BERTRAND COMPETITION IN OLIGOPSONISTIC MARKET STRUCTURES - THE CASE OF THE INDONESIAN RUBBER PROCESSING SECTOR

Thomas Kopp

thomas.kopp@agr.uni-goettingen.de

Department für Agrarökonomik und Rurale Entwicklung, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 5, 37073 Göttingen

2017

Vortrag anlässlich der 57. Jahrestagung der GEWISOLA
(Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V.)
und der 27. Jahrestagung der ÖGA
(Österreichische Gesellschaft für Agrarökonomie)
„Agrar- und Ernährungswirtschaft zwischen Ressourceneffizienz und gesellschaftlichen Erwartungen"
Weihenstephan, 13. bis 15. September 2017

1 Introduction

Economic theory predicts the law of one price (LOP), which states that prices for a homogenous good at different locations differ only by the transaction costs of moving the good between them. In practice prices are usually somehow integrated, but violations of the LOP appear to be more the rule than the exception in various markets.

It is difficult to differentiate between the economic reasons for the violation of the LOP. Since one key assumption of the LOP is a competitive market structure, possible causes of these deviations are market power on the supply and/or demand side.

What is also often unclear is the dynamic nature of the relationship of prices between different stakeholders (e.g. Stackelberg vs. Nash). In many instances of asynchronic price movements, knowledge of dynamics between different price setters is crucial for formulating policy responses.

Isolating the reasons for deviations from the LOP is further complicated by the role that aggregation and averaging over time plays. Prices that do not change in a perfectly synchronised manner in the very short run (i.e. in the exact same moment) violate the LOP, while in the long run (e.g. on a yearly basis) only little differences may be observed.

This article therefore addresses the following questions a) how to find evidence for violations of the LOP, b) the implications of deciding for a certain level of temporal aggregation and c) how to generate insights on the dynamics between stakeholders.

In order to answer these questions, we first develop a theoretical model that provides an explanation for diverse prices. Then we test for violations of the LOP based on the synchronisation and staggering literature (Loy and Weiss, 2002) with a special focus on the role that aggregation over time plays. We generate insights on the dynamics that lead to violations of the LOP with a vector error correction model (VECM) and impulse response functions (IRFs).

We apply the procedure to rubber processing in Indonesia, where indications of market power have been found previously, both at the level of intermediaries (Kopp and Brümmer, 2015; Peramune and Budiman, 2007) and of processors (Kopp et al., 2014). What remains open in these analyses are the dynamics between the processors. We make use of a unique dataset of daily buying and selling prices of each factory.

To sum up, we develop a model that explains price differences due to a fixed cost component of changing buyers, and test for and explain violations of the LOP. An emphasis is set on the difference between levels of aggregation over time. The empirical application focuses on the interface between agricultural supply (rubber farmers and intermediaries) and processing (crumb rubber factories) and employs a unique dataset of spatially and temporally disaggregated data.

This paper is structured as follows: in the subsequent literature review, an overview of analyses on demand-sided market power is given, as well as information on the rubber processing market in the Jambi province. Section three is dedicated to model development and section four describes the empirical approach and methods. The data is presented in section five and results are presented and discussed in section six. Section seven concludes.

2 Literature review

2.1 Market power

Market power (MP) is a common phenomenon, especially on agricultural markets due to the sectors' specific characteristics, such as the geographical spread of many small firms (Hallet, 1981), the high levels of uncertainty (Runge and Myers, 1985) and output volatility (Nedergaard, 2006). Evidence for MP exists at all stages of agricultural value chains (Aker, 2010; Subramanian and Qaim, 2011). This paper focuses on demand sided MP, which is less studied, and - to be more specific - at the interface between agricultural supply and processing in a Bertrand framework of price setters.

Gabszewicz and Thisse (2000) summarise the four conditions for a competitive market: a) sufficient firm size and number, b) free entry and exit, c) product homogeneity and d) perfect information. This analysis focuses upon conditions a), c) and d). Product homogeneity means - in the case of demand-sided MP - that suppliers are indifferent to which processor they sell to. In economic terms this is equivalent to the absence of costs for switching the processor the farmer sells to. Non-fulfilment of the second condition suspends the theoretical Bertrand Paradox (Dufwenberg and Gneezy, 2000): market stakeholders are able to set discriminatory prices also in Bertrand games, where - in theory - even oligopols and oligopsons would set competitive prices.

