributing to price differences could be nonstationary and time varying (Barrett 1996; Listorti and Esposti 2012). Such caveat has been partially overcome by identifying thresholds in the error correction term, which allows the parameters not to be constant, but dependent on these thresholds, leading the prices to be corrected only if the differentials lie within or outside an interval given by the thresholds. These models are described as Threshold Vector Error Correction Models (TVECM).

Most works describing spatial price transmission in agricultural markets have accounted for transaction costs using threshold autoregressive (TAR) and TVECM models (Brosig et al. 2011; Lo and Zivot 2001b; Meyer 2004; Serra, Gil and Goodwin 2006; Listorti and Esposti 2012; Greb et al. 2013).

Lo and Zivot (2001) used TVECM to detect threshold type cointegration and found evidence for this type of cointegration for several tradable goods, including agricultural commodities. Authors also compared the threshold magnitudes to distance between different markets, obtaining different prices' speed of adjustment for different cities but failed to detect a consistent significant effect of distance on threshold magnitude, suggesting that not only transportation costs would be affecting price transmission. Another alternative for this lack of relationship between threshold magnitude and market distances may be related to the accuracy of the estimated thresholds, as well as the assumption of constant thresholds.

Meyer (2004) applied a three regime TVECM to account for transaction costs in spatial price transmission in European pig markets, considering symmetric adjustment towards the long run equilibrium by allowing the existence of two thresholds of equal magnitude. Although the model allows for the presence of a band of inactivity, in which price deviations from the long run equilibrium are not sufficiently high to be corrected, such approach precludes the existence of asymmetric corrections and assume constant transaction costs. Brosig et al. (2011) applies a similar methodology to study wheat market integration in Turkey, using the determined threshold to infer on a minimum level of transaction costs which would impede full market integration. The same restriction on symmetrical adjustment and also on assuming constant transaction costs are the main shortcomings of the methodology.

Chen and Lee (2008), carrying out a similar methodology as Brosig et al. (2011), studied market integration and deviations from the LOOP in Taiwanese pig markets using a Band-Tar model, considering a symmetric transaction costs band of inactivity, and employing an IRF to check for estimated half-lifes of shocks to the prices between regions, taking one central market as reference. The authors found the market to be tightly integrated and estimated that shocks to prices in one central market are transferred to other markets in periods as short as four months. One shortcoming of this study is, besides assuming constant transaction costs, the use of monthly data, which may not be the most adequate to test for price transmission, as lower frequency data (e.g. daily) may better capture eventual price discrepancies within regions (Frey and Manera 2007). Another potential limitation for using TVECM to model transaction costs and evaluate market integration and efficiency is the absence of trade flow variables. While such information may be valuable to study market integration, it may not be necessarily needed to study market performance, as reported by Stephens et al. (2012) when evaluating price transmission in different tomato markets in Zimbabwe. They found that intermarket price adjustments occurred both in presence and absence of physical trade, with larger and more rapid adjustments occurring in periods without physical trade flows, which, according to the authors, potentially …“underscores the importance of information flow for market performance”. Following a similar rationale, Lence, Moschini and Santeramo (2018) developed a DGP which accounted for expectations of decision makers and delivery lags in the price determination. Under this framework, existence of price differences greater than transaction costs were fully consistent with market equilibrium, as authors showed that price movements due to trade decisions were made before shocks on supply and demand were realized on the terminal markets, which seems to be a reasonable assumption. Under this framework, this condition allows arbitrage and leads to price correction in the following period, which provides a useful condition to evaluate the performance of the TVECM, once the researcher knows the exact transaction costs, speed of adjustment and number of observations falling within each of the trade regimes occurring for different scenarios of interest.

Methodology

Monte Carlo experiments are conducted with data generation under the framework described by Lence et al. (2018). Briefly, the DGP accounts for delivery lags and rational expectations, considering the simple case of a two region equilibrium model where prices are determined according to stochastic supply and demand conditions in each market, assuming that the product is perishable (no storage is allowed, which holds for the case of live animals and perishable products), demand parameterization is built to ensure that every product that is shipped to a region is consumed. The model is also built under a complementarity slackness condition that implies that the expected price differential is exactly equal to transfer cost when there is a positive shipment between regions. Production in each region is assumed to follow a covariance stationary random process, which accounts for autocorrelation in supply. To generate I(1) prices, demand is then assumed to be subject to exogenous I(1) shocks, generating price series exhibiting threshold cointegration by construction. We encourage readers to refer to the original paper for details on data generating process and parametrization. To account for time varying transaction costs, we considered two scenarios of transaction cost variation described in (Lence et al. 2018): exogenous time varying per unit costs, and endogenous time-varying per unit costs. To simulate the conditions of potential empirical applications, we generated price series data under the assumption of equal demand elasticities between regions (demand elasticity of 0.7) and one region with inelastic demand (0.7) and another region with more elastic demand (1.5). We used this parametrization because in some empirical applications, it is likely that transmission may occur between regions with different demand elasticities, specially from those with more elastic demand to those with more inelastic demand.

In total, we generated 500 samples of 520 observations each under the following assumptions: stochastic exogenous transfer cost with equal demand elasticities between regions, stochastic exogenous transfer cost with different demand elasticity between regions, stochastic endogenous transfer cost with equal demand elasticities between regions and stochastic endogenous transfer cost with different demand elasticities between regions. Although some empirical applications involve data with more than 2000 observations (daily price series from e.g. a 10 year period), we used 520 observations in our MC study to reduce computational burden, as it was previously determined that this sample size, and even smaller sample sizes, were sufficient to evaluate the performance of the TVECM (Greb et al. 2013; Lence et al. 2018).

For each of the described scenarios, we generated 500 samples with known 3 price regimes (two thresholds) and 500 samples with known 2 price regimes (one threshold).

For those with 3 price regimes, all samples had at least 10% of observations falling within the outside price regimes (exceeding the thresholds in each region specific direction).

In our modelling framework, we do not restrict thresholds to be symmetric and we use the profile likelihood estimator (PL) to perform the Monte Carlo experiment. Although it has been proven that the regularized Bayesian estimator (RB) as described in Greb et al. (2013), outperforms the PL, computation of the posterior density demands much more computing power. Moreover, as our main objective is to evaluate whether using a flexible threshold specification improves inference, it is desired to use a method commonly applied in previous literature.

Our evaluation starts testing each of the price series for stationarity with the Augmented Dickey-Fuller (ADF) and DF-GLS (Elliott, Rothenberg and Stock 1996) tests under the null hypothesis of nonstationarity. Also, the KPSS (Kwiatkowski et al. 1992) test under the null hypothesis of stationarity is performed. The lag length to be used in the ADF and DF-GLS tests is obtained using the Schwarz criterion.

According to Enders and Granger (1998), for a given pair of two prices, say p_t^a and p_t^b, assumed to be integrated of order one, I(1), there is a long run relationship established by:

(1)

$$ECT_t = z_t = p_t^a - \alpha_0 - \alpha_1 p_t^b$$

Where the error term z_t represents the deviations from the long run equilibrium between the two price series at a given time period t. In our case study, we assume $\alpha_0 = 0$.

Linear cointegration between each pair of price series was evaluated using both the Johansen's approach (Johansen 1992a; Johansen 1992b; Johansen 1995), as well as the ADF test on z_t for both filtered and unfiltered prices. Samples known to have 3 regimes, which failed to reject the null of a unit root were subjected to the BBC test with the null hypothesis of linear no cointegration against the alternative of threshold cointegration (Bec, Ben Salem and Carrasco 2004). We followed with the Hansen test to determine the number of samples inferred to have one or two thresholds.

According to Hansen (1997), the conventional test used to test for linearity in the ECT is not appropriate given that the null hypothesis of linearity in the *AR* process does not follow a standard distribution. Therefore, to test for linearity and the presence of one or two thresholds, three versions of the Hansen (1997; 1999b) tests are used: Hansen's F_{12} (F_{13} , F_{23}) test postulates a null hypothesis of one (one,two) regime(s) versus an alternative of two (three, three) regimes. The test is performed sequentially: first F_{12} is performed. If the null of one price regime is rejected, then F_{23} is performed. If F_{23}'s null is rejected, the sample is inferred to have 3 price regimes. If F_{12}'s null is not rejected, then F_{13} is performed to distinguish samples with one price regime and 3 price regimes. We used the test based inference sample classification to evaluate the power of the tests with filtered and unfiltered prices. Therefore, we used all 500 samples to obtain the model estimates under 3 and 2 known price regimes.

Model Specification and Inference Strategy

Assuming that ECT_t represents the price difference between markets a and b (that is, α_0=0 from equation (1)), we have that ECT may be described as $\gamma' p_t = (p^a_{t-1} - p^b_{t-1})$, now representing the price differential between two markets, lagged by one period, assuming the connecting vector is equal to (1,-1).

The error correction model conditional on one threshold value may be specified as:

(2)

$$\binom{\Delta p^a_t}{\Delta p^b_t} = \binom{\mu_{1a}}{\mu_{1b}} + \binom{\vartheta_{1a}}{\vartheta_{1b}} \gamma' p_t + \begin{pmatrix} \sum_{n=1}^{j} \pi_{1na} \Delta p^a_{t-n} \\ \sum_{n=1}^{j} \pi_{1nb} \Delta p^b_{t-n} \end{pmatrix} + \begin{pmatrix} \sum_{n=1}^{j} \rho_{1na} \Delta p^a_{t-n} \\ \sum_{n=1}^{j} \rho_{1nb} \Delta p^b_{t-n} \end{pmatrix} + \binom{u_{1ta}}{u_{1tb}}$$

If $\gamma' p_t \leq \psi$, Regime 1

$$\binom{\Delta p^a_t}{\Delta p^b_t} = \binom{\mu_{2a}}{\mu_{2b}} + \binom{\vartheta_{2a}}{\vartheta_{2b}} \gamma' p_t + \begin{pmatrix} \sum_{n=1}^{j} \pi_{2na} \Delta p^a_{t-n} \\ \sum_{n=1}^{j} \pi_{2nb} \Delta p^b_{t-n} \end{pmatrix} + \begin{pmatrix} \sum_{n=1}^{j} \rho_{2na} \Delta p^a_{t-n} \\ \sum_{n=1}^{j} \rho_{2nb} \Delta p^b_{t-n} \end{pmatrix} + \binom{u_{2ta}}{u_{2tb}}$$

If $\gamma' p_t > \psi$, Regime 2.

Where Δ is the first difference operator, ϑ_i represents the speed of adjustment towards the long run equilibrium for each regime, π_{in} and ρ_{in} represent the short run relationships between the two markets a and b, ψ is the threshold value to be estimated, and u_{it} is an error term assumed to be iid and normally distributed. The Schwarz Information Criterion is employed to determine the appropriate lag structure of equation (2).