2.2 Characteristics of the market for rubber processing in Jambi

In the Jambi province on Sumatra island (Indonesia) around 251 000 rubber farmers are connected to nine processors - so-called *crumb rubber factories* - via a complex and dense network of traders (Kopp and Brümmer, 2015). Five of the factories are located in the province's capital. They buy raw rubber from smallholders and middlemen, process *International Standard Rubber* (SIR20) and then sell it on the world market. The majority of the buyers are car tire manufacturers (Hadi and Budhi, 1997). According to the Jambi Service for Trade and Industry (*Dinas Pedagangan dan Industri*), around 33% of the buyers are located in India and 18% in China and Malaysia, respectively.

While the Jambinese rubber processors are price takers on the world market, they set prices on the domestic procurement market, which this analysis is centred on. The structure of this market is therefore a Bertrand oligopsony or Bertrand competition. The prices are set on a daily basis. Kopp et al. (2014) find on an aggregate level across all processors that they engage in intertemporal marketing margin manipulation by transmitting world price changes asymmetrically and thereby enjoying excess profits.

On the supply side, farmers are - at least in the short run – 'attached' to processors. This means with reference to the above-mentioned conditions c) and d) that there appears to be a fixed cost component when switching from one buyer to another. This is indicated by the stickiness of individual farmers' sales quantities to a specific factory after price changes. Switching costs include economic costs (getting information on the daily prices of all five factories in advance) or unobserved, informal relationships between farmer and factory. A comprehensive discussion of switching costs is provided in Klemperer (1995). No institutional limitations (such as contracts) hinder suppliers from selecting processors they sell to on a daily basis. If there was perfect information AND zero switching costs, the suppliers would select the processor that pays the highest price each day.

3 Model

In this paper we look at the interface between input supply (farmers, traders) and processing (factories) by analysing the time series of the prices processors pay to input suppliers. One of the outcomes of this market is the violation of the LOP.[1] This can be explained by non-zero switching costs of suppliers. If suppliers were able to choose a processor every day without incurring any costs, prices would be synchronised, otherwise only the factory paying the highest price on a given day would be able to source any input. Loy and Weiss (2002) seemingly contradict this hypothesis, arguing that violations of the LOP actually indicate a competitive market: "[p]arallel pricing behavior [*sic!*] could be an indicator of collusion [...]." (Loy and Weiss, 2002, p. 1). The solution to this seeming contradiction is the influence of aggregation over time; only if prices are systematically equal on each day over extensive periods of time can collusion be inferred.[2]

In the following section a model is developed to explain price differences due to switching costs. We focus on the supply side, since the processors are price takers on the world market, meaning that international demand is perfectly inelastic and equal to all processors. However, there might be more room for manoeuvre in the short run concerning the price setting, for example due to the further downstream processors' (tire makers) desire to keep a broad supply base. In order to account for this, we assume monopolistic competition output demand on the world market (Krugman et al., 2012), focussing at the interval within which the processors can exercise their limited market power:

$$O_D^i = \rho p_O^i \tag{1}$$

O_D^i is world demand for factory i's output and p_O is factory i's output price. Note that ρ is not denoted with a superscript, as it is equal for all firms.

One processor's production function is depicted in equation 2. As we account only for technological differences in rubber processing we employ a linear-limitational production function, and abstract from other variable inputs such as labour, electricity, etc. O_S^i is factory i's output supply and coefficient A^i denotes factory i's technical efficiency in transforming the rubber input into output quantities. O_S^i is assumed to move within the firms' maximum processing capacity.

$$O_S^i = A^i I_D^i \tag{2}$$

The aggregate revenue R of all input suppliers combined is given by equation 3.[3]

$$R = r_1 q p^i + r_2 q \bar{p} + r_3 q p^i - \int_0^{r_3 q} \gamma x + r_4 q \bar{p} - \int_0^{r_4 q} \delta y \tag{3}$$

p^i is the price the farmer receives at factory i and $\bar{p}$ the average price received at other factories. Each of the farmers provides the same quantity q. r_1 (resp. r_2) stands for the share of farmers that sell their produce to factory i (resp. to any other factory) and have so in the previous period. Both groups do not incur switching costs. r_3 is the share of farmers who sell to factory i and have sold to another factory in the previous period, and r_4 vice versa. Both groups incur a cost component for changing buyers, which we assume to be approximable by the continuous functions γx and δy, respectively. These switching costs are heterogeneous across farmers. We define θ^i as the share of farmers who have

[1] In the methodological section we show how to test for this with a specific focus on the implications of aggregation over time.

[2] More elaboration on this is given in section 4.