When deviations ($\gamma' p_t$) are below the threshold value (ψ), the price transmission process is defined by regime 1, and arbitrage is not expected to happen, as the regime represents spatial price efficiency. As a consequence, no significant price adjustment is expected to be observed, or the speed of adjustment, as viewed through coefficient ϑ_{1a} and ϑ_{1b} is expected to be smaller than that for ϑ_{2a} and ϑ_{2b}, as the outer regime represent situations when the spatial equilibrium is broken, allowing profitable arbitrage, which is expected to drive prices faster towards the long run equilibrium. Greb et al. (2013), describes some restrictions on the coefficients ϑ that ensures that p^a and p^b are cointegrated. It is expected that (i) $-1 \leq \vartheta_{2a} < 0$, (ii) $0 < \vartheta_{2b} < 1$, (iii) $0 < (|\vartheta_{2a}| + \vartheta_{2b}) < 1$. Condition (i) ensures that p^a is reduced when spatial equilibrium is violated, while condition (ii) ensures that p^b increases. Both conditions ensure that changes in p^a and p^b will restore the spatial equilibrium. Condition (iii) ensures that there is no overshooting in price correction. The same rationale is valid for the model specification with two thresholds. The only difference is that there are two conditions in which spatial equilibrium is violated, which are related to trade in both directions. A two threshold, three regime TVECM may be specified as follows:

(3)

$$\begin{pmatrix}\Delta p_t^a \\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{1a} \\ \mu_{1b}\end{pmatrix} + \begin{pmatrix}\vartheta_{1a} \\ \vartheta_{1b}\end{pmatrix} \gamma' p_t + \begin{pmatrix}\sum_{n=1}^{j} \pi_{1na} \Delta p_{t-n}^a \\ \sum_{n=1}^{j} \pi_{1nb} \Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{1na} \Delta p_{t-n}^a \\ \sum_{n=1}^{j} \rho_{1nb} \Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}u_{1ta} \\ u_{1tb}\end{pmatrix} \;;$$

If $\gamma' p_t < \psi_1$, Regime 1

$$\begin{pmatrix}\Delta p_t^a \\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{2a} \\ \mu_{2b}\end{pmatrix} + \begin{pmatrix}\vartheta_{2a} \\ \vartheta_{2b}\end{pmatrix} \gamma' p_t + \begin{pmatrix}\sum_{n=1}^{j} \pi_{2na} \Delta p_{t-n}^a \\ \sum_{n=1}^{j} \pi_{2nb} \Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{2na} \Delta p_{t-n}^a \\ \sum_{n=1}^{j} \rho_{2nb} \Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}u_{2ta} \\ u_{2tb}\end{pmatrix}$$

If $\psi_1 \leq \gamma' p_t \leq \psi_2$, Regime 2.

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{3a}\\ \mu_{3b}\end{pmatrix} + \begin{pmatrix}\vartheta_{3a}\\ \vartheta_{3b}\end{pmatrix}\gamma' p_t + \begin{pmatrix}\sum_{n=1}^{j}\pi_{3na}\Delta p_{t-n}^a\\ \sum_{n=1}^{j}\pi_{3nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j}\rho_{3na}\Delta p_{t-n}^a\\ \sum_{n=1}^{j}\rho_{3nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}u_{3ta}\\ u_{3tb}\end{pmatrix}$$

If $\psi_2 < \gamma' p_t$, Regime 3.

Under specification (3), regimes 1 and 3 are compatible with spatial arbitrage, therefore coeffiecients ϑ_1 and ϑ_3 are expected to be significant and greater than ϑ_2. Same restrictions described for the one threshold model, which are expected to be met in order to have proper price adjustment, apply to the thre regime specification.

Equations (3) is commonly obtained by using the profile likelihood estimator, where for each possible pair of the threshold parameters $\psi = (\psi_1, \psi_2)$, the remaining parameters in the likelihood function corresponding to equation (3) are replaced by their maximum likelihood estimates. Then, the pair of thresholds that maximizes the resulting profile likelihood function is selected as the estimate (Hansen and Seo 2002; Lo and Zivot 2001a; Greb et al. 2013). This estimator is criticized because, to allow estimation possible, a minimum number of observations in each outer regimes have to be arbitrarily selected (trimming parameter), which bias the estimation (either when the number of observations is not large enough, or when the differences between the true thresholds is not large enough) , as well as the uncertainty inherent to the coefficient estimates for each combination of possible threshold values cannot be clearly measured (Greb et al. 2014).

The RB estimator, on the other hand, do not require a minimum number of observations to lie within each regime. Instead, the selection of thresholds is done using integral calculus, which also provides a way to account for inherent variability of estimates. The posterior median is a function used to choose optimal threshold values over the grid of ECTs (Greb et al. 2014), which is defined as:

(4) $$\int_{\min(\gamma' p_t)}^{\widehat{\psi}_i} P_{RB}(\psi_i \,|\Delta P, X) d\psi_i = 0.5, for\ i = 1,2$$

Where P_{RB} is the posterior distribution, X is a *n x d* matrix containing columns of ECTs, intercepts and values of lagged terms, and ΔP is the dependent variable. As noted by Serebrennikov and Götz (2015), P_{RB} is well defined in the whole threshold parameters space T = $\{\psi_1, \psi_2 | \min(\gamma' p_t) < \psi_1 < \psi_2 < \max(\gamma' p_t)\}$. Computation is based on a prior $P_{RB}(\psi|X) \propto I(\psi \in \mathrm{T})$ for ψ, where $I(\cdot)$ is an indicator function providing switching between regimes. The estimation is done in software R, using the package nlme, taking the optimal thresholds and estimating parameters using restricted maximum likelihood framework, implemented as part of mixed effects modelling.

To allow for time varying cointegration, we followed the description provided by Park, Mjelde and Bessler (2007). This approach consists in obtaining "filtered price series" by running the following regressions using OLS:

(5) $$p_t^i = \alpha_0 + \alpha_1 Tc_{t-1}^{ij} + \alpha_2 Tc_{t-1}^{ji} + \varepsilon_t^i$$

where Tc_{t-1}^{ij} is the lagged transportation cost from region *i* to region *j*, α_0 is a constant term and α_1 and α_2 are coefficients associated with lagged transportation costs, for *i,j* $\in$ a, b. The term ε_t^i will then represent the price in each region after considering the effect of transportation cost in the previous period, as decisions on shipment made on period *t* will effectively induce price changes on period *t+1*. So, to obtain the variable threshold model, instead of using p_t^i, we used the filtered price series $\widehat{\varepsilon_t^i}$. It follows from equation 4 , taking the middle regime, that time varying thresholds can be obtained from the relationship:

(6) $$\psi_1 \leq \widehat{\varepsilon_t^a} - \widehat{\varepsilon_t^b} \leq \psi_2$$

where $\widehat{\varepsilon_t^a} = p_t^a - \widehat{\alpha_0^a} - \widehat{\alpha_1^a} Tc_{t-1}^{ab} - \widehat{\alpha_2^a} Tc_{t-1}^{ba}$, as well as $\widehat{\varepsilon_t^b} = p_t^b - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} Tc_{t-1}^{ba} - \widehat{\alpha_2^b} Tc_{t-1}^{ab}$. Therefore, from algeabric manipulation we obtain that daily threshold values based on transportation costs are:

(7) $$\psi_{1t} = \psi_1 + (\widehat{\alpha_0^a} + \widehat{\alpha_1^a} Tc_{t-1}^{ab} + \widehat{\alpha_2^a} Tc_{t-1}^{ba} - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} Tc_{t-1}^{ba} - \widehat{\alpha_2^b} Tc_{t-1}^{ab})$$

(8) $$\psi_{2t} = \psi_2 + (\widehat{\alpha_0^a} + \widehat{\alpha_1^a} Tc_{t-1} + \widehat{\alpha_2^a} Tc_{t-1}^{ba} - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} Tc_{t-1}^{ba} - \widehat{\alpha_2^b} Tc_{t-1}^{ab})$$

Using daily values of transportation cost in equations 6 and 7 provide the time varying thresholds.

This approach allows one to consider the effect of different transference cost according to the transportation route (backhaul problem), which is more likely to happen and well described in transportation problems (Behrens and Picard 2011).

Finally, for each one of the four evaluated scenarios we obtain, before model fitting, the number of correct classification of cointegrated samples (expressed as percentage out of 500 samples), the number of correct classification of samples with two and three regimes using filtered (time varying threshold) and unfiltered prices (fixed threshold). After fitting models according to the known spatial price regimes, we compare the number of correct classifications of observations within and outside the band of inaction under the fixed and flexible threshold specifications and the estimated transference cost using a two sample t-test, as well as the mean speed of price adjustment using a one sample t-test.

Empirical Application

Our empirical application was carried out using daily farm gate hog prices of 6 different regions of the State of Parana, Brazil, namely: Cascavel, Curitiba, Maringa, Ponta Grossa, Londrina and Toledo. Time series price data from the period comprising Jan 2006 until November 2015 (2,575 observations) was obtained from Parana State Agriculture and Supplies Bureau website. These timeseries are specifically interesting to study because of the relevance of Hog production to the State of Parana, which is the second largest producer in volume, as well as because trade within the state is unrestricted, as long as legislation for transporting live animals is respected. Furthermore, transportation from and to each of the studied regions is feasible, and all regions have registered producing units and processing plants. To model time variation, we used a national freight cost index, which is elaborated by the Department of Economics of NTC&Logistica (National Association of Breakbulk Freight and Logistics from Brazil). This index is corrected monthly and accounts for variations in costs specifically regarding the transportation sector. Different indices are available according to transportation distance. In our study, we used indices for 50km, 400km and 500km transportation routes. As the index is reported monthly, we disaggregated the monthly index into daily observations using the Chow and Lin (1971) procedure with diesel prices for each region as a high frequency indicator (Chow and Lin 1971), and followed with procedures described in equations (5-8) to obtain filtered prices and time varying thresholds. This procedure allowed us to work with route specific disaggregated indices. Region specific diesel prices series were obtained from The National Agency for Oil, Natural Gas and Biofuels, Brazil.

Results For Monte Carlo Experiment

All generated filtered and unfiltered price series were found to be I(1). Sample classification according to results of Johansen, ADF and Hansen's test for samples generated under the assumption of stochastic exogenous transfer cost are shown in tables 1 and 2.

Table 1. Percentage of Samples generated under stochastic exogenous transfer costs assumption classified according to different test procedures.

True price regimes	Type	Johansen[1]	ADF [2]	BBC-test[3]	1 Inferred Regime[4]	2 Inferred regimes[5]	3 Inferred regimes[6]
DGP: Exogenous Stochastic Transfer Cost with Different Demand Elasticity							
3Z regimes	Unfiltered	0.107	0.069	0	0.236	0.266	0.498
	Filtered	0.105	0.060	0	0.204	0.262	0.534
2Z regimes	Unfiltered	0.016	0.011	-	0.394	0.147	0.459
	Filtered	0.016	0.011	-	0.399	0.174	0.427
DGP: Exogenous Stochastic Transfer Cost with Equal Demand Elasticity							
3Z regimes	Unfiltered	0.112	0.064	0	0.202	0.286	0.512
	Filtered	0.110	0.060	0	0.186	0.274	0.540
2Z regimes	Unfiltered	0.013	0.009	-	0.373	0.159	0.468
	Filtered	0.011	0.009	-	0.425	0.164	0.411

[1]Frequency of samples rejected for cointegration (trace statistic)
[2]Frequency of samples rejected for cointegration (non stationary z_t)
[3]Frequency of samples among [2] which failed to reject the null of linear no-cointegration
[4]Frequency of samples classified as having one stationary price regime (linear cointegration – Hansen test)
[5]Frequency of samples classified as having two price regimes (threshold cointegration with one threshold – Hansen test)
[6]Frequency of samples classified as having three price regimes (threshold cointegration with two thresholds – Hansen test)

Co-integration was rejected in 10-11% (Johansen test) and 6-7% (ADF test) of samples containing 3 price regimes, while more than 95% of samples containing 2 price regimes were correctly identified as cointegrated from both tests. None of the 3 regime price diferentials samples which were rejected for cointegration were still found to be I(1) after the BBC test. Results from the Hansen's tests correctly identified only approximately 50% of samples know to have 3 price regimes and at most 18% of samples know to have 2 price regimes. Lence et al. (2018) also reported a poor performance of the test in correctly identifying price regimes in a similar Monte Carlo experiment. Price diferentials obtained from filtered data showed slightly better results favoring correct regime specifications.