[3] As the farmers' output is stable due to long-term investment in rubber plantations we abstract from variable input costs and employ a revenue function instead of a profit function.

sold to factory i in the previous period, so $1-\theta^i$ are farmers who have sold to any other factory. ω^i is defined as the share of farmers who sell to factory i in the current period. This gives us equation 4:

$$R = q(\theta^i\omega^i p^i + (1-\theta^i)(1-\omega^i)\bar{p} + (1-\theta^i)\omega^i p^i + \theta^i(1-\omega^i)\bar{p}) - \int_0^{(1-\theta^i)\omega^i q} \gamma x - \int_0^{\theta^i(1-\omega^i)q} \delta y \quad (4)$$

The revenue-maximisation condition is realised by setting $\partial R/\partial\omega^i \stackrel{!}{=} 0$. Solving for ω^i leaves us with the maximising share ω^i of farmers that sell to factory i.

$$\omega^i = \frac{p^i - \bar{p} - \delta}{\delta + \gamma q(1-\theta^i)^2} \quad (5)$$

Considering that the supply that factory i receives $I^i_S = \omega^i Q$ with $Q = qF$ (Q is the total farm output and F the number of farmers), we get the input supply function for factory i in equation 6:

$$I^i_S = \frac{qF(p^i - \bar{p} - \delta)}{\delta + \gamma q(1-\theta^i)^2} \quad (6)$$

Market clearance at factory level is expressed by equations 7 and 8 for the input- and output markets, respectively.

$$I^i_S \stackrel{!}{=} I^i_D \quad (7)$$

$$O^i_S \stackrel{!}{=} O^i_D \quad (8)$$

Including equation 1 and 2 into 8 leads after reformulating to equation 9:

$$I^i_D = \frac{\rho p^i_O}{A^i} \quad (9)$$

Equation 9 shows that the processors' demand for agricultural input differs between factories only in their respective technologies, as all face the same global demand.

Including equation 9 and 6 into equation 7 and solving for the input price yields equation 10:

$$p^i_I = \rho p^i_O \frac{\delta + \gamma q(1-\theta^i)^2}{A^i qF} + \bar{p} + \delta \quad (10)$$

From equation 10 follows that the price each factory pays to its input suppliers depends - amongst its own technology - on the rubber supply it faces. The factories are only able to exercise market power if the switching costs γ and δ deviate from zero. The larger the supply base qF, the lower the price.

4 Methodology

4.1 Evidence for violation of the LOP

The literature on 'staggering vs. synchronisation' introduces an approach for assessing whether price changes occur in a synchronised way across firms or not (Dhyne and Konieczny, 2007; Fisher and Konieczny, 2000; Loy and Weiss, 2002) and is mainly employed for the analysis of price rigidity or 'stickiness' (Blanchard and Fischer, 1990). The basic idea is to provide evidence for whether or not prices change in parallel ('synchronized') within and across stores and products due to changes in the macroeconomic environment, such as inflation. In agricultural economics this procedure is usually applied at the retail level (Fisher and Konieczny, 2000; Kashyap, 1995; Lach and Tsiddon, 1996).

Price changes are 'synchronised' across products and/or stores of one/different retail chains if all prices change by the same share in one period. 'Staggering' means some prices change while others do not because firms are reluctant to adjust (some) prices to changes in the economic environment. Dhyne and Konieczny (2007) focus on spatial aggregation (across both goods and locations). They find that "the more aggregate the data, the closer the distribution to perfect staggering" is (Dhyne and Konieczny, 2007, p. 4). As we will show, the opposite is the case for aggregation over time.

We follow the empirical approach introduced by Fisher and Konieczny (2000) who set the standard deviations of instances of price changes in relation to two artificially constructed series: perfect staggering and perfect synchronisation. In order to do so, five binary variables are generated to indicate whether the price of each of the five processors deviates from the price in the previous period. Then we calculate the standard deviation of the perfect synchronization case and the observed data. There are six discrete possibilities for the share of prices that change in each period (0.0, 0.2, 0.4, 0.6, 0.8, 1.0). Under conditions of perfect synchronization, this share would always be 0 or 1. In the case of perfect staggering it would be the same as the average over the whole time of observation (Fisher and Konieczny, 2000).

To demonstrate the role that the levels of temporal aggregation play, analysis is carried out at different levels of aggregation. For the long-run perspective, we compare the average prices over the four years of observation. The short-run analysis is carried out with daily data. For the medium-term, weekly aggregates are generated as the summed price changes within the respective periods.

4.2 Evidence that prices affect each other, i.e. are integrated asymmetrically

4.2.1 VECM

As we will see, in dynamic settings of frequent price changes, weekly aggregation puts an end to this approach. We therefore continue the analysis with the estimation of a vector error correction model (VECM) and the resulting impulse response functions (IRFs).

Since the interdependencies between price developments are expected to be complex, the most general approach– a multivariate analysis – is employed to allow for all possible interactions. We estimate a VECM to generate insights into the horizontal (co-)integration of input prices and the vertical integration of output prices. In a subsequent step IRFs are calculated.

Since price data is often non-stationary, the Augmented Dickey-Fuller (ADF) test is employed, confirming this suspicion. The VECM is therefore specified with the first differences instead of price levels.

The long-run, co-integrating relationship between prices is given by equation 11. The notation is based on Ihle et al. (2012). p_t refers to the vector of input (i.e. buying) prices and the international output price at time t. β_0 is a vector of constants and matrix Θ_1 includes the coefficients of the linear combinations of all prices.

$$\ln p_t = \beta_0 + \Theta_1 lnp_t + \varepsilon \tag{11}$$

The vector of *error correction terms* (*ect*s) is defined as the residuals from equation 11.

$$ect_t := \ln p_t - \hat{\beta}_0 - \hat{\Theta}_1 \ln p_t \tag{12}$$

Equation 13 represents the error correction process:

$$\Delta \ln p_t = \alpha\, ect_{t-1} + \sum_{i=1}^{M} \Gamma_i \Delta \ln p_{t-i} + \eta \tag{13}$$

α is the vector of the adjustment coefficients, M stands for the number of lags and the matrix Γ_i includes the coefficients of short-run dynamics. η represents an error term.

The VECM is estimated with the Johansen method (Johansen, 1998). The size of the effect that the prices have on each other is given by three indicators: a) the *number* of coefficients that are significant at a 10%-level;[4] b) the *sum* of coefficients that are *significant* at a 10%-level;[5] and c) the *sum of all* coefficients. Only the coefficients that represent the effect on other variables are included in the indicators (i.e. not the reaction of a variable on its own past changes). The same is done for the size of the reaction that each price shows to changes in the other prices.

4.2.2 Impulse response analysis

IRFs were initially introduced by Sims (1980) and display each variable's response to changes ('shocks') in the system. This means that the variable is predicted as "a linear combination of past values" of the other variables (Sims, 1980, p. 34). This implies a *ceteris paribus* assumption, i.e. only the direct effect of a shock in variable A on variable B is accounted for. What is not captured is the effect of a shock in A which affects all other variables which in turn also affect B (Tsay, 2014, section. 2.10.1). The most common solution to this problem is an orthogonal transformation via the Cholesky decomposition (Tsay, 2014; Pesaran and Shin, 1997; Fackler and Goodwin, 2001). The drawback of this approach is the requirement of a non-data driven, a priori ordering of the variables according to the assumed sequence of the variables' effects on each other. Pesaran and Shin (1997) propose the generalised impulse response functions (GIRFs) to overcome the problem. This analysis reports the GIRFs.

5 Data

This analysis is based on individual buying prices of each of the five rubber processors in Jambi City on a daily basis. They were provided by the processors' association *Gapkindo* which calls each factory every morning for the price set that day. A price for each factory is available for every day between 1st January 2009 and 31st December 2012, excluding Sundays and public holidays. The world price is

[4]The effects are robust to changes in the desired level of significance, e.g. 1% or 5%.

[5]The effects are robust to changes in the desired level of significance, e.g. 1% or 5%.

available on a daily basis and is provided by Jakarta-based marketing company *PT. Kharisma*. These prices represent the average of the auctioning of Standard Indonesian Rubber (SIR20) on each day rubber was sold. Table 1 provides an overview of the six time-series. The combined data provides 701 days of observations for both selling and buying prices.

Table 1: Descriptives of price series.

6 Results and discussion

6.1 Synchronisation

6.1.1 Short run

Descriptives of instances of price changes show that Factory 5 pays the highest prices and changes prices most often. Factory 1 changes prices often, too, while Factory 2 pays the lowest prices and seldom changes prices positively but often negatively. Factory 4 changes prices least often. There seem to be substantial deviations from the LOP in the short-run.[6]

The average of total price changes are 237, 212, 229, 189, and 237, respectively, out of 705 which gives an average of 221 out of 705 observations or 0.31. This provides a hypothetical standard deviation (SD) of 0.464 in the case of perfect synchronization. The share of price changes per point in time in the actual data exhibits an SD of 0.30. The observed SD is therefore 2/3 of the level of perfect synchronisation, which suggests that prices are not synchronised on a daily basis. This high frequency (daily) motivates the comparison to a medium level of aggregation.