Table 2. Percentage of Samples generated under stochastic endogenous transfer costs assumption classified according to different test procedures

True price regimes	Type	Johansen[1]	ADF[2]	BBC-test[3]	1 Inferred Regime[4]	2 Inferred regimes[5]	3 Inferred regimes[6]
DGP: Endogenous Stochastic Transfer Cost with Different Demand Elasticity							
3Z regimes	Unfiltered	0.516	0.385	0	0.07	0.424	0.506
	Filtered	0.006	0.002	0	0.242	0.216	0.542
2Z regimes	Unfiltered	0.277	0.156	-	0.206	0.256	0.538
	Filtered	0.002	0.004	-	0.346	0.118	0.536
DGP: Endogenous Stochastic Transfer Cost with Equal Demand Elasticity							
3Z regimes	Unfiltered	0.447	0.305	0.119	0.056	0.428	0.516
	Filtered	0.006	0.002	0	0.288	0.218	0.494
2Z regimes	Unfiltered	0.177	0.093	-	0.244	0.226	0.530
	Filtered	0.002	0.002	-	0.334	0.123	0.543

[1]Frequency of samples rejected for cointegration (trace statistic)
[2]Frequency of samples rejected for cointegration (non stationary z_t)
[3]Frequency of samples among [2] which failed to reject the null of no-cointegration
[4]Frequency of samples classified as having one stationary price regime (linear cointegration – Hansen test)
[5]Frequency of samples classified as having two price regimes (threshold cointegration with one threshold – Hansen test)
[6]Frequency of samples classified as having three price regimes (threshold cointegration with two thresholds – Hansen test)

Samples generated under the assumption of endogenous transfer cost (table 2) were rejected for cointegration at a rate as high as 51% (Johansen test) and 38% (ADF test). Among this rejected samples, around 11% were still found to comprise only I(1) price regimes after the BBC test for the case of equal demand elasticities. Interestingly, less than 1% of filtered price series were rejected for cointegration. Identification of samples with 2 and 3 price regimes was only effective in around 25% and 53% of the samples, respectively. The use of filtered data slightly favored identification for 3 regime price samples under assumption of different demand elasticites, but also reduced correct identification of 2 price regime samples under both elasticities scenarios.

Given the poor performance of the tests, these results highlight the need for a deep understanding of the market to be analyzed, as well as the correct observation of economic theory and use of alternative model selection strategies while defining a methodology to evaluate price transmission and the assumption of the number of price regimes. Furthermore, the need to assume an arbitrary trimming value used for Hansen's test calculation may also affect the correct identification of different price regimes.

Estimation results for the three regime TVECM under the assumption of exogenous stochastic transfer cost are shown in tables 3 and 4.

Table 3. Summary of estimated and true parameters for three regimes TVECM under fixed and flexible threshold specifications – Samples generated under the assumption of exogenous stochastic transfer cost.

Parameter	Specification	Mean	S.D.	Median	[5% , 95%]
DGP: Exogenous Stochastic Transfer Cost with Different Demand Elasticity					
Violations of spatial price equilibrium	Fixed threshold	0.683***	0.197	0.714	[0.301 , 0.924]
	Flexible threshold	0.712***	0.181	0.750	[0.351 , 0.930]
	True value	0.556	0.114	0.555	[0.390 , 0.760]
Speed of adjustment[1]	Fixed threshold	0.830	0.274	0.800	[0.448 , 1.235]
	Flexible threshold	0.846	0.266	0.839	[0.453 , 1.270]
Inaction band	Fixed threshold	0.077	0.061	0.064	[0.019 , 0.174]
	Flexible threshold	0.074	0.067	0.058	[0.018 , 0.187]
	True Value	0.100	0.000	0.100	[0.099 , 0.101]
DGP: Exogenous Stochastic Transfer Cost with Same Demand Elasticity					
Violations of spatial price equilibrium	Fixed threshold	0.712***	0.192	0.747	[0.346 , 0.935]
	Flexible threshold	0.717***	0.187	0.764	[0.362 , 0.932]
	True value	0.544	0.108	0.538	[0.385 , 0.739]
Speed of adjustment[1]	Fixed threshold	0.824	0.258	0.823	[0.433 , 1.228]
	Flexible threshold	0.829	0.255	0.815	[0.459 , 1.244]
Inaction band	Fixed threshold	0.070	0.056	0.055	[0.014 , 0.192]
	Flexible threshold	0.069	0.058	0.054	[0.014 , 0.174]
	True Value	0.100	0.000	0.100	[0.099 , 0.101]

[1]True speed of adjustment is 1.

*** Denotes significant difference from the true value at 1%.

For the three price regimes case, we observe that the estimated number of observations falling in trade regimes (outside the spatial arbitrage inaction band) is significantly upward biased and skewed to the right. The speed of adjustment is roughly 15% lower than the true value, while the inaction band is also roughly 30% lower than the true value and skewed to the left, although those values were not significantly different from the true value. No noticeable differences were obtained when using filtered price data. Similar results were obtained in previous studies for fixed threshold specifications and may be caused by the limitations of the PL already reported (Greb et al. 2013; Lence et al. 2018).

Table 4. Summary of estimated and true parameters for two regimes TVECM under fixed and flexible threshold specifications – Samples generated under the assumption of exogenous stochastic transfer cost.