6.1.2 Medium run

For the weekly aggregation, the dummy indicating a price change is set to one if a processor changes the price at least once during the week, i.e. it is zero if $p_t = p_{t-1} = p_{t-2} = ... = p_{t-6}$. In 71% of all weeks, every processor changes prices at least once. In 16% all but one processor change prices at least once. In 13% at least two processors change price at least once. The mean is 0.9 and the SD 0.18. We observe therefore nearly perfect synchronisation on a weekly basis. (On a monthly basis, the synchronisation is perfect.) It must be noted, however, that this approach only captures whether a price has changed or not and does not suggest the magnitude. For a more profound understanding of the dynamics between the processors error correction analysis is employed in the next section.

6.1.3 Long run

The aggregation over four years (see Table 2) shows that the margins of the five processors - calculated as the difference between the mean input prices and the world market output prices - vary substantially. These systematic differences in the margins are as follows: processor 5 pays on average the highest prices for the input of raw rubber, while processor 2 pays the lowest. The highest and lowest mean margin differ by 5.9%.

Table 2: Long-run differences between margins.

[6] A table is available on demand.

6.2 VECM and IRFs

The AIC suggests a lag length of 3. According to the results of the ADF test the null hypothesis of a non-stationary process could not be rejected at a confidence level of 1%.

The results of the VECM are reported in table 5. Tables 3 and 4 report the indicators, summarising the effect of the prices on another.

Table 3: Effects of prices on others and Table 4: Effects by other prices.

The three indicators provide a perfectly consistent picture concerning the effect that each price receives by others (table 4). It is consistent with some exceptions for one price's impact on the others (table 3). Prices 3 and 5 are the most influential across all indicators and 2 is the least influential (table 3). Price 1 is influenced the most and 5 the least (table 4). This suggests that price 5 leads (influences others most and is influenced the least) while price 1 reacts most and influences least.

IRFs are displayed in figure 1. They show that differences exist rather between rows than between columns. This means that prices vary rather in the influence on others than in the influence by others. Again, price 5 affects other prices most strongly and persistently. Reactions to changes in price 2 occur with a delay of one period and reactions to price 3 occur in the third period.

Figure 1: Generalised impulse response functions.

6.3 Discussion

As equation 10 shows, the different supply elasticities each processor faces are a necessary condition for the differences in price levels in the long-run. Differences in the demand elasticity of the factories may exist too, and can only be caused by the processors' technology as they face the same demand on the world market. The short-run results show a deeply unsynchronised price setting behaviour, which rejects the idea of collusion between stakeholders.

The results of the VECM and IRFs suggest that factory 5 - which pays the highest price on average (see table 1) - tends to adjust prices first with the other prices following subsequently. Factory 1 is last. One possible explanation is asymmetric information: Roy et al. (1994) find the quality of demand forecasts as the determinant factor of Stackelberg leadership in one market of the US automotive sector. The equivalent explanation in this case is that processor 5 produces the most credible forecasts of the rubber supply base in the province and processor 1 the weakest.

7 Conclusion

In this paper we find indications for violations of the LOP in Jambi province's raw rubber market. These violations can be explained by the costs of switching processor, from the upstream suppliers' point of view. The estimation of a VECM and calculation of IRFs clearly indicate that one processor takes the role of price leader and another one of follower.

Caution must, however, be paid to this interpretation, as Stackelberg leadership is not necessarily reflected in price dynamics but rather in absolute price levels. Comparing the observed price levels with hypothetical levels under the assumption of perfect competition would be rewarding, but would also encompass an estimation of the whole demand-and-supply systems which would in turn require detailed data on traded quantities.

References

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, 2:46–59.

Blanchard, O. and Fischer, S. (1990). Lectures on Macroeconomics. *MIT Press*, 12(3):514.

Dhyne, E. and Konieczny, J. (2007). Temporal distribution of price changes: Staggering in the large and synchronization in the small. *National Bank of Belgium Working Paper*.

Dufwenberg, M. and Gneezy, U. (2000). Price competition and market concentration: an experimental study. *International Journal of Industrial Organization*, 18(1):7–22.

Fackler, P. L. and Goodwin, B. K. (2001). Spatial Price Analysis. In Gardner, B. and Rausser, G., editors, *Handbook of Agricultural Economics*, volume 1, chapter 17, pages 971–1024. Elsevier.