DGP: Exogenous Transfer Cost with Different Demand Elasticity					
Parameter	Specification	Mean	S.D.	Median	[5% , 95%]
Violations of spatial price equilibrium	Fixed threshold	0.329***	0.205	0.303	[0.076 , 0.712]
	Flexible threshold	0.491	0.285	0.486	[0.074 , 0.919]
	True value	0.492	0.039	0.500	[0.423 , 0.535]
Speed of adjustment[1]	Fixed threshold	0.933	0.371	0.981	[0.081 , 1.438]
	Flexible threshold	0.932	0.377	0.980	[0.094 , 1.485]
Transference cost	Fixed threshold	0.049	0.020	0.049	[0.017, 0.082]
	Flexible threshold	0.048	0.020	0.047	[0.018 , 0.081]
	True Value	0.050	0.000	0.050	[0.050 , 0.050]
DGP: Exogenous Transfer Cost with Same Demand Elasticity					
Violations of spatial price equilibrium	Fixed threshold	0.365***	0.212	0.331	[0.073 , 0.761]
	Flexible threshold	0.494	0.289	0.481	[0.083 , 0.930]
	True value	0.494	0.038	0.500	[0.425 , 0.535]
Speed of adjustment[1]	Fixed threshold	0.965	0.374	0.992	[0.237 , 1.530]
	Flexible threshold	0.946	0.352	0.984	[0.208 , 1.379]
Transference cost	Fixed threshold	0.048	0.020	0.047	[0.015, 0.083]
	Flexible threshold	0.048	0.020	0.048	[0.018 , 0.083]
	True Value	0.050	0.000	0.050	[0.050 , 0.050]

[1]True speed of adjustment is 1.

*** Denotes significant difference from the true value at 1% .

The two price regime scenario displayed similar results than the three price regimes. However, under the two regime specification, differences in the speed of price transmission and transaction cost estimation are less evident, although variation is still high. The number of observations compatible with spatial arbitrage was similar to the true value and less variable when using filtered price series, while the fixed threshold specification provided downwards biased estimates. Results were similar for both DGP assumptions.

Results obtained from samples generated under stochastic endogenous transfer cost (tables 5 and 6) show larger differences with regards to the true parameter values.

Table 5. Summary of estimated and true parameters for three regimes TVECM under fixed and flexible threshold specifications – Samples generated under the assumption of endogenous stochastic transfer cost.

DGP: Endogenous Stochastic Transfer Cost with Different Demand Elasticity					
Parameter	Specification	Mean	S.D.	Median	[5% , 95%]
Violations of spatial price equilibrium	Fixed threshold	0.693***	0.174	0.723	[0.376 , 0.917]
	Flexible threshold	0.689***	0.203	0.752	[0.279 , 0.926]
	True value	0.477	0.079	0.476	[0.350 , 0.617]
Speed of adjustment[1]	Fixed threshold	0.410**	0.284	0.346	[0.075 , 1.032]
	Flexible threshold	0.640	0.285	0.625	[0.216 , 1.146]
Inaction band	Fixed threshold	0.101***	0.065	0.088	[0.023, 0.208]
	Flexible threshold	0.060***	0.067	0.042	[0.010 , 0.171]
	True Value	0.148	0.036	0.138	[0.113 , 0.233]
DGP: Endogenous Stochastic Transfer Cost with Same Demand Elasticity					
Violations of spatial price equilibrium	Fixed threshold	0.687***	0.175	0.713	[0.370 , 0.917]
	Flexible threshold	0.701***	0.200	0.759	[0.314 , 0.923]
	True value	0.478	0.077	0.475	[0.350 , 0.610]
Speed of adjustment[1]	Fixed threshold	0.474*	0.274	0.431	[0.115 , 1.031]
	Flexible threshold	0.634	0.283	0.591	[0.220 , 1.099]
Inaction band	Fixed threshold	0.092***	0.056	0.083	[0.025, 0.193]
	Flexible threshold	0.056***	0.061	0.039	[0.010 , 0.155]
	True Value	0.138	0.031	0.129	[0.111 , 0.199]

[1]True speed of adjustment is 1.
***,**,* Denotes significant difference from the true value at 1%, 5% and 10%, respectively.

Percentage of observations identified in spatial arbitrage regimes were found to be systematically higher than the true value. Speed of adjustment was found to be downward biased and nearly 60% lower than the true value under fixed threshold specification, while transaction costs estimates were found to be downward biased for both specifications. Accounting for time variation markedly improved inference on speed of adjustment, but still provided biased results in terms of violations of spatial equilibrium and estimation of transaction costs.

Table 6. Summary of estimated and true parameters for two regimes TVECM under fixed and flexible threshold specifications – Samples generated under the assumption of endogenous stochastic transfer cost.

DGP: Endogenous Stochastic Transfer Cost with Different Demand Elasticity					
Parameter	Specification	Mean	S.D.	Median	[5% , 95%]
Violations of spatial price equilibrium	Fixed threshold	0.340***	0.191	0.317	[0.079 , 0.694]
	Flexible threshold	0.497	0.274	0.483	[0.091 , 0.917]
	True value	0.500	0.033	0.504	[0.460 , 0.537]
Speed of adjustment[1]	Fixed threshold	0.344**	0.331	0.245	[-0.031 , 0.992]
	Flexible threshold	0.883	0.302	0.896	[0.291 , 1.324]
Transference cost	Fixed threshold	0.170	0.064	0.170	[0.068, 0.282]
	Flexible threshold	0.170	0.062	0.164	[0.076 , 0.275]
	True Value	0.171	0.054	0.166	[0.093 , 0.269]
DGP: Endogenous Stochastic Transfer Cost with Same Demand Elasticity					
Violations of spatial price equilibrium	Fixed threshold	0.339***	0.196	0.311	[0.075 , 0.703]
	Flexible threshold	0.492	0.280	0.483	[0.087 , 0.919]
	True value	0.500	0.032	0.506	[0.462 , 0.535]
Speed of adjustment[1]	Fixed threshold	0.417*	0.350	0.349	[-0.009 , 1.056]
	Flexible threshold	0.902	0.337	0.900	[0.396 , 1.458]
Transference cost	Fixed threshold	0.147	0.059	0.143	[0.057, 0.261]
	Flexible threshold	0.150	0.058	0.144	[0.068 , 0.263]
	True Value	0.150	0.046	0.145	[0.085 , 0.232]

[1]True speed of adjustment is 1.

***,**,* Denotes significant difference from the true value at 1%, 5% and 10%, respectively.

Results for the 2 price regime specifications showed a similar pattern, except for the transaction cost estimation and the characterization of frequency of arbitrage opportunities: under flexible threshold specification, estimation of transaction costs, as well as number of observations outside the inaction band were found to be very close and significantly similar to the true values, while transaction cost estimate for the fixed threshold specification was similar to the true value, but speed of adjustment was downward biased in both DGP. The greatest and most important difference in terms of spatial arbitrage was observed for the speed of adjustment estimation, which was, for the flexible threshold specification, almost twice as high as the estimated under the fixed threshold specification.

Results demonstrate that, when transaction costs are more variable and even nonstationary (most of transaction cost generated series under endogenous transference cost were found to be nonstationary), the TVECM specification with a fixed threshold performs poorly in estimating transaction costs, speed of price adjustment and frequency of violations of spatial equilibrium in the presence of either one or two thresholds. Results were worse for the two threshold case, which was already demonstrated by Lence et al. (2018) and Greb et al. (2013) and may have been worsen due to the choice of the estimator. By specifying a time variable threshold using filtered price series, the model could be substantially improved, specially under the presence of one threshold, but also under the presence of two thresholds, although still did not provide satisfactory results under the latter case. Part of this limitations could be due to the use of the PL estimator, which was already shown to provide biased and more variable estimates (Greb et al. 2013). However, due to constraints in computing power, the replication for the study using the Bayesian estimator could not be completed and remains as a direction for future improvement.

Empirical Application Results

Our MC results revealed that a time varying TVECM which incorporated transaction cost information outperformed the fixed threshold specification. Therefore, this is the specification we used in our empirical application.

Summary statistics for the price series used, as well as route specific freight index series are shown in tables 7 and 8.

Table 7. Descriptive Statistics of Farm Gate Hog Prices (BRL$) for Each Studied Region

Region	Mean	SD[a]	CV[b]	Minimum	Maximum
Cascavel	2.336	0.672	0.288	1.000	4.020
Curitiba	2.518	0.781	0.310	1.000	4.850
Londrina	2.548	0.723	0.284	1.100	4.800
Maringa	2.561	0.732	0.286	1.100	4.850
Ponta-Grossa	2.494	0.760	0.305	1.000	4.850
Toledo	2.324	0.627	0.270	1.200	3.850

[a]Standard Deviation.
[b]Coefficient of Variation.

Table 8. Freight Cost Index for Each Specific Route

Route Freight Cost Index	Mean	SD[a]	CV[b]	Minimum	Maximum
Toledo-Cascavel	3.992	0.762	0.191	2.969	5.437
Toledo-Curitiba	4.036	0.742	0.184	3.033	5.478
Toledo-Londrina Toledo-PontaGrossa Toledo-Maringa	3.963	0.717	0.181	2.989	5.344
Cascavel-Toledo	3.992	0.762	0.191	2.969	5.435
Curitiba-Toledo	4.036	0.741	0.184	3.033	5.452
Londrina-Toledo	3.962	0.716	0.181	2.989	5.324
PontaGrossa- Toledo	3.963	0.717	0.181	2.982	5.342
Maringa-Toledo	3.962	0.715	0.180	2.989	5.347

[a]Standard Deviation.
[b]Coefficient of Variation.

Hog prices (filtered and unfiltered) as well as freight cost indices were found to be I(1) in levels (ADF-test and KPSS test).

Cointegration was further evaluated and confirmed for the filtered price series. Results for cointegration tests are reported in table 9.

Table 9. Results for Cointegration of Filtered Price Pairs

Price pair	Adf-test statistic[1]	Johansen (Trace statistic)[2]
Toledo-Cascavel	-6.616***	109.50***
Toledo-Curitiba	-6.252***	109.39***
Toledo-Londrina	-6.117***	100.17***
Toledo-Maringa	-6.336***	93.01***
Toledo-Ponta Grossa	-5.985***	86.30***

*** denotes the rejection of H_0 at 1% level.
[1] Engle-Granger Procedure – H_0 of I(1) price differences, H_1 of I(0) price differences.
[2]The number of maximum cointegrating vectors (r) =0.

Market structure for the evaluated regions allow us to assume that two thresholds and three regimes specification will better represent price transmission behavior. As transit between regions is unrestricted and there are both producing units and processing plants close to or located at each of the evaluated regions, we understand that transmission of prices may happen in both ways for each region pair. We have selected Toledo as the central market, as it concentrates most of hog production and processing in the state of Parana, and is a reference center nationwide. Cascavel is located 50km from Toledo and is the second largest producing center in the state. Ponta Grossa is also an important production and processing center (448km from Toledo) while Maringa (324km from Toledo), Londrina (413km from Toledo) and Curitiba (541km from Toledo) may be considered marginal markets in terms of production and processing, as compared to regions of Toledo, Cascavel and Ponta Grossa.

We have included estimation of a three regime, two thresholds TVECM using unfiltered data to compare differences in terms of inference while accounting for transaction costs difference (flexible versus fixed threshold assumption) throughout the evaluated time space. Estimation results are shown in table 10.

Table 10. Model Fit Results for Empirical Evaluations of Price Transmission for Each Eegion Pair.