Fisher, T. C. and Konieczny, J. D. (2000). Synchronization of price changes by multiproduct firms: evidence from Canadian newspaper prices. *Economics Letters*, 68(3):271–277.

Gabszewicz, J. and Thisse, J.-F. (2000). Microeconomic theories of imperfect competition. *Cahiers d'économie politique*, 37(1):47–99.

Hadi, P. and Budhi, G. (1997). Analysis of the economic efficiency and comparative advantage of the sumatran smallholder rubber using "PAM" method. *Southeast Asia Policy Research Working Paper, No. 4*.

Hallet, G. (1981). *The Economics of Agricultural Policy*. Basil Blackwell, Oxford, 2nd edition.

Ihle, R., Brümmer, B., and Thompson, S. R. (2012). Structural change in European calf markets: Decoupling and the blue tongue disease. *European Review of Agricultural Economics*, 39:157–179.

Johansen, S. (1998). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press, Oxford.

Kashyap, A. K. (1995). Sticky Prices: New Evidence from Retail Catalogues. *Quarterly Journal of Economics*, 110:245–274.

Klemperer, P. (1995). Competition when Consumers have Switching Costs - an Overview with Applications to Industrial-Organization, Macroeconomics, and International-Trade. *Review of Economic Studies*, 62(4):515–539.

Kopp, T., Alamsyah, Z., Fatricia, R. S., and Brümmer, B. (2014). Have Indonesian Rubber Processors Formed a Cartel? Analysis of Intertemporal Marketing Margin Manipulation. *CRC990 Discussion Paper Series: Efforts Discussion Paper 3*.

Kopp, T. and Brümmer, B. (2015). Moving Rubber to a Better Place – and Extracting Rents from Credit Constrained Farmers along the Way. *CRC990 Discussion Paper Series: Efforts Discussion Paper 9*.

Krugman, P. R., Obstfeld, M., and Melitz, M. J. (2012). *International economics : theory and policy*. Pearson Addison Wesley, Boston.

Lach, S. and Tsiddon, D. (1996). Staggering and Synchronization in Price-Setting: Evidence from Multiproduct Firms. *American Economic Review*, 86(5):1175–1196.

Loy, J.-P. and Weiss, C. (2002). Staggering and synchronisation of prices in a low-inflation environment: Evidence from German food stores. *Agribusiness*, 18(4):437–457.

Nedergaard, P. (2006). Market failures and government failures: A theoretical model of the common agricultural policy. *Public Choice*, 127:393–413.

Peramune, M. R. and Budiman, A. (2007). A Value Chain Assessment of the Rubber Industry in Indonesia. U.S. Agency for International Development. *Project Report, USAid*.

Pesaran, M. H. and Shin, Y. (1997). Generalized Impulse Response Analysis in Linear Multivariate Models. *Economic Letters*, 58(1):17–29.

Roy, A., Hanssens, D. M., and Raju, J. S. (1994). Competitive Pricing by a Price Leader. *Management Science*, 40(7):809–823.

Runge, C. and Myers, R. (1985). Shifting foundations of agricultural policy analysis: welfare economics when risk markets are incomplete. *Journal of Agricultural Economics*, 67(5):1010–1016.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1):1–48.

Subramanian, A. and Qaim, M. (2011). Interlocked village markets and trader idiosyncrasy in rural India. *Journal of Agricultural Economics*, 62:690–709.

Tsay, R. S. (2014). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley & Sons, Hoboken, USA.

Table 1: Descriptives of price series.

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_pBuy1	1186	10.10587	0.3500532	9.305651	10.70324
ln_pBuy2	1186	10.10194	0.3435944	9.350102	10.69195
ln_pBuy3	1186	10.09973	0.3530825	9.230143	10.70324
ln_pBuy4	1186	10.10578	0.3495077	9.350102	10.70324
ln_pBuy5	1186	10.10754	0.3478758	9.305651	10.70324
ln_pWorld	701	10.25528	0.3090773	9.561649	10.84005

Table 2: Long run differences between margins.

Variable	Mean	Std. Dev.	Min	Max
margin1	3.166.977	1.466.543	-1.291.311	14493.43
margin2	3.341.977	1.614.227	-6.495.039	14169.71
margin3	3.307.841	1.489.332	-2.913.105	12074.13
margin4	3.183.478	1.646.409	-2.291.311	12169.71
margin5	3.152.317	1.454.605	-2.913.105	12074.13

701 Observations

Negative margins occur because the transmission may take place with a delay.

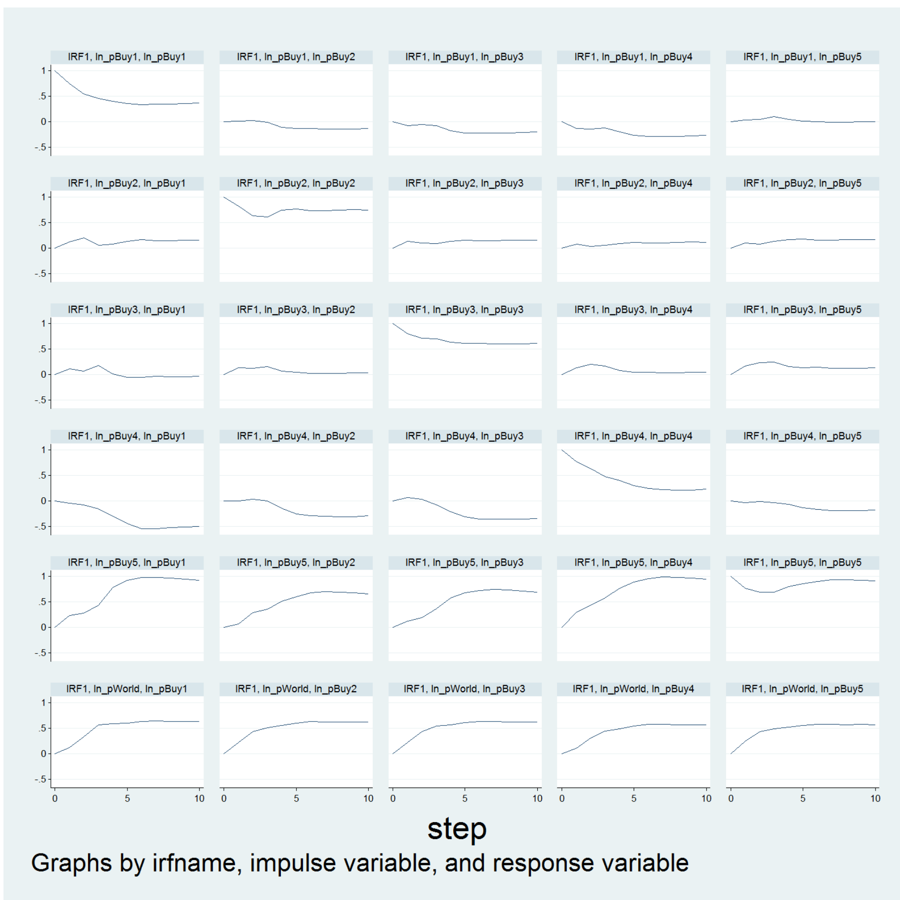
Table 3: Effects of prices on others.

Variable	D_ln_pBuy1	D_ln_pBuy2	D_ln_pBuy3	D_ln_pBuy4	D_ln_pBuy5
Number of significant coeff.	8	5	10	5	8
Rank A	**2-3**	**4-5**	**1**	**4-5**	**2-3**
Sum of significant coeff.	0.7518	0.5923	1.6054	0.6488	1.46
Rank B	**3**	**5**	**1**	**4**	**2**
Sum of all coeff.	0.83991	0.76856	1.7577	1.0315	1.7884
Rank C	**4**	**5**	**2**	**3**	**1**

Table 4: Reactions to other prices.

Variable	D_ln_pBuy1	D_ln_pBuy2	D_ln_pBuy3	D_ln_pBuy4	D_ln_pBuy5
Number of significant coeff.	9	6	8	8	5
Rank D	**1**	**4**	**2-3**	**2-3**	**5**
Sum of significant coeff.	1.698	0.662	1.1104	0.9706	0.6173
Rank E	**1**	**4**	**2**	**3**	**5**
Sum of all coeff.	1.8737	1.1243	1.2131	1.1432	0.83177
Rank F	**1**	**4**	**2**	**3**	**5**

Figure 1: Generalised impulse response functions.



The columns of the graphs display the shock of all other variables on the same variable. The rows show the effect of one variable on all others. On the diagonals lie therefore the reactions of prices to shocks from themselves.

Table 5: VECM results.