	# of lags	**(Δp)**	ϑ_1	ψ_1	ϑ_2	ψ_2	ϑ_3	$\psi_2 - \psi_1$	**Adj[1]1**	**Adj2**	**Adj3**
Flexible Threshold	2	Tol.	-0.098 (0.154)	**-0.554**	**-0.065** (0.009)	**0.495**	**-0.932** (0.123)	1.049	1.779	0.082	0.932
		Cas.	**1.678** (0.119)		**0.017** (0.005)		0.000 (0.078)		[1]	[2569]	[4]
Fixed Threshold	2	Tol.	0.020 (0.042)	**-0.533**	**-0.064** (0.009)	**0.474**	**-0.430** (0.052)	1.007	0.327	0.077	0.476
		Cas	**0.347** (0.028)		**0.013** (0.005)		0.046 (0.034)		[11]	[2548]	[16]
Flexible Threshold	2	Tol.	**-0.553** (0.273)	**-0.833**	**-0.073** (0.008)	**0.343**	-0.074 (0.048)	1.176	0.551	0.071	0.069
		Cur.	-0.002 (0.272)		-0.002 (0.008)		-0.005 (0.046)		[1]	[2561]	[12]
Fixed Threshold	4	Tol.	**-0.042** (0.019)	**-0.501**	**-0.051** (0.009)	**0.062**	**-0.034** (0.008)	0.563	0.080	0.070	0.049
		Cur	**0.038** (0.019)		**0.019** (0.009)		**0.015** (0.007)		[47]	[1527]	[1001]
Flexible Threshold	2	Tol.	**-0.720** (0.143)	**-0.868**	**-0.065** (0.008)	**0.381**	**-0.592** (0.060)	1.249	0.744	0.073	0.605
		Lon.	0.024 (0.142)		0.008 (0.008)		0.013 (0.059)		[3]	[2563]	[8]
Fixed Threshold	4	Tol.	-0.017 (0.025)	**-0.614**	**-0.054** (0.009)	**0.061**	**-0.026** (0.007)	0.675	0.029	0.051	0.033
		Lon.	0.012 (0.024)		-0.003 (0.008)		0.007 (0.007)		[26]	[1569]	[980]
Flexible Threshold	4	Tol.	**-0.119** (0.016)	**-0.479**	**-0.034** (0.014)	**-0.059**	**-0.081** (0.013)	0.420	0.134	0.056	0.065
		Mar.	0.015 (0.014)		0.022 (0.012)		-0.016 (0.011)		[176]	[2013]	[385]
Fixed Threshold	4	Tol.	**-0.052** (0.009)	**-0.009**	-0.041 (0.214)	**0.003**	**-0.033** (0.008)	0.675	0.062	0.039	0.040
		Mar.	0.010 (0.007)		-0.002 (0.214)		0.007 (0.006)		[1299]	[20]	[1256]
Flexible Threshold	3	Tol.	-0.036 (0.035)	**-0.479**	**-0.057** (0.008)	**0.332**	**-0.377** (0.058)	0.811	0.156	0.061	0.378
		PG.	**0.120** (0.030)		0.004 (0.007)		0.001 (0.051)		[20]	[2543]	[11]
Fixed Threshold	5	Tol.	**-0.055** (0.020)	**-0.606**	**-0.045** (0.009)	**0.007**	**-0.028** (0.008)	0.613	0.096	0.057	0.041
		PG.	**0.041** (0.016)		0.012 (0.007)		**0.013** (0.006)		[28]	[1298]	[1249]

Notes. ϑ_i denotes the adjustment coefficient for the i-th regime. ψ_1, ψ_2 denote lower and upper threshold. Flexible thresholds are average recovered values reported. [1]Refers to total adjustment ($\vartheta_{ib} - \vartheta_{ia}$) and number of observations for each regime are between brackets. Bold values represent significant estimates.

Our estimation results show evidemce of threshold cointegration for all evaluated price pairs. Different transaction costs were determined for each price pairs, which were not necessarily proportional to distance between regions, e.g. we observed an inaction band ($\psi_2 - \psi_1$) of 1.049 for a short distance (50km) pair Toledo-Cascavel (Tol.-Cas.), related to an average minimum price difference (transaction cost) of BRL$0.523 to trigger price transmission between regions, while for a longer distance (324km) specific price pair, the average minimum transaction cost was of BRL$0.210. This observation may be explained by the market structure of the regions in question and the interpretation of thresholds not only as costs of transport and restrictions to trade, but also to the so called sunk costs of arbitrage, as discussed in O'Connell and Wei (2000) and mentioned in Ihle and Cramon-Taubadel (2008). Toledo and Cascavel, although being closely located, have their own market structure, with cooperatives and contracted producers, which may prevent entry from other parties and increase the potential transference cost needed to trigger price transmission.

Overall, results observed for the empirical application are similar to those evidenced in our MC study: when considering time-varying thresholds, number of samples falling in arbitrage price regimes (outside regimes) were lower, and adjustment to the long-run equilibrium was greater (faster) as compared to the fixed threshold scenario, which is related to more integrated markets. Given the non-stationarity of freight indices, it is unlikely that the assumption of constant thresholds will hold for our empirical case. Therefore, we understand that the estimation obtained under flexible threshold specification better represents the behavior of price transmission for the evaluated markets. Additionally, coefficients obseverd for regimes 1 and 3, and consequently, total adjustment are more reasonable in terms of spatial price transmission theory (favoring market integration), given the information on market structure.

The modelling alternative incorporating freight indices as a source of variation in transference cost sounds appealing with regards to spatial price transmission theory. Different modelling alternatives able to account for time variation in cointegration when data on transference cost is unavailable remains to be further developed.

Conclusion

Our results showed that in the presence of variable transaction costs, specially when such costs are more variable, route specific and or nonstationary, a fixed threshold specification of a band TVECM may provide misleading results regarding inference of transaction costs, speed of adjustment to the long run equilibrium and the frequency of violations to the spatial equilibrium. Specifying a variable threshold model improved inference and provided unbiased estimates of both adjustment to the long run equilibrium and estimation of transaction costs, specially when modelling transmission on presence of one threshold, as compared to the case of two thresholds. Further research to extend this work will involve the use of the regularized Bayesian estimator to estimate the threshold variables, as well as extension of the empirical applications (either evaluating more regions and different commodities). Other forms of modelling time variation on the absence of transference cost data may also help to improve inference, as it is unlikely that a fixed threshold will hold in empirical applications, specially when evaluating large time series data.

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