VARIABLES	(1) D_ln_pBuy1	(2) D_ln_pBuy2	(3) D_ln_pBuy3	(4) D_ln_pBuy4	(5) D_ln_pBuy5	(6) D_ln_pWorld
L._ce1	-0.196***	-0.0880***	-0.127***	-0.161***	0.0265	-0.0591
	(0.0329)	(0.0276)	(0.0267)	(0.0247)	(0.0248)	(0.0389)
LD.ln_pBuy1	-0.0728	0.0878**	0.0384	0.0280	-0.00213	-0.00498
	(0.0491)	(0.0413)	(0.0399)	(0.0369)	(0.0370)	(0.0581)
L2D.ln_pBuy1	-0.0660	0.122***	0.126***	0.0933***	0.0269	0.00302
	(0.0466)	(0.0392)	(0.0379)	(0.0350)	(0.0351)	(0.0552)
L3D.ln_pBuy1	-0.0283	0.0677*	0.0824**	0.108***	0.0724**	-0.0456
	(0.0448)	(0.0377)	(0.0365)	(0.0337)	(0.0338)	(0.0530)
LD.ln_pBuy2	0.150***	-0.162***	0.151***	0.0925**	0.0985**	0.0155
	(0.0531)	(0.0447)	(0.0432)	(0.0399)	(0.0400)	(0.0628)
L2D.ln_pBuy2	0.122**	-0.237***	0.0245	-0.0197	-0.00473	0.0920
	(0.0530)	(0.0446)	(0.0432)	(0.0399)	(0.0400)	(0.0628)
L3D.ln_pBuy2	-0.0243	-0.114**	0.0351	0.0251	0.0382	0.178***
	(0.0530)	(0.0446)	(0.0431)	(0.0398)	(0.0399)	(0.0627)
LD.ln_pBuy3	0.193***	0.175***	-0.140***	0.205***	0.158***	-0.128*
	(0.0652)	(0.0548)	(0.0530)	(0.0490)	(0.0491)	(0.0771)
L2D.ln_pBuy3	0.0734	0.0930	-0.0770	0.175***	0.162***	-0.107
	(0.0674)	(0.0567)	(0.0549)	(0.0507)	(0.0508)	(0.0798)
L3D.ln_pBuy3	0.195***	0.108*	-0.00220	0.0837*	0.130***	-0.0955
	(0.0653)	(0.0550)	(0.0532)	(0.0491)	(0.0492)	(0.0773)
LD.ln_pBuy4	0.153**	0.0828	0.189***	-0.0825*	-0.0485	0.0990
	(0.0612)	(0.0515)	(0.0498)	(0.0460)	(0.0461)	(0.0724)
L2D.ln_pBuy4	0.116*	0.0935*	0.101**	-0.0412	-0.0496	-0.0182
	(0.0612)	(0.0515)	(0.0498)	(0.0460)	(0.0461)	(0.0724)
L3D.ln_pBuy4	0.0739	0.0795	0.0206	-0.0853*	-0.0557	-0.176**
	(0.0581)	(0.0489)	(0.0473)	(0.0437)	(0.0438)	(0.0688)
LD.ln_pBuy5	-0.234***	-0.137*	-0.177**	-0.0952	-0.169**	-0.0769
	(0.0895)	(0.0753)	(0.0728)	(0.0673)	(0.0674)	(0.106)
L2D.ln_pBuy5	-0.324***	0.0250	-0.187***	-0.113*	-0.0973	0.0885
	(0.0847)	(0.0712)	(0.0689)	(0.0637)	(0.0638)	(0.100)
L3D.ln_pBuy5	-0.239***	-0.116*	-0.151**	-0.100*	-0.112*	-0.00432
	(0.0794)	(0.0668)	(0.0646)	(0.0597)	(0.0599)	(0.0940)
LD.ln_pWorld	0.0882**	0.203***	0.197***	0.0899***	0.245***	0.107**
	(0.0365)	(0.0307)	(0.0297)	(0.0275)	(0.0275)	(0.0432)
L2D.ln_pWorld	0.0966**	0.160***	0.147***	0.0804***	0.160***	-0.0724
	(0.0383)	(0.0323)	(0.0312)	(0.0288)	(0.0289)	(0.0454)
L3D.ln_pWorld	0.147***	0.0262	0.0756**	0.0274	0.0356	0.00561
	(0.0384)	(0.0323)	(0.0313)	(0.0289)	(0.0290)	(0.0455)
Constant	-0.000220	0.000143	7.06e-05	-6.35e-05	0.000527	0.000772
	(0.000690)	(0.000580)	(0.000562)	(0.000519)	(0.000520)	(0.000817)
Observations	697	697	697	697	697	697

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1